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JEL Classification: G12, G15, Q53, Q54

Keywords: air pollution, climate change, migration, property prices

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Exposure to climate and environmental risk is likely to cause reallocation of labor and capital at unprecedented levels in the coming decades.[1] Very recently, research is emerging documenting such reallocation within specific countries where reliable data on migration and labor skills are available, and quantifying the productivity consequences of such reallocation (Khanna, Liang, Mobarak and Song (2021); Albert, Bustos and Ponticelli (2021)).[2] In this paper, we examine cross-border migration and capital flight from China, a country regarded as a major sources of toxic and greenhouse gas emissions, and show that such a process, triggered by unusually high air pollution levels, has been going on at least for the last two decades. We show that spikes in our indicator of air pollution lead to more cross-border migration and capital flight from China, and these are associated with significantly more residential property price appreciation and real economic activity in international destinations with stronger ethnic links to China. Possibly unique to China, the process has gathered momentum in recent decades largely due to the willingness of Chinese parents to send their children abroad in response to worsening air pollution in China, and to invest in foreign residential property in the metropolitan areas where their children study. We provide evidence of such an educational channel using both U.S. and international data.

Cross-border moves of labor and capital are costly and difficult-to-reverse decisions (especially capital outflow decisions for Chinese citizens). Even for those who are more exposed or sensitive to pollution, these decisions are likely to be only triggered when beliefs about the persistence of harmful air pollution change significantly. It is possible that these are shared beliefs in society, though only those who are most exposed, or can afford to, make these

[1] See, for example, a ProPublica and New York Times Magazine feature "The Great Climate Migration" at https://www.propublica.org/series/the-great-climate-migration.

[2] A major challenge for research on this issue is that data that track individual's locations over time is hard to come by, making it difficult to link the location of origin and destination. In China, the Household Registration or the *Hukou* system provides information on every citizen's registered residence. Recent papers have combined *Hukou* status with the latest Population Census Data, as well as other longitudinal data with history of location changes (Khanna, Liang, Mobarak and Song (2021)).

costly decisions. Thus, our findings address how beliefs are evolving about the long-term trajectory of environmental risk in China. This is useful for several reasons.

First, extreme air pollution events are likely to reflect lower trust in the government in general, and in particular, its ability to deal with environmental and climate disasters. Climate and environmental risk are correlated – not only do the same activities (such a burning fossil fuel) emit greenhouse gases and pollutants, there is also a feedback loop whereby air pollution and global warming reinforce each other.[3] Thus, beliefs of Chinese citizens about the government's commitment to, or success in, reducing air pollution also inform us regarding beliefs about the government's efforts towards arresting climate change.

Second, and related, our results also speak to how salient Chinese citizens themselves consider environmental and climate change to be, which is important because of China's position as the second most important emitter of greenhouse gases. Wang and Zhou (2020) argue that the government tends to design and implement climate policies with references to public opinion. The authors summarize the findings of available survey research and conclude that Chinese citizens surveyed in the last decade have a relatively high awareness of climate change, and the majority understand that the issue is caused by human activity. However, a recent worldwide poll found that 30% of those surveyed in China did not express an opinion on the question of the seriousness of climate change in the next 20 years – far higher than any other country, and only 23% considered it a very serious threat.[4] Our results suggest that the Chinese citizens are paying attention to climate and environmental risks and are taking costly decisions to avoid or mitigate these risks to their personal lives, or those of their children.

[3] Carbon dioxide and Methane raise the earth's temperature, which worsens smog and increases the production of allergenic air pollutants. Emissions of pollutants into the air can result in changes to the climate. Ozone in the atmosphere warms the climate, while different components of particulate matter (PM) can have either warming or cooling effects on the climate.

[4] The Lloyd's Register Foundation World Risk Poll was conducted in 2019 by Gallup and was based on interviews with over 150,000 people worldwide.

Third, since it is less costly to transfer labor and capital within-country than across borders, our results support recent evidence (Khanna et al. (2021)) that regions with significant air pollution problems are likely to lose the more mobile skilled workers, or incur higher costs of retaining them, and the associated economic costs could be substantial.

