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Impact of air pollution on short-term movements: evidence from air travels in China

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Abstract

While there is abundant evidence demonstrating that residents permanently migrate in search of locations with cleaner air, there are considerably fewer studies that investigate if travellers also take short-term trips to reduce their exposure to air pollution. In this study, we use a complete dataset of flights at Beijing International Airport to investigate if travel patterns are indeed correlated with air quality-differences across cities in China. Our identification strategy is aided by instrumenting air quality using thermal inversions. We find that a one-unit increase in the Air Pollution Index of origin over destination city would lead to a 0.36% increase in number of passengers on the flight. When considered separately by cabin-class, the number of first-class passengers increased about three-times faster than economy-class. Using lagged air quality information, we also find that averting-related travel decisions are most sensitive to destination's air quality on day-of-travel. This indicates that flight passengers likely rely on air quality forecast information to make air pollution-induced travel decisions.

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JEL classifications: O15, Q53, R40
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1. Introduction

There is abundant evidence from various disciplines showing that environmental conditions are significant factors behind decisions to relocate permanently (e.g., Roback, 1982; Clark et al., 2003; Timmins, 2005; Bayer et al., 2009; Gray and Mueller, 2012; Tan-Soo, 2017; Minale, 2018). The seminal work by Roback (1982) found that a location's quality-of-life is partly influenced by climatic factors (such as snowfall, temperature and cloud conditions), which in turn affect its perceived attractiveness to migrants. Similarly, Timmins (2005, 2007) showed using general equilibrium models that migration patterns in Brazil are sensitive to changes in temperature and rainfall. Moving on to more hazardous environmental conditions, Gray and Mueller (2012) found using reduced-form approach, that floods increase the probability of within-district migration by around 57% in Bangladesh, with disproportionate impacts on women and lower-income groups. Lastly, Bayer et al. (2009), Tan-Soo (2017), and Chen et al. (2019), respectively, found that populations in the USA, Indonesia and China migrate to other locations within the country to avoid high levels of air pollution. A commonality behind all these studies is that they focused on permanent migration as the behavioural response to adverse environmental conditions. However, as effective as permanent migration may be in reducing one's exposure to adverse environmental conditions, these are extremely complex decisions with multiple considerations and trade-offs to be made (Timmins, 2005; Bayer et al., 2009; Tan-Soo, 2017). On the other hand, a simpler and less costly option to avoid environmental harms is to move away for a short period of time.

Compared with permanent migration, short-term movements impose much lower moving costs on individuals and can be just as equally effective, especially if the opportunity costs of moving are high and that environmental harms are temporary. However, short-term movements as behavioural responses to adverse environmental conditions have been under-studied in the literature, possibly due to data constraints. In this regard, we attempt to fill this knowledge gap by investigating the extent to which population in China undertake short-term travels in response to short-term fluctuations in air quality. There are several reasons to believe why short-term movements are also an appropriate strategy for avoiding poor air quality in China.

First, earlier studies on the relationship between air pollution and migration found that residents from developing countries place large premiums on access to economic opportunities. For example, Tan-Soo (2017) found that without controlling for the positive correlation between air pollution and economic opportunities, Indonesians would voluntarily move towards places with high air pollution as these are locations with better employment prospects. Hence, high opportunity costs of moving permanently away from places with high air pollution could also exist in the Chinese context. Second, while much has been said about poor air quality in China (and much of the developing world), the nature of the problem is more varied. For instance, even though Beijing's average $PM_{2.5}$ level in 2015 is 79 $\mu g/m^3$, around eight times higher than World Health Organization's stipulated safe level, there were >223 days in 2015 where air quality is within safe levels. Third, unlike many other countries, domestic migration in China is highly controlled as residents need to show proof of employment before they are allowed access to local public services, government subsidies, and even be allowed to purchase properties.[1] This policy thus act as an additional level of hindrance for permanent migration in China. It should also be emphasized that the purpose of this study is not to compare the effectiveness of short-term movements against permanent migrations to avoid air pollution. Indeed, there are scenarios (e.g., if severe air pollution is a perennial problem) where permanent migration could be the better option.

Towards this end, we use a novel and complete dataset of flights load factors (i.e., occupancy rates) to study the relationship between short-term movements and fluctuations in daily air quality. Just as air pollution and economic opportunities were observed to be highly correlated in earlier studies of permanent migrations, we encounter the same endogeneity issue here. Hence, we deploy an instrumental variable (IV) based on the climatic phenomenon of thermal inversions to provide an exogenous source of variation for air quality. In all, we find that the number of passengers on a flight towards the 'cleaner' city increases by about 0.36% for every unit-difference in the air quality between two cities. When differentiated by cabin-class, it is telling that the marginal impacts of economy and

1 Conversely, while a household could move to another province without proof of employment. In these situations, the household would not be able to access any public services, such as public education or healthcare.

first-class passengers are 0.34% and 0.87%, respectively. We also found that travel decisions to avoid air pollution are likely made using air quality forecasts as the number of flight passengers are most sensitive to air quality on day-of-travel, rather than at lagged days.

In all, this study contributes to the literature in the following ways. First, as mentioned, while there are increasing number of studies showing that permanent migrations respond to adverse environmental conditions, this is one of the first attempts to empirically examine the relationship between short-term movements and air pollution. Second, we gain a deeper understanding on the decision-making mechanisms behind flight travels as averting behaviours by using lead and lag air quality as regressors, spline regression models for non-linearities, and air quality at origin and destination cities to differentiate between push and pull factors. Third, our findings have important implications for both the public and private sectors (e.g., urban planning, tourism and transportation sectors) as there will be changes to the utilization of public utilities and private services prompted by short-term visitors.

The rest of the paper is structured as follows. Section 2 introduces the empirical strategy and statistical identification of IV strategy. Section 3 provides a description of the datasets used in this study. Empirical results are presented in Section 4. Finally, we summarize all findings and discuss their implications in Section 5.

2. Empirical strategy

We estimate the following equation to investigate if air travel patterns are indeed influenced by air quality levels:

$$\ln(FP_{ijkt}) = \beta_0 + \beta_1(P_{jt} - P_{kt}) + (W_{jt} - W_{kt})\theta + D_t + \varphi_i + \varepsilon_{ijkt}. \tag{1}$$

FP_{ijkt} is the number of passengers on flight-code i on day t travelling from city j to city k. P_{it} is the daily air pollution index (API) of origin city i on day of departure. Similarly, P_{jt} is the daily API of destination city j on day of arrival. Hence, put together, $(P_{jt} - P_{kt})$ represent the difference in air quality between origin and destination where a positive $(P_{jt} - P_{kt})$ indicates that origin city has lower levels of air pollution compared with destination city. It should be clarified that even though air quality on the date of travel is used as the main covariate in our empirical specification, this does not necessarily imply that the decision to travel are made on day of travel itself. Just as weather forecasts, projections of future air quality has been made widely available through governmental and other credible sources in China since at least 2001 (Tong, 2006).[2] As such, it is possible that individuals make travel decisions based on forecasted air quality. For example, if it is forecasted that air quality will deteriorate in 5 days' time, an individual will stand most to gain by departing on the day that air quality will deteriorate. We will use lag- and lead air quality to test this decision-making mechanism.

We also include, up to second-order polynomial, a vector of weather controls, W in similar fashion as the pollution index. These weather controls are temperature, precipitation, sunshine duration, wind speed, relative humidity, and atmospheric pressure. It is

2 Chinese air quality forecasts are available on websites such as the National Meteorological Center (http://www.nmc.cn/publish/environment/air_pollution-24.html) and weather site (http://tianqi.eastday.com).

important to include these weather controls as air quality can sometimes be correlated with climatic factors. For example, we tend to see poorer air quality in northeast China during winter months, and travel patterns are also independently associated with temperature. Hence, the estimated impact of air quality on travels may be confounded if climatic variables are not included as controls. The weather controls are included as polynomials because unlike air quality-difference, the relationship between climatic factors and travels may be multi-directional. D_t is included as a vector of date-related fixed effects, that is, months, year, day-of-week, holidays and holiday-makeup weekends, to account for the seasonal nature of travels. Lastly, we also include a flight-code fixed effect φ_i. This fixed effect controls for all characteristics that are identical to the particular flight-code, such as origin and destination city, airline, aircraft type and scheduled time of departure and arrival.[3] Hence, with the inclusion of flight-code fixed effect, identification of β_1 is based on the air quality-difference within each flight-code. If Chinese residents do indeed use flight travels as a way to avoid air pollution episodes, we should expect β_1 to be positive, that is, there will be more passengers on a flight if the air quality at origin city is worse than air quality at destination city.

2.1. Statistical challenges and identification

There are three endogeneity concerns or threats to statistical identification.

First, cities with high level of air pollution tend to be economic centres or cities of interests that naturally draw in more visitors compared with other locations. Hence, if we do not take into account of the 'attractiveness' of a location, it would seem as though people are travelling towards places with high air pollution (Bayer et al., 2009; Tan-Soo, 2017; Freeman et al., 2019). On a similar note, the 'attractiveness' of a location could also be time-varying as cities may concurrently experience temporary changes to number of visitors and air quality due to hosting of major events or activities. For instance, air pollution in the city of Haikou typically spike during peak tourism period due to an influx of visitors (Figure A1). On the other hand, Beijing's air quality ironically improves when major events of national significance are conducted (e.g., Summer Olympics and 2014 APEC meetings) as the central government imposes temporary bans on all industrial activities.

The implication is that we may underestimate (or overestimate in the case of Beijing where major events that draw a lot of visitors are correlated with good air quality) the extent to which people take on averting behaviours to protect themselves from air pollution.

