

Improved Transportation Networks Facilitate Adaptation to Pollution and Temperature Extremes

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Abstract

The social costs of pollution and climate change hinge critically on humans' ability to adapt. Based on transaction records from the world's largest payment network, this research compiles daily travel flows and documents that China's rapid expansion of high-speed railways (HSR) facilitates the use of intercity travel as an effective adaptation strategy. Access to HSR reduces travelers' exposure to extreme air pollution and temperature by 7% and 10%, leading to substantial health benefits. These reductions are attributed to both contemporaneous responses to unexpected adverse conditions and also longer-horizon changes in travel patterns.

Keywords: Air Pollution, Adaptation, Climate Change, Transportation Infrastructure

JEL Classification Codes: O18, Q53, Q54, R41

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1 Introduction

Environmental degradation and climate change pose growing risks to humans.¹ The social costs of pollution and climate change depend crucially on the extent to which humans can adapt to extreme environmental conditions. While long-term migration could be an effective strategy to adapt to a changing environment (Banzhaf and Walsh, 2008; Deschenes and Moretti, 2009; Kahn, 2010; Freeman et al., 2019), it entails significant costs especially for residents in developing countries with severe market frictions and institutional constraints. In contrast, short-term intercity travel may offer a more practical and affordable adaptation strategy to reduce the negative effects of local environmental conditions. Indeed, “haze-avoidance tourism” and “smog refugees” have become important trends in intercity travel in China with the advent of cheap and fast transportation modes (Arlt, 2017; Sharkov, 2016; Chen et al., 2021).

This study provides to our knowledge the first analysis of how improved transportation infrastructure facilitates behavioral changes in response to adverse environmental conditions. Our analysis uses a unique data set of daily travel flows between all city-pairs in China, constructed based on credit and debit card transactions from the world’s largest inter-bank payment network (Union-Pay). The estimation takes advantage of the unprecedented and staggered expansion of high-speed railways (HSR) in China shown in Figure A1. Since 2008, China has built by far the largest HSR network in the world, reaching nearly 38,000 km by 2020 and more than twice as long as the HSR network of all other countries combined. In the meantime, with rapid economic growth and heavy reliance on fossil fuels, air pollution has become one of the most pressing challenges in large urban centers in China (Greenstone et al., 2021; The Health Effects Institute, 2019). Many Chinese cities regularly rank among the most polluted cities in the world. In addition, climate change has increased both the frequency and the intensity of heat waves, exacerbated by the heat island effect in mega cities (Ye et al., 2014; Luo and Lau, 2017). Pollution and temperature extremes raise serious concerns given the size of the affected population in China, and technological or financial constraints for adaptation, especially for the urban poor.

Our analysis uses an empirical framework that combines the difference-in-differences and triple-difference strategies: comparing the exposure to extreme air pollution and temperature among travelers from cities with HSR access to that among travelers from cities without such access, under different environmental conditions in home cities. The causal effect of HSR connection on adaptation to environmental extremes is established based on the variation in travel patterns and environmental

¹ A large literature has documented various impacts of pollution and climate change on economic growth (Nordhaus, 2006; Dell et al., 2012; Carleton and Hsiang, 2016), social stability (Burke et al., 2010; Hsiang et al., 2013), and health (Deschenes et al., 2009; Currie and Neidell, 2005; Chen et al., 2013; Landrigan et al., 2018) among others.

conditions by leveraging the expansion of the HSR network. The key identification assumption is that the timing of a city's connection to HSR network is not driven by or in response to unobserved factors that affect daily variation in travel patterns. After controlling for a rich set of fixed effects including city fixed effects, day-of-sample fixed effects, the date when a city connects to the HSR network is assumed to be random. The event study analysis shows no clear trend in the outcome variable before HSR connection, supporting our identification assumption.

Our results show that China's rapid expansion of the HSR network has facilitated the adaption to environmental extremes: residents can more easily travel to destinations that have better environmental conditions. When home cities are subject to pollution extremes, travelers from cities without HSR access are 12.8% more likely to experience these detrimental conditions than those from cities with HSR connection. When home cities encounter temperature extremes, travelers without HSR access are 27.7% more likely to expose to temperature extremes than those with HSR access. In comparison, when home cities are not subject to pollution or temperature extremes, travelers' exposure to environmental extremes is similar regardless of the access to the HSR network. Longer travel distances as a result of the HSR expansion explain 43% of the reduction in exposure to extreme pollution and 50% of the reduction in exposure to extreme temperatures. The remaining effect can be attributed to travelers' ability to leverage HSR connection and deliberately choose destination cities with better environmental conditions, conditioning on the distance to the origin city. Finally, longer term adaptation to predictable environmental conditions in travel patterns before and after HSR access explains 71% of the reduction in extreme pollution exposure and 83% of the reduction in extreme temperature exposure. The remaining impacts are attributed to contemporaneous responses to environmental extremes. Altogether, these reductions in exposure to environmental extremes entail substantial health benefits through reduced mortality.

This study contributes to two stands of literature. First, a large literature examines the benefit of transportation networks through promoting the mobility of people and goods ([Behrens and Pels, 2012](#); [Donaldson, 2018](#); [Bernard et al., 2019](#)), fostering market integration ([Baum-Snow, 2010](#); [Zheng and Kahn, 2013](#); [Faber, 2014](#); [Donaldson and Hornbeck, 2016](#); [Lin, 2017](#)), and facilitating knowledge sharing ([Agrawal et al., 2017](#); [Dong et al., 2020](#)). Leveraging the rapid expansion of the HSR network in China and high-frequency data on intercity travel, our paper adds to this literature by demonstrating how improved transportation networks can facilitate adaptation to air pollution and temperature extremes. Second, this paper contributes to the literature on adaptation to adverse environmental conditions such as climate change and local pollution. Studies show that behavioral changes play an important role in mitigating the risks associated with air pollution and climate change through reducing outdoor activities ([Graff Zivin and Neidell, 2014](#); [Moretti and Nei-](#)

dell, 2011a; Barwick et al., 2020), increasing defensive investments (Barreca et al., 2016; Ito and Zhang, 2020; Zheng and Kahn, 2017; Zhang and Mu, 2018), as well as changing residential locations (Banzhaf and Walsh, 2008; Bayer et al., 2009; Deschenes and Moretti, 2009; Kahn, 2010; Black et al., 2011; Chen et al., 2017; Freeman et al., 2019). Our study demonstrates that improved transportation infrastructure renders short-term intercity travel as a practical adaptation strategy to mitigate the negative effects of adverse environmental conditions.

2 Data and Descriptive Evidence

Intercity Travel Flow We construct daily bilateral passenger flows across cities by leveraging the universe of credit and debit card transactions conducted through the UnionPay network. UnionPay is the only inter-bank payment network in China, and the largest network in the world. The database covers 34 trillion *yuan* (\$4.9 trillion) of annual economic activities from 2.7 billion cards from 2011 to 2016. The date and location information of transaction records allows us to trace traveler flows between city pairs on a daily basis. This enables us to overcome a major data limitation in the literature where high-frequency measures of city-pair travel flows at the national level are unavailable until very recently with the proliferation of mobile positioning data.

Our traveler flow is calculated from a 1% card sample, which includes the stream of transactions made by 270 million cards during 2013-2016. We focus on offline transactions, for which the cardholder is physically present at the merchant’s location. A trip occurs if the city of the transaction differs from the home city.² Using credit and debit cards is a popular payment method and accounted for over 40% of national retail consumption during our data period. Electronic payment methods such as Wechat and Alipay were limited during our data period, accounting for less than 2% of aggregate retail sales in 2013 and about 10% in 2016.

Air Pollution and Temperature Data Air quality data come from China’s Ministry of Ecology and Environment (MEE, formerly the Ministry of Environmental Protection). From 2013, ground-level monitoring stations were installed or upgraded in over 1600 sites throughout China and hourly air quality data from these monitoring stations are publicly reported on the MEE website. The number of monitoring stations and cities covered increased steadily from 1003 stations in 159 cities in 2013 to 1615 stations in 367 cities in 2015. We calculate the daily concentration of PM_{2.5} at the city-daily level by averaging hourly readings from monitoring stations within a city. The nationwide average concentration of PM_{2.5} during the 2013-2016 period was 48 $\mu\text{g}/\text{m}^3$ (with a standard devi-

²We limit our sample to trips up to seven days. The majority of trips last for one to two days.

ation of $41 \mu\text{g}/\text{m}^3$), much higher than the annual air quality standards of $12 \mu\text{g}/\text{m}^3$ set by the U.S. Environmental Protection Agency and $35 \mu\text{g}/\text{m}^3$ by China's MEE.

We collect hourly temperature data from NOAA's Integrated Surface Database (ISD) for all weather stations in China. ISD includes 408 weather stations in China that has complete time series from 2013 to 2016. We match each city to the nearest weather station in ISD using their geographical coordinates. All timestamps in the dataset are adjusted by an 8-hour lead to offset the difference between Beijing Time and Greenwich Mean Time. We average over hourly readings to obtain the daily average temperature.

HSR Network The expansion of the HSR network has been unprecedented in China (Figure A1). While the country had no HSR at the beginning of 21st century, the total lengthen of HSR reached 37,900 km by 2020, linking all of its major cities. The rapid expansion of the HSR network has led to one of the most significant increases in human mobility in modern history: the passenger trips via HSR increased from 290 million to 2.3 billion during 2010-2019.

We gather information on the opening dates of HSR station from government official reports. If a city has multiple HSR stations, we use the date when the first HSR station started operation in the city. For HSR connections, we use national railway timetables which report the origin and destination cities for all train services on a given day. The number of connections via HSR is defined as the number of distinct cities that are directly connected to the origin city via HSR. China's airport network also expanded during our sample period. To control for the expansion of the air transport network, we collect data on airport connections based on monthly reports from the Official Aviation Guide that cover schedules on all of China's domestic flights from 2013 to 2016.

Figure 1 provides the first descriptive evidence on the benefit of improved transportation networks in mitigating households' pollution exposure. The top panel plots travelers' pollution exposure against the corresponding day's pollution in the home city. Travelers' pollution exposure is defined as the weighted average of the daily pollution levels across destination cities, where the weights are daily origin-destination traveler shares. Travelers based in cities with active HSR connections experience a statistically significant lower pollution exposure than those without HSR connections throughout the entire spectrum of home pollution levels, with a widening gap as home conditions deteriorate. When the home city suffers from hazardous pollution – $\text{PM}_{2.5}$ higher than $100 \mu\text{g}/\text{m}^3$ (the 90th percentile), the wedge between travelers from HSR cities and those from non-HSR cities exceeds $9 \mu\text{g}/\text{m}^3$ and can reach as high as $30 \mu\text{g}/\text{m}^3$.

Table 1 provides the second piece of descriptive evidence by further tabulating travel patterns – the share of traveler flows to destination cities with different pollution quintiles – for each pollution

quintile of the home city. Panels (a) and (b) present the statistics for HSR city travelers and non-HSR city travelers, respectively, and Panel (c) reports their difference. Consistent with the evidence in Figure 1, the last column of Panel (c) shows that intercity travelers from cities with HSR access experience a lower pollution exposure than travelers from cities without HSR across all five quintiles of home pollution. The gap increases monotonically with home pollution levels. While the difference is a modest $0.44 \mu\text{g}/\text{m}^3$ when the home city's pollution is in the lowest quintile, the gap enlarges to $8.35 \mu\text{g}/\text{m}^3$ at the highest quintile. Much of this reduction is driven by a noticeably smaller fraction of HSR city travelers who visit dirty destinations (47.3%) than non-HSR city travelers (55.1%).

Appendix Table A1 and Section A provide the summary statistics of key variables and additional descriptive evidence. Results for temperature exposure are similar and are shown in Appendix Figure A2 and Table A2. These patterns present strong suggestive evidence that travelers benefit from improvements in passenger transportation infrastructure by experiencing reduced exposure to adverse environmental conditions.

