The effect of air pollution on China's internal migration

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Online Appendix

A Background

The Household Registration System (HRS, or *Hukou*) heavily regulates the internal migration in China. The *Hukou* system records the legal residence and the family relationship of each person in China. Migrants without local *Hukou* had limited access to local healthcare, education, and welfare, and obtaining local *Hukou* was difficult, often requiring the purchase of a local residence, stable employment and income, and high education and talent. Despite these restrictions, the internal migration in China grew rapidly in the 1990s, with the total floating population rising from 21 million in 1990 to 102 million in 2000.[1] Since 2003, the central government has gradually made local welfare accessible to migrants without local *Hukou*. For example, migrants without local *Hukou* only needed to provide proof of local residence and legal employment to get their children to attend a local school. At the same time, the central government relaxed the requirement for migrants to acquire local *Hukou*, starting with the smaller cities. In part as a result of these policy changes, the total floating population grew and reached 253 million in 2014. Our study highlights a period when these restrictions on internal migration were being relaxed.

In part because of the remaining *Hukou* restrictions, family separation characterizes the experience of many internal migrants in China. For example, it is common for working-age individuals to migrate and leave their young children and aging parents behind. According to Wei (2022), in 2020, nearly half of the rural out-migrating parents in China left their children behind. These children, commonly referred to as the "left-behind children," have increased risk of depression, anxiety, suicidal ideation, conduct disorder, substance use, wasting, and stunting (Fellmeth *et al.*, 2018). Similarly, the parents that are left behind experience lower utility due to less physical care and psychological support from their out-migrating children (Cai *et al.*, 2022), creating the "empty nest syndrome." Another distinct feature of partial out-migration is the remittances sent by the migrants to their origin households. Cheng

[1]See Report on China's Migrant Population Development. `https://new.qq.com/omn/20181227/20181227A0F4MY.html` (in Chinese)

and Xu (2005) estimate that, in 2005, the total remittances sent by rural migrants to their families ranged from 191 to 330 billion Yuan. These remittances increase consumer demand in their origins and boost the local economy.

In addition to the *Hukou* restrictions, partial out-migration also results from the differential response to incentives to migrate, in this case, finding a good job, by family members of different age groups. In contrast, family members of different age groups likely respond similarly to other incentives, such as local food price levels, which, in turn, lead to whole-household out-migration. Nevertheless, partial out-migration and whole-household out-migration should not be seen as completely distinct outcomes. In fact, households with existing partial out-migrants are more likely to later whole-household out-migrate than households without existing partial out-migrants. In this way, partial out-migration can be a necessary first step towards whole-household out-migration. Assessing whether air pollution affects the first step and/or the second step is one of the objectives of this paper.

Although rarely quoted as the primary reason to migrate, air pollution can be a conclusive one. The Chinese government enacted the Ambient Air Quality Standard (GB3095-1996) in 1996 and started disclosing air pollution information. These data reveal a gradual worsening of air quality until 2013, when the State Council enacted the Air Pollution Prevention and Control Action Plan, which marked the beginning of a series of measures by the central government to combat air pollution. As a result, air pollution in China steadily declined. According to data from the Ministry of Ecology and Environment, the particulate matter with a diameter of less than 10 micrometers (PM_{10}) concentrations dropped by 22.7% across Chinese cities from 2013 to 2017.[2] Thus, the amount of air pollution in China peaked after the time period considered in the second part of our analysis and before the time period considered in the first part of our analysis. To the extent that people only responded to air pollution when the air pollution was severe, the second part of our analysis, which covers an earlier time period when the air quality in China was worse, might reveal a more substantial

[2] https://xmexpo.cn/216597.html (in Chinese)

effect.

Among the primary air pollutants, particulate matter causes severe damage to residents' cardiopulmonary system. At low concentrations of particulate matter in the context of the U.S., a 10 $\mu g/m^3$ increase in particulate matter concentration has been shown to decrease life expectancy by 0.6 year (Pope III *et al.*, 2009), increase heart failure by 1.3% (Dominici *et al.*, 2006), and lead to four-seven more infant deaths per 10,000 live births (Chay and Greenstone, 2003). For this reasons, we center on fine particulate matter concentrations to measure air pollution, specifically particulate matter with a diameter of less than 2.5 micrometers ($PM_{2.5}$) concentrations. Compared to PM_{10}, the finer $PM_{2.5}$ can reach the lower regions of the respiratory tract, and is more closely linked to adverse respiratory health effects (Choi *et al.*, 2004).

B Spatial distribution of air pollution in China

Figures A1 and A2 demonstrate the spatial distribution of annual average $PM_{2.5}$ concentrations across cities in China in 2014 and 2016, respectively. Air pollution was most severe in North China and Central China. From 2014 to 2016, a decline existed in air pollution across China, with the decline being the most substantial where air pollution was the most severe.

