Improved Transportation Networks Facilitate Adaptation to Pollution and Temperature Extremes

Panle Jia Barwick[a,c], **Dave Donaldson**[b,c,1], **Shanjun Li**[a,c], **Yatang Lin**[d], **and Deyu Rao**[a]

[a]Cornell University, Ithaca, NY 14853, USA; [b]Massachusetts Institute of Technology, Cambridge, MA 02139, USA; [c]National Bureau of Economic Research, Cambridge, MA 02138, USA; [d]Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong

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The social costs of air pollution and climate change hinge critically on humans' ability to adapt. Based on high-resolution transaction records from the world's largest payment network, this research shows how China's rapid expansion of high-speed railways and air-travel networks (HSR/air) has facilitated the use of intercity travel as an effective means of adaptation. On average, HSR/air connection would reduce travelers' exposure to both extreme pollution and temperature by 16% when home cities are experiencing pollution and temperature extremes. Longer-horizon changes in travel patterns before and after HSR/air access explain 56% of the reduction in pollution exposure and 81% for temperature exposure. Contemporaneous responses to unexpected adverse conditions account for the remaining impact. These reductions in exposure to environmental extremes entail substantial health benefits. This study contributes to our understanding of the role of adaptation and the benefit of transportation infrastructure investment in a changing environment.

Climate Change | Transportation Infrastructure | Temperature shocks | Air Pollution | Adaptation

Air pollution and climate change are among the most pressing environmental challenges of our time. These challenges impose large social costs by affecting economic growth,[1,2,3] social stability,[4,5] and health.[6,7,8,9] The social costs of climate change and air pollution depend crucially on the extent to which humans can adapt to extreme environmental conditions. While long-term migration can be an effective strategy for adaptation to a changing environment,[10,11,12,13] 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 new themes in intercity travel in China with the advent of cheap and fast transportation modes.[14,15,16]

This study provides the first analysis of how improved transportation infrastructure facilitates behavioral changes in response to adverse environmental conditions. We do so in the context of China's rapid expansion of high-speed-railways (HSR) and air-travel networks ("air"). Since 2008, China has extended HSR dramatically to a total length of over 29,000 km by the end of 2018, twice as long as the HSR networks of all other countries combined (Panel (a) of Figure S1 in Supplementary Information (SI)). China's air network has also grown considerably, with the number of direct flights nearly doubling between 2011 and 2016 (Panels (b) and (c) of Figure S1). Our analysis uses the first high-frequency (daily) measure of traveler flows between all city-pairs in China and compares the intensity of extreme air pollution and temperature that is actually realized by travelers from cities with HSR/air access to that by travelers without such access. An estimate of the causal effect is established based on the day-to-day variation in travel patterns and the expansion of HSR and air networks.

Data and Descriptive Evidence

Our primary data source is the universe of credit- and debit-card transactions made through UnionPay, the only inter-bank payment network in China and the largest payment network in the world. We construct cross-city travel between all city pairs during 2013-2016 using offline transactions where the cardholder is physically present at the merchant's location. We then merge this daily travel data with daily air pollution and temperature readings at the city level, as well as data on the HSR and air network expansion over time. The outcome variables of interest in our analysis measure the realized exposure to pollution (and, separately, to temperature extremes) among travelers, constructed on the basis of the environmental conditions at their destination cities. Such a measure cannot be constructed without the high-frequency and high-spatial travel and environmental data merge that we develop here. Table S1 and Section A in SI provide the summary statistics of key variables and further details on data sets used in this analysis.

Figure 1 provides our first piece of descriptive evidence on the benefit of improved transportation networks in mitigating households' pollution exposure. The top panel plots the average realized pollution exposure of travelers – defined as the weighted average of the daily pollution levels across destination cities, with weights based on daily origin-destination traveler shares – as a function of the corresponding day's pollution in each traveler's home city. Travelers based in cities with active HSR connections experience a statistically significantly 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 – $PM_{2.5}$ higher than 100 $\mu g/m^3$ (the 90^{th} percentile) – the wedge between HSR-travelers and non-HSR travelers exceeds 9 $\mu g/m^3$ and can reach as high as 30 $\mu g/m^3$.

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 non-HSR city travelers and 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 $\mu g/m^3$ when the home city's pollution is in the lowest quintile, the gap enlarges to 8.35 $\mu g/m^3$ 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%).

Results for temperature exposure are similar (Figure S2 and Table S2 in SI). These patterns present clear

Significance Statement

Climate change and environmental degradation pose growing risks to humans and the impacts of these risks largely depend on the ability of humans to adapt. This study investigates the role of China's breathtaking investment in transportation infrastructure, including high-speed railways (HSR) and air travel networks, in facilitating residents' adaptation to pollution and temperature extremes via intercity travel. The analysis leverages high-resolution transaction records to track intercity travel from the world's largest payment network. Our analysis show that a city's connection to these transportation networks would significantly reduce travelers' exposure to both extreme pollution and temperature when home cities are experiencing adverse environmental conditions. Our findings highlight that improved transportation infrastructure could facilitate adaptation in addressing environmental risks.

P.B., D.D., S.L., Y.L., and D. R. designed research, performed research, and wrote the paper. Y.L. and D.R. analyzed data.

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P.B., D.D., S.L., Y.L., and D. R. contributed equally to this work.

[1]To whom correspondence should be addressed. E-mail: ddonald@mit.edu.

evidence that travelers benefit from improvements in passenger transportation infrastructure by experiencing reduced exposure to adverse environmental conditions.

Regression Model

To quantify the benefit of improved transportation infrastructure in mitigating pollution, we follow the standard difference-in-differences strategy in a panel regression framework:

$$\mathtt{TravExpo}_{it} = \beta_1\,\mathtt{Expo}_{it} + \beta_2\,\mathtt{HSR}_{it} \times \mathtt{Expo}_{it} + \beta_{3i} \times \mathtt{HSR}_{it} + \mu_i + \delta_t + \epsilon_{it}. \qquad [1]$$

In this expression, $\mathtt{Expo}_{it}$ measures pollution exposure in city i at time t, which we construct as a simple indicator that equals one whenever i experiences extreme pollution ($PM_{2.5} > 100\mu g/m^3$, the 90th percentile of the empirical distribution).* The dependent variable, $\mathtt{TravExpo}_{it}$, analogously measures the pollution exposure at time t of travelers whose home city is i. We calculate this from the extreme pollution that was realized in the destination cities that each traveler from city i visited at time t; see Equation (S1).

The variable $\mathtt{HSR}_{it}$ is an indicator set equal to one if city i has direct access to the HSR network at time t. We let the impact of HSR access on travelers' pollution exposure be a function of both the home city's exposure (captured in the coefficient β_2) and the identity of the home city itself (via the set of coefficients β_{3i}, one for each city i). Finally, all regressions control for city fixed effects μ_i, which capture time-invariant city-level unobservables that affect travelers' exposure (e.g. economic connections with other cities), as well as year-day (i.e. day-of-sample) fixed effects δ_t that control for phenomena such as holidays and seasonality.

We estimate the total benefit of the expansion of the HSR network on travelers' pollution exposure by $-\sum_{i,t} \omega_{i,t}(\beta_2 \times \mathtt{Expo}_{it} + \beta_{3i})$, where $\omega_{i,t}$ is the city-i and day-t share of travelers among all HSR city-days in our sample period. 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 travel.

We also present two variants on specification 1. First, we include an indicator for airport access in city i at time t, denoted $\mathtt{Air}_{it}$, both instead of and in addition to the variable $\mathtt{HSR}_{it}$. This allows us to compare the benefits of rail and air travel infrastructure. Second, we study temperature exposure analogously to pollution exposure by letting $\mathtt{Expo}_{it}$ take the value one if city i at time t experiences extreme temperature (daily temperature $> 90°$F or $< 30°$F) and adjusting $\mathtt{TravExpo}_{it}$ accordingly.†

Section C of SI presents more details about our regression framework and examines alternative cutoffs for extreme pollution and temperature conditions.

Empirical Results

Panel (a) of Table 2 reports OLS estimates as specified in Equation (1). Columns (1)-(3) examine the effects on travelers' pollution exposure from obtaining access to HSR, air, and both, respectively. The estimates of β_1 in all columns are much lower than one and vary from 0.19 to 0.27, implying that intercity travel reduces substantially the correlation between home pollution and travelers' realized exposure. The estimates of β_2 are negative, significant and economically large in all columns, suggesting that improvements in the transportation network (both HSR and air) can change travel patterns in a way that further flattens the relationship between home extreme pollution and travelers' exposure.‡

*China's Ministry of Ecology and Environment's standard for daily maximum $PM_{2.5}$ is 75 $\mu g/m^3$. In comparison, in the U.S. the Environmental Protection Agency's daily $PM_{2.5}$ standard is 35 $\mu g/m^3$.

†Using 30°F and 90°F as cutoffs, extreme temperature occurs in around 10% of city-days.

‡The estimate for β_2 is -0.05 for HSR and -0.14 for Air, respectively, largely because air travel spans a longer distance and the spatial correlation of pollution decays with distance.

We summarize HSR/air's aggregate benefit, $-\sum_{i,t} \omega_{i,t}\{\beta_2 \times \mathrm{Expo}_{it} + \beta_{3i}\}$, in the last row of panel (a). In theory, its sign is ambiguous. While HSR/air expansion allows individuals to visit further places and leads to a lower correlation between home conditions and travelers' actual exposure, this does not imply that HSR/air automatically *reduces* travelers' exposure. For example, when the home city is clean, travel could increase travelers' exposure as destination cities could be dirtier. Nevertheless, consistent with the descriptive evidence above, we estimate that the aggregate benefit of HSR/air expansion across all cities and home conditions is a 1.8 percentage-point reduction in the likelihood of being exposed to extreme pollution (relative to the sample mean of 11 percentage points). This represents a 16% decrease in travelers' likelihood of experiencing extreme pollution.