3 Empirical Framework

Our empirical framework combines the difference-in-differences (DID) and triple-differences to examine how improved transportation infrastructure affects travelers' exposure to environmental extremes:

$$TravExpo_{it} = \beta_1 Expo_{it} + \beta_2 HSR_{it} + \beta_3 HSR_{it} \times Expo_{it} + X_{it} + \mu_i + \delta_t + \varepsilon_{it}. \quad (1)$$

The outcome variable of our analysis, travelers' exposure, $TravExpo_{it}$ captures the average exposure to environmental (either air pollution or temperature) extremes for travelers from city i on day t . It is defined as a weighted average of environmental conditions at the destination cities, where the weight for a destination city is the share of travelers from a given city to the corresponding destination city:

$$TravExpo_{it} = \sum_{j \neq i} Expo_{jt} \cdot \frac{N_{ijt}}{\sum_{k \neq i} N_{ikt}}, \quad (2)$$

where $Expo_{jt}$ is the environmental condition in destination city j on day t , N_{ijt} is the number of travelers from city i visiting city j on day t , and $\sum_{k \neq i} N_{ikt}$ is the total number of travelers from city i on day t . In our baseline specification, $Expo_{jt}$ is constructed as an indicator being one when city i experiences extreme air pollution or temperature on day t . Extreme pollution is defined as PM_{2.5} larger than $100 \mu\text{g}/\text{m}^3$ (the 90th percentile of the empirical distribution) and extreme temperature is

defined as daily average temperature below 30°F or above 90°F (about 10% of the observations).³ In robustness checks, we use different cutoffs to define extreme conditions and also estimate a model with continuous environmental variables.

HSR_{it} captures the connectivity of city i at time t . We use two measures: an indicator variable indicating whether city i is connected to the network or not at time t , and a continuous connectivity measure that is a weighted number of destination cities that can be reached from city i via HSR at time t . The weight for each destination city j is its total inflow of visitors in the base year of 2012 over the squared distance between the origin and destination city-pair:

$$\begin{aligned}\widetilde{HSR}_{it}^C &= \sum_{j \neq i} \left[\frac{\text{TotalInflow}_{j,2012}}{\text{Distance}_{ij}^2} \times HSR_{ijt} \right], \\ HSR_{it}^C &= (\widetilde{HSR}_{it}^C - \mu) / \sigma.\end{aligned}$$

$\text{TotalInflow}_{j,2012}$ is city j 's total number of visitors in 2012, distance_{ij} is the great circle distance, and HSR_{ijt} is an indicator for HSR connection between city-pair ij on date t . We normalize the connectivity measure to have zero mean and unit variance and define it as HSR_{it}^C . Unlike the HSR dummy (HSR_{it}) used in the main analysis whose value remains the same after a city is first connected to the HSR network, HSR_{it}^C increases whenever city i is connected to additional destinations as the HSR network expands. In addition, this measure also reflects cities' centrality in the transportation network.

The coefficient β_1 in Equation (3) captures the relationship between a home city's environmental condition and its travelers' exposure. While both pollution and temperature are correlated geographically, the spatial correlation decays across space. In the absence of a strong correlation between the trip direction and destination conditions (e.g., all trips going from dirty to dirty cities), one should expect to see $0 < \beta_1 < 1$. The second coefficient, β_{2i} , varies by city and allows for differential changes in travelers' exposure before and after the HSR connection. The key parameter of interest is β_3 on the interaction term, $HSR_{it} \times Expo_{it}$. It captures how HSR connection affects the slope of the relationship between local environmental conditions and travelers' exposure. If HSR facilitates residents' ability to mitigate adverse environmental conditions at home, β_3 should be negative. Time-varying city attributes X_{it} include whether city i has airports at time t and the number of destination airports with direct flights from city i . We incorporate city-level controls X_{it} city-fixed effects μ_i to control for time-invariant unobservables (e.g., connectivity or centrality) at the city level and

³China's standard for daily maximum PM_{2.5} is 75 $\mu\text{g}/\text{m}^3$. In comparison, the US Environmental Protection Agency's daily PM_{2.5} standard is 35 $\mu\text{g}/\text{m}^3$.

day-of-sample fixed effects δ_t to control for seasonality and temporal shocks in travel patterns.⁴

The identification of β_{2i} relies on the DID strategy and the staggered roll-out of the HSR expansion across cities. The identification of β_3 relies on a triple-difference design: it compares changes in the outcome variable (before and after the HSR connection) when the home city is subject to environmental extremes relative to changes in the outcome when the home city has mild environmental conditions. As illustrated in both Figure 1 and Panel (c) in Table 1, when home city is clean, travelers from cities with HSR connection experience a negligible or small reduction in pollution exposure compared to those from cities without HSR connection. However, when home city is polluted, the reduction in pollution exposure is much more pronounced. The differences in the pollution exposure reduction across different pollution levels in the home city pin down the magnitude of β_3 .

The key identification assumption is that the exact timing of a city's connection to the HSR network is exogenous. That is, there are no confounding factors that affect the relationship between a home city's environmental conditions and its travelers' exposure before and after the HSR connection. The assumption would be violated if the connection is driven by or in response to time-varying and city-specific unobservables that also affect travel patterns hence travelers' exposure to environmental extremes.

In practice, the HSR network's expansion is a complicated process involving many entities and numerous steps from siting to obtaining building permissions, securing the financing and implementing the physical construction. The exact timing (day or month) of a city's connection to the HSR network is often driven by a host of idiosyncratic factors. Most HSR lines in our sample started construction in 2005 or right after 2008, directly following the passage of the Mid-to-Long Railway Plan in 2004 and its revision in 2008. However, their completion dates spread out across years. The duration of the construction progress depends on engineering difficulties which increases with the railway's length and bridge/tunnel ratio. For instance, the opening of the Wuhan-Guangzhou line must wait for the completion of the Wuhan Tianxingzhou Yangtze River Bridge, the longest combined road and rail span bridge in the world. It is also affected by political factors, accidents, and other exogenous factors that expedite or delay these projects. Notable examples include the Wenzhou train crash in July 2011 that has halted the construction of ongoing projects for more than a year.⁵

The event study in Figure 2 displays no clear trend in changes in travelers' exposure to extreme pollution on either clean or polluted days before the HSR connection, lending support to our identification assumption. In addition, the HSR treatment effects appear stable over time, supporting the

⁴All regressions are weighted by the number of travelers from home city i on day t , so that the effect sizes reported below can be interpreted as the national average across all travelers.

⁵<https://www.ft.com/content/a9337b06-fe20-11e0-a1eb-00144feabdc0>

causal interpretation of the coefficient estimates from our regressions (Goodman-Bacon, 2021).

All regressions are weighted by the number of home city i 's travelers at time t , so that the effect sizes reported below can be interpreted as the national average across all travelers.⁶ In theory, if HSR connection simply enables travelers to travel further to destinations whose pollution and temperature are less correlated to those at home, the aggregate benefit in terms of pollution mitigation could be either negative or positive. For example, travelers might visit dirty places when home cities are clean and such a negative effect could cancel out or dominate the benefit from mitigation when the home city is polluted. Hence, whether improved transportation facilitates adaptation on net is an empirical question.

4 Empirical Findings

4.1 Baseline Results

Table 2 reports OLS estimates as specified in Equation (3) for travelers' exposure to air pollution and temperature in Panel (a) and (b), respectively. Column (1) uses the indicator variable to measure HSR connectivity while Column (2) uses the continuous measure. The estimates of β_1 in both columns and both panels are significantly lower than one, implying that intercity travel reduces the correlation between the environmental condition in the home city and travelers' realized exposure. The estimates of β_1 for temperature exposure are slightly larger than those for pollution exposure, likely due to stronger spatial correlation in temperature than air pollution.

The estimates of β_{2i} , not shown in the table, tend to be small and statistically insignificant on average, consistent with the negligible differences in the two lines' intercept as shown in Figure 1. In Column (1) for example, the set of β_{2i} estimates has an average of -0.002 and standard error of 0.033 for air pollution, and an average of 0.008 and standard error of 0.018 for temperature.⁷

In contrast to the small estimates of β_{2i} , the estimates of β_3 are negative and economically large in all columns. In other words, the impact of HSR connection on adaptation is mainly through the change in the slope, rather than the intercept. As a result, the expansion of the HSR network has flattened the relationship between environmental extremes in the home city and travelers' exposure.

The last row of Panel (a) presents the HSR connection's aggregate impact across all city-days on travelers' exposure to environmental extremes. HSR connection leads to a 0.7 percentage-point

⁶The aggregate benefit of the HSR network's expansion on travelers' pollution exposure is estimated based on $-\sum_i \sum_t \omega_{it}(\beta_{2i} + \beta_3 \times \text{Expo}_{it})$, where ω_{it} is the share of travelers in city i and on day t among all HSR city-days in our sample period.

⁷The inter-quartile range is from -0.015 to 0.020 for pollution and from 0.003 to 0.020 for temperature.

reduction in the likelihood of being exposed to extreme pollution (relative to the sample mean of 11 percentage points), based on the discrete measure of HSR connectivity. This represents a 7% decrease in travelers' likelihood of experiencing extreme pollution over all environmental conditions in home cities. Using the continuous measure, HSR connectivity leads to a 1.1 percentage-point reduction, or 10% decrease in travelers' exposure to extreme pollution. The larger estimates reflect the continuous measure's ability to capture not only the home city's connection to the HSR network, but also the improved connectivity as the network expands.

Results on travelers' exposure to extreme temperatures are reported in Panel (b). These findings mirror those for pollution exposure: intercity travel reduces the correlation between home conditions and travelers' realized exposure. In addition, connection to a better passenger transportation network reduces travelers' likelihood of exposure to extreme temperatures by 0.6 percentage points (using the discrete HSR connection measure) and 0.7 percentage points (using the continuous HSR connection measure) out of a sample mean of 6 percentage points, which is equivalent to a 10-11% reduction.

Figure 3 illustrates the magnitude of the estimates in Column (1) of Table 2 by contrasting the actual exposure to extreme conditions with counterfactual exposure for travelers with HSR connections. The counterfactual exposure is simulated as the predicted outcome from Equation (3) when HSR dummies are switched to zero. This comparison allows us to focus on the same set of city-days with HSR connections and avoid the differences between HSR cities and non-HSR cities that are unrelated to pollution mitigation. Panels (a) and (b) display results for pollution exposure and temperature exposure separately.

When a traveler's home city is clean, the traveler can expect to experience a modest chance (8 percentage points) of being subject to severe pollution – a reflection of mean reversion and the spatial heterogeneity of air pollution. Removing HSR only moderately increases the traveler's chance of experiencing severe pollution to 8.1 percentage points. In contrast, when the home city is suffering from extreme pollution, removing access to the HSR network would raise the traveler's probability of experiencing extreme pollution from 38.4 to 43.3 percentage points, amounting to a 12.8% increase. Results for extreme temperature exposure are similar. The impact of HSR connection is negligible when home cities have mild temperatures. But when home cities are subject to extreme temperatures, removing HSR would increase travelers' exposure to such extremes from 38.6 to 49.3 percentage points, a 27.7% jump.

4.2 Robustness Checks

This section explores the robustness of our findings to alternative specifications. Table A3 reports a host of robustness checks for both the discrete measure of HSR connectivity (Panel (a)) and contin-

uous measure of HSR connectivity (Panel (b)). In Columns (1) and (2), we replace the indicator of extreme pollution with the continuous PM2.5 reading and replace the indicator of extreme temperature with the absolute deviation from 70°F. One $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} at home translates into 0.34 $\mu\text{g}/\text{m}^3$ increase in travelers' exposure for cities not connected to HSR and only 0.28 $\mu\text{g}/\text{m}^3$ for travelers from HSR cities, using the discrete measure of HSR connectivity. The patterns are similar for the effect on temperature exposure. Columns (3)-(6) use alternative cutoffs to define environmental extremes: Columns (3) and (4) use 120 $\mu\text{g}/\text{m}^3$ and 150 $\mu\text{g}/\text{m}^3$ for extreme pollution, Column (5) uses 25 °F and 95 °F as the cutoffs for extreme temperature, and Column (6) uses 35 °F and 85 °F for the temperature cutoff. The coefficient estimates have the same signs and are similar in magnitude to the baseline estimates in Table 2. Results are similar using the continuous measure of HSR connectivity.