Second and related, there may also be a simultaneity relationship between air travels among two cities and their associated air quality difference. That is, suppose air quality of city A and B are initially similar. However, there are more people subsequently travelling from city A to city B because city B has say improved transport connectivity or for some other exogenous reasons. Hence, one may expect the increased travels towards city B would promote more economic activities, and thus worsen the air quality. In this case, the reverse causality would cause the coefficient of air quality to be under-estimated.

Third, there is evidence that Chinese city governments manipulated air quality data by systematically reducing actual readings so that the threshold of 'polluted' days will not be

3 For example, CA1501 leaves from Beijing daily at 8:30 a.m. and lands at Shanghai at 10:40 a.m. using a Boeing 777-300ER plane.

breached (Ghanem and Zhang, 2014). As such, the pollution data used in this study may also be measured with a systematic error that is correlated with the actual air pollution. If so, coefficients estimated using the 'manipulated' air pollution data may be biased if this systematic bias is uncorrected.

As such, we address endogeneity concerns of the air pollution variable by using a natural climatic phenomenon—thermal inversions—as the IV. Generally speaking, temperature is lower at higher altitudes due to difference in air pressure. Combined with the fact that cold air is denser than warm air, this phenomenon allows warm air to rise from lower elevations and circulate throughout the atmosphere (Jacob, 1999). However, due to a confluence of various meteorological factors, thermal inversions—situation where temperature at higher elevation is *instead* warmer than temperature at lower elevation—can also occur (Jacob, 1999; Wu et al., 2014). During such occurrences, the cold air will be trapped at lower elevations (due to their higher density). The implication is that air pollutants are unable to be circulated upwards and thus trapped nearer to ground level, thus deteriorating air quality (Schwartz, 1994). As thermal inversions are purely meteorological and short-term phenomenon, it is unlikely that they have any correlation with economic activities or manipulation of data. More specifically, the IV satisfy the exclusion restriction condition because thermal inversions only affect flight passengers' movement through their impacts on air quality. Because thermal inversions is strongly correlated with air quality and satisfy the exclusion restriction, there has been increasing usage of thermal inversions as an exogenous source of variation for air pollution (e.g., Arceo et al., 2016; Hicks et al., 2016; Chen et al., 2017; Fu et al., 2018; Jans et al., 2018). Figure 1 plots the daily time trend of thermal inversion frequency and API from 1 March 2008 to 30 April 2010, the course of our study period. The blue bar represents average API for all 60 cities across every day, while the red line represents average number of thermal inversions in the same cities and days. The figure shows a strong positive correlation between daily thermal inversions and API. Hence, using thermal inversion as the IV, we propose to estimate a two-stage least squares (2SLS) model to measure the causal effect of air pollution on flight passengers. This model can be written as follows:

$$(P_{jt} - P_{kt}) = \alpha_0 + \alpha_1(T_{jt} - T_{kt}) + (W_{jt} - W_{kt})\theta + D_t + \varphi_i + \mu_{ijkt}. \tag{2}$$

$$\ln(FP_{ijkt}) = \beta_0 + \beta_1\left(P_{jt} \hat{-} P_{kt}\right) + (W_{jt} - W_{kt})\theta + D_t + \varphi_i + v_{ijkt}. \tag{1'}$$

Equation (2) is the first stage of the 2SLS estimation and we are using daily thermal inversion counts, T_{jt} and T_{kt} as the instrument variables for API-difference. Equation (1′) is simply a re-writing of Equation (1) where API-difference is replaced by its instrumented counterpart.

There are however two empirical concerns with using thermal inversions as an exogenous source of variation for air quality. First, due to it being a climatic phenomenon, thermal inversion is associated with lower elevations' climatic patterns such as low temperature and wind velocity (Chen et al., 2017). As such, we also control for a host of climatic factors (temperature, precipitation, sunshine duration, wind force, relative humidity, and atmospheric pressure) to further isolate the impact of thermal inversions on air quality, and thus flight passengers. For comparisons, we also estimate a model without any weather controls. Second, as thermal inversions occurrences are more favoured in certain locations than others (e.g., valley-type areas), it is possible that people of different

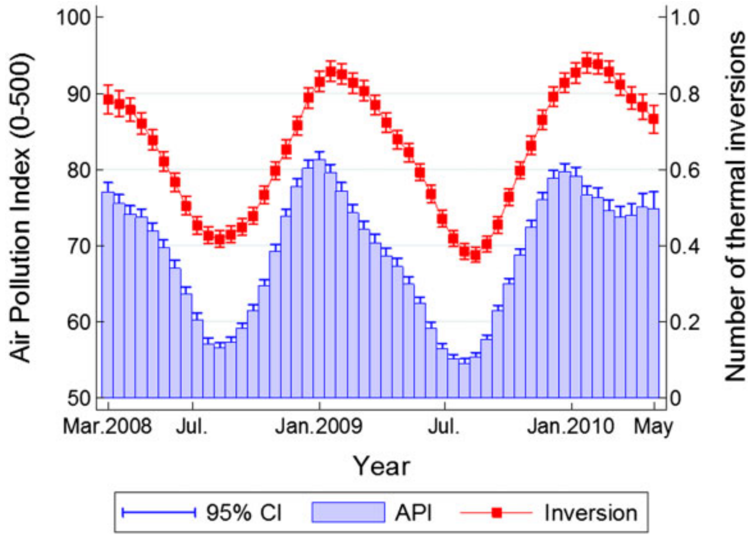

Figure 1. Correlations between API and thermal inversions. This figure plots daily API and average daily counts of thermal inversions for all 60 (destination or origin) cities from 1 March 2008 to 30 April 2010. The plot is created using local polynomial smoothing function. See Figure A3 for the direct scatter plots.

preference types migrate or systematically sort themselves along the same variation as thermal inversions. Flight-code-fixed effects (which essentially act as location-fixed effects) would thus control for any sorting behaviours and purely exploit variation in thermal inversion over time.

3. Data

3.1. Data sources

The empirical analysis is conducted by combining four different datasets.

3.1.1. Flights information

First, we make use of a dataset consisting of flights towards and from Beijing Capital International Airport (IATA code: PEK). From this dataset, we know (i) the number of passengers on each flight, (ii) airline and aircraft information, (iii) destination and origin city, and (iv) scheduled and actual arrival and departure time. This dataset spans from 1 March 2008 to 20 April 2010, consisting of 499,180 domestic direct flights that either travelled towards or departed from PEK.[4] These flights belong to 115 unique city routes or 122 unique airport routes (Figure 2 shows the flights connectivity of Beijing Capital Airport and the average number of daily passengers for each flight-route).[5] Of the unique

4 We removed all multiple-legs flights (i.e., flights that travel from origin to intermediate to destination in the same journey) from the sample as it is unclear how many passengers alight and boarded at the intermediate city.

5 There are several cities with more than one airport.

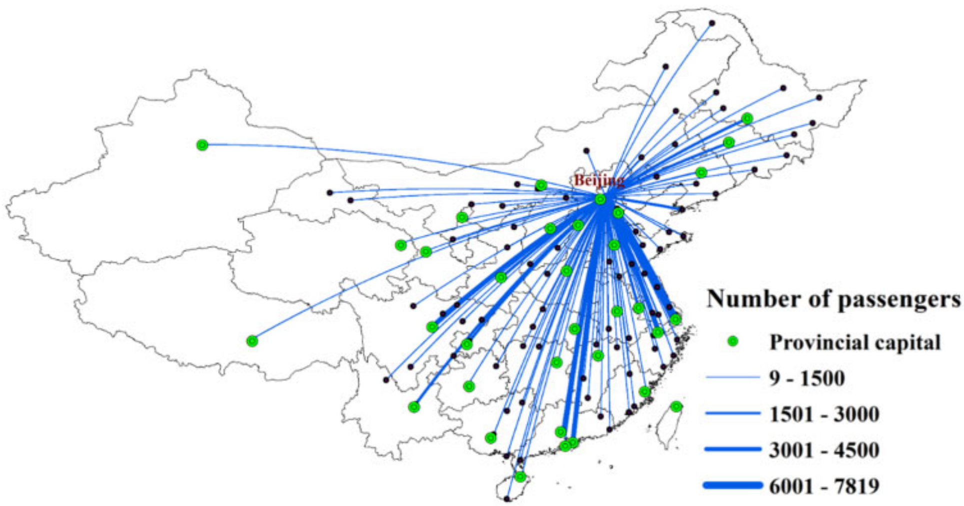

Figure 2. Number of flight passengers (daily). This figure depicts the average daily number of flight passengers between Chinese cities from 1 March 2008 to 30 April 2010. These numbers are taken from direct domestic flights that either depart from or arrive at Beijing Capital International Airport (PEK).

city routes, 56 of these routes have Beijing as the arrival city and 59 routes have Beijing as the departure city. These 499,180 flights thus belong to 17 different airlines, operating 32 different types of aircrafts, and servicing 1743 unique flight-codes.