C Locations of the CLDS sample

We use the panel component of the 2014 and 2016 CLDS, i.e., 7,744 households that were interviewed in 2014 and 2016. Figure A3 depicts the locations of cities represented by this panel.

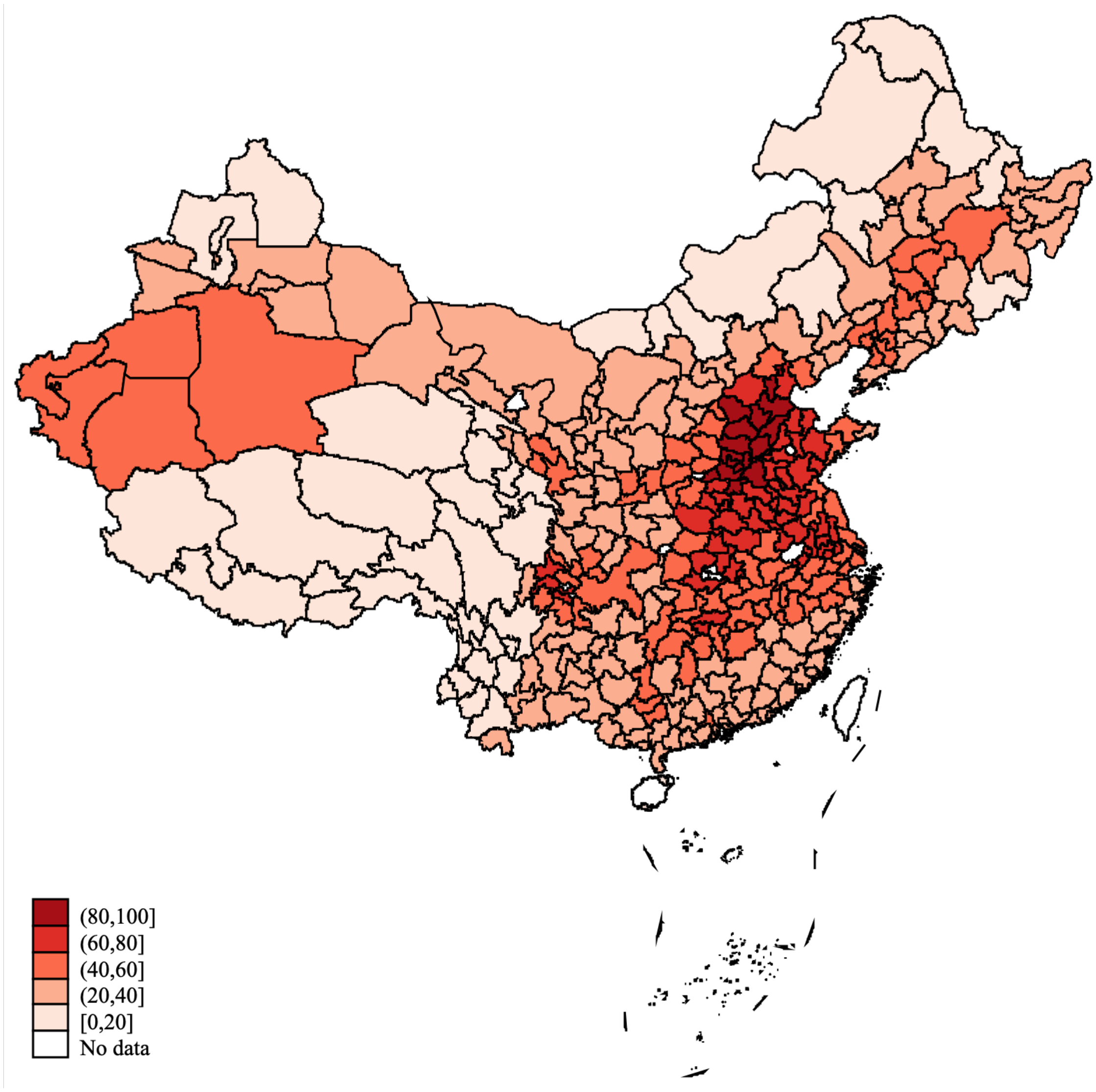

Figure A1. Spatial distribution of annual average $PM_{2.5}$ concentrations in 2014.

Note: The map was created based on remote-sensing satellite data provided by Hammer et al. (2020) and Van Donkelaar et al. (2019).