Table A4 examines robustness to different sample cuts for both the discrete (Panel (a)) and continuous measures (Panel (b)) of HSR connectivity. The number of travelers in our analysis is derived from card transactions and subject to measurement errors. To examine robustness to potential measurement errors, Columns (1) and (2) exclude each city's 5% of days with the most card transactions and 5% of days with the least card transactions. Columns (3) and (4) exclude 10% of days with the most and 10% of days with the least transactions. In addition, since card penetration rates are lower in small cities, Columns (5) and (6) only keep the large cities defined in the top three tiers. There are 117 cities in the top three tiers out of a total of 336 cities. These cities have larger populations than the lower-tier cities and account for over 80% of travelers in our sample. All of these regressions demonstrate that our results are robust to measurement errors and that the expansion of the passenger transportation infrastructure makes the intercity travel an effective strategy to reduce exposure to environmental extremes.

Our specifications so far relate travelers' exposure to home conditions on the same day. This implicitly assumes that households can respond quickly to negative shocks. Given the easy access to pollution and weather forecasts during our sample period, and the expansive train network and frequent services, households can and often do use forecasts to travel to desirable places in the event of (anticipated) pollution episodes and heat waves (Arlt, 2017; Sharkov, 2016; Chen et al., 2021).

Nonetheless, to allow for the possibility that households react with a lag to pollution and temperature shocks (due to the time constraint it takes to respond) or respond in advance of these shocks (due to the wide availability and increasing accuracy of forecasts), Table A5 replaces the daily environmental measure $Expo_{it}$ with its average in the following week in Column (1) and with its average in the previous week in Column (2). Similar to Tables A3-A4, Panel (a) presents results using the discrete HSR connectivity and Panel (b) reports results using continuous connectivity. Travelers

respond to both leading and lagged home pollution/temperature, though the magnitudes are smaller than responses to contemporary conditions. These results suggests that HSR facilitates adaptation to both contemporaneous environmental shocks and recent and future shocks.

5 Channels of Impacts and the Extensive Margin

5.1 Channels of Impacts

Changes in Travel Distance HSR access reduces travel costs, expands the set of feasible destinations, and allows individuals to travel to more distant destinations. Panels (a) and (b) of Appendix Figure A3 plot the distribution of trip distance for travelers from cities with and without HSR connection. As the associated benefit is more pronounced when a traveler's home city experiences high pollution as shown above, we plot the distributions separately for clean and polluted days (with PM_{2.5} exceeding 100 μg/m³). Panel (c) presents the difference in trip distances between travelers from HSR cities and those from non-HSR cities during days that are polluted (red bars) and clean (green bars). HSR connection has significantly shifted the travel distribution to the right: the fraction of trips exceeding 500 km increases from 35% among travelers without HSR connection to 52% among those with access when home cities are clean. The difference in the fraction of trips exceeding 500 km is even more pronounced and widens to 21 percentage points during polluted days.

These patterns suggest that HSR expansion allows people to travel farther. As correlations in environmental conditions decay spatially, traveling farther reduces travelers' probability of experiencing adverse conditions similar to those observed at home. Can distance alone explain the entirety of HSR's mitigation effect? To answer this question, we replace the environmental conditions at destination cities with the concurrent environmental conditions in cities that are of a similar distance to the origin in the construction of travelers' exposure:⁸

$$TravExpo_{it}^1 = \sum_{j \neq i} \widehat{Expo}_{jt} \cdot \frac{N_{ijt}}{\sum_{k \neq i} N_{ikt}},$$

where \widehat{Expo}_{jt} is the pollution level of a randomly-chosen city that is similarly distant from the original city as city j on the same day t . We simulate this alternative traveler exposure $TravExpo_{it}^1$

⁸We allow for a maximum difference of 100 km when defining cities of similar distance to the origin. Specifically, for each origin-destination pair, we draw a circular band centering around the origin, with the inner and outer radius being the distance between the city pair ±100 km. One of the cities within the band is randomly picked and its pollution level of the day is used as the counterfactual.

for all origin cities and all days in the sample. Then we use this alternative measure of travelers' exposure as the outcome variable in equation (3).

We replicate this simulation exercise 100 times and report results in the top panel of Table A6.⁹ This analysis preserves the distribution of travel distance for all cities. If distance is the only channel underlying HSR's mitigation effect, we should expect estimates from these simulations to be close to those using real data. Instead, HSR's coefficients center around -0.02 and -0.06 for pollution and temperature exposure, respectively, and are much smaller in absolute value than the baseline estimates of -0.05 and -0.12 in Table 2. Correspondingly, the aggregate benefit of HSR in this simulation exercise is only a 0.3 percentage point reduction in exposure to extreme pollution and extreme temperatures. This constitutes 43% of HSR's baseline effects for pollution mitigation and 50% of HSR's baseline effects for temperature mitigation. We conclude that distance-based factors cannot explain all of HSR's mitigation benefits documented in the main text. Instead, travelers appear to be able to leverage HSR connection and deliberately choose destination cities with better environmental conditions, conditioning on the distance to the origin city.

Adaptation Horizons Adaptation to environmental extremes through intercity travel could arise from multiple margins. First, individuals can travel to places with predictably desirable environmental conditions, such as trips to southern cities during polluted and harsh winter months in northern cities. Second, residents can spontaneously evade unexpected environmental extremes at home by visiting cities with better environmental conditions. Both margins of adjustment are associated with reduced exposure to environmental extremes and could generate mortality and morbidity benefits, though the second margin has shorter (planning) horizons than the first one. The changes in travel behavior as illustrated in Appendix Figure A3 are consistent with both margins. This section presents simulations that disentangle these different margins.

To quantify the benefit of HSR that derives from (longer horizon) responses to predictable environmental extremes as distinct from (short horizon) adaptation to unpredicted environmental conditions, we use each home city's average shares of travel destinations, separately for before and after HSR connection, instead of daily travel shares to construct travelers' exposure:

$$TravExpo_{it}^2 = \sum_{j \neq i} Expo_{jt} \cdot \frac{N_{ij}^{\text{No HSR}}}{\sum_{k \neq i} N_{ik}^{\text{No HSR}}} \cdot \mathbb{1}\{t \text{ before HSR}\} + \sum_{j \neq i} Expo_{jt} \cdot \frac{N_{ij}^{\text{HSR}}}{\sum_{k \neq i} N_{ik}^{\text{HSR}}} \cdot \mathbb{1}\{t \text{ post HSR}\},$$

where $N_{ij}^{\text{No HSR}}$ is the total number of travelers from city i to city j prior to the HSR access and

⁹The reported β 's are the average estimates from the simulation runs, and their standard errors are directly calculated using the simulation estimates.

N_{ij}^{HSR} is the total number of travelers from city i to city j post the HSR access. By construction, this formulation removes deliberate travel responses to temporal, day-to-day variations in environmental conditions. Then we use this alternative measure of travelers' exposure as the outcome variable in Equation (3). The lower panel of Appendix Table A6 suggests that this margin accounts for 71% of HSR's aggregate benefit in pollution mitigation and 83% for temperature. We attribute the remaining benefit (29% of pollution reduction and 17% of temperature mitigation) to day-to-day avoidance behavior, whereby residents deliberately seek cities with better environmental conditions when the home city is hit by unpredicted environmental extremes. HSR access has a relatively smaller impact on day-to-day temperature mitigation than pollution mitigation because temperature extremes exhibit less geographical variation and hence are harder to escape from.

5.2 The Extensive Margin

Our analysis has so far focused on the intensive margin of travel responses: the role of HSR in helping travelers from cities hit by pollution and temperature extremes to escape to other places on a short-term basis. However, adjustments at the extensive margin could also be relevant. It is unclear ex-ante whether people travel more or less when the home city is highly polluted. On the one hand, people might have stronger incentives to travel to cleaner cities as a means of avoidance. On the other hand, people might reduce outdoor activities entirely, thus limiting their intercity travel. Appendix Table A7 evaluates the extensive margin by using the number of travelers (in logarithm scale) in a city-day as the outcome variable.

Consistent with the findings in the literature (Moretti and Neidell, 2011b; Graff Zivin and Neidell, 2014; Barwick et al., 2018), we find that residents travel less when their home cities are subject to extreme pollution. This is consistent with the observation that residents stay indoors to avoid exposure, as advocated by the government and news media. On the other hand, having access to the HSR network increases the frequency of travel, especially for trips with a medium or long distance (longer than 300km or 500km). The coefficient estimates on the $\text{HSR}_{it} \times \text{Expo}_{it}$ interaction term are all positive but noisy in some specifications. Overall, the analysis provides somewhat limited evidence on the impact in the extensive margin and suggests that it is unlikely to be the primary channel underlying the avoidance behavior documented above.

6 Mortality Benefits

HSR connection is associated with a 0.7 percentage-point reduction in travelers' likelihood of experiencing extreme pollution (Table 2), or a 7% reduction in travelers' average pollution exposure,

equivalent to a drop of $3.9 \mu\text{g}/\text{m}^3$ PM_{2.5} for an average traveler on traveling days. Using 2.5 days as the average trip duration calculated from the UnionPay dataset, the benefit translates to $0.027 \mu\text{g}/\text{m}^3$ unit reduction in travelers' annual average PM_{2.5} exposure.

Ebenstein et al. (2017) estimate that one $\mu\text{g}/\text{m}^3$ increase in average PM₁₀ exposure reduces life expectancy by 0.064 years. The pollution monitoring data in China suggest that one $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} corresponds to $1.5 \mu\text{g}/\text{m}^3$ increase in PM₁₀. Hence, we consider the health consequence per-unit of PM_{2.5} exposure equivalent to 1.5 times that of PM₁₀. In 2016, 700 million passengers traveled via HSR (Xinhua, 2017)¹⁰. Our estimate therefore implies that the annual reduction in pollution exposure induced by improved HSR transportation networks translates into a potential savings of 1.8 million life-years in 2016.

For the mortality impact of temperature extreme, we follow the age-specific dose-response functions from Deschenes and Greenstone (2011). Based on the age structure of China's population, their estimates suggest that an increase of one-day exposure to temperature extremes raises the mortality rate by 5 to 10 per million population.¹¹ Our estimates from Table 2 show that the expansion of HSR network reduces an average travelers' exposure to temperature extremes by two days per year. Taken together, these estimates suggest that mitigation in exposure to temperature extremes as a result of the HSR expansion leads to reduction of 7,000 to 14,000 deaths each year.

7 Conclusion

This study provides to our knowledge the first analysis of how transportation infrastructure promotes short-term mobility and facilitates behavioral changes in response to adverse environmental conditions. The empirical analysis exploits high-frequency data of traveler flows across Chinese cities constructed using credit- and debit-card transactions from the world's largest payment network. It takes advantage of China's massive and staggered expansion of the HSR network, as well as the rich variation in daily pollution and temperature at the city level.

Our analysis shows that the rapid expansion of HSR has made intercity passenger travel an effective strategy for adaptation to adverse environmental conditions, leading to significant health benefits. Such adaptation can be attributed to both short-run deliberate responses to unexpected environmental extremes at home and also shifts in longer-term travel patterns due to reduced travel costs. These findings contribute to our understanding of the role of adaptation and the benefit of transportation infrastructure investment in a changing environment. Examining the potential feed-

¹⁰We assume all trips are round trips, thus the number of travelers is half of the total ridership.