3.1.2. Pollution data

Second, daily air pollution data are obtained from the website of the China National Environmental Monitoring Center (CNEMC).[6] From 2008 to 2010, the Chinese Ministry of Environmental Protection (MEP) reports daily API for 120 major Chinese cities. The API is a composite index consisting of primary air pollutants (PM_{10}, SO_2, and NO_2), and thus indicative of the overall air quality. This index ranges from 0 to 500, where larger numbers indicate worse air quality. The MEP defines six levels of API, with 0–50 for excellent air quality, 51–100 for good air quality, 101–150 for lightly polluted air, 151–200 for moderately polluted air, 201–300 for heavily polluted air, and >300 for severely polluted air.[7]

3.1.3. Climatic data

Weather data are obtained from the China Meteorological Data Service Center (CMDC), which is affiliated to the National Meteorological Information Center of China.[8] The CMDC records daily maximum, minimum, and average temperatures, precipitation, relative humidity, wind speed and sunshine duration for 820 weather stations in China. We

6 The data can be obtained from http://www.cnemc.cn/.

7 See http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/jcgfffbz/201203/W020120410332725219541.pdf for detailed API calculation formula and explanation.

8 The data can be obtained from http://data.cma.cn/.

use the inverse-distance weighting (IDW) method to generate city-level weather statistic (Currie and Neidell, 2005; Deschenes and Greenstone, 2007; Schlenker and Walker, 2015). Essentially, we draw a 100 km radius around the centroid of the city and take the weighted average of climate data of all stations contained within this radius.[9] In all, the weather controls include second order polynomials in daily weather conditions, including temperature, precipitation, sunshine duration, wind force, relative humidity and atmospheric pressure.

3.1.4. Temperature inversion data

Lastly, daily thermal inversion count (at 6-h intervals) are computed using satellite imageries from the MERRA-2 satellite released by the National Aeronautics and Space Administration (NASA) of the USA.[10] Over the course of a day, the MERRA-2 records temperature at four regular intervals for various elevations. The grid size used by MERRA-2 is 0.5 by 0.625° (0.5° is around 55 km at the Equator and shorter towards the poles). As such, we first spatially match each city to their respective grid(s) and compute average temperature. Next, a thermal inversion is counted when the temperature in first atmospheric layer (110 m) is lower than temperature in the second layer (320 m). In this regard, there are a maximum of four thermal inversions in a day and minimum of zero.[11]

3.2. Descriptive statistics

The descriptive statistics are collected in Tables 1 and 2. First, there are around 6.7 daily flights for each unique city routes, with the most popular routes having more than 40 daily flights (Figure A2). The average number of passengers per flight is around 144 with an occupancy rate of 65%, and the average economy-class ticket is priced at 586 CNY (around US$90). When considered separately by cabin-class, there are on average 138 economy-class passengers and six first-class passengers on a flight.

Air quality is quantified using the Chinese API—a composite metric designed to take into account of three major air pollutants (i.e., particulate matters, sulfur dioxide and nitrous oxide). API at origin (destination) city on day of departure (arrival) averages at around 80 (75). For reference, the average annual API for Beijing in 2008 is around 87.6. Next, the average API difference between origin and destination is around 5.3, and there is wide variation as API-difference ranges from −467 to 467 (Figure 3 shows a histogram of the daily variation). As the API is a composite metric, its value is mostly driven by the pollutant with the highest level at time of measurement. In this regard, we also present the average API when its value is driven by particulate matters (PM_{10}). Compared with overall API, PM-dominated API is about 10 units higher for both origin and destination cities. Lastly, thermal inversion is a count variable and measured at 6-h interval daily. Out of a maximum of four inversions per day, there are an average of 0.6 thermal inversions

9 Different radii distance is used in the robustness checks to ensure results are not driven by this assumption.

10 The data can be downloaded at https://disc.sci.gsfc.nasa.gov/uui/datasets/M2I6NPANA_V5.12.4/summary?keywords=\%22MERRA-2\%22\%20M2I6NPANA\&start=1920-01-01\&end=2017-01-16.

11 We also conduct a robustness check by coding inversions using differences in temperature between the first and third layers (540 m). We then aggregate the number of thermal inversions by each date and match to cities on the flight routes.

Table 1. Number of city pairs, airlines, types, routes and flights in our research sample

	Total (1)	Arrival PEK (2)	Departure PEK (3)
Number of			
Fly routes	115	56	59
Airport routes	122	59	63
Airline companies	17	13	16
Aircraft types	32	27	31
Flight codes	1743	709	1058
Number of observations	499,180	335,414	163,766

Number of sample cities = 60. Sample period is from 1 March 2008 to 30 April 2010.

observed daily. Thermal inversions can also be defined as a binary variable if we aggregate temperature to a daily level. In this regard, there is a 0.5% chance of observing thermal inversion on any particular day.[12]

4. Results

4.1. Baseline results

Results for the baseline estimation are collected in Tables 3 and 4. Using a 2SLS model with thermal inversion as the IV, we find that in the most basic model with no control variables and fixed effects, the number of passengers on an average flight increased by around 0.18% for every unit increase in air pollution of origin city over destination's API (Table 4, Column 1). In other words, this means that flights from a more-polluted location to a less-polluted one has more passengers. The impact of air pollution on number of passengers increases following the gradual inclusion of controls, i.e., flight-code fixed effects, weather controls, date-fixed effects and population weights (Table 4, Columns 2–5). In the full specification with all controls and fixed effects included, the marginal impact of air quality differential increases to around 0.36% (Table 4, Column 5). To examine if the IV strategy is working as intended, we can see that the first stage KP-*F* statistics is high at around 40–80 for the various model specifications (Table 3). This means that thermal inversion is a good predictor of air quality. Second, results in Table 4, Panel B confirm the nature of our endogeneity concerns as the OLS coefficients are consistently smaller (and even negative) compared with their instrumented counterparts (Table 4, Panel A). Negative API-difference coefficients can be interpreted as that flights travelling from low-pollution to high-pollution locations are carrying more passengers. This counter-intuitive result of moving towards high-pollution locations has been observed in multiple air quality valuation studies in low-and-middle income settings such as Indonesia and China (Tan-Soo, 2017; Freeman et al., 2019). The most likely reason is because highly polluted locations tend to have more economic activities and larger population base, thus making them more popular destinations. Hence, we would have under-estimated the extent to which

12 Descriptive statistics for climatic variables are reported in Table A1.

Table 2. Summary statistics

Variables	Definition	Both arrival and departure PEK					Departure PEK			Arrival PEK		
		Mean	SD	Min	Max	*N*	Mean	SD	*N*	Mean	SD	*N*
Flights and passengers (number)												
Flights	Number of flights per unique city-pair	6.738	6.116	1	43	74,132	8.329	7.143	40,294	4.843	3.817	33,838
Passengers	Average number of passengers per flight	143.8	54.89	1	569	499,180	143.5	54.15	335,414	144.6	56.35	163,766
Economy	Average number of passengers per flight	137.5	52.27	1	542	499,180	137.1	51.58	335,414	138.2	53.68	163,766
First class	Average number of passengers per flight	6.372	2.636	0	27	494,023	6.359	2.600	333,262	6.398	2.709	160,761
Occupancy	Passengers/capacity (flight-date rate)	0.654	0.171	0.011	1	499,180	0.653	0.166	335,414	0.657	0.173	163,766
Delays	Flight delays (hour)	0.306	0.828	0	23.75	499,180	0.321	0.848	335,414	0.276	0.785	163,766
Ticket	Ticket price (RMB/passenger)	586.2	211.6	94.2	2035	499,180	575.1	205.4	335,414	608.9	222.2	163,766
Air Pollution Index (API, 0–500)												
API_O	Origin-based API	80.62	45.25	0	500	499,180	86.36	48.84	335,414	68.86	33.91	163,766
API_D	Destination-based API	75.32	40.03	0	500	499,180	69.59	33.11	335,414	87.06	49.35	163,766
API-Diff	API_O-API_D	5.297	56.06	−467	467	499,180	16.77	53.22	335,414	−18.19	54.39	163,766
Thermal inversions (times)												
TINum_O	Origin-based number (6-h measures)	0.680	0.833	0	4	499,180	0.712	0.790	335,414	0.616	0.911	163,766
TINum_D	Destination-based number (6-h)	0.656	0.877	0	4	499,180	0.632	0.916	335,414	0.707	0.790	163,766
TI-Diff	TINum_O-TINum_D	0.024	1.125	−4	4	499,180	0.080	1.121	335,414	−0.091	1.124	163,766

Number of unique city-pair is 115. Our research sample only contains domestic direct flights that includes both departure and arrival Beijing Capital Airport (BEK) in each day over the period 1 March 2008–30 April 2010. Occupancy is defined as the rate of flight passengers relative to the capacity of aircrafts. API data are reported at city-date level, and then are subtracted from origin-city to destination-city. TINum is counted if thermal inversion occurs within each 6-h period (=1), that is, temperature in the layer of 110 m is lower than that in the layer of 330 m, and then is summed for each day.

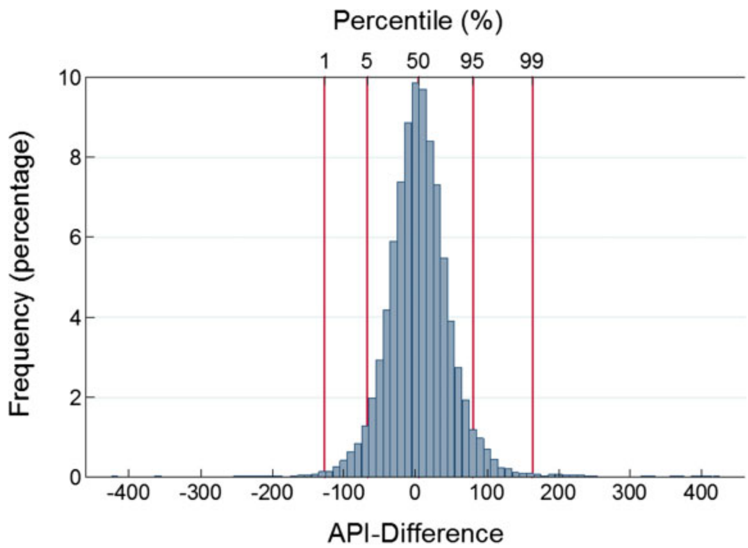

Figure 3. Histogram of API-difference. This figure plots the histogram of API-difference across the entire sample.