Finally, as recent research has documented, beliefs about long-term environmental or climate risk have significant effects on asset prices. Much of the current financial research on the salience of climate risk has tried to examine whether the impact of extreme events on asset prices is consistent with investors factoring in long-term climate risk. For example, Choi, Gao, and Jiang (2020) find that when local temperatures are abnormally high, individuals search more online (as proxied by Google search volume) and local investors sell more carbon-intensive stocks. Engle, Kelly, Lee and Stroebel (2020) document that stocks of firms with lower exposure to regulatory climate risk have higher returns when there is negative news about the future path of climate change. Giglio et al. (2020) construct a measure of attention to climate risk in the housing market, and find that the premium enjoyed by properties in flood zone areas, likely due to their greater amenity value, compresses in periods when the attention to climate risk is higher.[5] Like these papers, we also examine extreme episodes as instances when beliefs are likely to change. Such beliefs not only concern the slow-moving processes of environmental and climate change, but also trust in the government's ability to address these issues. We show that the impact of such belief revisions can be significant enough to affect not only foreign asset prices, but also economic activity abroad. We focus on residential property prices as foreign residential property is anecdotally known to be a popular investment asset for the Chinese and housing is a major asset for households.[6]

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[5] Ortega and Taspinar (2018), Gibson and Mullins (2020), and Eichholtz et al. (2019) study the effect of hurricanes in the New York area and find that the valuations of exposed properties were adversely affected even when they did not suffer damage, suggesting increasing salience of flood risk following these events.

[6] China overtook Canada as the top foreign country investing in U.S. residential real estate in 2014-2015. Anecdotal evidence, reports in the popular press, global investment outlook blogs of real estate companies, and

Based on news items reported in Factiva on air pollution in China (at annual frequency), we construct a time series of such news items starting in the late 1970s. This enables us to work with a significantly longer time series than alternatives such a web-based search indices.[7] We fit this series to an AR(1) model, and the residual is regarded as innovation in air pollution news. The underlying assumption is that when air pollution in China is particularly high, the innovation in air pollution news coverage will also be high. We validate this measure in a number of ways – for example, both the level and the innovation of our air pollution news measure correlate very highly with the corresponding measures based on annual averages of daily air quality values (AQI) of major Chinese cities available from the People's Republic of China Ministry of Environmental Protection Information Centre for the period 2000-2015. We also construct a similar measure based on research publications on air pollution in China that are covered in Google Scholar, and find that our news measure predicts the number of academic research outputs with a lag of two years.

We then consider cross-border migration response to air pollution news. We utilize OECD data to construct a panel of inflow of people with Chinese nationality covering 30 countries, and find that these inflows are significantly and positively related to the innovation in air pollution news, as well as the lagged value of the air pollution news itself. While there could be "demand side" reasons as to why air pollution news about China could create more opportunities for Chinese citizens abroad (discussed below), a possible interpretation of these results is that the unexpected increases in air pollution in China cause more Chinese to migrate.[8] Less subject to demand side issues is the movement of Chinese students for studies abroad.

industry reports indicate that one of the important destinations of capital flight from China is foreign housing markets.

[7] Engle et al. (2020) construct a "climate news" index based on coverage of climate change by The Wall Street Journal.

[8] Qin and Zhu (2018) use the Baidu (largest search engine in China with about 50% of market share) search index to create a daily city index of the Chinese term for "emigration" and show that for the year 2014, higher air pollution levels are associated with higher next-day searches for emigration.

Chinese parents are more likely to financially support their children's education abroad when air pollution worsens. Such decisions could be triggered either by an immediate reaction to spikes in pollution levels that enable children to escape from unhealthy exposure, or because foreign study provides more mobility if local air quality deteriorates in the future. Based on a sample of student visas given to Chinese students by the U.S., Canada, the U.K. and Germany for which there is publicly available data, we find that the number of visas issued to Chinese students is positively related to the innovation in air pollution news, as well as its lagged value.

We also find that the innovation in air pollution news is positively and significantly related to estimates of annual capital flight from China. Capital flight could be related to migration or intention to migrate, but could also be a direct consequence of diminished trust in the government's ability or commitment to mitigating serious environmental or climate-related risks in the future, as well as less trust in effective governance generally, and the associated risks. We hypothesize that a significant part of such capital ends up being invested in residential properties abroad, especially in regions where there are strong ethnic links to China. These social links are likely to be important in mitigating information asymmetries, e.g., general information about the local property market, or locating realtors and lawyers who speak the language of the buyers and understand their requirements. Moreover, socially connected individuals can also perform an important monitoring role, essentially "looking after" the property or screening and monitoring tenants if the property is rented out. Ethnicity-specialized real estate agents can also facilitate sales of residential units at a later point of time.

We next examine whether residential property prices increase more when the innovation in China-related air pollution news is higher in major cities around the world, when these cities have stronger Chinese links. The strength of Chinese links is captured by the three-year lagged values of number of individuals born in China in the country in which the city is located. We find that the interaction of the three-year lagged value of Chinese stock and the innovation in air pollution news is significant and positive. Instead of the three-year lagged value of Chinese stock, we also examine whether the innovation has a stronger impact on housing prices in "global" cities, where the number of Chinese is typically much larger.[9] We find that the effect of the innovation on the housing price growth of these global cities is almost twice or three times as large as that for all cities in our sample.