¹¹Specifically, for an increase of one-day exposure to temperature extremes, the mortality rate will increase from 5629.6 deaths per year per million people to 5634.2-5638.2 deaths per year per million people.

back effects of these behavioral changes on air pollution and carbon emissions is an important topic for future research.

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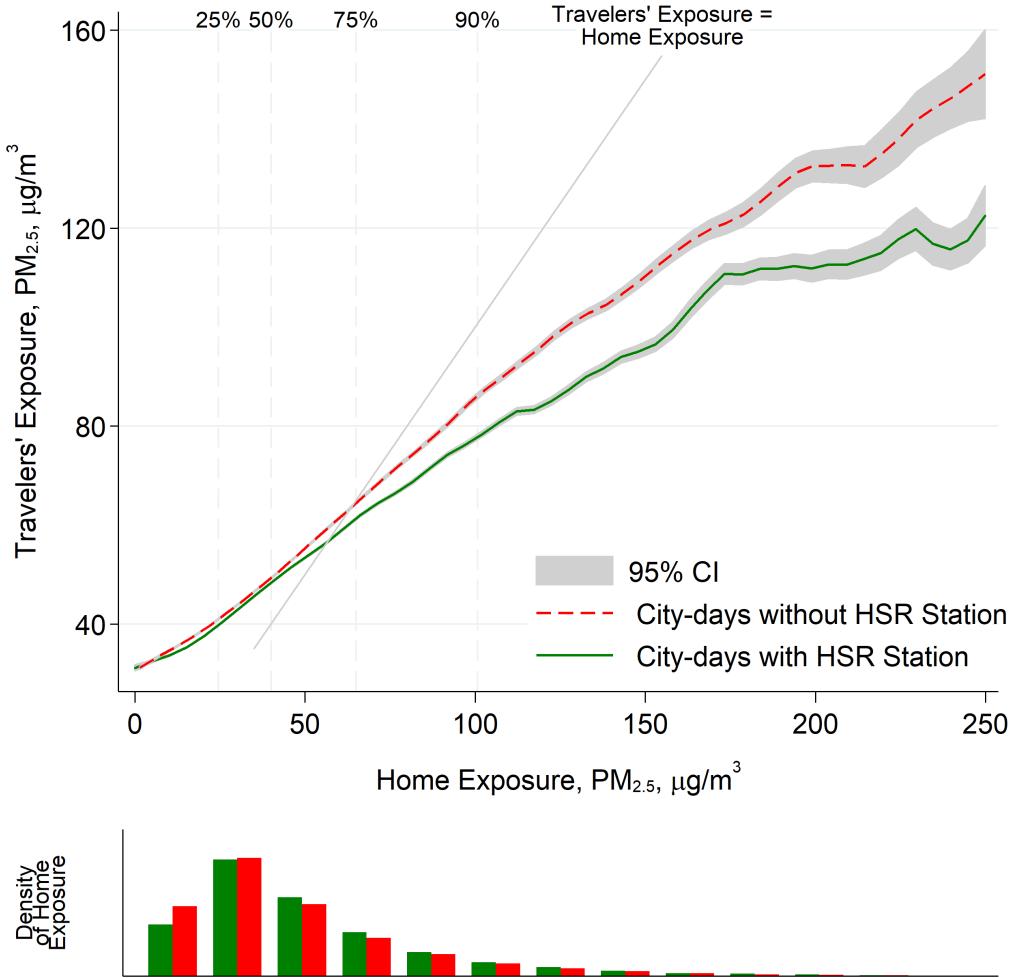
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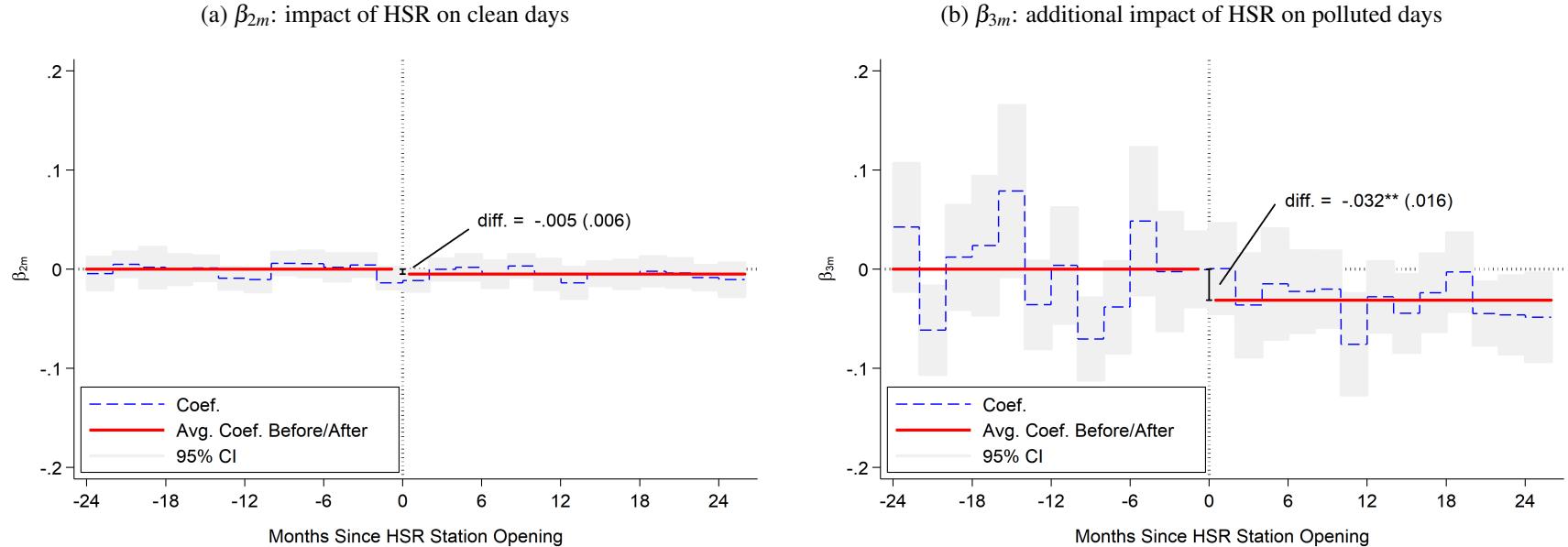
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Figure 1: Travelers' exposure to PM_{2.5} vs. home exposure



Notes: The top figure plots travelers' average exposure to PM_{2.5} (y-axis) against PM_{2.5} level at the travelers' home city (x-axis), separately for city-days with access to HSR (green line) and city-days without access to HSR (red dash line). Both lines are local polynomial regressions weighted by Epanechnikov kernel with optimal bandwidth. The gray area is the 95% confidence interval. Gray vertical lines mark the 25th, 50th, 75th, and 90th percentiles of the PM_{2.5} distribution. The bottom figure displays the distribution of daily PM_{2.5} at home cities, separately for city-days with access to HSR (green bars) and city-days without access to HSR (red bars).

Figure 2: Event study of HSR impact



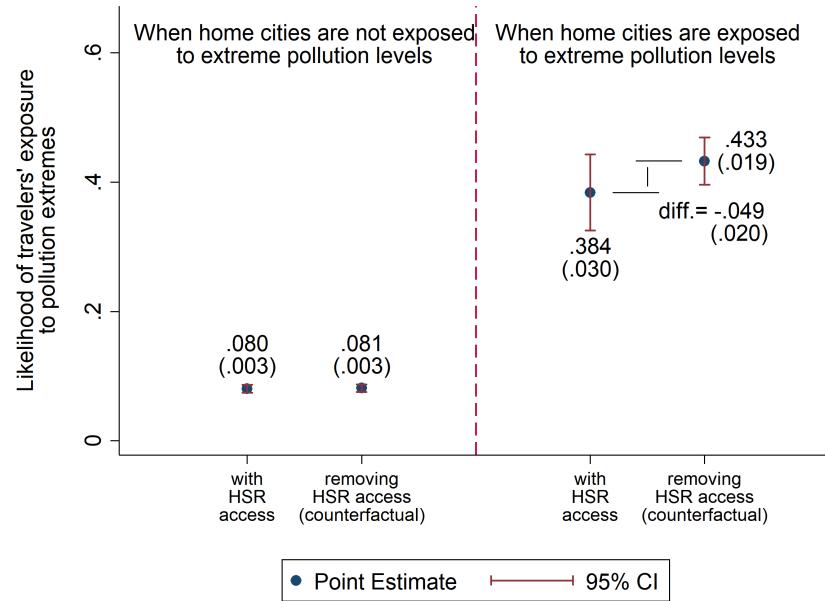
Notes: The figures plot coefficient estimates (blue dashed line) by month relative to HSR station openings from the following equation:

$$TravExpo_{it} = \beta_1 Expo_{it} + \sum_{m \in [-25, 25]} \beta_{2m} HSR_{it} + \sum_{m \in [-25, 25]} \beta_{3m} HSR_{it} \times Expo_{it} + X_{it} + \mu_i + \delta_t + \epsilon_{it}, \quad (3)$$

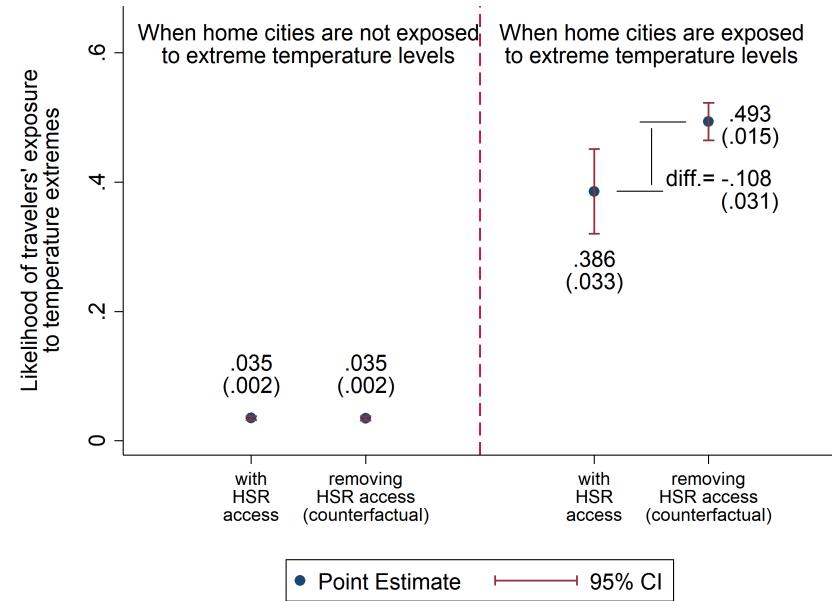
where $TravExpo_{it}$ is exposure to extreme pollution for traveler i on day t . We group city-days that are more than 24 months before the HSR connection (including cities that are never connected) to $m = -25$ and city-days that are more than 24 months post the HSR connection to $m = 25$. The gray area denotes the 95% CI for the monthly coefficient estimates. The red line denotes the simple averages for months before and after the station opening. The bar denotes the difference between the two averages with its standard error in the bracket. We test the difference with a t-test and label the statistical significance with the following notations: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. We normalize the average of the pre-opening coefficients to zero (instead of the coefficient on a single period to zero) following [Miller \(2021\)](#).

Figure 3: Access to HSR and reduction in exposure to pollution and temperature extremes

(a) Exposure to extreme pollution



(b) Exposure to extreme temperature



Notes: Actual and counterfactual likelihood of travelers experiencing extreme pollution (panel (a)) and extreme temperature (panel (b)), based on coefficient estimates in column (1) of Table 2. Dots to the left (right) of the red dashed line refer to days when home cities experience mild (extreme) conditions. Extreme pollution is defined as PM_{2.5} above 100 µg/m³ and extreme temperature is defined as daily average temperature below 30°F or above 90°F. Counterfactual exposure is the predicted outcome from Equation (3) when HSR dummies are switched to zero. Blue dots (whiskers) denote point estimates (95% confidence intervals). Standard errors in brackets are estimated from 100 block bootstrap replications with each home city as a block.