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. On average, connection to a better passenger transportation network reduces travelers' likelihood of exposure to extreme temperatures by 0.98 percentage points (out of a sample mean of 6 percentage points), a 16% drop.

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

When a typical traveler's home city is clean, she can expect to experience a modest 8.19 percentage-point likelihood of being subject to severe pollution – a reflection of mean reversion and the spatial heterogeneity of air pollution – and removing HSR/air only moderately increases this traveler's exposure to 8.22 percentage points. In contrast, on a typical day when her home city is suffering from extreme pollution, removing access to the HSR/air travel network would raise this traveler's probability of experiencing extreme pollution from 38.7 to 54.2 percentage points, amounting to a 40.05% increase.

Results for temperature exposure are similar. HSR/air's effect is negligible when home cities have mild temperatures. But when home cities are affected by extreme temperature, removing HSR/air would increase travelers' exposure to such extremes from 39.9 to 56.1 percentage points, a very pronounced hike.

Robustness Checks. Section C2 in SI presents evidence on the robustness of these findings and evaluates the extensive margin. Table S3 replaces the indicator variables, HSR_{it} and Air_{it}, with continuous connectivity measures that are defined in Equation Eq. (S3) in SI. Table S4 in SI examines continuous measures of environmental conditions (columns 1-2) and different extreme-event cutoffs (columns 3-6). Table S5 in SI excludes days with the most and least card transactions (columns 1-4) and small cities (columns 5-6). Table S6 uses lagged and leading terms of key independent variables. Results from these specifications all demonstrate that the expansion of the passenger transportation infrastructure makes intercity travel an effective strategy for reducing exposure to environmental extremes.

Mortality Benefits. Expanded HSR/air is associated with a 16 percentage-point reduction in travelers' likelihood of experiencing extreme pollution (Table 2), or a 14% reduction in travelers' average pollution exposure (Table S4 in SI), equivalent to a drop of 9.1 $\mu g/m^3$ $PM_{2.5}$ for an average traveler on traveling days. This amounts to an annual reduction of 59.2 billion $\mu g/m^3$ by day in $PM_{2.5}$ exposure. Using dose-response function estimates in the literature (17), the mortality benefit from such a reduction in pollution exposure translates to an annual savings of 5.7 million life-years. Similarly, the benefit from mitigation of temperature extremes amounts to 143,000-268,000 fewer deaths per year (see Appendix E for details).

Margins of Adaptation. Our finding that improved transportation infrastructure facilitates adaptation to environmental extremes could arise from different margins. First, individuals can more easily reach places with predictably desirable environmental conditions, such as trips to southern cities during polluted and harsh winter months in northern cities. Second, travelers have greater scope to spontaneously visit cities with better environmental conditions in response to unexpected environmental extremes at home.

Figure S3 in SI illustrates changes in travel behavior consistent with both margins. It plots the distribution of trip distance for travelers with and without HSR/air access, separately for clean and polluted days (with $PM_{2.5}$ exceeding 100 $\mu g/m^3$). HSR/air access has significantly shifted the travel distribution: the fraction of trips exceeding 500 km increases from 35% among travelers without HSR/air access to 52% among those with access when home cities are clean. The difference in the fraction of trips exceeding 500 km further increases to 21 percentage points during polluted days.

To quantify the benefit of HSR/air 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 travel destination shares, separately before and after HSR/air access, instead of daily travel shares to construct travelers' exposure in equation (S1). By construction, this formulation removes deliberate travel responses to temporal, day-to-day variations in environmental conditions. Then we regress this alternative travelers' exposure on access to HSR/air following equation (1). The lower panel of Table S8 in SI suggests that this margin accounts for 56% of HSR/air's aggregate benefit in pollution mitigation and 81% for temperature. We attribute the remaining benefit (44% of pollution reduction and 19% 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. In Section D, additional simulation exercises that hold travel distance constant corroborate the notion that travelers with access to HSR/air networks choose destinations (conditional on distance) with more desirable environmental situations. HSR/air 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.

Conclusion

Using high-frequency data on intercity travel in China, our analysis shows that the rapid expansion of HSR and air networks 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 shifts in long-horizon travel patterns from reduced travel costs and short-run deliberate responses to unexpected environmental extremes at home. The net impact on air pollution and carbon emissions from these behavioral changes depends on the environmental footprint of alternative adaptation measures (e.g., turning on air conditioning and air purifiers, and substituting away from highway driving), an important topic for future research.

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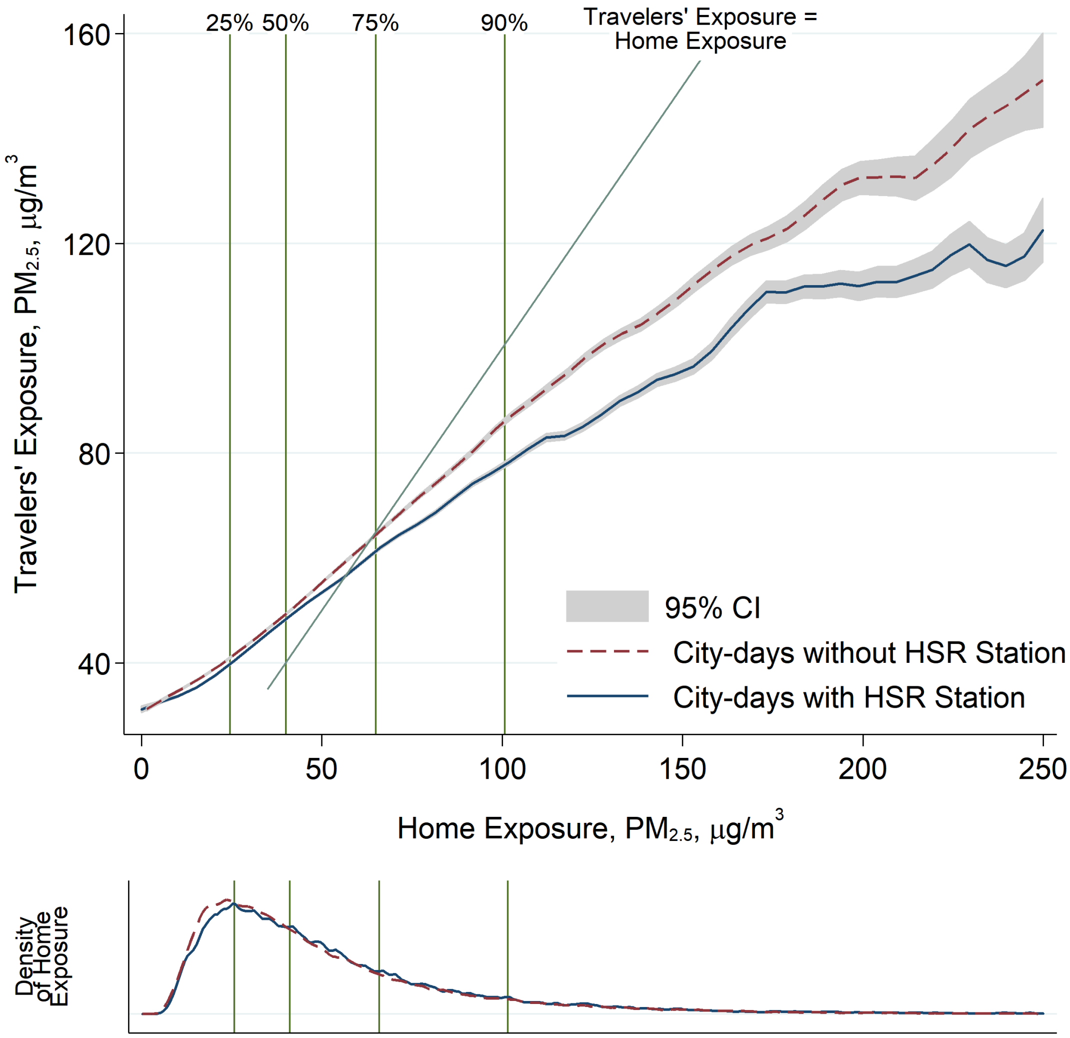

Fig. 1. Travelers' exposure to $PM_{2.5}$ vs. home exposure

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 without access to HSR (red dash line) and city-days with access to HSR (blue 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 $PM_{2.5}$ at home cities, separately for city-days without access to HSR (red dash line) and city-days with access to HSR (blue line), fitted by Epanechnikov kernel with optimal bandwidth. Green vertical lines mark the 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles of the $PM_{2.5}$ distribution.