Table 3. First-stage estimates

	Dependent variable: API-difference				
	(1)	(2)	(3)	(4)	(5)
TINum-difference	4.4995***	4.3513***	3.7755***	3.8300***	3.3480***
	(0.5324)	(0.4772)	(0.4908)	(0.4935)	(0.5278)
Flight FE	No	Yes	Yes	Yes	Yes
Weather controls	No	No	Yes	Yes	Yes
Date FEs	No	No	No	Yes	Yes
Population weight	No	No	No	No	Origin
First-stage *F*-stat.	71.40	83.14	434.1	428.5	501.5

Total observations = 499,180; number of flight-code=1410. Weather controls include second order polynomials in daily weather conditions, including temperature, precipitation, sunshine duration, wind force, relative humidity and atmospheric pressure. All climatic covariates are also included as difference between the origin city and the destination city. Date fixed effects include dummies for weekdays, holidays and holiday-makeup. Observations in Column (5) are weighted according to the population of the flight origin city. Standard errors are clustered by 1410 flight-code and are listed in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

people use air travels to escape from air pollution if we did not control for this confounding effect. In all, the baseline results confirm that flights generally have more passengers if they are originating from a location with worse air quality than the destinations.

Next, we examine if air quality at either origin or destination are stronger factors in influencing flight travels, i.e., whether push or pull factors matter more. To do so, air quality at origin and destination cities are included as separate regressors (Table 5, Column 2). Holding air quality at destination city constant, the marginal impact of increase in API at

Table 4. Second-stage estimates

	Dependent variable: Log(passengers)				
	(1)	(2)	(3)	(4)	(5)
Panel A: IV estimates (2SLS)					
API-difference	0.0018**	0.0017***	0.0023***	0.0027***	0.0036***
	(0.0007)	(0.0005)	(0.0007)	(0.0007)	(0.0008)
KP *F*-statistics	71.40	83.14	59.18	60.24	40.24
Panel B: OLS comparison					
API-difference	0.0000	−0.0001***	−0.0001***	−0.0001***	−0.0001***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R-squared	0.0000	0.3892	0.3904	0.4072	0.4445
Flight FE	No	Yes	Yes	Yes	Yes
Weather controls	No	No	Yes	Yes	Yes
Date FEs	No	No	No	Yes	Yes
Population weight	No	No	No	No	Origin

Total observations = 499,180; number of flight-code=1410. Weather controls include second-order polynomials in daily weather conditions, including temperature, precipitation, sunshine duration, wind force, relative humidity and atmospheric pressure. All climatic covariates are also included as difference between the origin city and the destination city. Date fixed effects include dummies for weekdays, holidays and holiday-makeup. Observations in Column (5) are weighted according to the population of the flight origin city. Standard errors are clustered by 1410 flight-code and are listed in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5. Origin and destination

	Dependent variable: Log(passengers)			
	Baseline	Both origin- and destination-based pollution	Flights departure PEK	Flights arrival PEK
	(1)	(2)	(3)	(4)
API-difference	0.0036***		0.0031***	0.0005
	(0.0008)		(0.0009)	(0.0017)
API_O		0.0037***		
		(0.0007)		
API_D		−0.0030***		
		(0.0009)		
IV-Number of inversions	TINum-difference	TINum_O and TINum_D	TINum-difference	TINum-difference
KP *F*-statistics	40.24	23.47	29.88	55.72
Observations	499,180	499,180	335,414	163,766
Number of flights	1410	1410	850	570
F-test between API_O and API_D		Coef.: 0.0007** (SE: 0.0003)		

All specifications contain the full set of controls and fixed effects as in the baseline specification, that is, Column (5) of Table 4. The climatic covariates are included in similar fashion as API. Standard errors are clustered by flight-code and are listed in parentheses;
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

origin city increases number of passengers on each flight by around 0.37%. On the other hand, the coefficient for API at destination is smaller in magnitude at −0.3%. An *F*-test comparison of these two coefficients confirms this observation as the coefficient for API at origin city is statistically larger in magnitude than the coefficient for API at destination city. This finding provides evidence that the results observed so far are, to a larger extent driven by averting behaviours from places with poor air quality. As our dataset is centred around flights at PEK, we can test specifically the 'attractiveness' of Beijing city as a destination for short-term travels to avoid air pollution. For flights departing PEK, there are an additional 0.31% passengers per flight for every unit-increase in API over the destination city (Table 5, Column (3)). Conversely, we do not observe a statistically significant API coefficient for flights entering PEK (Table 5, Column (4)). This means that Beijing (even on low pollution days) is not generally considered as a location for clean air.

4.2. Decision-making mechanisms

We used air quality on day-of-travel as the main covariate in our empirical specification with the assumption that travellers rely on air quality forecasts to make decisions. However, it is also possible that individuals make air pollution-avoidance travel decisions based on air quality from days before the travel date. If decisions are indeed made in the latter way, we would then expect to see a stronger or at least similar effect of lagged API-difference on number of flight passengers. We test this hypothesis in two ways. First, we use the average of the current day API-difference and its various days lag as the main covariate. From the results shown in Figure 4, the coefficient for API-difference is largest for current day and decreases accordingly as API from subsequent lagged-days are combined. Second, destination's and origin's air quality are included separately where destination's API is fixed on day of departure while origin's API is allowed to take on values at various daily lags *k*. From Table 6, Panel A, we can see that coefficients for API closer to the travel date are the largest. On the other hand, we fix origin's API on day of departure and allow destination's API to take on values at various daily leads *k* (Table 6, Panel B). We now see that only coefficients for current-day and up to 2-day lead API are large and statistically significant, indicating that travellers are also using forecast information to choose destinations.

In all, these results point to that air pollution-avoidance travel decisions are most likely made using air quality on day of travel. The intuitive explanation is that for the traveller to fully yield the benefits of avoiding pollution, he/she should ideally depart on the day where air pollution is worst at the home city and arrive at a city when air quality is good. This decision-making mechanism is especially helped by the availability of daily air quality forecasts provided by the Chinese government through various media reports since at least 2001 (Tong, 2006).[13]

4.3. Robustness checks

In this section, we undertake a series of robustness tests to ensure that the baseline results are not driven by modeling assumptions.

13 According to Tong (2006), these forecasts are on average around 78% accurate when evaluated at the category level.

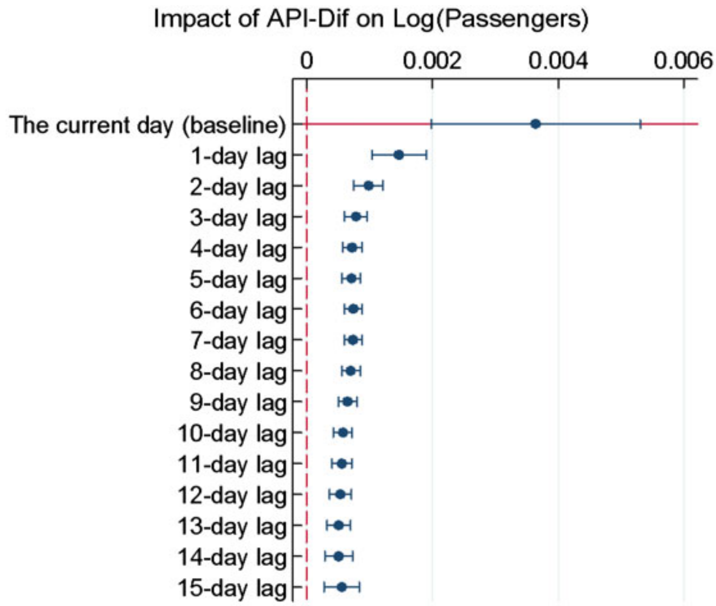

Figure 4. Coefficients of average lagged-API-difference on flight passengers. This figure depicts the impacts of API-difference on Log(passengers) by various exposure windows. API-difference is calculated using the average from the past days until the current day. The circle denotes the point estimate, while the whisker denotes the 95% confidence interval.

First, the identification strategy is partially altered where the fixed effects are introduced at the city by month-of-year level (previously at flight-code level). The main purpose of these fixed effects is to control for any city-unique temporal factors that may also confound the relationship between air quality and travel decisions, e.g., major events such as the 2008 Olympics. Column (1) of Table 7 shows that the coefficient for API-difference at 0.37% is similar to that of the baseline results, hence confirming that our baseline results were not driven by confounding temporal factors. Similarly, fixed effects are included at the most granular level: date. In this regard, statistical identification is now obtained from variation in API-difference and flight passengers on the same date (Table 7, Column (2)). The results with the inclusion of daily fixed effects are again highly similar to the baseline results.

Second, we test for the sensitivity of the standard errors by clustering at different levels. Columns (3) and (4) of Table 7 show clustered standard errors at the city-level, and route- and date-level, respectively. The significance level of the coefficient of API-difference did not change from the baseline in both instances.