Table 1: Travelers' travel patterns and pollution exposure

(a) For travelers from city-days with HSR

Home in		Flow shares by pollution quintile at destination					Avg. Exposure of	
							PM _{2.5} ($\mu\text{g}/\text{m}^3$) at	Dest.
		Clean	1	2	3	4		
Home in	Clean 1	40.1%	24.7%	15.4%	11.4%	8.4%	15.9	34.9
	2	23.4%	29.6%	21.6%	14.8%	10.7%	27.5	41.3
	3	14.7%	21.2%	27.5%	22.3%	14.2%	40.4	48.6
	4	10.5%	14.0%	21.6%	31.2%	22.6%	59.1	58.2
	Dirty 5	7.2%	9.8%	13.6%	22.0%	47.3%	120.0	83.8

(b) For travelers from city-days without HSR

Home in		Flow shares by pollution quintile at destination					Avg. Exposure of	
							PM _{2.5} ($\mu\text{g}/\text{m}^3$) at	Dest.
		Clean	1	2	3	4		
Home in	Clean 1	37.0%	26.4%	17.2%	11.5%	7.9%	15.7	35.3
	2	21.1%	28.0%	23.5%	16.7%	10.8%	27.5	42.3
	3	13.0%	20.7%	27.4%	23.8%	15.2%	40.2	49.6
	4	8.5%	12.5%	21.0%	32.4%	25.7%	59.1	61.1
	Dirty 5	4.9%	7.3%	11.0%	21.8%	55.1%	115.4	92.2

(c) Difference between Panel (a) and Panel (b)

Home in		Difference in flow shares by pollution quintile					Diff. in	
							PM _{2.5} ($\mu\text{g}/\text{m}^3$) at	Dest.
		Clean	1	2	3	4		
Home in	Clean 1	3.0%	-1.7%	-1.8%	-0.1%	0.5%	0.18	-0.44
	2	2.3%	1.6%	-1.8%	-1.9%	-0.1%	0.03	-1.03
	3	1.7%	0.5%	0.1%	-1.4%	-0.9%	0.14	-1.03
	4	2.1%	1.5%	0.7%	-1.2%	-3.1%	0.00	-2.92
	Dirty 5	2.3%	2.5%	2.6%	0.2%	-7.7%	4.61	-8.35

Notes: This table complements Figure 1 and illustrates that travelers from HSR cities are more likely to visit cleaner cities than those from non-HSR cities. Each row represents the shares of travels to destination cities with different pollution quintile, conditioning on the home city-day's pollution quintile. Panel (a) refers to travelers from city-days with HSR, panel (b) refers to travelers from city-days without HSR, and panel (c) presents the difference between the two. Positive (negative) values are colored in different shades of green (red) according to the magnitude. The quintile cutoffs for daily PM_{2.5} are 22, 33, 48, and 73 $\mu\text{g}/\text{m}^3$.

Table 2: Travelers' likelihood of experiencing environmental extremes

	(1) Discrete HSR_{it}	(2) Continuous HSR_{it}
Panel (a) : Air Pollution Daily $PM_{2.5} > 100\mu g/m^3$	Likelihood of experiencing pollution extremes	
$\mathbb{1}\{\text{home extreme}\}$	0.27*** (0.01)	0.19*** (0.01)
$\mathbb{1}\{\text{home extreme}\} \times HSR_{it}$	-0.05*** (0.02)	-0.04*** (0.01)
<i>N</i>	330,801	330,801
<i>R</i> ²	0.79	0.79
HSR's overall impact	-0.007** (0.003)	-0.011** (0.004)
<hr/>		
Panel (b) : Temperature Daily temp. < 30°F or > 90°F	Likelihood of experiencing temperature extremes	
$\mathbb{1}\{\text{home extreme}\}$	0.40*** (0.03)	0.32*** (0.01)
$\mathbb{1}\{\text{home extreme}\} \times HSR_{it}$	-0.12*** (0.03)	-0.07*** (0.01)
<i>N</i>	466,257	466,257
<i>R</i> ²	0.79	0.79
HSR's overall impact	-0.006*** (0.002)	-0.007** (0.003)

Notes: All regressions are weighted by home cities' number of travelers on day t . The dependent variable in Panel (a) and (b) is the likelihood that travelers experience extreme pollution ($PM_{2.5} > 100\mu g/m^3$) and extreme temperature (daily average temperature $< 30^\circ F$ or $> 90^\circ F$), respectively, defined in Eq. (2). The average of the dependent variables for pollution and temperature is 0.11 and 0.06, indicating the likelihood of travelers being subject to extreme pollution and temperature of 11% and 6%. $\mathbb{1}\{\text{home extreme}\}$ is an indicator for extreme conditions at home city i on day t . In Column (1), HSR_{it} is the indicator variable for access to HSR stations in the home city. In Column (2), we instead use the standardized continuous connectivity measure, HSR_{it}^C . The number of observations is smaller in panel (a) as not all cities had $PM_{2.5}$ monitoring stations in 2013 and 2014. Day-of-sample fixed effects (FEs), city FEs, and interactions between city FEs and HSR connection are included in all regressions. The last row of each panel reports HSR's aggregate mitigation effect, which is a 0.7 percentage-point reduction in traveler's likelihood of experiencing extreme pollution in column (1) of Panel (a) and a 0.6 percentage-point reduction in column (1) of Panel (b). Standard errors for coefficient estimates are clustered at the city level. Standard errors for the aggregate impact are estimated from 100 block bootstrap replications with each home city as a block. *** p < 0.01, ** p < 0.05, and * p < 0.10.

Online Appendix

A Additional Data Description and Evidence

Summary Statistics Table A1 presents summary statistics for key variables used in this analysis. There are a total of 330,819 city-day observations for PM_{2.5} readings and 466,551 city-day observations for temperature from 2013 to 2016. Some cities did not have PM_{2.5} monitoring stations in the beginning of our sample, which explains PM_{2.5}'s lower number of observations. The average daily PM_{2.5} is 52.19 $\mu\text{g}/\text{m}^3$. This is considerably higher than U.S.'s daily standard of 35.4 $\mu\text{g}/\text{m}^3$. About 19% of the city-days also exceeded China's daily standard of 75 $\mu\text{g}/\text{m}^3$ (which became effective in 2016).

PM_{2.5} varies considerably in our sample period, with a standard deviation of 44.51 $\mu\text{g}/\text{m}^3$ and an inter-quartile range of 40.3 $\mu\text{g}/\text{m}^3$. The 90th, 95th, and 99th percentiles are 100.8, 131.8, and 219.8 $\mu\text{g}/\text{m}^3$, respectively. About 80% of the variation comes from day-to-day changes within a city, while the remaining 20% arises from differences across cities (within vs. between variation in a panel setting). The average temperature is 57.96 °F, also with a sizeable standard derivation (20.2 °F) and inter-quartile range (29.3 °F). Similar to pollution, within-city variation accounts for a lion's share (three-quarters) of total variation in temperature. The cutoff for extreme heat in our baseline analysis is 90°F, the 99th percentile of the temperature distribution. The 95th percentile is 83°F = 26°C, which appears as a very mild cutoff for hot days. The cutoff for extreme cold is 30°F. Using 30°F and 90°F as cutoffs, extreme temperature occurs in around 10% of city-days.

Additional Descriptive Evidence We present additional descriptive evidence on patterns of adaptation to environmental extremes and the role of transportation infrastructure in facilitating such adaptation. Figure A2 is analogous to Figure 1 and presents descriptive evidence on the benefit of improved transportation networks in mitigating households' exposure to extreme temperature. The top panel plots the temperature level experienced by travelers against temperature levels at their home cities. The colored lines represent the local polynomial smoothed averages of the raw data for city-days with HSR connections (blue) and city-days without HSR (red), respectively. The bottom panel presents the empirical temperature distribution for city-days with HSR (blue) and city-days without HSR (red).

Travelers with HSR connections experience warmer temperatures during cold seasons (temperature below 37°F) at home and cooler temperatures during mild and hot seasons (temperature above 37°F). These differences can reach 5 degrees and are statistically significant throughout most of the

distribution, except in the tails when estimates are noisier.¹² The bottom panel shows that the home city's temperature is slightly higher for city-days with HSR access. This is largely due to cross-sectional variation, as cities with HSR are more likely to be found in the warmer south. Figure A2 complements Figure 1 in the main text and provides descriptive evidence on the benefit of improved transportation networks in mitigating households' exposure to adverse environmental conditions.

Figure A4 further maps the geographical distribution of HSR's impact in reducing pollution exposure across cities during each city's 50 most polluted days between 2014 - 2016. The outcome variable is the difference in $\mu\text{g}/\text{m}^3$ between the pollution level at the home city and travelers' actual exposure. Hence the figure illustrates travelers' benefit of leaving their home city during their home city's 50 most polluted days between 2014 - 2016. A larger positive number denotes a higher benefit. Cities outlined by thick black borders were connected to the HSR network by 2013. We use the most polluted days between 2014-2016 instead of 2013-2016 since some cities did not have HSR connections during the winter of 2013 when several episodes of extreme pollution occurred.

Cities that experience larger reductions in travelers' pollution exposure, on days of intense home exposure, are shown in darker green. It is evident from the map that cities with HSR connections are more likely to exhibit larger reductions relative to their neighbors without such connections. Cities that reap the greatest benefit in pollution reduction tend to be located in Northern China, which has experienced the country's worst pollution over the past decade, especially in winter months.

Figure A5 presents travelers' benefits in terms of temperature exposure in each city's 50 hottest (left panel) and 50 coldest days (right panel) during 2014 - 2016. Travelers' benefit is measured by the difference between their actual exposure and the temperature at the home city. Darker green colors represent travelers experiencing cooler temperatures during hottest days (left panel) and warmer temperatures during coldest days (right panel). Cities in Southeastern China with HSR access display the largest benefits during the hottest days, as the majority of these cities falls into the humid subtropical climate category and are vulnerable to heat waves. Similarly, cities in Northeastern China with HSR access benefit more on the coldest days, when the temperature falls below zero. These trips are facilitated by several north-south HSR lines that travel across a wide temperature range (e.g. the Beijing - Wuhan line). The contrast between cities on and off the HSR lines reflects the mitigating effect of HSR connections, except for southeastern cities in cold days when these cities are much warmer than the rest of the country.