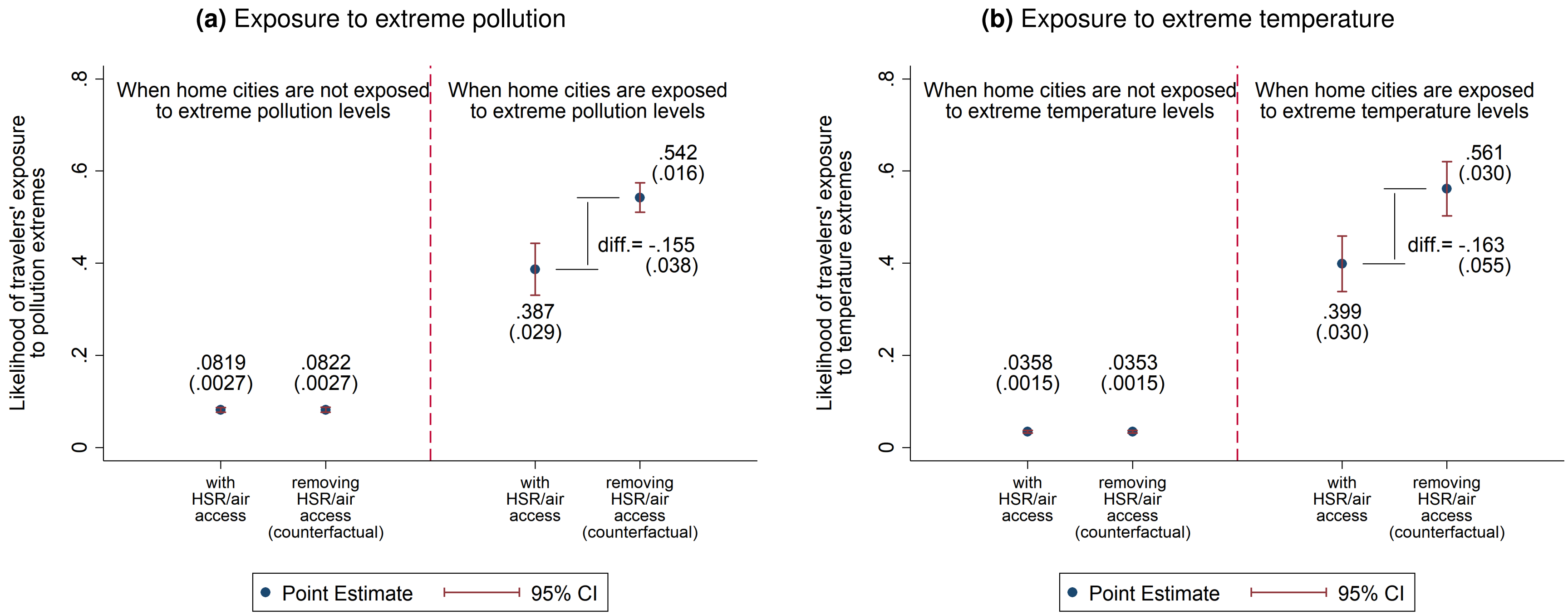

Fig. 2. Access to HSR/air and reduction in exposure to pollution and temperature extremes

Notes: actual and counterfactual likelihood of travelers experiencing extreme pollution (panel (a)) and extreme temperature (panel (b)), based on coefficient estimates in column (3) 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 $\mu g/m^3$ and extreme temperature is defined as daily average temperature below 30°F or above 90°F. Counterfactual exposure is the predicted outcome from Equation (1) when HSR/air dummies are switched to zero. Blue dots (whiskers) denote point estimates (95% confidence interval). 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 without HSR

		Flow shares by pollution quintile at destination					Avg. Exposure of $PM_{2.5}$ ($\mu g/m^3$) at	
		Clean 1	2	3	4	Dirty 5	Home	Dest.
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

(b) For travelers from city-days with HSR

		Flow shares by pollution quintile at destination					Avg. Exposure of $PM_{2.5}$ ($\mu g/m^3$) at	
		Clean 1	2	3	4	Dirty 5	Home	Dest.
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

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

		Difference in flow shares by pollution quintile					Diff. in $PM_{2.5}$ ($\mu g/m^3$) at	
		Clean 1	2	3	4	Dirty 5	Home	Dest.
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 HSR-travelers are more likely to visit cleaner cities than non-HSR travelers. 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 without HSR, panel (b) refers to travelers from city-days with 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 $\mu g/m^3$.

Table 2. Travelers' likelihood of experiencing environmental extremes

Panel (a): Air Pollution Daily $PM_{2.5} > 100\mu g/m^3$	Likelihood of experiencing pollution extremes		
$\mathbb{1}${home extreme}	0.19***	0.23***	0.27***
	(0.01)	(0.01)	(0.01)
$\mathbb{1}${home extreme} $\times \mathrm{HSR}_{it}$	-0.09***		-0.05***
	(0.03)		(0.02)
$\mathbb{1}${home extreme} $\times \mathrm{Air}_{it}$		-0.15***	-0.14***
		(0.03)	(0.02)
N	330,801	330,801	330,801
R^2	0.78	0.78	0.79
HSR/Air's overall impact	-0.010**	-0.016***	-0.018***
	(0.004)	(0.005)	(0.006)

Panel (b): Temperature Daily temperature	Likelihood of experiencing temperature extremes		
$< 30°$F or $> 90°$F	(1)	(2)	(3)
$\mathbb{1}${home extreme}	0.33***	0.33***	0.40***
	(0.01)	(0.02)	(0.03)
$\mathbb{1}${home extreme} $\times \mathrm{HSR}_{it}$	-0.13***		-0.12***
	(0.04)		(0.03)
$\mathbb{1}${home extreme} $\times \mathrm{Air}_{it}$		-0.12***	-0.09***
		(0.04)	(0.03)
N	466,257	466,257	466,257
R^2	0.78	0.78	0.79
HSR/Air's overall impact	-0.006**	-0.006**	-0.010**
	(0.003)	(0.003)	(0.004)

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 $< 30°$F or $> 90°$F), respectively. The average of the dependent variables in panel (a) and (b) is 0.11 and 0.06, indicating the likelihood of travelers being subject to extreme pollution and temperature of 11% and 6%. $\mathbb{1}\{\cdot\}$ is an indicator for extreme conditions at home city i on day t. HSR_{it} and Air_{it} are indicator variables for access to HSR stations and airport in the home city, respectively. 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 (and/or air) dummy are included in all regressions. The last row of each panel reports HSR/air's aggregate mitigation effect, which is a 1.8 percentage-point reduction in traveler's likelihood of experiencing extreme pollution in column 3 of panel (a) and a 0.9 percentage-point reduction in column 3 of panel (b). Standard errors for coefficient estimates are clustered at 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 * $p < 0.10$.

Supplementary Information

This study provides the first analysis of how transportation infrastructure promotes short-term mobility and facilitates behavioral changes in response to adverse environmental conditions, in the context of China's rapid expansion of high-speed-railways (HSR) and air-travel networks. Our analysis exploits high-frequency data of traveler flows across Chinese cities that are constructed using the universe of credit- and debit-card transactions through UnionPay, the world's largest payment network. It also takes advantage of China's massive and staggered expansion of passenger transportation networks from 2011 to 2016, as well as the rich variation in daily pollution and temperature at the city level.

Air Pollution and Temperature Extremes in China. 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.[24,25] Air pollution and temperature extremes in China raise serious concerns given the size of the affected population.

Expansion of China's Passenger Transportation Network. Transportation networks can promote the mobility of people and goods,[26,27,28] foster market integration,[29,30,31,28,32,33] and facilitate knowledge sharing.[34,35] Improved transportation networks also provide households opportunities to mitigate the adverse effect of local shocks (including pollution and weather shocks) so that local conditions no longer "impose a death sentence on some fraction of the citizens inhabiting the affected region".[36] China has made great strides in developing its passenger transportation infrastructure over the past decade. Since 2008, China has expanded HSR to two-thirds of all prefecture level cities (Panel (a) of Figure S1), with a total length that exceeded 29,000 km by the end of 2018. Its HSR network is twice as long as the HSR networks of all other countries combined. Because of its fast speed (155-217 miles/hr), low cost and reliability, HSR offers an attractive substitute to traditional travel options, such as driving or taking regular railways, and has transformed how Chinese residents travel. At the same time, China's air network has also expanded, with the number of direct flights increasing dramatically from 2011 to 2016 (Panel (b) and (c) of Figure S1). The rapid expansion of HSR and air networks 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, and those via airlines increased from 268 million to 660 million during the past decade (2010-2019).

Adaptation and Short-Term Travels. Households' demand for environmental quality usually grows with their income. With increasingly more resources, households are more likely to undertake adaptation measures to deal with adverse environmental conditions. For example, studies have documented that Chinese residents have significantly increased spending on air purifiers and face masks to protect themselves from air pollution over the past decade.[18,19,20,21,22]

In addition to defensive investments, households can change locations and move away from an adverse environment. Long-term migration, however, entails significant moving costs, especially for residents in developing countries with severe market frictions and institutional constraints. The household registration system (or *hukou*) in China has long hindered formal migration and is still in-place in most cities.[21] In contrast, short-term intercity travel is not affected by the *hukou* system and offers a more practical and affordable adaptation strategy to mitigate the negative effects of local environmental conditions.

Our analysis compares differential exposure to adverse environmental conditions among travelers with HSR/air access and travelers without such access. We present both descriptive evidence and regression analysis. We evaluate two environmental conditions (air pollution and temperature shocks) and two transportation modes (HSR and air).

A. Data and Descriptive Evidence

A1. Data Sources and Description. Our analysis relies on the following data sources: (1) data on daily passenger flow across cities derived from credit/debit card transactions; (2) information on daily air pollution and temperature by city; and (3) HSR and commercial air networks between city pairs over time.

Traveler Flow We construct daily bilateral passenger flows across cities using the universe of credit and debit card transactions conducted through the UnionPay network. UnionPay is the only inter-bank payment network in China, and it is the largest network in the world, ahead of Visa and Mastercard. The database covers 34 trillion *yuan* ($4.9 trillion) of annual economic activities from 2.7 billion cards across more than 300 merchant categories from 2011 to 2016. The dataset includes the time and value of transaction, the merchant's name, category, and location. 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 card's home location at month m is calculated as the city with the most frequent usage over a rolling 12-month window between month $m-6$ and month $m+5$. A trip occurs if the city of the transaction differs from the home city.[§] 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 China's Ministry of Ecology and Environment (MEE, formerly the Ministry of Environmental Protection) rolled out a nation-wide pollution monitoring and information disclosure program across cities in three-waves from 2013. Ground-level monitoring stations were installed or upgraded in over 1600 sites throughout China and hourly air quality data on $PM_{2.5}$, PM_{10}, CO, SO_2, NO_2, and O_3 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 across hourly readings from monitoring stations within a city. The nationwide average concentration of $PM_{2.5}$ during the 2013-2016 period was 48 $\mu g/m^3$ (with a standard deviation of 41 $\mu g/m^3$), much higher than the annual air quality standards of 12 $\mu g/m^3$ set by the U.S. Environmental Protection Agency (EPA) and 35 $\mu g/m^3$ 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 Bejing Time and Greenwich Mean Time (GMT). We average over hourly readings to obtain the daily average temperature.