There may be some concern that trade or business links between China and some countries may result in economic activities in China and in these countries being correlated. These economic ties could create opportunities that attract Chinese citizens to these countries when economic activity in both China and these countries is higher. If economic growth is associated with more air pollution in China and higher property prices in major cities of these countries, the results described above could be spurious. To mitigate this concern, we control for both contemporaneous and realized future GDP growth in these countries in our regressions. To further address this concern, we turn to the U.S., where we have data on Chinese settlement in counties as early as 1870. We use the 1870 distribution of Chinese population to classify counties with stronger and weaker ties with China.[10] We find that counties with stronger ties to China experience higher housing price growth when innovation in air pollution news about China is higher. We reach the same conclusion when the classification is conducted within the same Metropolitan Statistical Area (MSA), although the magnitude of the difference is smaller. One possible reason for the weaker economic significance is spillover effects from the counties with stronger Chinese links to adjacent counties with weaker links (Chang and Dasgupta, 2021).

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[9] In particular, we consider Los Angeles, San Francisco, Seattle, New York, Toronto, Vancouver, London, Paris, Sydney, and Melbourne as global cities that are typically major destinations of Chinese immigrants and students.

[10] We verify that the numbers for 1870 are significantly and positively correlated with those from the latest census available to us, i.e., 2010. This speaks to the fact that these ethnic ties established by early Chinese migrants have endured over time.

Finally, we examine how the effects of air pollution in China spread through educational links. The Economist reported in 2016 that "… Chinese dads and mums now make up a majority of Chinese buyers in America's housing market. Last year China became the largest source of foreign property investment in America, pouring in $28.6 billion. Roughly 70% of inquiries from the Chinese indicated that education was the chief motive".[11] Chinese parents buy property and often move in with their children, and sometimes the purchase is an investment, with the extra bedrooms being rented out to classmates to pay for gas and electricity bills etc. Parents also help with down payments if the children stay after graduating.

As previously noted, we find that more Chinese students are issued student visas when China's air pollution is higher. We examine the effects of such influx of Chinese students on housing prices and employment. We find that the difference in housing price growth between MSAs that are major destinations of international students and those that are not, within the same state in the same year, is significantly and positively related to the number of Chinese student visas granted by the U.S. (instrumented by our measures of air pollution news).[12] We find similar results for employment growth and construction sector employment growth. We also find that, in the countries for which we have student visa numbers, the difference in housing price growth and employment growth between global cities (which attract more Chinese students) and other major cities increase in the predicted student inflow.

We address a number of concerns with regard to the interpretation of our results. For example, although Figure 2 shows no obvious time trend, our recent sample period contains large values of innovation in air pollution news. Such a period could have coincided with

[11] "A Roaring Trade: Chinese Tiger Mums Start a College-Town Housing Boom", The Economist, June 18, 2016.

[12] We find similar results if we regress housing price growth, total employment growth, or employment growth of the construction sector on the (instrumented) estimate of Chinese student inflows to an MSA, given by the product of the yearly total number of student visas granted by the U.S. to Chinese students, the state's proportion of Chinese students in the U.S., and the MSA's proportion of foreign student visas in the state.

China's GDP per capita passing the income threshold above which the upper middle class starts to buy assets or houses aboard, send children to study abroad, consider immigration, etc. This could drive the real estate prices in regions with more connection with China. Controlling GDP per capita would not necessarily solve the problem, as this effect could be nonlinear in GDP per capita. To address this issue, we lag all our air pollution news variables by two years. We find no significant results, suggesting that our results are not simply capturing a time-period effect. We also address possible time period effects by examining the sensitivity of air passenger outflows from major Chinese cities to the US to local air quality and to average air quality in other major cities. We find that the former effect is much more significant. We also show that all our results generally hold (though statistical significance is sometimes weaker) if, instead of air pollution news, we use the average major city air quality measures as the main explanatory variables. Finally, for the U.S., we show that our results survive if we exclude the state of California, which is by far the most important destination of the Chinese.

The rest of the paper is organized as follows. Section 1 introduces our data and defines the key variables used in this study. Section 2 discusses our empirical analysis and the results. Section 3 presents some concluding comments.

1. Data and variables

In this section, we first motivate our explanatory variables of interest and then describe other data and variables.

1.1 *Main explanatory variables and their validation*

A major challenge for empirically examining the effect of air pollution in China on cross-border migration, and the associated impact on foreign housing markets and their local economies, is the lack of availability of a sufficiently long time series of indices for air quality in China. Air quality data for China (at the city level) is only available for a relatively short period (from 2000).