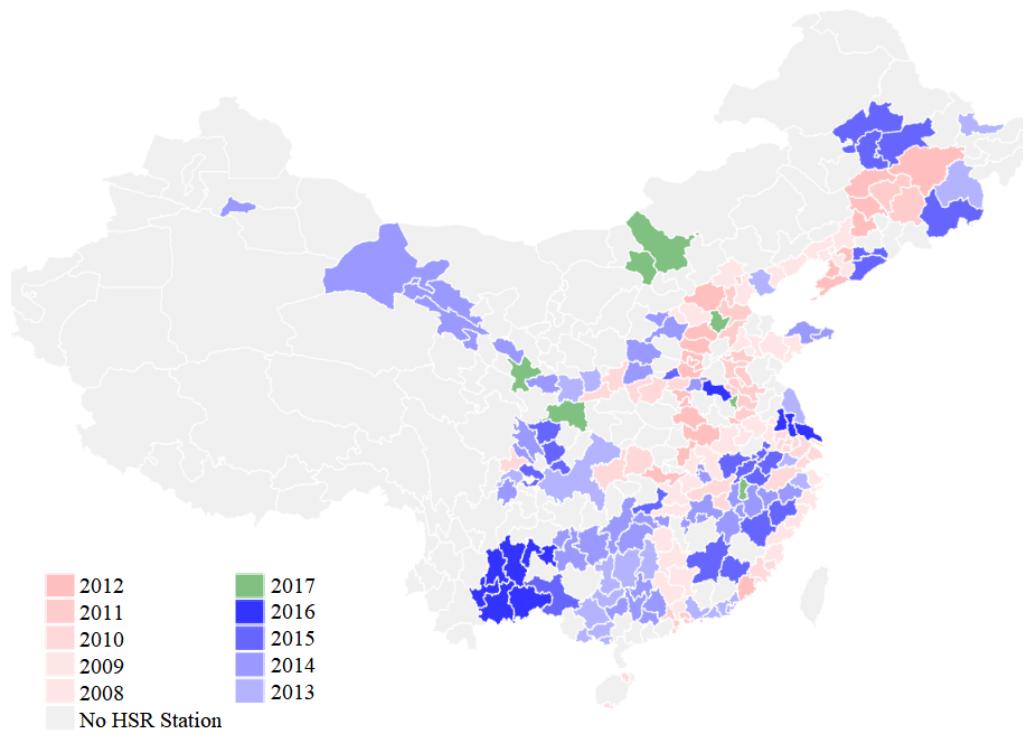
Table A2 illustrates travel patterns by destination cities' temperature, analogous to Table 1. Since extreme temperature includes both cold and hot days, we divide the temperature distribution into ten bins (decile), five bins for temperatures below 61 °F (the median) and five bins for temperatures

¹²The standard errors are calculated using the Epanechnikov kernel and optimal bandwidth in STATA.

above 61 °F. Each row of the table reports the fraction of travelers visiting each of the ten temperature bins, conditioning on the decile of home temperature. The last two columns report the average temperature experienced by travelers and that at their home city. Panels (a) and (b) present the statistics for travelers' from non-HSR cities and those from HSR cities, respectively, and Panel (c) reports their difference. For example, when the home city's temperature is in the coldest decile, travelers with HSR access are 8.6 percentage points more likely to visit warmer destinations than travelers without HSR access. Similarly, when the home city's temperature is in the highest decile, travelers with HSR access are 7.7 percentage points more likely to visit cooler destinations than travelers without HSR access. Table A2 complements Table 1 in the main text and provides additional descriptive evidence on the benefit of improved transportation networks.

B Appendix Figures and Tables

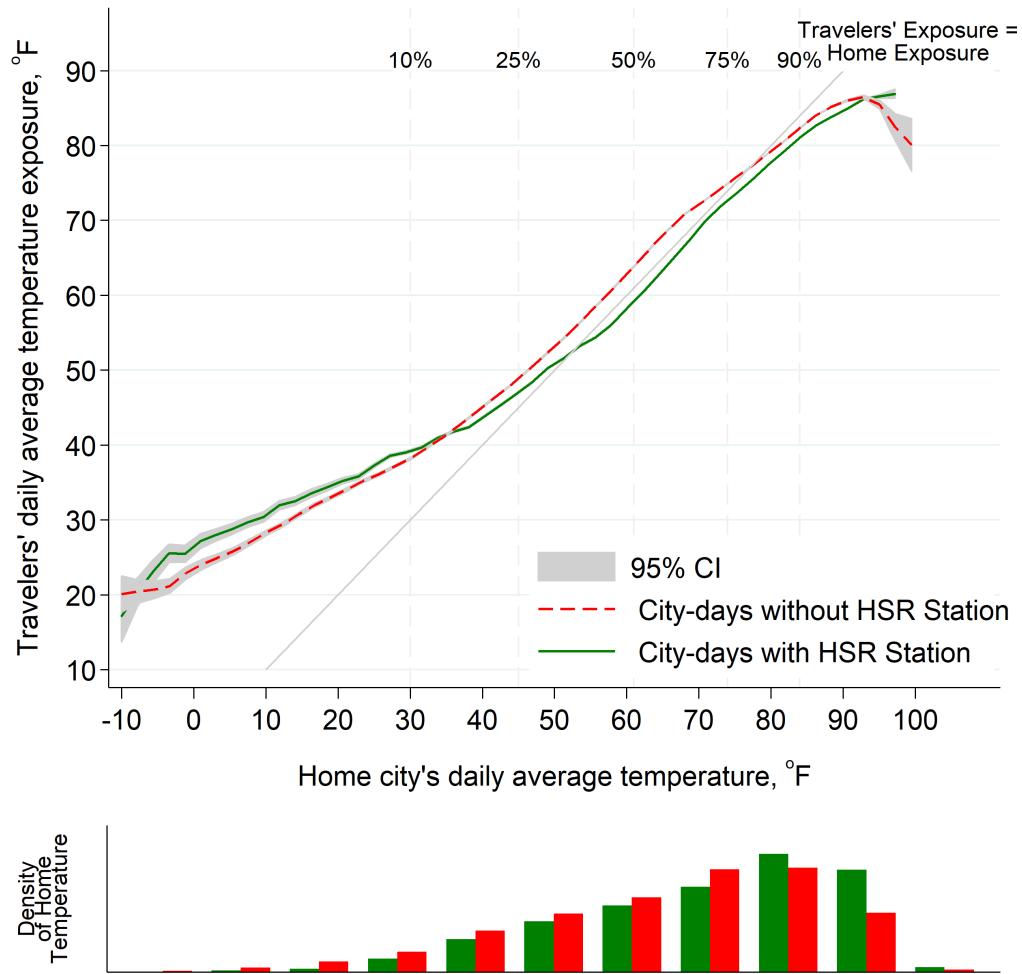
Figure A1: Expansion of the HSR network



Year	In 2010	'11	'12	'13	'14	'15	'16	'17
HSR network								
# Cities Added	55	16	21	23	40	25	11	7
# Cities in Network	55	71	92	115	155	180	191	198
# City-pairs Connected	196	524	2710	4234	6042	6884	-	-

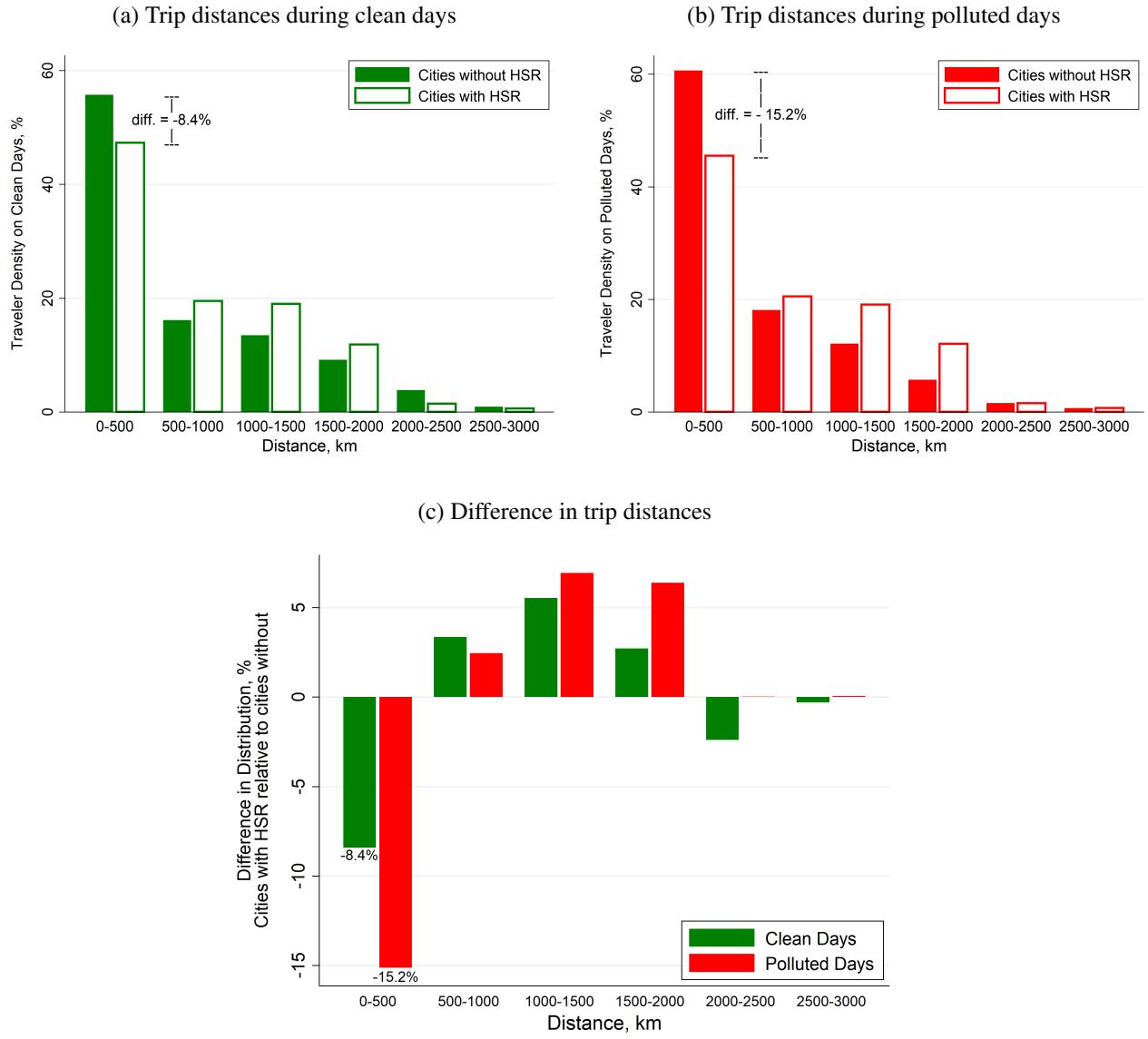
Notes: Colors represent years when a city is first connected to the HSR network.

Figure A2: Travelers' exposure to temperature vs. home exposure



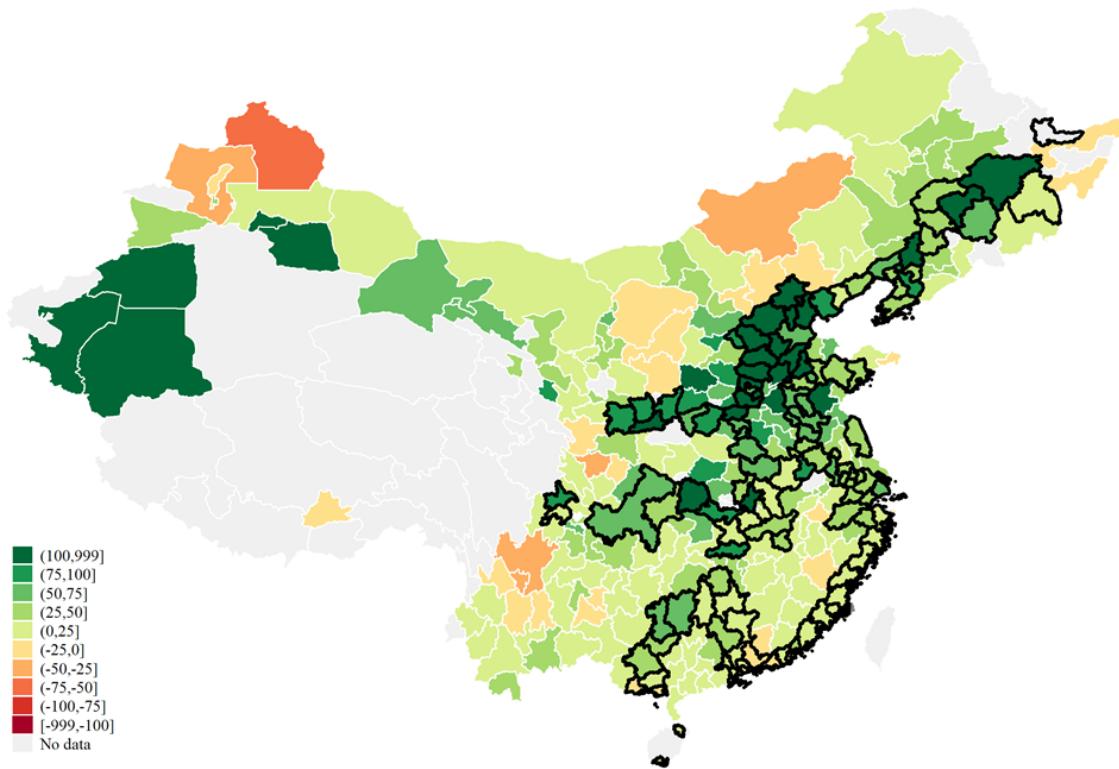
Notes: The top figure plots temperature level experienced by travelers (y-axis) against temperature level at home city (x-axis), separately for city-days with access to HSR (green line) and city-days without access to HSR (red dash line). Both lines are local polynomial regressions weighted by Epanechnikov kernel with optimal bandwidth. The gray area is the 95% confidence interval. The bottom figure displays the distribution of daily temperature at home cities, separately for city-days with access to HSR (green bars) and city-days without access to HSR (red bars). Gray vertical lines mark the 10th, 25th, 50th, 75th, and 90th percentiles of the temperature distribution.