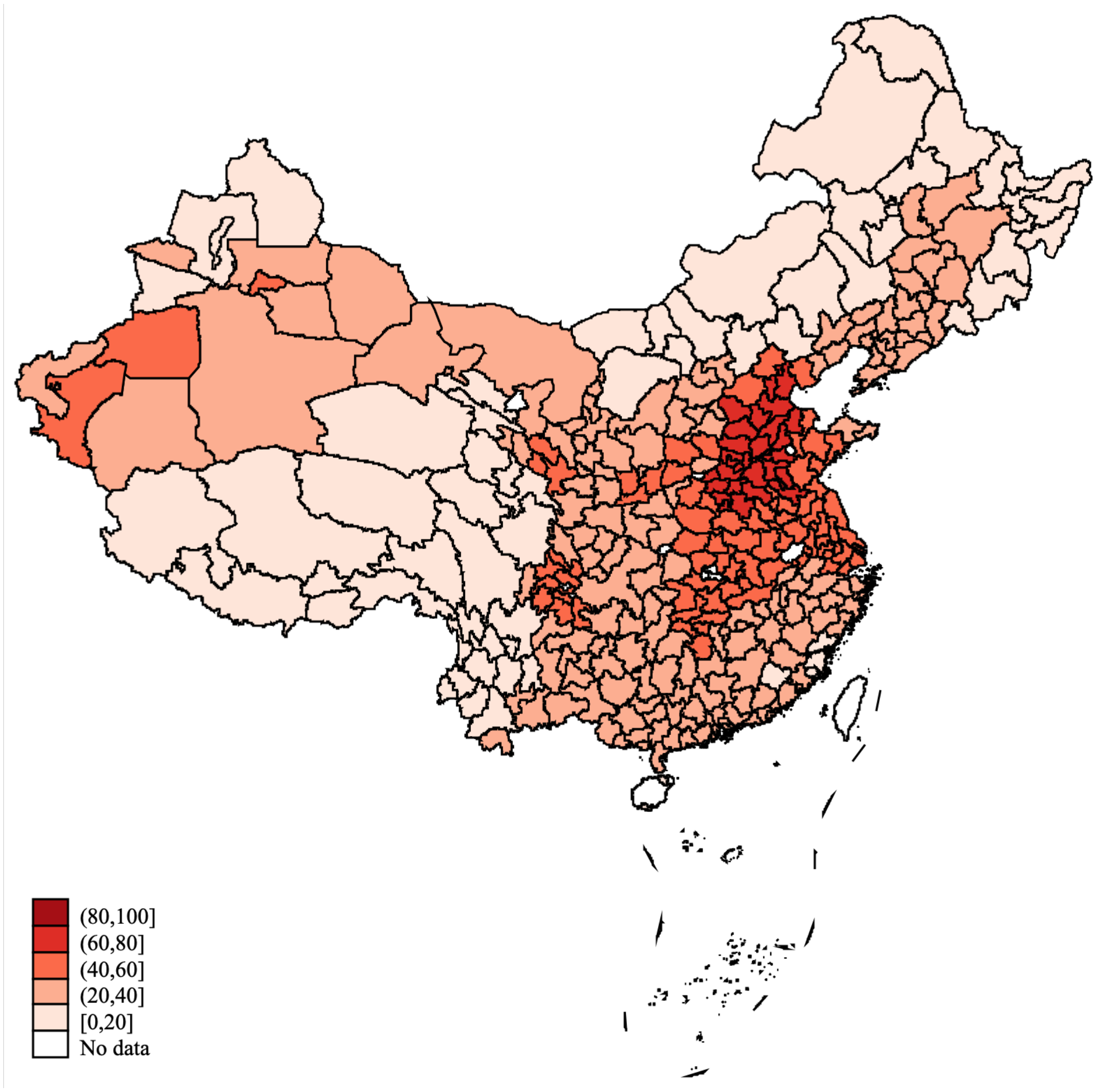

Figure A2. Spatial distribution of annual average $PM_{2.5}$ concentrations in 2016.

Note: The map was created based on remote-sensing satellite data provided by Hammer et al. (2020) and Van Donkelaar et al. (2019).