Third, we modify the definition of the IV. Thermal inversion was originally defined as the number of times in which inverse temperature gradient between ground level and the next higher level of 320 m is observed daily at four intervals of 6-h each. In Column (5), we compare ground level and the 540 m layer instead. This is a more stringent definition of thermal inversion as temperature at higher altitudes tend to be cooler. In Column (6), we aggregate temperature to daily level and thus thermal inversion is defined as binary variable. In both cases, the coefficient for air quality difference remains stable at around

Table 6. Leads and lags air quality

	Dependent variable: Log(Passengers) (t)									
	(1) $k=0$	(2) $k=1$	(3) $k=2$	(4) $k=3$	(5) $k=4$	(6) $k=5$	(7) $k=6$	(8) $k=7$	(8) $k=8$	(8) $k=9$
Panel A. Origin ($t-k$) and destination (t)										
API_Origin ($t-k$)	0.0037***	0.0040***	0.0028***	0.0029***	0.0022***	0.0020***	0.0033***	0.0020***	0.0002	0.0001
	(0.0007)	(0.0007)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
API_Destination (t)	−0.0030***	−0.0029***	−0.0008	0.0004	0.0005	0.0002	0.0005	0.0005	−0.0001	−0.0000
	(0.0009)	(0.0009)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
KP F-statistics	23.47	38.15	57.25	146.5	161.1	185.1	441.2	321.9	181.2	170.7
Panel B. Origin (t) and Destination ($t+k$)										
API_Origin (t)	0.0037***	0.0046***	0.0039***	0.0025***	0.0024***	0.0022***	0.0024***	0.0027***	0.0027***	0.0031***
	(0.0007)	(0.0008)	(0.0008)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
API_Destination ($t+k$)	−0.0030***	−0.0040***	−0.0018***	−0.0005	−0.0005	−0.0002	0.0001	−0.0005*	0.0001	0.0001
	(0.0009)	(0.0009)	(0.0007)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
KP F-statistics	23.47	40.07	48.46	209.2	129.2	205.9	211.9	214.1	191.6	161.2

Total observations = 499,180; number of flight-code=1410. All specifications contain the full set of controls and fixed effects as in the baseline specification, that is, Column (5) of Table 4. The climatic covariates are included in similar fashion as API. Standard errors are clustered by flight-code and are listed in parentheses;
***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table 7. Robustness checks

Dep. var.	Log(Passengers)											Occupancy
	City–year–month FE	Date FE	Alternative clustering		Alternative IVs		Air pollutant		Weather controls		Route level	Alternative dep. var.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
API-Dif.	0.0037***	0.0038***	0.0036***	0.0036***	0.0034***	0.0035***	0.0032***	0.0021***	0.0028***	0.0043***	0.0049***	0.0019***
	(0.0010)	(0.0013)	(0.0008)	(0.0006)	(0.0009)	(0.0003)	(0.0008)	(0.0006)	(0.0006)	(0.0011)	(0.0017)	(0.0004)
KP *F*-Stat.	30.85	24.09	63.34	61.13	19.33	56.23	40.29	201.8	59.80	25.88	35.92	40.24
Observation	499,180	499,180	499,180	499,180	499,180	499,180	396,643	102,537	499,180	499,180	74,131	499,180
Number of flights	1410	1410	1410	1410	1410	1410	1333	1110	1410	1410	NA	1410
Scenarios												
Weather	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	No	Cubic	Quadratic	Quadratic
Clustering	City pairs	City pairs	City pairs	Flight and hour	Flight	Flight	Flight	Flight	Flight	Flight	Flight	Flight
API dominant	Comp.	Comp.	Comp.	Comp.	Comp.	Comp.	PM	Other	Comp.	Comp.	Other	Comp.
Inversions	Layer 1: 6-h	Layer 1: 6-h	Layer 1: 6-h	Layer 1: 6-h	Layer 2: 6-h	Layer 1: 24-h	Layer 1: 6-h	Layer 1: 6-h	Layer 1: 6-h	Layer 1: 6-h	Layer 1: 6-h	Layer 1: 6-h

All specifications contain the full set of controls and fixed effects as in the baseline specification, that is, Column (5) of Table 4. The climatic covariates are included in similar fashion as API. API-differential ranges from −446 to 467 for $PM_{2.5}$-dominant days in Column (7), and ranges from −467 to 89 for non-$PM_{2.5}$ dominant days. Standard errors are clustered by flight-code and are listed in parentheses;
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

0.34–0.35%. Hence, this suggests that the baseline results are not driven by how the IV is defined.

Fourth, the data are separated according to the dominant air pollutant. Recall that the main covariate, API, is essentially a composite score of various air pollutants. In Column (7), we limit the sample to only between city-pairs where dominant air pollutant is particulate matters (or more commonly known as PM) for both cities. On the other hand, the regression model in Column (8) consists of observations where the main pollutants for both cities are not concurrently particulate matters. We can see that the result in Column (7)—where particulate matters is the main air pollutant—is closer to the baseline results compared with Column (8). One possible explanation for the different estimation results is that days where air quality is exceptionally bad are also when PM is the dominant pollutant (as seen in the much larger average API-differential). As such, the larger effects observed for PM-dominant days most likely reflect a non-linear relationship between air quality-differential and travel behaviours, which we will examine in further detail in a latter section.

Fifth, weather controls are excluded and included as cubic functions, respectively. API-difference has a smaller coefficient (0.028%) in the specification where weather controls are excluded (Table 7, Column (9)). This suggests that climatic factors are correlated with API-difference and affect travel movements in an opposite direction. On the other hand, the coefficient for API-difference increases to around 0.4% when weather covariates are included in a cubic manner (Table 7, Column (10)).

Sixth, we aggregate observations from the current flight-code level to daily route-level to investigate if the earlier results were mostly driven by substitution between different flights. For instance, it could be the case that the total number of passengers between two cities remained the same as passengers selectively choose certain flights over others serving the same route. The estimated coefficient for API-difference at the route-level is larger at around 0.49% suggesting that earlier results are not driven by substitution patterns (Table 7, Column (11)).

Seventh, instead of the number of passengers, we use the occupancy rate as the dependent variable (Table 7, Column (12)). Similar to the baseline specification, the API-difference coefficient is positive and statistically significant. The marginal impact of API-difference is now a 0.19 increase in occupancy rate of a flight travelling from a more polluted city to a less polluted one.

Eighth, it is possible that flights are more likely to be cancelled or delayed at times of poor air quality. If so, cities with poor air quality may see a lower arrival rate, thus biasing our estimates upwards.[14] We check for this possibility in two ways. First, using the same baseline specification, the dependent variable is now recorded as a binary observation which takes the value of 1 if the flight is delayed, and zero otherwise. Table A2, Column (1) shows no statistical relationship between probability of a flight being delay with the API-difference. API is weakly significant for departure flights and not statistically significant for arrival flights (Table A2, Columns (2) and (3)). Second, we investigate if the cancelled flights are correlated with API-difference by aggregating the total number of daily completed flights at the route-level. Similarly, we do not observe any results that suggest flights are more likely to be cancelled when API is high at origin or destination

14 However, going by this logic, it is also possible that flights from the more polluted city are more likely to be delayed or cancelled, thus biasing estimates downwards.

(Table A2, Column (4)–(6)). Third, the baseline model is re-estimated by including flight delays and total number of daily flights as additional covariates. The coefficient for API-difference is similar to the baseline result (Table A2, Column (7)).

Ninth, we do not observe in the dataset the actual origin or destination cities. For instance, while we observe the total number of passengers travelling from Beijing to Shanghai, a proportion of these travellers could move on to secondary city from Shanghai. In such cases, our results may be over- or under-estimated depending on the similarity of API between the observed and actual destination (or origin). Towards this end, even if we do not have full information on passengers' itineraries, we can conduct an approximate test by only using observations on flights from Beijing to smaller cities (defined as non-provincial capital cities). The rationale is that due to their lower connectivity, passengers typically do not go to these smaller cities to continue the next leg of their journeys. Hence, we are reasonably sure these passengers are travelling towards their final destination cities. The results collected in Table A3, Column (2) show that coefficient for API-difference, using only travels towards smaller cities, is around 0.6% which is much larger than the baseline. The most likely explanation is that smaller cities tend to have better air quality, and thus this has the effect of magnifying the API coefficient. In comparison, we also estimated separately for flights travelling only to large cities (defined as provincial capital cities). The coefficient is understandably smaller at 0.32% as we can see that the average API-difference is larger for small cities compared with large cities (Table A3, Column (3)). As our full sample consists of both travel-types and it is likely that some passengers travelling to larger cities will go on to smaller cities, it is likely that our baseline results are under-estimated.

Lastly, we conduct a falsification test by using passengers on international flights as the dependent variable (Table A4). While it is true that there are many international locations with better air quality compared with China, it is unlikely that many Chinese residents would use international travels as a means to escape from air pollution for two reasons. First, there are many cheaper and nearer domestic locations. Second, Chinese passport holders are required to obtain a travel visa for entry to most countries. Hence, given the daily variability in air quality and the lengthy process in obtaining travel visas, it is unlikely international locations are commonly used for avoiding poor air quality at home city. Again, we do not find any effects of air quality on international flights travellers.[15]

4.4. Heterogeneity analysis

In this section, we examine how the relationship between flights and air quality differs by seat-types, and various temporal and spatial constructs.

4.4.1. Cabin class

While total number of passengers were used in the prior analyses, it is important to examine if there are any differential impacts according to cabin-class, that is, economy- and first-class passengers. The coefficient for economy-class passengers is 0.34% and highly similar to the baseline estimate (Table 8). However, there is a much larger impact for first-class seats at 0.87%. One interpretation of these results is that not only are short-term

15 We could not use API-difference as the covariate for this analysis because there is no corresponding information on API for international locations.