HSR and Air Network We gather information on the opening dates of HSR station and airports from government official reports. If a city has multiple HSR stations or airports, we use the date when the first HSR station or airport 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. For the air network, we use monthly reports from the Official Aviation Guide (OAG) that cover schedules on all of China's domestic flights from 2013 to 2016. The number of connections via HSR and air network is defined as the number of distinct cities that are directly connected to the origin city via the two travel modes respectively.

Summary Statistics Table S1 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 $\mu g/m^3$. This is considerably higher than U.S.'s daily standard of 35.4 $\mu g/m^3$. About 19% of the city-days also exceeded China's daily standard of 75 $\mu g/m^3$ (which became effective in 2016).

$PM_{2.5}$ varies considerably in our sample period, with a standard deviation of 44.51 $\mu g/m^3$ and an inter-quartile range of 40.3 $\mu g/m^3$. The 90th, 95th, and 99th percentiles are 100.8, 131.8, and 219.8 $\mu g/m^3$, respectively. About 80% of the variation comes from day-to-day changes within a city, while the remaining 20% arises from differences

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

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.

B. Additional Descriptive Evidence

In this section, we present additional descriptive evidence on patterns of adaptation to environmental extremes and the role of transportation infrastructure in facilitating such adaptation.

Figure S2 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 of Figure S2 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.[¶] 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 S2 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 S4 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 $\mu g/m^3$ 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 S5 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 S2 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

[¶]The standard errors are calculated using the Epanechnikov kernel and optimal bandwidth in STATA.

temperatures below 61 °F (the median) and five bins for temperatures 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 non-HSR travelers and HSR-travelers, 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 S2 complements Table 1 in the main text and provides additional descriptive evidence on the benefit of improved transportation networks.

C. Empirical Framework

C1. Regression Model. The outcome variable of our analysis, traveler's exposure, is defined by 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:

$$\mathsf{TravExpo}_{it} = \sum_{j \neq i} \mathsf{Expo}_{jt} \cdot \frac{N_{ij,t}}{\sum_{k \neq i} N_{ik,t}} \qquad \text{[S1]}$$

Here $\mathsf{TravExpo}_{it}$ denotes the average exposure to environmental shocks for travelers from city i at time t, Expo_{jt} is the environmental reading in destination city j at time t, $N_{ij,t}$ is the number of travelers from city i visiting city j on day t, and $\sum_{k \neq i} N_{ik,t}$ denotes the total number of travelers from city i on day t.

The empirical framework examines how HSR and air connections mitigate travelers' exposure to adverse environmental conditions in their home city. Our analysis on the impact of HSR is based on the following equation:

$$\mathsf{TravExpo}_{it} = \beta_1\, \mathsf{Expo}_{it} + \beta_2\, \mathsf{HSR}_{it} \times \mathsf{Expo}_{it} + \beta_{3i} \times \mathsf{HSR}_{it} + \mu_i + \delta_t + \epsilon_{it}, \qquad \text{[S2]}$$

where Expo_{it} is the environmental condition in home city i at time t. It is either a continuous variable representing the level of pollution or temperature readings, or dummies variables for extreme environmental conditions. We show robustness to different cutoff values for extreme conditions later in this section.

The model includes a rich set of fixed effects to adsorb unobservables in both temporal and spatial dimensions. δ_t are day-of-sample fixed effects that control for national shocks such as holidays and seasonality that could affect travel and be correlated with pollution and weather patterns. μ_i are city fixed effects, which control for time-invariant city-specific unobservables. In addition, we incorporate different city fixed effects post-HSR (β_{3i}) to allow differential travel patterns after a city gains access to the HSR network. Our preferred specification controls for both HSR and air, their interaction terms with Expo_{it}, as well as the interaction between city fixed effects and HSR/air ($\beta_{3i} \times \mathsf{HSR}_{it}$ and $\beta_{4i} \times \mathrm{air}_{it}$).

In the main text, HSR_{it} (Air_{it}) is a dummy variable that takes the value one if city i has direct access to the HSR (air) network at time t. We have experimented with several continuous measures of the HSR/air connectivity. One measure uses a weighted number of destination cities that can be reached from the origin city via HSR or air, following.[23] 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:

$$\begin{aligned} \widetilde{\mathsf{HSR}^C_{it}} &= \sum_{j \neq i} \left[\frac{\text{Total Inflow}_{j,2012}}{\mathsf{Distance}^2_{ij}} \times \mathsf{HSR}_{ijt} \right] \\ \mathsf{HSR}^C_{it} &= (\widetilde{\mathsf{HSR}^C_{it}} - \mu)/\sigma \end{aligned} \qquad \text{[S3]}$$

where Total Inflow$_{j,2012}$ is city j's total number of visitors in 2012, $\mathsf{distance}_{ij}$ 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^C_{it}. 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, $\mathtt{HSR}^{C}_{it}$ increases whenever city i is connected to additional destinations as the HSR network expands. In addition, this measure also depends on cities' centrality in the transportation network. The connectivity measure for air ($\mathtt{air}^{C}_{it}$) is defined analogously. Other connectivity measures include replacing distance squared with distance and/or removing the destination city's inflow (Total $\text{Inflow}_{j,2012}$) in the weights. Our results are robust to these different measures of connectivity.

Parameter β_1 captures the relationship between a given 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 $0 < \beta_1 < 1$.

Parameter β_2 measures how HSR access affects the relationship between home conditions and travelers' exposure. If HSR facilitates residents' ability to mitigate adverse environmental conditions at home, β_2 should be negative. The identification of β_2 is based on the standard difference-in-differences (DID) design. Taking pollution ($PM_{2.5}$) as an example, when $\mathtt{Expo}_{it}$ is a dummy variable for local extreme pollution, the DID estimator of β_2 measures HSR's impact on travelers' exposure during polluted days relative to its impact during clean days, while using cities without HSR as a control group. The key identification assumption is the standard common-trend assumption, where there are no confounding factors that affect the relationship between home city's pollution level and traveler's exposure before and after the HSR connection.

In principle, 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 dominate the benefit from mitigation when the home city is polluted. Hence, whether improved transportation facilitates mitigation on net is an empirical question. Our measure of the aggregate benefit of improved transportation infrastructure is $-\sum_{i,t}\omega_{i,t}(\beta_2 * \mathtt{Expo}_{it} + \beta_{3i})$, where $\omega_{i,t}$ is city-i-day-t's share of travelers among all cities with HSR access in our sample period. 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 travel.

C2. Robustness Checks. This section explores the robustness of our findings to alternative specifications. Table S3 replaces the indicator variables $\mathtt{HSR}_{it}$ and $\mathtt{Air}_{it}$ with the continuous connectivity measures $\mathtt{HSR}^{C}_{it}$ and $\mathtt{Air}^{C}_{it}$ that are defined in Equation Eq. (S3). Results are similar qualitatively.

Our findings are robust to alternative measures of environmental conditions. Panel A of Table S4 replicates the analysis for the discrete measure of HSR/air connections, while Panel B replicates the analysis using the continous measure of HSR/air connections. In columns 1 and 2, we replace the dummy of extreme pollution with the continuous PM2.5 reading and replace the dummy of extreme temperature with the absolute deviation from 70°F. One $\mu g/m^3$ increase in PM2.5 at home translates into 0.34 $\mu g/m^3$ increase in non-HSR travelers' exposure and only 0.28 for HSR travelers. The patterns are similar for the effect of air and for temperature exposure. Columns 3-6 use alternative cutoffs to define environmental extremes. Columns 3 and 4 use 120 $\mu g/m^3$ and 150 $\mu g/m^3$ for extreme pollution. Column 5 uses 25 °F and 95 °F as the cutoffs for extreme temperature, while column 6 uses 35 °F and 85 °F. The coefficient estimates have the same signs and are similar in magnitude to the baseline estimates that are reported in Table 2.

Table S5 examines robustness to different sample cuts, again for both the discrete (Panel A) and continuous measures (Panel B) of HSR/air connections. Our estimates of the number of travelers are derived from card transactions and subject to measurement errors. To examine robustness to potential measurement errors, columns 1-2 exclude each city's 5% of days with the most card transactions, and 5% of days with least card transactions, and columns 3-4 exclude 10% of days with the most/least transactions. In addition, since card penetration rates are lower in low-tier cities, columns 5-6 only keep cities in the top three tiers. These cities have larger populations than bottom-tier cities and account for over 80% of travelers in our sample. All of these regressions demonstrate that our results are robust to potential measurement errors and that the expansion of the passenger transportation infrastructure makes the intercity travel an effective strategy to reduce exposure to environmental shocks.

Our specifications so far relate travelers' exposure to home conditions on the same day. This implicitly assumes that households can respond quickly (within a day) to negative shocks. Same-day travel in China is made possible by the expansive network and numerous train- and flight-departures that are scheduled daily for most cities. Ample evidence cites households using pollution and weather forecasts to travel to desirable places in events of extreme pollution and heat waves.[14,15,16] As a result, "Haze-avoidance tourism" and "smog refugees" have become new themes in intercity travel in recent years.

Nonetheless, to allow the possibility that households react with a lag to pollution and temperature shock (due to the time constraint it takes to respond), or even in advance of such a shock (due to the wide availability and increasing accuracy of forecasts), Table S6 replaces the daily environmental measure Expo_{it} with its average leads in the following week (column 1) and average lags in the previous week (column 2). Similar to Tables S3-S5, Panel A presents results for discrete HSR/air connections and panel B reports results using continuous measures of connections. 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/air facilitates adaptation to both contemporaneous environmental shocks and recent and future shocks.