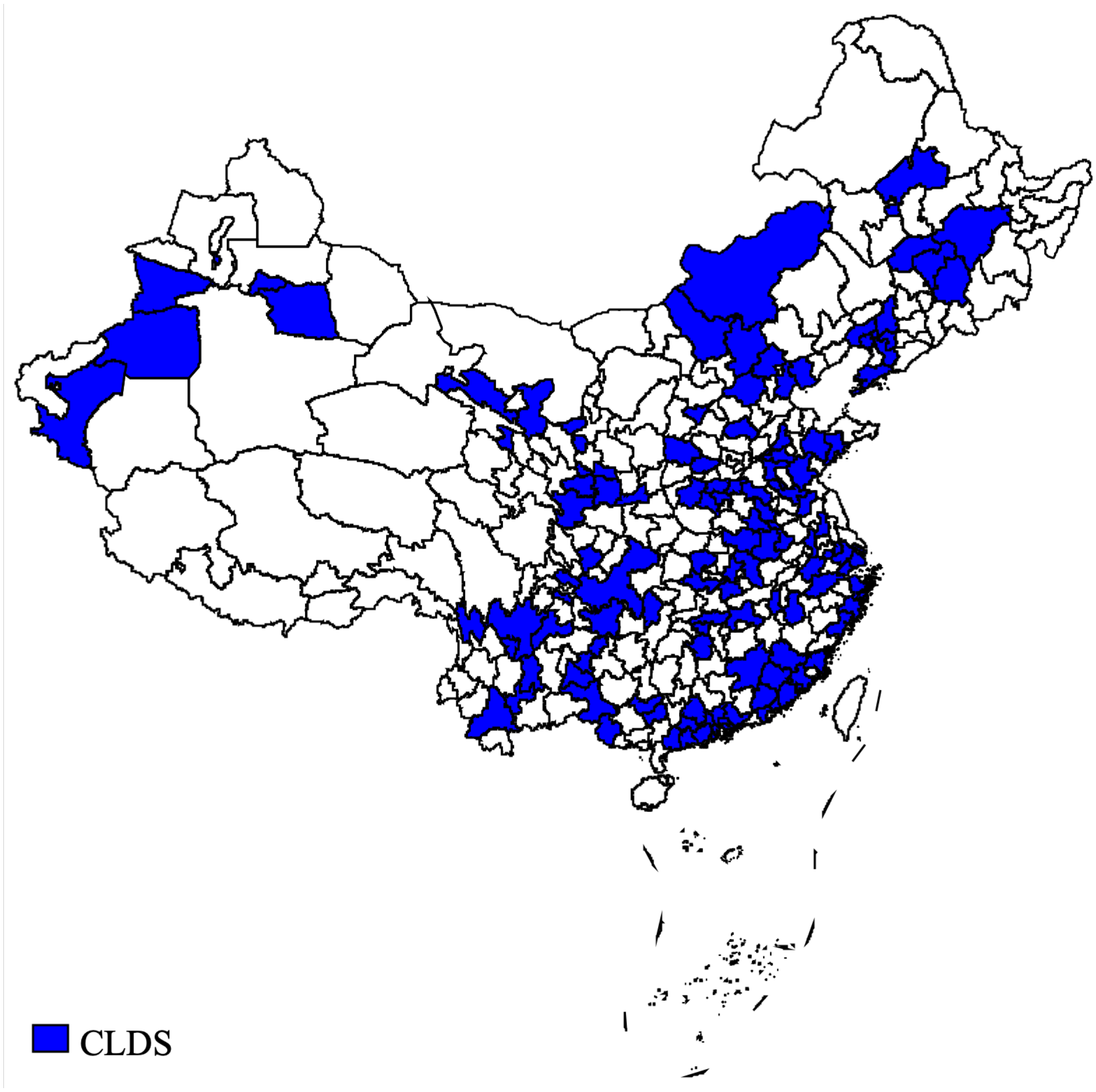

Figure A3. Cities represented by the 2014 and 2016 CLDS samples.

Notes: The cities represented by the panel component of the 2014 and 2016 CLDS samples are denoted blue. For confidentiality reasons, the CLDS does not provide geographic identifiers within a city.

D Choice of exclusion distance

To select the exclusion distance that makes the instrument satisfy both relevance and the exclusion restriction, we summarize the correlation between air quality measures and observable local economic activities variables collected from the China City Statistical Yearbook in table A1. The air quality measures are in the top row of table A1 and comprise average $PM_{2.5}$ concentrations, pollution from sources>50 km, pollution from sources>80 km, and pollution from sources>120 km. The local economic activities variables are in the left-most column. The numbers in the parentheses are the standard errors while regressing an air quality measure on a city characteristic one characteristic at a time on a sample of cities. One of the observable local economic activities variables, gross industrial output, is correlated with average $PM_{2.5}$ concentrations, but no observable local economic activities variable is correlated with air pollution from distant sources.