Figure A3: Trip distance for city-days during clean and polluted days



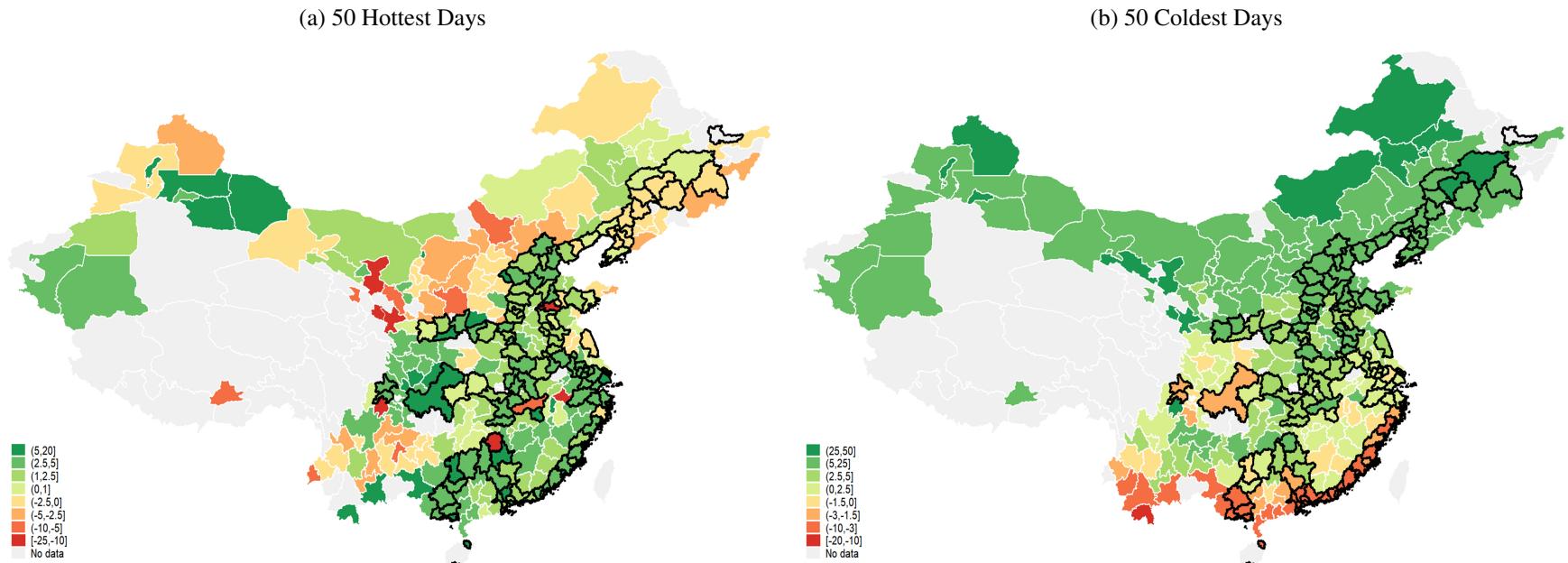
Notes: Panels (a)-(b): histograms for trip distances for cities without or with HSR access during clean and polluted ($\text{PM}_{2.5} > 100 \mu\text{g}/\text{m}^3$) days. Panel (c) plots differences in traveler density between cities with HSR access and cities without, on clean days (green bars) and polluted days (red bars). Travelers from cities with HSR access are more likely to visit distant destinations and especially so when home cities experience extreme pollution.

Figure A4: The HSR network and exposure to pollution extremes



Notes: This figure plots the difference in pollution levels ($\mu g/m^3$) between home and travel destinations, weighted by the number of travelers, during each city's 50 most polluted days between 2014 - 2016. Green colors indicate travelers experiencing less pollution in their destinations than at home; red colors denote travelers experiencing more pollution in their destinations than at home. Cities outlined in black are connected to the HSR network by 2013. Cities with the fewest 10% travelers are not color-coded as traveler exposure in these cities is more prone to measurement error.

Figure A5: The HSR network and exposure to temperature extremes



Notes: This figure plots the difference in temperature levels between home and travel destinations, weighted by the number of travelers, during each city's 50 hottest days (left panel) and 50 coldest days (right panel) between 2014 - 2016. The difference is measured as home temperature minus weighted temperature at destinations for the hottest days (left panel) and reversely as weighted temperature at destinations minus home temperature for the coldest days (right figure). Green colors indicate travelers experiencing milder temperatures than at home; red colors denote travelers experiencing more extreme temperatures than at home. Cities with black borders are connected to the HSR network by 2013. The contrast between cities on and off the HSR lines reflects the mitigating effect of HSR connections, except for southeastern cities in cold days when these cities are much warmer than the rest of the country. Cities with the fewest 10% travelers are not color-coded as traveler exposure in these cities is more prone to measurement error.

Table A1: Summary statistics

	Mean	Std. Dev.	Min	Max	Number of Obs.
PM _{2.5} , $\mu\text{g}/\text{m}^3$	52.19	44.51	0	1782.98	330,819
$\mathbb{1}\{\text{PM}_{2.5}>100\}$	0.10	0.30	0	1	330,819
Temperature, °F	57.96	20.22	-37.5	104.7	466,551
$\mathbb{1}\{\text{Temperature}< 30^\circ\text{F or } > 90^\circ\text{F}\}$	0.10	0.30	0	1	466,551
Number of travelers	189.65	500.12	1	15013	486,209
HSR	0.42	0.49	0	1	486,209

Notes: Variable $\mathbb{1}\{PM_{2.5} > 100\}$ takes value 1 if a city's daily average PM_{2.5} concentration is greater than 100 $\mu\text{g}/\text{m}^3$ and 0 otherwise. Variable $\mathbb{1}\{\text{Temperature}< 30^\circ\text{F or } > 90^\circ\text{F}\}$ takes value 1 if a city's daily average tempearture is lower than 30°F or higher than 90°F and 0 otherwise. Variable HSR takes value 1 if a city has an HSR station in operation on a given day and takes value 0 otherwise.

Table A2: Travelers' travel patterns and temperature exposure

(a) For travelers from city-days with HSR

Home in		Flow share by temperature decile at destination										Average	
		Cold 1	2	3	4	5	6	7	8	9	Warm 10	temperature (°F) at Home	Dest.
Home in	Cold 1	40.6%	24.0%	11.9%	7.5%	7.8%	4.3%	2.4%	1.0%	0.4%	0.0%	21.8	35.8
	2	14.3%	42.5%	16.6%	9.7%	7.8%	4.5%	2.6%	1.2%	0.6%	0.0%	36.0	41.7
	3	7.0%	18.8%	37.6%	15.2%	9.2%	5.4%	3.3%	2.0%	1.2%	0.2%	44.8	46.9
	4	4.0%	10.8%	16.0%	35.2%	16.0%	7.3%	4.7%	3.0%	2.3%	0.6%	52.1	52.2
	5	3.3%	6.9%	8.5%	16.4%	35.6%	13.7%	6.3%	4.6%	3.4%	1.2%	58.6	56.9
	6	1.8%	4.1%	5.3%	7.6%	16.5%	33.1%	15.0%	7.8%	5.8%	3.0%	64.4	62.5
	7	0.8%	1.9%	2.7%	4.5%	7.3%	15.2%	33.1%	17.9%	10.1%	6.6%	69.4	68.2
	8	0.3%	0.8%	1.6%	2.5%	4.8%	7.2%	16.1%	34.6%	19.8%	12.4%	74.1	72.8
	9	0.1%	0.3%	0.7%	1.6%	2.8%	4.3%	7.9%	17.4%	40.7%	24.2%	79.0	76.8
	Warm 10	0.0%	0.0%	0.1%	0.4%	0.8%	2.0%	4.2%	9.1%	20.5%	62.9%	85.1	81.8

(b) For travelers from city-days without HSR

Home in		Flow share by temperature decile at destination										Average	
		Cold 1	2	3	4	5	6	7	8	9	Warm 10	temperature (°F) at Home	Dest.
Home in	Cold 1	49.2%	22.0%	9.6%	6.7%	5.9%	3.4%	2.0%	0.9%	0.3%	0.0%	18.9	32.6
	2	10.9%	45.6%	19.8%	8.8%	6.4%	3.7%	2.3%	1.3%	0.9%	0.2%	35.9	41.9
	3	3.9%	13.8%	40.2%	20.0%	9.6%	5.2%	3.2%	2.1%	1.4%	0.5%	44.8	48.6
	4	2.2%	6.0%	12.9%	37.4%	19.8%	8.7%	5.3%	3.8%	2.7%	1.2%	51.9	54.8
	5	0.9%	2.5%	4.6%	13.4%	36.0%	18.4%	9.1%	6.6%	5.4%	3.1%	58.6	61.2
	6	0.4%	1.1%	1.9%	4.3%	13.5%	31.2%	19.3%	11.2%	9.2%	7.9%	64.4	67.3
	7	0.2%	0.5%	0.9%	1.9%	4.6%	13.5%	31.7%	20.9%	13.1%	12.6%	69.3	71.7
	8	0.1%	0.2%	0.5%	1.0%	2.4%	5.2%	15.0%	35.6%	24.2%	15.9%	74.0	75.0
	9	0.0%	0.1%	0.3%	0.6%	1.4%	2.5%	5.8%	16.0%	43.3%	29.9%	78.8	78.4
	Warm 10	0.0%	0.0%	0.0%	0.2%	0.5%	1.3%	2.8%	6.0%	18.8%	70.5%	85.0	83.0

(c) Difference between Panel (a) and Panel (b)

Home in		Flow share by temperature decile at destination										Average	
		Cold 1	2	3	4	5	6	7	8	9	Warm 10	temperature (°F) at Home	Dest.
Home in	Cold 1	-8.6%	2.1%	2.3%	0.9%	1.9%	0.9%	0.3%	0.2%	0.0%	0.0%	2.9	3.2
	2	3.4%	-3.1%	-3.1%	0.9%	1.4%	0.8%	0.2%	-0.1%	-0.3%	-0.1%	0.1	-0.2
	3	3.1%	5.0%	-2.6%	-4.8%	-0.3%	0.3%	0.1%	-0.1%	-0.3%	-0.3%	0.0	-1.7
	4	1.9%	4.7%	3.1%	-2.1%	-3.8%	-1.4%	-0.6%	-0.8%	-0.4%	-0.6%	0.1	-2.6
	5	2.4%	4.4%	3.9%	3.0%	-0.4%	-4.7%	-2.9%	-1.9%	-2.0%	-1.8%	0.0	-4.3
	6	1.4%	2.9%	3.3%	3.3%	3.0%	1.8%	-4.3%	-3.4%	-3.4%	-4.9%	0.0	-4.7
	7	0.6%	1.4%	1.9%	2.5%	2.7%	1.6%	1.4%	-3.0%	-3.0%	-6.1%	0.1	-3.5
	8	0.2%	0.6%	1.1%	1.6%	2.4%	2.0%	1.1%	-1.0%	-4.4%	-3.5%	0.1	-2.2
	9	0.0%	0.2%	0.4%	1.0%	1.4%	1.8%	2.0%	1.5%	-2.6%	-5.7%	0.1	-1.6
	Warm 10	0.0%	0.0%	0.0%	0.2%	0.4%	0.8%	1.5%	3.1%	1.6%	-7.7%	0.1	-1.2

Notes: This table complements Figure A2 and illustrates that travelers from cities with HSR are more likely to go to cities with milder temperature levels, compared to travelers from cities without HSR. Panel (a) refers to travelers from city-days with HSR, panel (b) refers to travelers from city-days without HSR, and panel (c) presents the difference between the two. Positive (negative) values are colored in different shades of green (red) according to the numerical magnitude. In panel (a) and (b), each row represents the shares of travelers to destination cities with different temperature decile, conditioning on home-city-day's temperature decile. The decile cutoffs for daily temperature are 30, 41, 49, 55, 61, 67, 71, 76, and 82 °F.