C3. Extensive Margin. Up to now, our analysis has focused on the intensive margin of travel responses: the role of HSR/air in assisting travelers from pollution-hit cities to access cleaner destinations. However, adjustments at the extensive margin could also be relevant. It is unclear ex-ante whether people might be expected to travel more when pollution is worse in their home city. On the one hand, people might travel to cleaner cities as a means of avoidance. On the other hand, people might reduce outdoor activities entirely, thus limiting their intercity travel. Table S7 evaluates such extensive margin responses by using the log number of travelers in a city-day.

Corroborating existing findings in the literature,[38,39,40] we find that residents travel significantly 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 government and media. On the other hand, having access to HSR/air networks increases the frequency of travel, especially for trips with a medium or long distance (longer than 300km or 500km). The coefficients are somewhat small and noisy, suggesting that the extensive margin is unlikely to be the primary channel underlying the avoidance behavior documented above.

D. Margins of Adaptation

D1. Changes in Travel Distance. HSR/air access reduces travel costs, expands the set of feasible destinations and allows individuals to travel to more distant destinations. Panels (a)-(d) of Figure S3 plot the distribution of trip distance for travelers with and without HSR/air access. 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 $\mu g/m^3$). Panel (e) presents the difference between HSR-travelers and non-HSR travelers, for city-days that are polluted (red bars) and non-polluted (blue bars). HSR/air access has significantly shifted the travel distribution: the fraction of trips exceeding 500 km increases from 35% among travelers without HSR/air access 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.

HSR/air expansion allows people to travel farther. As correlations in environmental conditions decay spatially, traveling farther reduces travelers' probability of experiencing similar adverse conditions observed at home. Can distance alone explain the entirety of HSR/air'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:[‖]

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

where $\widehat{\mathrm{Expo}_{jt}}$ 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 $\mathrm{TravExpo}^{1}_{it}$ for all origin cities and all days in the

‖We 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. One of the cities within the band is randomly picked and its pollution level of the day is used as the counterfactual.

sample. Then we regress this alternative travelers' exposure on access to HSR/air analogous to Equation (S2):

$$\mathsf{TravExpo}^1_{it} = \beta_1\ \mathsf{Expo}_{it} + \beta_2\ \mathsf{HSR}_{it} \times \mathsf{Expo}_{it} + \beta_{3i} \times \mathsf{HSR}_{it} + \mu_i + \delta_t + \epsilon_{it}$$

We replicate this simulation analysis 100 times and report results in the upper panel of Table S8.[**] This exercise preserves the distribution of travel distance for all cities. If distance is the only channel underlying HSR/air'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. Results are very similar for Air's coefficients. In addition, the aggregate benefit of HSR/air in this simulation exercise is only a 0.6 percentage point reduction in exposure to extreme pollutions and a 0.5 percentage point reduction in exposure to extreme temperatures. This constitutes 33% of HSR/air's baseline effects for pollution mitigation and 51% of HSR/air's baseline effects for temperature mitigation. We conclude that distance-based factors cannot explain all of HSR/air's mitigation benefits documented in the main text. Instead, travelers appear to be able to leverage HSR and air connections in order to deliberately choose destination cities that are clean with mild temperatures, even among a set of destinations that are the same distance to the origin city.

D2. Margins of Adaptation. Mitigation of exposure to environmental extremes could arise from several margins. First, individuals can more easily reach 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 that have better environmental conditions. Both margins of adjustment are associated with mitigation and could lead to reduced mortality and morbidity, though the second margin has shorter horizons than the first one. This section presents simulations that disentangle these different margins.

To quantify the benefit of HSR/air that derives from longer-horizon responses to predictable environmental extremes, as distinct from short-horizon adaptation to unpredicted environmental conditions, we use the average travel shares before and after HSR/air access instead of daily travel shares to construct travelers' exposure:

$$\mathsf{TravExpo}^2_{it} = \sum_{j\neq i} \mathsf{Expo}_{jt} \cdot \frac{N^{\text{No HSR}}_{ij}}{\sum_{k\neq i} N^{\text{No HSR}}_{ik}} \cdot \mathbb{1}\{t \text{ before HSR}\} + \sum_{j\neq i} \mathsf{Expo}_{jt} \cdot \frac{N^{\text{HSR}}_{ij}}{\sum_{k\neq i} N^{\text{HSR}}_{ik}} \cdot \mathbb{1}\{t \text{ post HSR}\},$$

where $N^{\text{No HSR}}_{ij}$ is the total number of travelers from city i to city j before city i's HSR/air connection, and N^{HSR}_{ij} is the total number of travelers after the connection. While this formulation allows HSR connections to affect the overall travel patterns (e.g., residents traveling farther), it does not allow deliberate travel responses to temporal, day-to-day variations in environmental conditions. In other words, the travel flows used in calculating the dependent variable are fixed at the pre/post HSR level for each ij pair, and as a result, purged of day-to-day variations.

We regress this alternative travelers' exposure on access to HSR/air, analogously to Equation (S2):

$$\mathsf{TravExpo}^2_{it} = \beta_1\ \mathsf{Expo}_{it} + \beta_2\ \mathsf{HSR}_{it} \times \mathsf{Expo}_{it} + \beta_{3i} \times \mathsf{HSR}_{it} + \mu_i + \delta_t + \epsilon_{it},$$

and report results in the lower panel of Table S8. In terms of pollution mitigation, the coefficient estimates on β_2 are -0.02 for HSR and -0.11 for air, respectively, in contrast to -0.05 and -0.14 in the baseline specification (Panel (a) of Table 2). The aggregate benefit of HSR/air, shutting down day-to-day avoidance responses, is a one percentage point reduction in travelers' likelihood of experiencing extreme pollution. This accounts for 56% of the baseline effect size. Results on temperature mitigation are similar. When purged of daily responses, the aggregate benefit of HSR/air is a 0.8 percentage point reduction in travelers' likelihood of experiencing extreme temperature, equivalent to 81% of the baseline effect size.

We associate the remaining benefit that cannot be explained by changes in long-horizon travel patterns with day-to-day avoidance behavior, whereby residents deliberately seek cities with better environmental conditions when home

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

city is hit by environmental extremes. For pollution mitigation, both the long-horizon and short-horizon adaptations matter, with the former and latter margins accounting for 56% and 44% of the aggregate benefit, respectively. For temperature exposure, day-to-day mitigation is less important and only explains 19% of the aggregate effect. This is because temperature extremes exhibit less geographical variation and hence are harder to escape from.

E. Mortality Benefits of Reduced Exposure

According to the estimates in Column (1), Table S4, improved transportation infrastructure leads to a reduction of 9.1 $\mu g/m^3$ units in terms of exposure to $PM_{2.5}$ for an average traveler on traveling days. This is equivalent to a 14% reduction in an average traveler's pollution exposure. Using 2.5 days as the average trip duration calculated from the UnionPay dataset, the benefit translates to 0.062 $\mu g/m^3$ unit reduction in travelers' annual average $PM_{2.5}$ exposure.

One $\mu g/m^3$ unit increase in average PM_{10} exposure is estimated to reduce life expectancy by 0.064 years.[17] The pollution monitoring data in China suggest that one $\mu g/m^3$ increase in $PM_{2.5}$ corresponds to 1.5 $\mu g/m^3$ increase in PM_{10}. Hence, we consider the health consequence per-unit of $PM_{2.5}$ exposure equivalent to 1.5 times that of PM_{10}. In 2016, 1.4 billion passengers traveled via HSR and 0.5 billion passengers traveled via airlines in China[††].[42,43] Our estimate therefore implies that the annual reduction in pollution exposure induced by improved HSR/air transportation networks translates into a potential savings of 5.7 million life-years in 2016.

For the mortality impact of temperature extreme, we follow the age-specific dose-response functions from Deschênes et al.[44] Based on the age structure of China's population, their estimates suggest that an increase of one-day exposure to temperature extremes will raise the mortality rate by 5 to 10 per million population.[‡‡] Our estimates from Table S4 show that the improved transportation network reduces an average traveler's exposure to temperature extremes by 3.28 days per year. Taken together, these estimates suggest that mitigation in exposure to temperature extremes as a result of the HSR/air expansion leads to 143 to 268 thousand lives saved each year.

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[††] We assume all trips are round trips, thus the number of travelers being half of the total ridership.