Table 8. Heterogeneous analysis: by cabin

Dependent variable	Log(passengers)		
	Total (1)	Economy class (2)	First class (3)
API-difference	0.0036***	0.0034***	0.0087***
	(0.0008)	(0.0008)	(0.0015)
Observations	499,180	499,180	494,023
Flight FE	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes
Population weight	Origin	Origin	Origin
KP F-statistics	40.24	40.24	40.77

Weather controls include second-order polynomials in daily weather conditions, including temperature, precipitation, sunshine duration, wind force, relative humidity and atmospheric pressure. All climatic covariates are also included as difference between the origin city and the destination city. Date-fixed effects include dummies for weekdays, holidays and holiday-makeup. Regressions are weighted according to the population of the flight origin city. Standard errors are clustered by flight-code and are listed in parentheses;
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

travels used as a strategy to avoid air pollution, but this strategy is likely to be more highly utilized by those with higher income.

4.4.2. Temporal variation

The data are divided according to the flight take-off time: (midnight) 12 am to 5 am inclusive; (morning) 6 am to 11 am inclusive; (afternoon) 12 pm to 5 pm inclusive; (evening) 6 pm to 11 pm inclusive. First, we see that the coefficient for earliest time period is not significant (Table A5, Panel A). While this suggests that people are not taking flights during this time period to escape from bad air pollution, it should also be noted that the sample size for this time period is much smaller than the others as there are very few flights operating during these hours due to regulations. The coefficient for the next time period of 6 am–11 am (0.27%) is smaller than the coefficients for afternoon (12 pm–5 pm) and evening (6 pm–11 pm) (both 0.39%). One possible explanation is that morning flights are typically in higher demand compared with other hours.

Second, we divide the data according to the four climatic seasons (Table A5, Panel B). The coefficient for winter (typically when air quality is at its worst) is largest at 0.65% while the coefficient for summer (typically when air quality is at its best) is statistically insignificant. On the other hand, the coefficients for spring and autumn are roughly similar at around 0.20–0.25%. These results appear to suggest that Chinese residents are more sensitive to air quality in winter seasons. One possible explanation is due to projection biases where Chen et al. (2019) showed that Chinese residents' marginal willingness-to-pay (MWTP) for air quality improvements is affected by the most current air quality. Another interpretation of this result is that Chinese residents display non-linear responses towards air pollution where the propensity to take on averting behaviours increases more than proportional as air quality worsens. We further examine the possibility of a non-linear response in a later section.

Third, we split the data into three 2-month periods (March and April).[16] The rationale for this demarcation is to examine if the propensity to avoid air pollution using flight travels has increased over the years due to rising income and elevated awareness of the dangers of air pollution. The results shown in Table A5, Panel C confirm our hypothesis as the API-difference coefficient is positive and not statistically significant for 2008. However, the coefficient became statistically significant for 2009 travels, and doubled in magnitude while remaining statistically significant for 2010 travels. Given that general awareness of air pollution has been increasing steadily in the ensuing years, it is likely that these results are a lower bound of current behaviours (Johnson et al., 2017).

4.4.3. Spatial variation

In this sub-section, we now investigate if travels are induced by geographical difference. First, we distinguish cities according to their 'winter heating' status. There is a long-standing government policy in China where cities north of the Huai river will receive free heating coals in the winter.[17] As a result, air quality during winter tend to be comparatively worse in these cities that receive free heat (Chen et al., 2013). Columns (1) and (3) in Panel A of Table A6 examine travels towards cities that are currently receiving heating at time of travels. The API-difference coefficient is not statistically significant in both columns. Conversely, Columns (2) and (4) examine travels towards cities that are not currently receiving free heat. Both results are positive and statistically significant. In particular, we see more much travels (marginal impact of API-difference: 0.51%) taking place from cities with free winter heat (Table A6, Panel A, Column (2)). Movements from non-winter heating cities to other non-winter heating cities are somewhat smaller at around 0.15% per unit of API-difference. In all, this suggests that travel movements towards cities while receiving free heat are generally not motivated by averting behaviours.

Second, we split up the data into three quantiles according to distances of flight route. The results in Table A6, Panel B show clearly that travels between cities <900 km apart are not likely to be induced by air quality difference as the coefficient for AQI difference is negative and not statistically significant. On the other hand, the coefficient for AQI difference between cities of between 900 to 1400 km apart is now positive, but not statistically significant. Lastly, the coefficient for AQI difference between cities of at least 1400 km apart is at 0.17% and is statistically significant. These results suggest that Chinese residents tend to choose locations that are far from their origin cities when using flights as the means to avoid air pollution. This is not surprising as air travel is currently the most feasible and cost-effective way of travelling long distances.

4.5 Nonlinearities

Earlier results showed that there may be nonlinear responses towards air pollution where propensity to engage in averting behaviours increase more than proportional to the deterioration in air quality. In this section, we investigate nonlinear responses towards to

16 The reason why we chose March and April is because these are the only 2 months where we can obtain 3 years of data (i.e., 2008–2010).

17 There is also a temporal variation in effect here as different cities enter 'winter' season at different time.

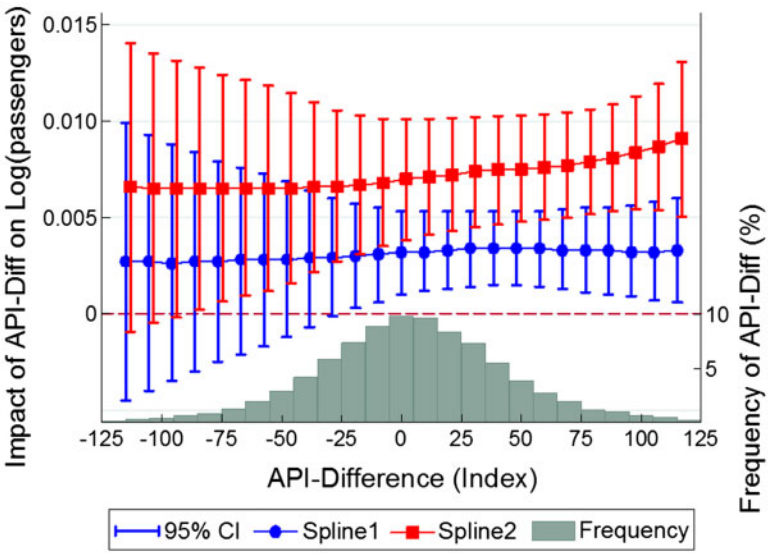

Figure 5. Nonlinear impacts using spline regression. This figure shows the marginal impact of API-difference on Log(passengers) impact and its corresponding 95% confidence interval at ascending knots of API-difference on a spline regression. The blue dots and red dots represent marginal impacts for observations where API-difference is smaller and larger than the knot, respectively.

the air quality differential by introducing a spline term. Equation (1) can thus be re-written as:

$$\ln(FP_{ijkt}) = \beta_0 + \beta_1(P_{it} - P_{jt}) + \beta_2[(P_{it} - P_{jt}) - \kappa] \cdot I((P_{it} - P_{jt}) \geq \kappa) + (W_{it} - W_{jt})\theta + D_t + \varphi_{ijk} + \varepsilon_{ijkt}. \tag{3}$$

First, κ represents the point at which nonlinearity is assumed to occur. Second, β_1 is now interpreted as the marginal effect of API-difference on number of passengers when the API-difference is numerically smaller than κ. Conversely, $\beta_1 + \beta_2$ is the marginal effect of API-difference on flight occupancy rate when API-difference is larger than or equal to the numerical value of κ. Hence, a non-zero β_2 provides evidence of non-linear responses. Since it is a matter of empirical investigation the point or range at which non-linearity occurs, we estimate different versions of Equation (3) using the entire range of API-difference or $(P_{it} - P_{jt})$. The results are presented in Figure 5 and Table A7. The first point on the *x*-axis of Figure 5 shows the associated coefficients (β_1 and $\beta_1 + \beta_2$) when κ is set at −125 (i.e., origin's air quality is better than destination's air quality), and κ increases in value as we move along the *x*-axis. Figure 5 shows that the estimated magnitude of β_1 is fairly similar across all κ at around 0.3%. However, β_1 only start turning significant when API-difference approaches positive. This is because β_1 measures the marginal impact of API-difference at values lower than κ. Hence, it is unlikely that air quality would be a motivation for travels when air quality at origin city is better than destination city. Second, we see that $\beta_1 + \beta_2$ is generally larger than β_1. This suggests evidence of non-linearities as $\beta_1 + \beta_2$ measures the marginal impact of API-difference above κ. Figure 5 shows $\beta_1 + \beta_2$ being on an increasing trend as API-difference increases in value and turned statistically significant at the 0.05 level at around $\kappa = -75$. The increasing trend indicate that the population will increasingly use flight travels as a means for averting behaviours as air quality at origin city worsens compared with destination cities. At its largest, $\beta_1 + \beta_2$ measures at around 0.8%, which is twice as large as our baseline estimate.