E Marginal effects as implied by the conditional logit model

To compare the effect of air pollution in the origin on out-migration between the linear model and the conditional logit model, we translate the coefficient estimates in the conditional logit model into marginal effects with equation (5). The effect is the largest when the probability of choosing a city is 0.5 and the smallest when the probability of choosing a city is zero or one. It is the case, because, when the probability of choosing a city is 0.5, whether someone there out-migrated is most marginal; in contrast, when the probability of choosing a city is zero or one, no out-migration occurred. That is, changing the coefficient estimates of α and γ only changes the scale of the marginal effect. We plot the effect of air pollution in the origin on out-migration over the probability that a city was chosen as implied by the conditional logit model. Figure A4 shows this plot. Since the probability of choosing the person's current

Table A1. Correlation between air pollution measures and local characteristics

	Average $PM_{2.5}$ concentrations	Pollution from sources>50 km	Pollution from sources>80 km	Pollution from sources>120 km
Average $PM_{2.5}$ concentrations	1	0.407	0.446	0.338
	(0)	(0.060)	(0.058)	(0.061)
Per capita GDP (in million Yuan)	0.078	-3.060	-1.800	-3.044
	(2.037)	(2.132)	(2.130)	(2.123)
Gross industrial output	261.967	-0.590	49.522	6.246
	(101.726)	(108.599)	(108.123)	(108.141)
(in quadrillion Yuan)				
Unemployment rate	-1.466	3.246	2.476	1.429
	(2.435)	(2.575)	(2.568)	(2.569)

Notes: Each cell contains the correlation between the corresponding city characteristic (listed in the left-hand column) and the measure of air quality (listed in the top row) in the city. The air quality measures are average $PM_{2.5}$ concentrations, air pollution from sources more than 50 km away from the receiving city, air pollution from sources more than 80 km away from the receiving city, and air pollution from sources more than 120 km away from the receiving city. The numbers in parentheses are the standard errors while regressing an air quality measure on a city characteristic one characteristic at a time on a sample of cities.

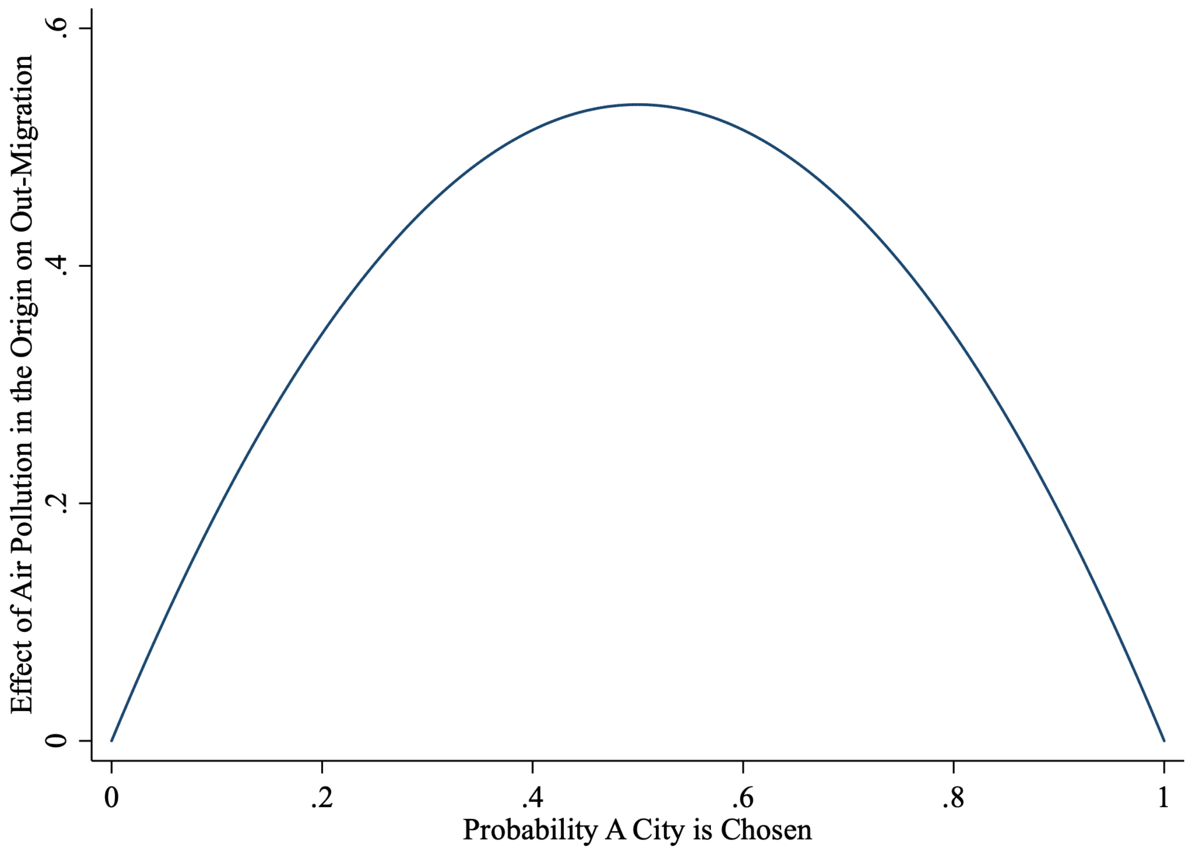

Figure A4. Effect of air pollution in the origin on out-migration as implied by the conditional logit model.