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

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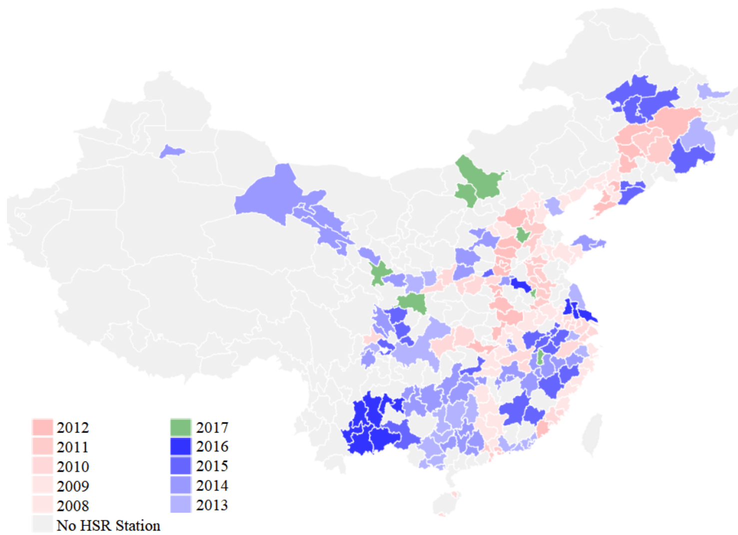
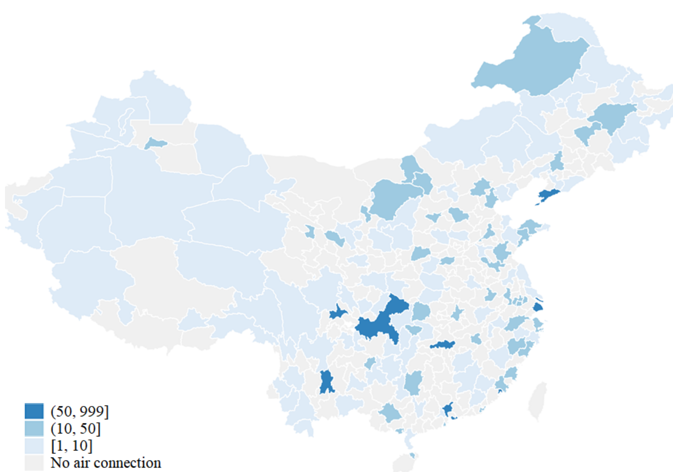
F. Supplementary Information: Figures and Tables

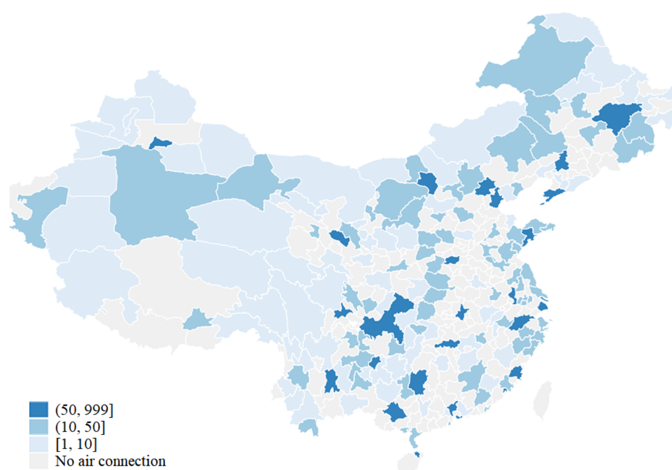
(a) Year when cities are added to the HSR network



(b) Number of direct flights via air, Jan. 2011



(c) Number of direct flights via air, Dec. 2016



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	-	-
Air network								
# Cities Added	152	6	4	6	6	4	6	4
# Cities in Network	152	158	162	168	174	178	184	188
# City-pairs Connected	2626	2797	3134	3624	4059	4198	4626	5542

Fig. S1. Expansion of the HSR and air network

Notes: Colors represent years when a city is first connected to the HSR network in panel **(a)**. Panels **(b)** and **(c)** plot a city's number of direct flights in Jan. 2011 and Dec. 2016. Cities in gray did not have an airport. The number of cities in the network is calculated at the year end. The numbers of city-pairs connected via HSR in 2016 and 2017 are not available.

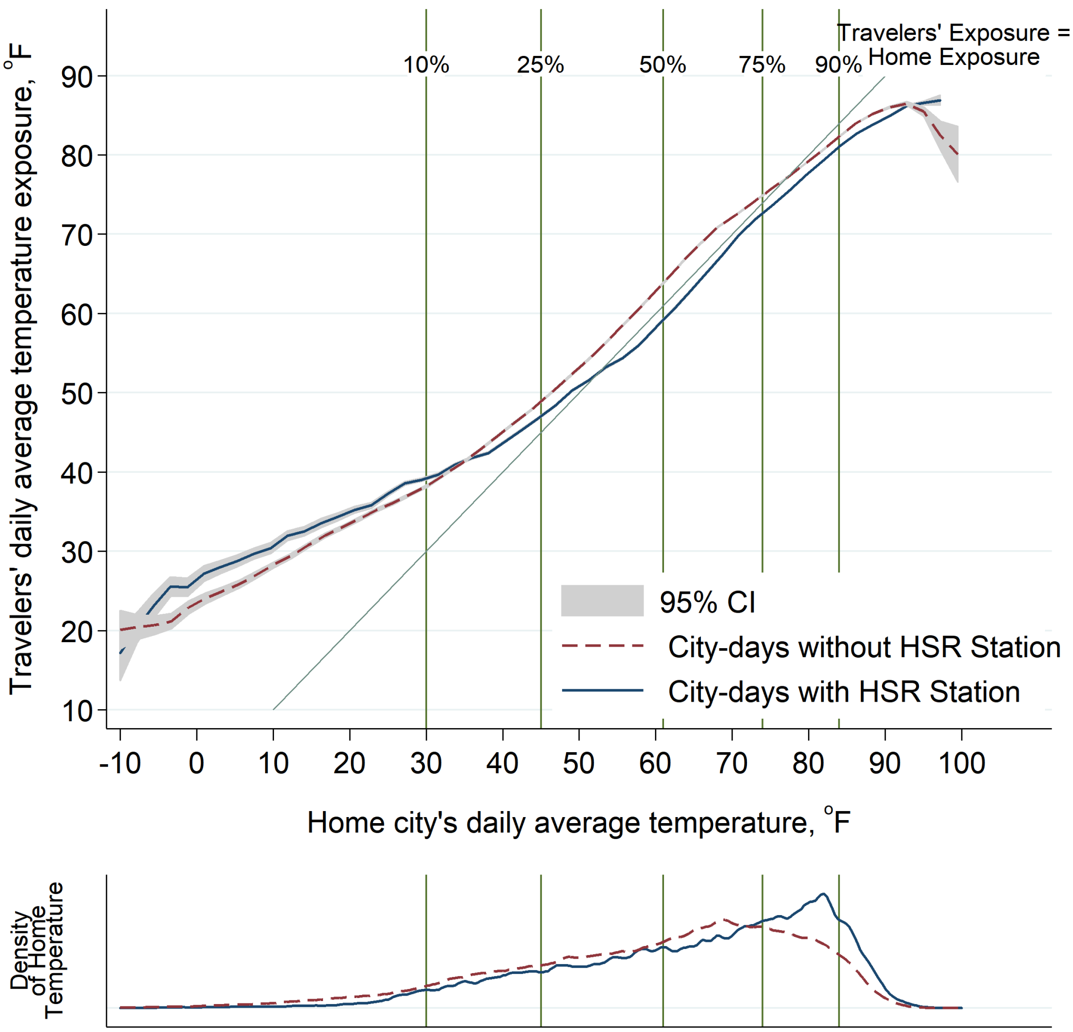
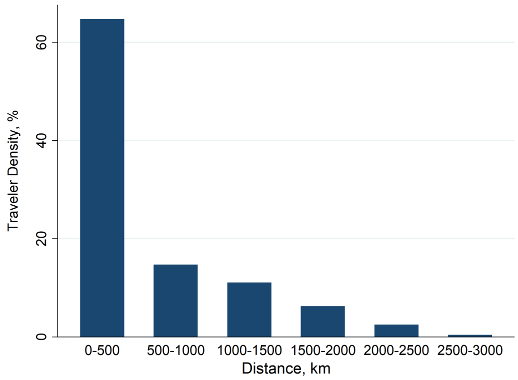


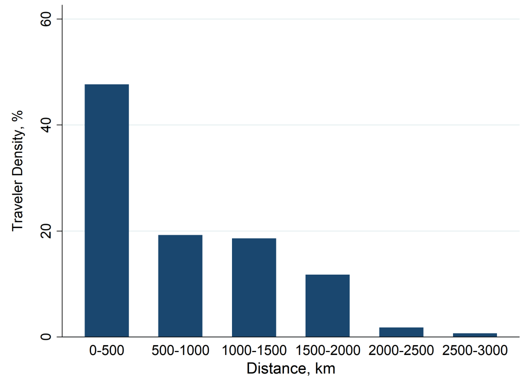
Fig. S2. Travelers' exposure to temperature vs. home exposure

Notes: the top figure plots temperature level experienced by travelers (y-axis) against temperature level at home city (x-axis), separately for city-days without access to HSR (red dash line) and city-days with access to HSR (blue 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 without access to HSR (red dash line) and city-days with access to HSR (blue line), fitted by Epanechnikov kernel with optimal bandwidth. Green vertical lines mark the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles of the temperature distribution.

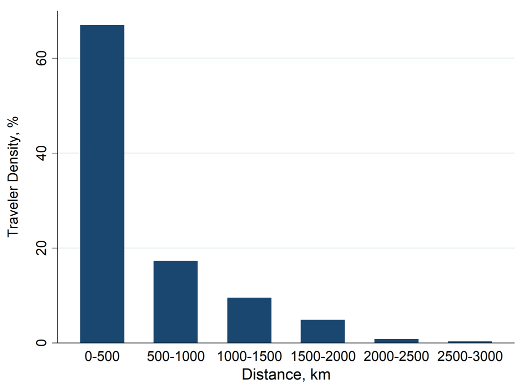
(a) Trip distances for cities without HSR/air access during clean days



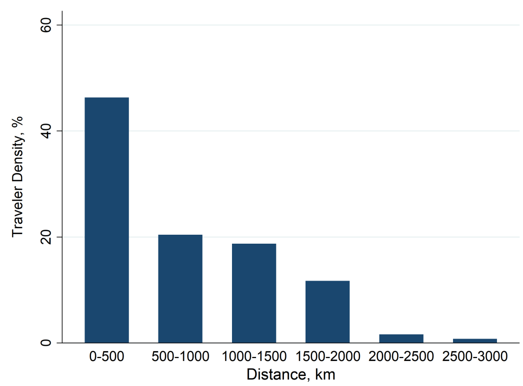
(b) Trip distances for cities with HSR/air access during clean days