5. Conclusions

In the absence of stringent government enforcement and regulations against polluting activities, private citizens will need to take on actions to protect themselves from environmental harms. Earlier studies found that long-term migration is a viable and effective strategy as individuals move to places with lower levels of environmental hazards (Timmins, 2005; Tan-Soo, 2017). Here, we use information on air travels at Beijing Capital International Airport to assess if short-term travel patterns are affected by short-term differences in air quality between cities. Towards this end, we find robust evidence that Chinese residents use air travels to flee from air pollution, where a one-unit difference in API between two cities leads to an increase in 0.36% in number of passengers on a plane leaving for the cleaner city. Due to the endogeneity between air quality and the 'attractiveness' of a location, our empirical strategy necessitates the usage of daily thermal inversion incidences as an IV for air quality. Using a simple back-of-the-envelope calculation, our baseline results thus imply that for a unit increase in Beijing's average annual API (around 86.4 from our dataset), there would be approximately 92,671 additional flight passengers taking air pollution-induced travels from PEK annually.[18]

When considered across spatial and temporal dimensions, we see that (i) passenger occupancy on afternoon and evening flights are more sensitive to air quality-differences, (ii) higher sensitivity towards air pollution during winter months, (iii) increasing sensitivity towards air quality-difference in later years, and (iv) people are more likely to travel to cities at least 1000 km away and less likely to travel to locations that are in winter-heating season. Results from a spline model confirm non-linear responses as the marginal impact of air quality differential increases with larger disparity in API between cities. Using lagged air quality, we also find the number of passengers on a flight is most sensitive to air quality on the day-of-travel. As it is unlikely that flights are booked on the day-of-departure, this implies that Chinese residents rely on air quality forecasts to plan air pollution-avoidance trips. Lastly, we also show that for the *same* flight, first-class seats are filled up around three times faster than economy-class'. As all passengers on the same flight are travelling to the same destination (and thus experience the same API-difference), the different results between first-class and economy-class imply that the former group have a much higher utility gain from such short-term strategies.

When combined with the broader literature on air pollution, our findings add to the arsenal of strategies that Chinese residents have been documented to utilize to reduce their exposure to air pollution, e.g., permanent migration, air purifiers, and face-masks (e.g., Ito and Zhang, 2016; Barwick et al., 2017; Sun et al., 2017; Zhang and Mu, 2017). Future work should thus attempt to correlate these strategies with noticeable socioeconomic status to gather further insights. Finally, it should be noted that our results are obtained from

18 This is calculated by 365 days × 59 routes × 8.33 daily flights/route × 143.5 passengers/flight × 0.36%.

flights centred around Beijing Capital International airport (the largest airport in China by passenger loads) from the years 2008 to 2010. First, this means that we should be cautious in extending findings from this study to flights at other airports in China. Second, income and household wealth in China were considerably lower in this period compared to now. Similarly, knowledge on the harms of air pollution were not as widespread. If we were to conduct this study in current conditions where income has risen, knowledge on air pollution has increased, and long-range transport options such as high-speed train are more accessible and cheaper, it is likely that we will find larger impacts of air quality on short-term travels.

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Appendix

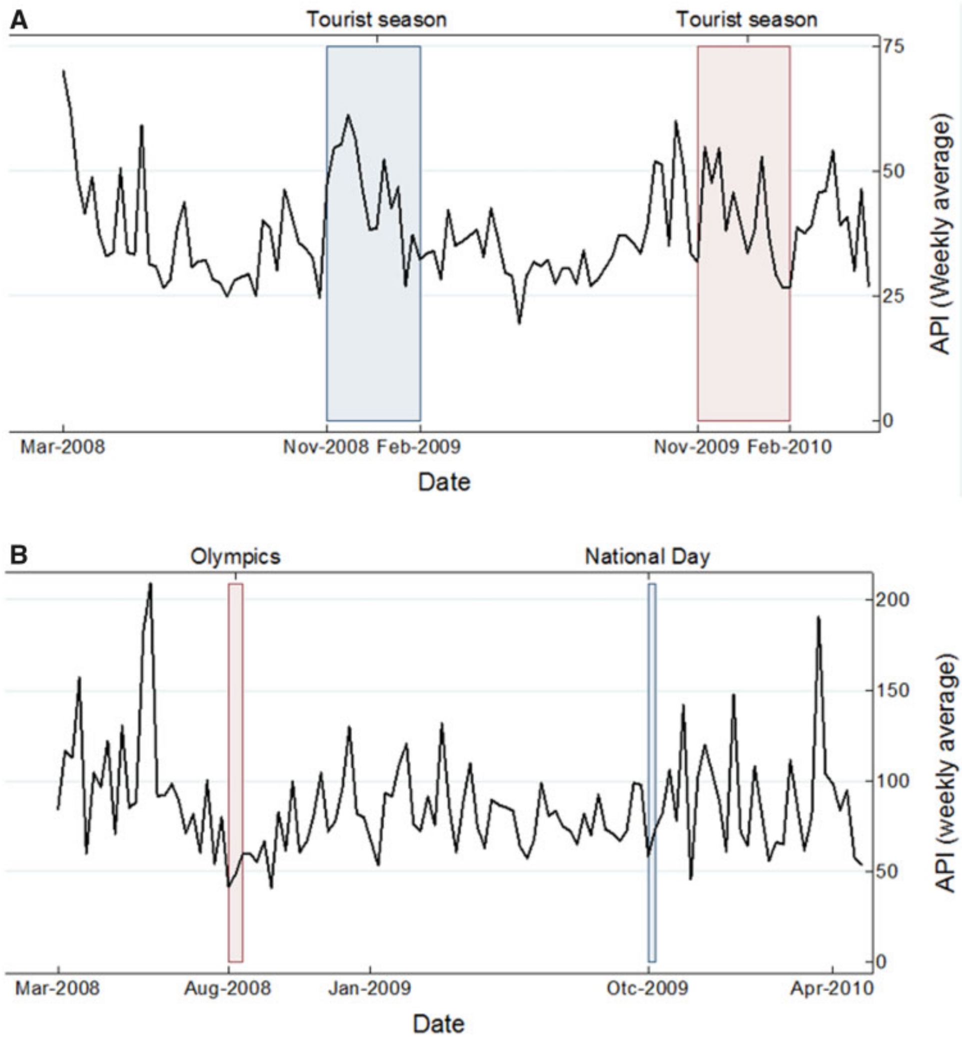

Figure A1. Temporal trends of air quality in representative Chinese cities. This figure depicts the time trend (weekly average) of API in Haikou (**A**) and Beijing (**B**) during our study period. The shadow areas denote special days that vary by city and by date.

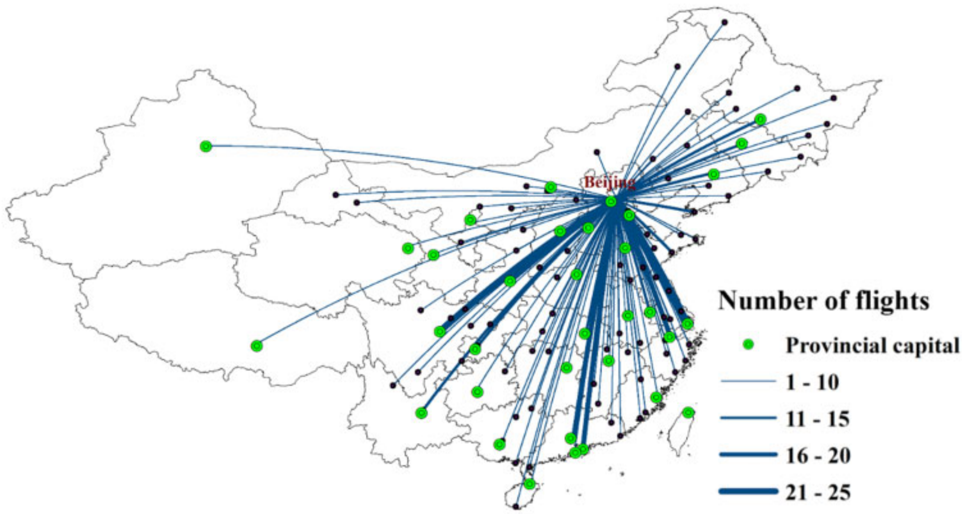

Figure A2. Daily average number of flights in Beijing Capital Airport. Flights include both arrival and departure BEK. Data period March 2008–May 2010.

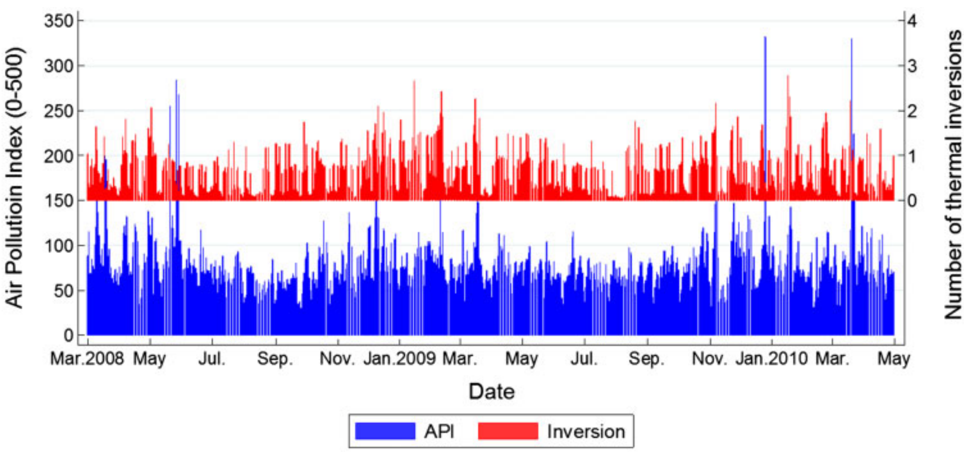

Figure A3. Positive correlation between air pollution index (API) and thermal inversions (daily plot).