Note: This figure plots the effect of air pollution in the origin on out-migration over the probability that a city was chosen as implied by the conditional logit model.

city as implied by the model ranges from 0.91 to 1, the magnitude of the effect in this range is comparable to that of the linear model.

F Robustness

Tables A2, A3, and A4 present robustness checks for partial out-migration, whole-household out-migration, and location choice, respectively. Firstly, since weather conditions may determine air pollution, and can independently affect out-migration, in column (1) of table A2, we additionally control for weather conditions, including the annual averages of mean, maximum, and minimum temperature, dew point, precipitation, and wind speed. Although the magnitude of the coefficient estimate is larger than that of our baseline estimate, the results are robust to the inclusion of these weather controls.

Secondly, the $PM_{2.5}$ data are aggregated to the city level using city boundaries defined in 2019. Nevertheless, two cities in our sample, Liu'an and Kashi, ceded the jurisdiction of a portion of the cities to other cities between 2014 and 2019. The $PM_{2.5}$ concentrations experienced by people in our sample who were potentially in the ceded areas may be incorrectly measured by the $PM_{2.5}$ concentrations of the cities overtaking these areas. Thus, column (2) of table A2 estimates equation (1), excluding Liu'an and Kashi. The results are robust to the exclusion of these two cities.

Thirdly, as mentioned in section 3.2 of the paper, we choose 80 km as the exclusion distance within which the emissions do not count toward air pollution from distant sources in our baseline results. We now test the robustness of our results to alternative exclusion distances. This exercise is critical, because increasing this exclusion distance also reduces the measurement error due to a source city being partially in the prevailing direction of a receiving city. In particular, the emission level of a source city partly lying in the prevailing wind direction but whose centroid lies outside the prevailing wind direction does not count toward the IV of the receiving city. It mainly presents a problem for the source cities closer

Table A2. Robustness - partial out-migration

Dependent var.: Having a migrant in the household	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IV	IV	IV	IV	IV	IV	IV
IV Exclusion distance:	80 km	80 km	50 km	120 km	80 km	80 km	80 km
IV Pollution measure:	Emission	Emission	Emission	Emission	Emission	$PM_{2.5}$	Emission
Average $PM_{2.5}$ concentrations	0.261	0.219	0.206	0.143	0.203	0.090	0.161
	(0.103)	(0.060)	(0.059)	(0.084)	(0.122)	(0.024)	(0.102)
Weather controls	Yes	No	No	No	No	No	No
Exclude cities that changed boundaries	No	Yes	No	No	No	No	No
Alternative exclusion distance for IV	No	No	Yes	Yes	No	No	No
Cluster standard errors at the city level	No	No	No	No	Yes	No	No
Air pollution before interview dates	No	No	No	No	No	Yes	No
Rotate wind direction by 90 degrees	No	No	No	No	No	No	Yes
R^2	0.08	0.07	0.07	0.08	0.07	0.05	0.08
Mean of Dep. var.	0.281	0.279	0.281	0.281	0.281	0.281	0.258
F	25.543	38.813	38.677	37.802	11.059	39.860	49.888
N	14046	13870	14046	14046	13976	14046	14046

Notes: The average $PM_{2.5}$ concentrations, $PM_{2.5}$ from distant sources, and air pollution from distant sources are normalized to z-scores. All regressions have per capita GDP, gross industrial output, and the unemployment rate as city-level controls and age, years of education, and *Hukou* of the household head, as well as total family income as household-level controls. In addition, column (1) controls for weather conditions, including the annual averages of mean temperature, maximum temperature, minimum temperature, dew point, precipitation, and wind speed. Column (2) excludes Liu'an and Kashi, two cities in the sample that ceded the jurisdiction over a portion of the cities to other cities between 2014 and 2019. Column (3) and column (4) apply 50 km and 120 km, respectively, as the exclusion distances in constructing the instrument. Standard errors are clustered at the household level in all regressions except in column (5), which clusters the standard errors at the city level. Column (6) adopts $PM_{2.5}$ data from land-based monitoring stations between May 13th and June 12th of each survey year to measure air pollution, and uses the average $PM_{2.5}$ concentration of this month in each source city in constructing the instrument for a receiving city. Column (7) conducts a falsification test by rotating the prevailing wind direction of each receiving city clockwise by 90 degrees. Standard errors are in parentheses.