(c) Trip distances for cities without HSR/air access during polluted days



(d) Trip distances for cities with HSR/air access during polluted days



(e) Difference in trip distances

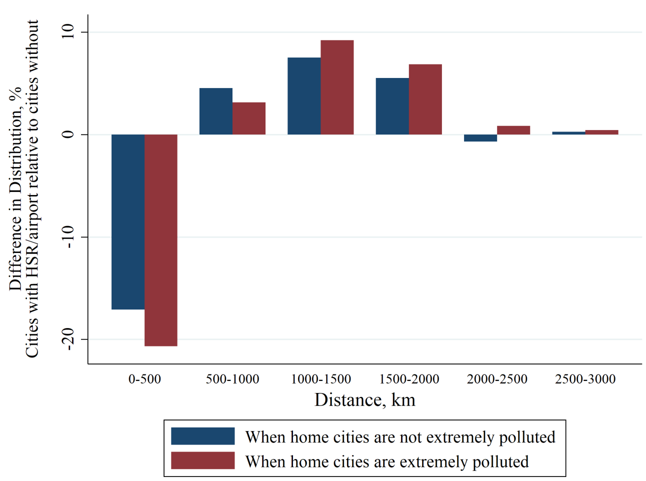


Fig. S3. Trip distance for city-days w. and w/o HSR/air during clean and polluted days

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

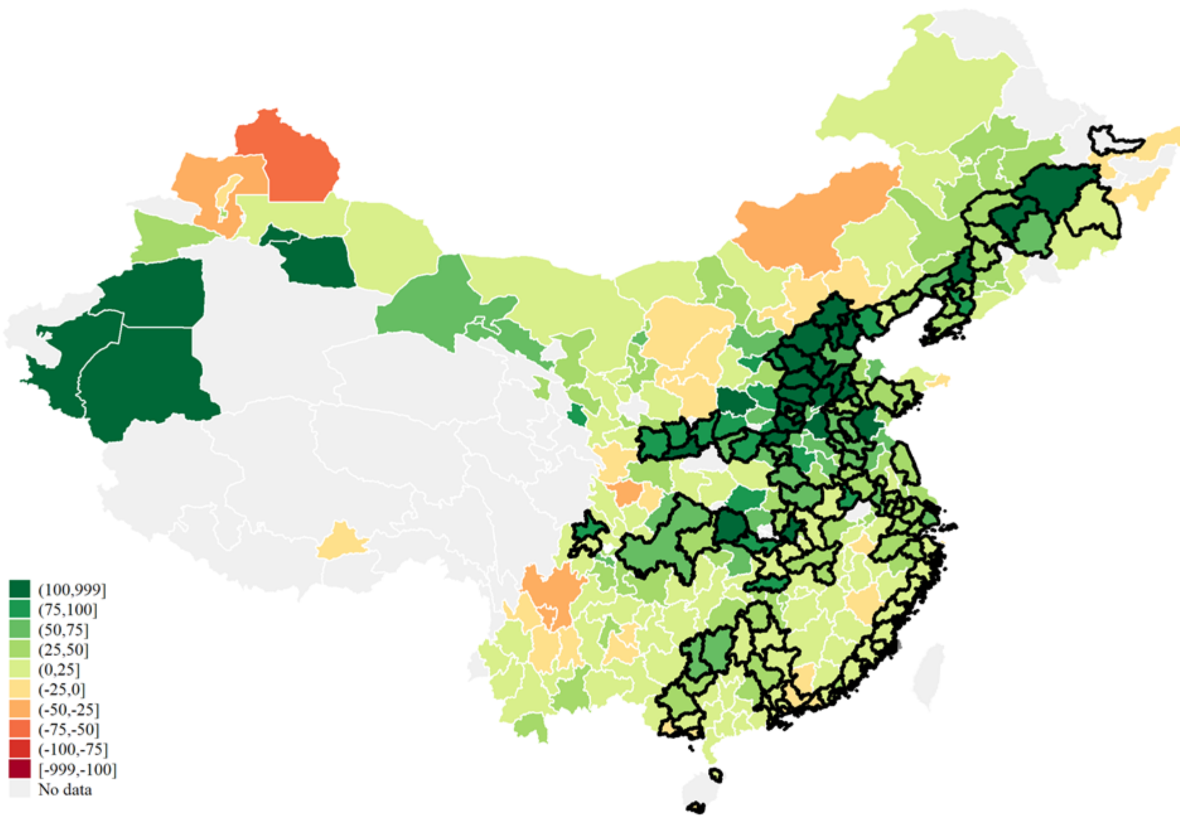


Fig. S4. The HSR network and exposure to pollution extremes

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.

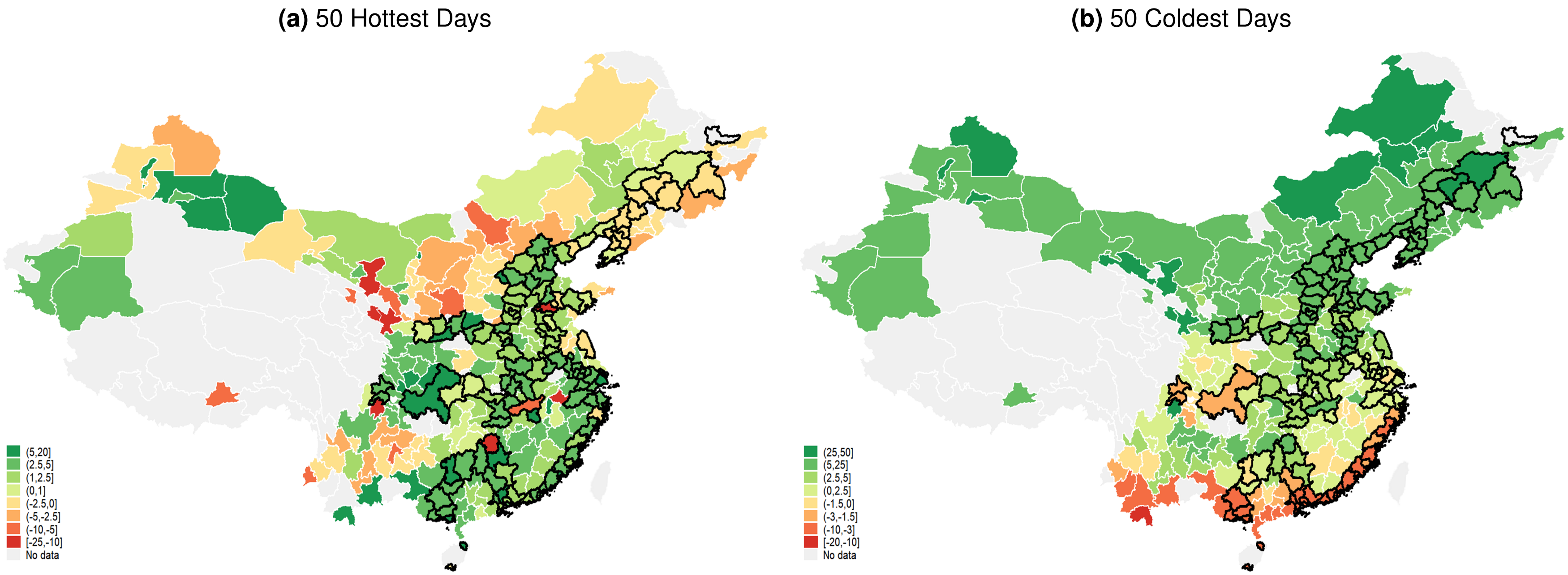


Fig. S5. The HSR network and exposure to temperature extremes

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 S1. Summary statistics

	Mean	Std. Dev.	Min	Max	Number of Obs.
$PM_{2.5}$, $\mu g/m^3$	52.19	44.51	0	1782.98	330,819
$\mathbb{1}\{PM_{2.5}>100\}$	0.10	0.30	0	1	330,819
Temperature, $^{\circ}$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
Air	0.50	0.50	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 $\mu g/m^3$ 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 (Air) takes value 1 if a city has an HSR station (or airport) in operation on a given day and takes value 0 otherwise.

Table S2. Travelers' travel patterns and temperature exposure

(a) For travelers from city-days without HSR

Home in	Flow share by temperature decile at destination										Average temperature (°F) at	
	Cold 1	2	3	4	5	6	7	8	9	Warm 10	Home	Dest.
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

(b) For travelers from city-days with HSR

Home in	Flow share by temperature decile at destination										Average temperature (°F) at	
	Cold 1	2	3	4	5	6	7	8	9	Warm 10	Home	Dest.
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

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

Home in	Flow share by temperature decile at destination										Average temperature (°F) at	
	Cold 1	2	3	4	5	6	7	8	9	Warm 10	Home	Dest.
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 S2 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 without HSR, panel (b) refers to travelers from city-days with 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 S3. Travelers' exposure to environmental extremes with different connectivity measures

Panel A: Air Pollution Daily $PM_{2.5} > 100\mu g/m^3$	Exposure to pollution extremes		
	(1)	(2)	(3)
$\mathbb{1}\{\text{home extreme}\}$	0.18***	0.13***	0.19***
	(0.01)	(0.03)	(0.01)
$\mathbb{1}\{\text{home extreme}\} \times \mathrm{HSR}^C_{it}$	-0.04***		-0.04***
	(0.01)		(0.01)
$\mathbb{1}\{\text{home extreme}\} \times \mathrm{Air}^C_{it}$		-0.04***	-0.04***
		(0.01)	(0.01)
N	330,801	330,801	330,801
R^2	0.78	0.78	0.79

Panel B: Temperature Daily temperature	Exposure to temperature extremes		
$< 30°F$ or $> 90°F$	(1)	(2)	(3)
$\mathbb{1}\{\text{home extreme}\}$	0.30***	0.23***	0.32***
	(0.01)	(0.04)	(0.01)
$\mathbb{1}\{\text{home extreme}\} \times \mathrm{HSR}^C_{it}$	-0.06***		-0.07***
	(0.01)		(0.01)
$\mathbb{1}\{\text{home extreme}\} \times \mathrm{Air}^C_{it}$		-0.004	-0.02***
		(0.01)	(0.01)
N	466,257	466,257	466,257
R^2	0.80	0.77	0.80