Table A1. Summary statistics for weather variables

Variable	Definition	Mean	SD	Min	Max
Origin-based only					
Temperature_O	0.1°C	126.86	112.79	−302.75	347.99
Precipitation_O	0.1 mm	19.24	67.53	0.00	2604.51
Sunshine duration_O	0.1 h	60.92	38.29	0.00	146.67
Wind speed_O	0.1 m/s	21.92	8.67	0.31	118.27
Relative humidity_O	%	59.66	18.34	11.28	99.89
Atmospheric pressure_O	0.1 hPa	9935.99	371.05	7526.13	10,379.29
Destination-based only					
Temperature_D	0.1°C	139.72	109.60	−302.75	347.99
Precipitation_D	0.1 mm	23.98	81.22	0.00	2604.51
Sunshine duration_D	0.1 h	56.29	39.45	0.00	146.67
Wind speed_D	0.1 m/s	22.49	10.12	0.05	118.27
Relative humidity_D	%	64.19	17.87	11.28	99.92
Atmospheric pressure_D	0.1 hPa	9851.96	478.99	6511.61	10,382.99
Difference between origin and destination					
Temperature-diff	0.1°C	−12.86	83.44	−381.55	381.55
Precipitation-diff	0.1 mm	−4.74	102.73	−2604.51	2604.51
Sunshine duration-diff	0.1 h	4.63	52.22	−145.82	145.82
Wind speed-diff	0.1 m/s	−0.57	12.27	−102.97	102.97
Relative humidity-diff	%	−4.54	24.14	−80.60	77.34
Atmospheric pressure-diff	0.1 hPa	84.03	621.13	−2582.37	3676.75

Total observations = 499,180; number of flight-code = 1410.

Table A2. Flight delays and cancelation

Dep. var.	Flight delays (flight-date)			Flight number (route-date)			Log (passengers)
	Total	Departure PEK	Arrival PEK	Total	Departure PEK	Arrival PEK	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
API-difference	0.0017	0.0029*	−0.0014	0.0001	0.0024	0.0012	0.0035***
	(0.0014)	(0.0017)	(0.0030)	(0.0030)	(0.0034)	(0.0033)	(0.0008)
Flight number							0.0089***
							(0.0014)
Flight delays							−0.0131***
							(0.0017)
Observations	499,180	335,414	163,766	74,131	40,294	33,837	499,180
Number of flights	1410	850	570	NA	NA	NA	1410
Number of routes	NA	NA	NA	114	59	55	114
KP *F*-statistics	40.24	29.88	55.72	53.73	40.36	32.80	40.46

Columns (1)–(3) and (4) contain the full set of controls and fixed effects, and are weighted according to the population of the flight origin city as in the baseline specification, that is, Column (5) of Table 4. Columns (4)–(6) replace the county fixed effects by route fixed effects. Standard errors listed in parentheses are clustered by flight-code in Columns (1)–(3) and (4), and are clustered by route-id in Columns (4)–(6).
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A3. Heterogeneous analysis: by city scale

	Dependent variable: Log(passengers)		
	Whole sample (1)	PEK-small cities (2)	PEK-large cities (3)
API-difference	0.0036***	0.0060**	0.0032***
	(0.0008)	(0.0029)	(0.0007)
Observations	499,180	123,579	375,592
Number of flights	1410	360	1067
Flight FE	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Date character	Yes	Yes	Yes
Population weight	Origin	Origin	Origin
Mean [SD] of passengers	137.46 [52.36]	131.10 [50.28]	148.01 [55.69]
Mean [SD] of API-Dif.	5.30 [56.06]	8.51 [56.26]	4.23 [55.92]
KP F-statistics	40.24	38.21	53.40

All specifications contain the full set of controls and fixed effects as in the baseline specification, that is Column (5) of Table 4. Small cities are defined as non-provincial capital cities. The climatic covariates are included in similar fashion as API. Standard errors are clustered by flight-code and are listed in parentheses;
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4. Falsification tests: international flights and numbers of flights

Dep. var.	Log(Passengers)	
	International departure PEK (4)	International arrival PEK (5)
API_O	−0.0006	
	(0.0006)	
API_D		−0.0014
		(0.0016)
KP F-statistics	831.1	149.5
Observations	72,389	16,156
Number of flights/fly routes	290	162
Flight FE	Yes	Yes
Weather controls	Yes	Yes
Date FEs	Yes	Yes
Population weight	Origin	No
Mean [SD] of Dep. Var.	162.52 [72.21]	154.84 [72.40]

Standard errors are clustered by flights and are listed in parentheses;
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A5. Heterogeneous analysis: by time

	Dependent variable: Log(passengers)			
	(1)	(2)	(3)	(4)
Panel A: By times of day	Midnight	Morning	Afternoon	Evening
API-difference	−0.0107	0.0027**	0.0039**	0.0039**
	(0.0317)	(0.0013)	(0.0017)	(0.0018)
Observations	1469	154,448	177,336	165,761
Number of flights	46	569	567	615
Hourly subsample	00:00–05:59	06:00–11:59	12:00–17:59	18:00–23:59
KP *F*-statistics	63.01	135.1	117.5	84.55
Panel B: By season	Spring	Summer	Autumn	Winter
API-difference	0.0025***	−0.0002	0.0020***	0.0065***
	(0.0009)	(0.0006)	(0.0002)	(0.0022)
Observations	153,046	114,724	115,327	115,720
Number of flights	1113	906	927	941
Monthly subsample	March–May	June–August	September–November	December–February
KP *F*-statistics	22.38	108.5	41.16	35.39
Panel C: By year	2008–2010	2008	2009	2010
API-difference	0.0021***	0.0015	0.0016***	0.0033***
	(0.0005)	(0.0036)	(0.0004)	(0.0011)
Observations	115,469	33,675	40,793	40,971
Number of flights	1097	803	803	818
Monthly subsample	March–April	March–April	March–April	March–April
KP *F*-statistics	61.24	97.49	47.47	38.11

Panel A consists of sub-samples according to flight take-off time. Panel B consists of sub-samples according to climatic seasons. Panel C consists of sub-samples from March to April for each year as these are the 2 months where data are available for all years. All specifications contain the full set of controls and fixed effects as in the baseline specification, that is Column (5) of Table 4. Standard errors are clustered by flight-code and are listed in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A6. Heterogeneous analysis: by region

	Dependent variable: Log(passengers)			
	(1)	(2)	(3)	(4)
Panel A:	WinterHeat	WinterHeat	NonWinterHeat	NonWinterHeat
Heating regions	−WinterHeat	−NonWinterHeat	−WinterHeat	−NonWinterHeat
API-difference	0.0003	0.0051**	−0.0197	0.0015***
	(0.0007)	(0.0024)	(0.0369)	(0.0004)
Observations	57,826	75,995	46,339	318,870
Number of flights	442	519	482	1214
KP *F*-statistics	32.54	79.72	30.08	159.8
Panel B: Distance	Total sample	Distance Quantile 1	Distance Quantile 2	Distance Quantile 3
API-difference	0.0034***	−0.0043	0.0081	0.0017***
	(0.0008)	(0.0084)	(0.0057)	(0.0005)
Observations	499,180	137,634	175,639	186,103
Number of flights	1410	439	494	507
Distance	[121–2564 km]	[121–923 km]	[923–1401 km]	[1411–2564 km]

Panel A consists of sub-samples according to the 'winter heating' status of origin and destination cities. Panel B consists of sub-samples according to the straight-line distance between origin and destination cities. All specifications contain the full set of controls and fixed effects as in the baseline specification, that is Column (5) of Table 4. Standard errors are clustered by flight-code and are listed in parentheses;
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A7. Piecewise-linear regression

	Dependent variable: Log(passengers)												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
API-Dif_spline1 (β_1)	0.0032	0.0032	0.0032	0.0032	0.0033*	0.0033**	0.0034***	0.0035***	0.0036***	0.0035***	0.0035***	0.0034***	0.0035**
	(0.0038)	(0.0032)	(0.0027)	(0.0024)	(0.0018)	(0.0014)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0013)	(0.0014)
API-Dif_spline2 (β_2)	0.0040***	0.0040***	0.0039***	0.0039***	0.0039***	0.0039***	0.0039***	0.0040***	0.0041***	0.0043***	0.0045***	0.0050***	0.0056**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0011)	(0.0017)	(0.0028)
Lincom ($\beta_1+\beta_2$)	0.0072*	0.0072**	0.0071***	0.0071***	0.0071***	0.0072***	0.0073***	0.0075***	0.0077***	0.0078***	0.0080***	0.0084***	0.0091***
	(0.0039)	(0.0035)	(0.0031)	(0.0028)	(0.0023)	(0.0019)	(0.0016)	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0015)	(0.0021)
KP F-statistics	19.89	19.19	19.06	17.41	19.50	22.84	28.21	31.81	32.65	30.67	24.51	17.07	9.414
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date character	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population weight	Origin	Origin	Origin	Origin	Origin	Origin	Origin	Origin	Origin	Origin	Origin	Origin	Origin
Spline cutoff													
API-Dif=	−120	−100	−80	−60	−40	−20	0	20	40	60	80	100	120
Percentile of API-dif (%)	1.13	1.83	3.29	6.58	13.69	26.99	46.02	66.11	81.5	90.6	95.15	97.2	98.32

Total observation = 499,180; number of flights = 1410. We use the number of thermal inversions of the departure city (TINum-0) and the arrival city (TINum-D) to instrument two endogenous API-Difference, that is, API-Dif_spline1 and API-Dif_spline2. Weather controls include the second order polynomials in daily weather conditions, including temperature, precipitation, sunshine duration, wind force, relative humidity and atmospheric pressure. All weather variables are also taken difference value between the origin and the destination city. Date fixed effects include dummies for weekdays, holidays and holiday-makeup. Standard errors are clustered by 1410 flights and are listed in parentheses;

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.