Table A3. Robustness - whole-household out-migration

Dependent var.: Whole household moved Away by 2016			
	(1)	(2)	(3)
	IV	IV	IV
IV Exclusion distance:	50 km	120 km	80 km
Changes in average $PM_{2.5}$	0.124	0.063	0.065
concentrations from 2014 to 2016	(0.035)	(0.058)	(0.042)
Alternative exclusion distance for IV	Yes	Yes	No
Recode HHs with left-behind elderly	No	No	Yes
R^2	-	-	-
Mean of Dep. var.	0.262	0.262	0.214
F	-	-	-
N	9759	9759	9759

Notes: All regressions are estimated on a cross-section of the 2014 CLDS households not due to rotate out in 2016, and use changes in air pollution from distant sources from 2014 to 2016 as the instrument for changes in average $PM_{2.5}$ concentrations from 2014 to 2016. The average $PM_{2.5}$ concentrations and air pollution from distant sources are normalized to z-scores. All regressions have the changes in per capita GDP, gross industrial output, and the unemployment rate as city-level controls. None of the columns includes any fixed effect. Column (1) and column (2) apply alternative exclusion distances in constructing the instrument. Column (3) reassigns all households consisting only of left-behind elderly people in 2014 and disappeared in 2016 to the category of not having whole-household out-migrated. All regressions apply sampling weights. Standard errors are in parentheses.

Table A4. Robustness - coefficient estimates of conditional logit model

Dependent var.: City being chosen			
	(1)	(2)	(3)
Estimation method:	GMM	GMM	GMM
IV Exclusion distance:	50 km	80 km	120 km
Location $PM_{2.5}$	-0.817	-2.003	-1.318
	(0.167)	(0.185)	(0.349)
Current	9.090	9.765	19.142
	(0.198)	(1.502)	(10.414)
Current×Location $PM_{2.5}$	1.132	-0.140	-4.776
	(0.139)	(0.955)	(4.532)
Distance	-0.276	-0.692	-0.505
	(0.028)	(0.152)	(0.119)
N	40390360	40390360	40390360

Notes: The sample is a retrospective panel from 2003 to 2010 constructed from the 2014 individual-level CLDS. Each year, the individuals chose among 214 cities, determined by the cities that all individuals in the sample chose across all sample years. Location $PM_{2.5}$ and the instrument, air pollution from distant sources, are standardized to z-scores. Column (1) and column (3) apply alternative exclusion distances in constructing the instrument. Standard errors are in parentheses.

to the receiving city, since the situation where only part of a source city lies in the prevailing wind direction cone of the receiving city occurs for a smaller share of source cities of a specific distance from the receiving city as the distance increases. Thus, increasing the exclusion distance should reduce this measurement error, as closer-by source cities, comprising those that only partly lie within the prevailing wind direction of the receiving city, do not count toward the instrument.

Column (3) and column (4) of table A2 show the results for partial out-migration with 50 km and 120 km, respectively, as the exclusion distances. Both coefficient estimates of $AveragePM2.5_{ct}$ are positive. The coefficient estimate with 50 km as the exclusion distance is statistically significant at the 1 per cent level, while the coefficient estimate with 120 km as the exclusion distance is statistically signficant at the 10 per cent level. This indicates that our results for partial out-migration are robust to alternative exclusion distances. Column (1) and column (2) of table A3 show the results for whole-household out-migration with 50 km and 120 km, respectively, as the exclusion distances. The coefficient estimates for $\Delta PM2.5_{ct}$ are positive and statistically significant with 50 km as the the exclusion distance, and positive but statistically insignificant with 120 km as the exclusion distance. Thus, we cannot reject the hypothesis that changes in air pollution did not affect whole-household out-migration. In either case, however, whole-household out-migration was less responsive to air pollution than partial out-migration. Column (1) and column (3) of table A4 present the results for location choice with 50 km and 120 km, respectively, as the exclusion distances. The coefficient estimates for $LocationPM2.5_{ijt}$ are all negative and statistically significant, suggesting that the result that migrants were less likely to choose a city with more air pollution is robust to alternative exclusion distances. The coefficient estimates for the interaction term between $Current_{ijt}$ and $LocationPM2.5_{ijt}$ decline with the exclusion distance. The coefficient estimates for the interaction term may be particularly sensitive to the exclusion distance, because, compared to one's knowledge of the economic opportunities of a city he/she was not currently in, his/her knowledge of the economic opportunities of his/her current city may extend beyond 50 km from his/her current city, making an instrument with a smaller exclusion distance less capable of correcting the bias in the coefficient estimate of the interaction term due to local economic activities.