Notes: the dependent variable is the likelihood that travelers are exposed to extreme pollution ($PM_{2.5} > 100\mu g/m^3$) in panel (a) and extreme temperature in panel (b). $\mathbb{1}\{\text{home extreme}\}$ is an indicator for $PM_{2.5} > 100\mu g/m^3$ in panel (a) and daily temperature $< 30°F$ or $> 90°F$ in panel (b). HSR^C_{it} and Air^C_{it} denote the standardized continuous connectivity measures. All regressions are weighted by the number of travelers from city i on day t. Day FEs, city FEs and interactions between city FEs and HSR/air are included. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table S4. Travelers' exposure to environmental extremes with alternative exposure measures and extreme cutoffs

	Traveler's Exposure					
	Continuous Measures		Alternative Cutoffs			
	$PM_{2.5}$	$\lvert T - 70°F \rvert$	$PM_{2.5} > 120$	$PM_{2.5} > 150$	$T < 25°F$ or $T > 95°F$	$T < 35°F$ or $T > 85°F$
Panel A						
$Expo_{it}$	0.34***	0.45***	0.28***	0.27***	0.39***	0.41***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
$Expo_{it} \times HSR_{it}$	-0.06*	-0.04*	-0.05**	-0.04	-0.09**	-0.09***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)
$Expo_{it} \times Air_{it}$	-0.15***	-0.07***	-0.15***	-0.15***	-0.08*	-0.11***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(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						
$Expo_{it}$	0.25***	0.40***	0.19***	0.18***	0.32***	0.33***
	-0.02	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
$Expo_{it} \times HSR^C_{it}$	-0.04***	-0.03***	-0.04***	-0.04***	-0.07***	-0.06***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
$Expo_{it} \times Air^C_{it}$	-0.04***	-0.02***	-0.04***	-0.04***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(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: $PM_{2.5}$ 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 Air_{it}, as well as HSR^C_{it} and Air^C_{it}, denote the discrete and continuous HSR/air connectivity measures, respectively. All regressions are weighted by number of travelers from city i on day t. Day fixed effects, city fixed effects and interactions between city fixed effects and HSR/air are included. Standard errors are clustered at city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table S5. Travelers' exposure to environmental extremes using sub-samples

	Traveler's Exposure					
	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						
$\mathbb{1}\{$home extreme$\}$	0.27***	0.40***	0.27***	0.39***	0.27***	0.42***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)	(0.04)
$\mathbb{1}\{$home extreme$\} \times HSR_{it}$	-0.05***	-0.12***	-0.05**	-0.12***	-0.07***	-0.10***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.04)
$\mathbb{1}\{$home extreme$\} \times Air_{it}$	-0.14***	-0.09***	-0.13***	-0.08**	-0.13***	-0.15***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(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						
$\mathbb{1}\{$home extreme$\}$	0.19***	0.31***	0.19***	0.31***	0.18***	0.31***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}\{$home extreme$\}HSR^C_{it}$	-0.04***	-0.07***	-0.04***	-0.07***	-0.04***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}\{$home extreme$\}Air^C_{it}$	-0.04***	-0.02***	-0.04***	-0.02***	-0.03***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(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: $PM_{2.5}$ and T denote the daily average $PM_{2.5}$ concentration and temperature level, respectively. $\mathbb{1}\{$home extreme$\}$ is an indicator for $PM_{2.5} > 100\mu g/m^3$ in odd columns and daily temperature $< 30°F$ or $> 90°F$ in even columns. HSR_{it} and Air_{it}, as well as HSR^C_{it} and Air^C_{it}, denote the discrete and continuous HSR/air connectivity measures, respectively. All regressions are weighted by number of travelers from city i on day t. Day fixed effects, city fixed effects and interactions between city fixed effects and HSR/air are included. Standard errors are clustered at city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table S6. Travelers' exposure to extreme pollution using leads and lags

	Travelers' Exposure to Pollution	
	Following Week	Preceding Week
Panel A		
% of extreme days in home city	0.21***	0.22***
	(0.01)	(0.01)
% of extreme days $\times \mathrm{HSR}_{it}$	-0.04***	-0.04***
	(0.01)	(0.01)
% of extreme days $\times \mathrm{Air}_{it}$	-0.08***	-0.08***
	(0.01)	(0.01)
N	325,255	325,000
R^2	0.75	0.75
Panel B		
% of extreme days in home city	0.14***	0.15***
	(0.01)	(0.01)
% of extreme days $\times \mathrm{HSR}^{C}_{it}$	-0.02***	-0.02***
	(0.01)	(0.01)
% of extreme days $\times \mathrm{Air}^{C}_{it}$	-0.03***	-0.03***
	(0.01)	(0.01)
N	323,807	323,554
R^2	0.75	0.75

Notes: % of extreme days is the fraction of days with extreme pollution in the following or preceding week. HSR_{it} and Air_{it}, as well as HSR^{C}_{it} and Air^{C}_{it}, denote the discrete and continuous HSR/air connectivity measures, respectively. All regressions are weighted by number of travelers from city i on day t. Day fixed effects, city fixed effects and interactions between city fixed effects and HSR/air are included. Standard errors are clustered at city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table S7. Number of travelers in response to extreme pollution at home (extensive margin)

Dependent Variable: log(number of travelers)

	Current Day Exposure			Average Exposure, $\pm$3 days		
	All Travel	>300km	>500km	All Travel	>300km	>500km
$\mathbb{1}\{\text{home extreme}\}$	-1.32**	-0.021***	-0.015**	-3.37***	-0.053***	-0.038***
	(0.56)	(0.0061)	(0.0063)	(1.26)	(0.014)	(0.015)
$\mathbb{1}\{\text{home extreme}\} \times \mathrm{HSR}_{it}$	0.59	0.013*	0.012	1.51	0.029*	0.027*
	(0.61)	(0.0070)	(0.0075)	(1.31)	(0.015)	(0.016)
$\mathbb{1}\{\text{home extreme}\} \times \mathrm{Air}_{it}$	0.24	0.0085	0.0058	1.21	0.028*	0.023
	(0.66)	(0.0076)	(0.0082)	(1.45)	(0.017)	(0.018)
N	330819	329626	329255	325541	324901	324609
R^2	0.98	0.97	0.96	0.98	0.97	0.96

Notes: 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 $PM_{2.5} > 100 \mu g/m^3$. All regressions are weighted by number of travelers from city i on day t. Day fixed effects, city fixed effects and interactions between city fixed effects and HSR/air are included. Standard errors are clustered at city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table S8. Travelers' exposure to extreme pollution: Margins of Adaption

Panel A: Changes in Travel Distance		
	Hypothetical Travelers' Exposure	
	PM>100	T $<30°$F or T $>90°$F
$\mathbb{1}$\{home extreme\}	0.11***	0.21***
	(0.003)	(0.002)
$\mathbb{1}$\{home extreme\} $\times$ HSR_{it}	-0.02***	-0.06***
	(0.002)	(0.002)
$\mathbb{1}$\{home extreme\} $\times$ Air_{it}	-0.04***	-0.03***
	(0.003)	(0.003)
N	330,801	466,257
HSR/Air's overall impact	-0.006	-0.005

Panel B: Longer Horizon Adaptation		
	Hypothetical Travelers' Exposure	
	PM>100	T $<30°$F or T $>90°$F
$\mathbb{1}$\{home extreme\}	0.30***	0.49***
	(0.01)	(0.02)
$\mathbb{1}$\{home extreme\} $\times$ HSR_{it}	-0.02	-0.07**
	(0.01)	(0.03)
$\mathbb{1}$\{home extreme\} $\times$ Air_{it}	-0.11***	-0.07**
	(0.01)	(0.03)
N	330,801	466,257
R^2	0.66	0.74
HSR/Air's overall impact	-0.010	-0.008

Notes: The dependent variable of Panel A is hypothetical traveler's exposure that is constructed by replacing destination cities' environmental conditions with the concurrent conditions in cities of a similar distance to the origin, $TravExpo^1_{it} = \sum_{j \neq i} \widehat{Expo_{jt}} \cdot \frac{N_{ijt}}{\sum_{k \neq i} N_{ikt}}$, where $\widehat{Expo_{jt}}$ is the pollution level of a randomly-chosen city that is similarly distant from the original city as city j. $\mathbb{1}$\{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/air dummy are included in both regressions. The last row reports HSR/air's aggregate effect holding trip distance constant, a 0.6 percentage-point reduction in traveler's likelihood of experiencing extreme pollution and a 0.5 percentage-point reduction in exposure to extreme temperature.

The dependent variable of Panel B is hypothetical traveler's exposure that is constructed using the average traveler flow from the origin city before and after HSR: $TravExpo^2_{it} = \sum_{j \neq i} Expo_{jt} \cdot \frac{N^{\text{No HSR}}_{ij}}{\sum_{k \neq i} N^{\text{No HSR}}_{ik}} \cdot \mathbb{1}\{t \text{ before HSR}\} + \sum_{j \neq i} Expo_{jt} \cdot \frac{N^{\text{HSR}}_{ij}}{\sum_{k \neq i} N^{\text{HSR}}_{ik}} \cdot \mathbb{1}\{t \text{ post HSR}\}$, where $N^{\text{No HSR}}_{ij}$ is the total number of travelers from city i to city j prior to the HSR access and N^{HSR}_{ij} is the total number of travelers from city i to city j post the HSR access. The last row reports HSR/air's aggregate mitigation effect in the absence of day-to-day avoidance responses, which is a 1.0 percentage-point reduction in traveler's likelihood of experiencing extreme pollution and a 0.8 percentage-point reduction in exposure to extreme temperature. Standard errors are clustered at city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.