Table A3: Travelers' exposure to environmental extremes with alternative exposure measures

	(1)	(2)	(3)	(4)	(5)	(6)
	Continuous measures of exposure		Alternative cutoffs for extremes			
	PM _{2.5}	T - 70°F	PM _{2.5} > 120	PM _{2.5} > 150	T < 25°F or T > 95°F	T < 35°F or T > 85°F
Panel (a) : Discrete measure of connectivity						
<i>Expo_{it}</i>	0.34*** (0.02)	0.45*** (0.02)	0.28*** (0.02)	0.27*** (0.02)	0.39*** (0.03)	0.41*** (0.02)
<i>Expo_{it}</i> × <i>HSR_{it}</i>	-0.06* (0.03)	-0.04* (0.02)	-0.05** (0.02)	-0.04 (0.02)	-0.09** (0.04)	-0.09*** (0.02)
N	330,801	466,257	330,801	330,801	466,257	466,257
R ²	0.88	0.95	0.76	0.72	0.77	0.81
Panel (b) : Continuous measure of connectivity						
<i>Expo_{it}</i>	0.25*** -0.02	0.40*** (0.02)	0.19*** (0.01)	0.18*** (0.02)	0.32*** (0.02)	0.33*** (0.01)
<i>Expo_{it}</i> × <i>HSR_{it}^C</i>	-0.04*** (0.02)	-0.03*** (0.01)	-0.04*** (0.01)	-0.04*** (0.02)	-0.07*** (0.01)	-0.06*** (0.01)
N	330,801	466,257	330,801	330,801	466,257	466,257
R ²	0.88	0.96	0.76	0.72	0.79	0.83

Notes: This table examines robustness to alternative measures of exposure to pollution and temperature, as well as different cutoffs for environmental extremes. The dependent variable is the likelihood that travelers experience environmental extremes defined in Eq. (2). $PM_{2.5}$ and T denote the daily average $PM_{2.5}$ concentration and temperature level, respectively. The column heading denotes the $Expo_{it}$ measure used in the regression. HSR_{it} and HSR_{it}^C denote the discrete and continuous HSR connectivity measures, respectively. All regressions are weighted by number of travelers from city i on day t . Day-of-sample fixed effects, city fixed effects and interactions between city fixed effects and HSR are included. Standard errors are clustered at the city level. *** p < 0.01, ** p < 0.05, and * p < 0.10.

Table A4: Travelers' exposure to environmental extremes using sub-samples

	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding 5% days with most/least travels		Excluding 10% days with most/least travels		Cities in top 3 tiers	
	PM _{2.5} > 100	T < 30°F or T > 90°F	PM _{2.5} > 100	T < 30°F or T > 90°F	PM _{2.5} > 100	T < 30°F or T > 90°F
Panel (a): Discrete measure of connectivity						
1{home extreme}	0.27*** (0.01)	0.40*** (0.03)	0.27*** (0.01)	0.39*** (0.03)	0.27*** (0.02)	0.42*** (0.04)
1{home extreme} × HSR _{it}	-0.05*** (0.02)	-0.12*** (0.03)	-0.05** (0.02)	-0.12*** (0.03)	-0.07*** (0.02)	-0.10*** (0.04)
N	330,029	423,888	273,539	378,911	144,369	165,535
R ²	0.79	0.79	0.78	0.79	0.82	0.81
Panel (b) : Continuous measure of connectivity						
1{home extreme}	0.19*** (0.01)	0.31*** (0.01)	0.19*** (0.01)	0.31*** (0.01)	0.18*** (0.01)	0.31*** (0.01)
1{home extreme} × HSR _{it} ^C	-0.04*** (0.01)	-0.07*** (0.01)	-0.04*** (0.01)	-0.07*** (0.01)	-0.04*** (0.01)	-0.07*** (0.01)
N	301,714	423,888	272,364	378,912	144,369	165,535
R ²	0.79	0.81	0.79	0.81	0.83	0.83

Notes: This table examines robustness using sub-samples. Columns (1) and (2) exclude each city's 5% of days with the most card transactions and 5% of days with the least card transactions. Columns (3) and (4) exclude 10% of days with the most and 10% of days with the least transactions. Columns (5) and (6) only keep the large cities defined in the top three tiers. The dependent variable is the likelihood that travelers experience environmental extremes defined in Eq. (2). PM_{2.5} and T denote the daily average PM_{2.5} concentration and temperature level, respectively. 1{home extreme} is an indicator for PM_{2.5} > 100 μg/m³ in odd columns and daily temperature < 30°F or > 90°F in even columns. HSR_{it} and HSR_{it}^C denote the discrete and continuous HSR connectivity measures, respectively. All regressions are weighted by number of travelers from city *i* on day *t*. Day-of-sample fixed effects, city fixed effects and interactions between city fixed effects and HSR are included. Standard errors are clustered at the city level. *** p < 0.01, ** p < 0.05, and * p < 0.10.

Table A5: Travelers' exposure to extreme pollution using leads and lags

	(1)	(2)
	Following Week	Preceding Week
Panel (a): Discrete measure of connectivity		
% of extreme days in home city	0.21*** (0.01)	0.22*** (0.01)
% of extreme days $\times HSR_{it}$	-0.04*** (0.01)	-0.04*** (0.01)
<i>N</i>	325,255	325,000
<i>R</i> ²	0.75	0.75
Panel (b): Continuous measure of connectivity		
% of extreme days in home city	0.14*** (0.01)	0.15*** (0.01)
% of extreme days $\times HSR_{it}^C$	-0.02*** (0.01)	-0.02*** (0.01)
<i>N</i>	323,807	323,554
<i>R</i> ²	0.75	0.75

Notes: This table examines the effect of HSR using the fraction of days when home experiences extreme pollution in the following or preceding week. The dependent variable is the likelihood that travelers experience environmental extremes defined in Eq. (2). Variable ‘% of extreme days in home city’ is the fraction of days with extreme pollution in the following or preceding week. HSR_{it} and HSR_{it}^C denote the discrete and continuous HSR connectivity measures, respectively. All regressions are weighted by number of travelers from city i on day t . Day-of-sample fixed effects, city fixed effects and interactions between city fixed effects and HSR are included. Standard errors are clustered at the city level. *** p < 0.01, ** p < 0.05, and * p < 0.10.

Table A6: Travelers' exposure to extreme pollution: channels of impacts

Panel (a) : Changes in Travel Distance		
Hypothetical Travelers' Exposure		
	PM> 100	T < 30°F or T > 90°F
$\mathbb{1}\{\text{home extreme}\}$	0.11*** (0.003)	0.21*** (0.002)
$\mathbb{1}\{\text{home extreme}\} \times HSR_{it}$	-0.02*** (0.002)	-0.06*** (0.002)
N	330,801	466,257
HSR's overall impact	-0.003	-0.003

Panel (b) : Longer Horizon Adaptation		
Hypothetical Travelers' Exposure		
	PM> 100	T < 30°F or T > 90°F
$\mathbb{1}\{\text{home extreme}\}$	0.30*** (0.01)	0.49*** (0.02)
$\mathbb{1}\{\text{home extreme}\} \times HSR_{it}$	-0.02 (0.01)	-0.07** (0.03)
N	330,801	466,257
R ²	0.66	0.74
HSR's overall impact	-0.005	-0.005

Notes: The dependent variable of Panel (a) is hypothetical travelers' exposure that is constructed by replacing destination cities' environmental conditions with the concurrent conditions in cities of a similar distance to the origin, $TravExpo_{it}^1 = \sum_{j \neq i} \widehat{Expo}_{jt} \cdot \frac{N_{ij}}{\sum_{k \neq i} N_{ik}}$, where \widehat{Expo}_{jt} is the pollution level of a randomly-chosen city that is similarly distant from the original city as city j. $\mathbb{1}\{\text{home extreme}\}$ is an indicator variable of extreme conditions. Day-of-sample fixed effects, city fixed effects, and interactions between city fixed effects and HSR dummy are included in both regressions. The last row reports HSR's aggregate effect holding trip distance constant, which is a 0.3 percentage-point reduction in traveler's likelihood of experiencing extreme pollution as well as a 0.3 percentage-point reduction in exposure to extreme temperature.

The dependent variable of Panel (b) is hypothetical travelers' exposure that is constructed using the average traveler flow from the origin city before and after HSR: $TravExpo_{it}^2 = \sum_{j \neq i} Expo_{jt} \cdot \frac{N_{ij}^{\text{No HSR}}}{\sum_{k \neq i} N_{ik}^{\text{No HSR}}} \cdot \mathbb{1}\{t \text{ before HSR}\} + \sum_{j \neq i} Expo_{jt} \cdot \frac{N_{ij}^{\text{HSR}}}{\sum_{k \neq i} N_{ik}^{\text{HSR}}} \cdot \mathbb{1}\{t \text{ post HSR}\}$, where $N_{ij}^{\text{No HSR}}$ is the total number of travelers from city i to city j prior to the HSR access and N_{ij}^{HSR} is the total number of travelers from city i to city j post the HSR access. The last row reports HSR's aggregate mitigation effect in the absence of day-to-day avoidance responses, which is a 0.5 percentage-point reduction in traveler's likelihood of experiencing extreme pollution as well as a 0.5 percentage-point reduction in exposure to extreme temperature. Standard errors are clustered at the city level. *** p < 0.01, ** p < 0.05, and * p < 0.10.

Table A7: Number of travelers in response to extreme pollution at home (extensive margin)

	Current Day Exposure			Average Exposure, ± 3 days		
	All Travel	>300km	>500km	All Travel	>300km	>500km
$\mathbb{1}\{\text{home extreme}\}$	-1.32** (0.56)	-0.021*** (0.0061)	-0.015** (0.0063)	-3.37*** (1.26)	-0.053*** (0.014)	-0.038*** (0.015)
$\mathbb{1}\{\text{home extreme}\} \times HSR_{it}$	0.59 (0.61)	0.013* (0.0070)	0.012 (0.0075)	1.51 (1.31)	0.029* (0.015)	0.027* (0.016)
N	330819	329626	329255	325541	324901	324609
R^2	0.98	0.97	0.96	0.98	0.97	0.96

Notes: This table examines the extensive margin: the number of travelers when home experiences extreme pollution. The dependent variable is log number of travelers in city i at time t in columns (1) and (4), log number of travelers journeying farther than 300km in columns (2) and (5), and log number of travelers journeying farther than 500km in columns (3) and (6). $\mathbb{1}\{\text{home extreme}\}$ is an indicator for $\text{PM}_{2.5} > 100\mu\text{g}/\text{m}^3$. All regressions are weighted by number of travelers from city i on day t . Day-of-sample fixed effects, city fixed effects and interactions between city fixed effects and HSR are included. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.