Fourthly, thus far, we have clustered the standard errors at the household level to allow for serial correlation in the error term in all panel data regressions. In the presence of household fixed effects, the city effects are differenced out in the demeaned regression, thereby allowing the error terms to correlate within a city, under the assumptions of the additive random effects model. This addresses the concern that the model systematically overpredicts (or underpredicts) the tendency to out-migrate in a city. Nevertheless, to allow for completely non-parametric residual correlation within a city, column (5) of table A2 reports the results after clustering the standard errors in equation (1) at the city level. The coefficient estimate is positive and statistically significant at the 10 per cent level.

Fifthly, as mentioned in section 2.2 of the paper, we measure the air quality that each CLDS household experienced in each survey wave by the average $PM_{2.5}$ concentration of that calendar year of the city where the household resided. Nevertheless, no household could respond to the air quality after the interview dates in that calendar year. Since the majority of the CLDS surveys were conducted between July and August of each survey year, we collect air quality data from land-based monitoring stations published by the China National Environmental Monitoring Center for the month between May 13th and June 12th of each survey year, and let their average be an alternative measure of air quality before the interview dates.[3] To construct an instrument based on air pollution from distant sources before the interview dates, we measure air pollution from distant sources of a receiving city by the average $PM_{2.5}$ concentrations between May 13th and June 12th of each survey year in source cities lying in the prevailing wind direction of the receiving city. The adoption of

[3]We collect daily air pollution data from land-based monitoring stations, because the remote-sensing satellite data provided by Hammer et al. (2020) and Van Donkelaar et al. (2019) are only available at the annual frequency. We choose the time window of a month between May 13th and June 12th, because daily air pollution data from land-based monitoring stations have only been available since May 13th, 2014. To the best of our knowledge, no study thus far has questioned the reliability of these recent data published by the China National Environmental Monitoring Center.

particulate matter concentration instead of emission level in the source city in calculating the instrument is due to the unavailability of subannual emission level data, but is consistent with the approach taken by Barwick et al. (2018). Column (6) of table A2 depicts the second-stage results. The coefficient estimate is positive and statistically significant, suggesting that our results are robust to this alternative measure of air pollution before the interview dates.

Nevertheless, if households' migration decisions responded to air pollution at all, they most likely responded to the air pollution in the period immediately before the interview dates, and households that were interviewed earlier should have responded to the air pollution in an earlier time period compared to other households in the same city. In this sense, our alternative measure of air pollution based on mean observations between May 13th and June 12th of each survey year may still measure the true air pollution each household experienced with an error. The Classicial Errors in Variable Model predicts a potential attenuation bias to the coefficient estimate for air pollution. The bias to the standard error is unclear, but the t-statistic would be biased downwards. Furthermore, although the measurement error may be larger the farther away the interview date was from the end date of the period that our air pollution measure spanned, there is little reason to believe that local air pollution determined interview dates. This avoids introducing any additional bias to the standard error. In sum, the true migration response to air pollution could be larger than the response we estimate.

Sixthly, as mentioned in section 3.2 of the paper, we test the validity of our IV approach based on wind directions by conducting a falsification test after rotating the wind direction of each receiving city clockwise by 90 degrees. Column (7) of table A2 illustrates the second-stage results. The coefficient estimate is not statistically significant, a finding that corroborates the validity of our IV approach.

Lastly, as mentioned in section 2.2 of the paper, we define a household as having whole-household out-migrated if and only if the household not due to rotate out in 2016 existed in the 2014 CLDS but not in the 2016 CLDS. It is possible that elderly people who were alive in

2014 were more likely to die by 2016 given an increase in air pollution, and we might mistake households that consisted only of left-behind elderly people in 2014 and disappeared from the sample in 2016 due to the death of the elderly people for households that had whole-household out-migrated. If the disappearance of a household in the 2016 CLDS is due to the death of a left-behind elderly person, under the assumption that left-behind elderly people were more likely to die given an increase in air pollution, our baseline estimate in table 3 of the paper will be an upper bound of the true estimate. We provide a lower bound of the true estimate by reassigning all the households that consisted only of left-behind elderly people in 2014 and disappeared in 2016 to the category of not having whole-household out-migrated. These reassigned households include those that consisted only of left-behind elderly people in 2014 and had whole-household out-migrated by 2016 and those that consisted only of left-behind elderly people in 2014 but whose disappearance in 2016 was due to the death of an elderly person. Under the assumption that a household that consisted only of left-behind elderly people was not less likely to whole-household out-migrate given an increase in air pollution, this estimate after the reassignment is a lower bound of the true estimate. Column (3) of table A3 presents the results of this exercise. The coefficient estimate is still positive and statistically insignificant, but slightly smaller in magnitude than the upper bound provided by our baseline estimate in column (2) of table 3 in the paper. The lack of a substantial difference between the upper and lower bounds indicates that such a bias caused by mistaking the death of an elderly person for the household having whole-household out-migrated should be small.

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