Ginsberg et al. (2009) show that flu-related keyword search in Google can estimate influenza epidemics across different geographical regions. The Baidu Index (akin to Google SVI (Search Volume Index)) may capture time-varying broad Chinese interest and attention to a particular topic/issue, including air pollution. However, the index is also only available from June 2006.

In a similar spirit of Google SVI, we use Factiva coverage, for which we have data since the late 1970s, to construct a proxy for public attention to the issue of air pollution in China. We construct our main explanatory variable as follows. We use the keywords "air pollution" and "China" to conduct Factiva search and obtain the annual number of items associated with "air pollution" and "China", denoted as X1. Next, we use the keyword "China" to conduct another Factiva search to obtain the annual number of news items associated with "China", denoted as X2. The ratio of X1 to X2, which we denote as *APC*, then measures the proportion of news about China that involves air pollution. We expect Chinese citizens to respond mainly to unpredictable changes in air pollution levels. Therefore, in our subsequent empirical analysis, we include both a residual *APC* (hereinafter denoted by *RAPC* and referred to as "surprise" or "innovation" in air pollution news) from an autoregressive model of order 1, and lagged APC (hereinafter denoted as *L1.APC* and referred to as "old news") as our key explanatory variables. In alternative specifications, we drop *L1.APC* and include *RAPC* and its lags.[13]

We verify that *APC* and *RAPC* are valid measures of attention to air quality in various ways. First, to show that these measures likely reflect air quality of major cities in China, we

[13] Our results also hold when the change in APC is the key explanatory variable. These results are not reported, but available on request.

plot the time series of *APC* and air quality in Figure 1 and their residuals in Figure 2, on a standardised scale.[14] To this end, we obtain daily air quality value (*AQI*) of Beijing, Shanghai, Guangzhou and Shenzhen from based on data from the People's Republic of China Ministry of Environmental Protection Information Centre for the period 2000-2015, and take the daily average in a year for each of these four major cities.[15,16] We also obtain the residual of air quality value (residual AQI) from an autoregressive model of order 1. Figure 1 shows that *APC* and *AQI* move similarly. Figure 2 reveals that their residuals move extremely closely together over time. There is no obvious trend before 2012. A spike of both residuals occurs in 2013, which is almost four times the second peak. Based on the national surveys of the Pew Research Center for years 2008, 2012, 2013, 2014 and 2015, we find that 2013 is also the year for which most Chinese respondents (83%) consider air pollution as “a very big problem” or “a moderately big problem”.[17]

Second, we broaden the set of keywords to construct 4 additional versions of *APC*, based on Factiva search. The broadest set, with the highest *APC*, is “(air pollutants OR air pollution OR air quality OR toxic air OR carbon dioxide emissions OR smog OR soot OR toxic emissions OR particulate OR haze OR clean air) AND China”. The second highest *APC* excludes “soot” from the broadest set. The third highest *APC* excludes “haze” from the broadest set. The last *APC* version excludes both “soot” and “haze” from the broadest set. Figure 3 shows fairly parallel time trends of different versions of *APC* although there is a stronger upward trend for the four broader APCs. As a robustness check, we repeat our regressions using the broadest *APC*, and find that the results remain.

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[14] The standardization is done by subtracting the raw value from its mean and then dividing by its standard deviation.
[15] The air quality data from China is highly correlated with the PM2.5 data of the corresponding cities from the U.S. Department of State, with correlation coefficients between 0.68 and 0.74.
[16] The data is sourced from https://github.com/mingcheng/AQI.
[17] As a robustness check, in our subsequent analysis, we revisit our main regressions by running robust regressions. Alternatively, we re-run these regressions by replacing RAPC and L1.APC by their ranks. Our results hold.

Third, we verify our method beyond the context of China by examining how Google SVI regarding air pollution changes as the Factiva count associated with air pollution changes, in the following steps. First, we calculate the proportion of all Factiva items that is associated with “air pollution”, denoted as S1. Second, we use the keyword ‘air pollution” to obtain Google SVI, denoted S2. To mitigate the concern that there may be a common time trend, we consider the first difference of both S1 and S2. We find that their correlation is 0.44. Hence, *APC* plausibly tracks interest in or attention to air pollution.

1.1.1 *Validation based on published academic outputs on air pollution in China*

Finally, we validate our measure in the context of a different outcome variable that is also likely to be influenced by extreme air pollution situations in China, but not by our outcome variables of interest. To do so, we consider the relation between *APC* and academic research on air pollution. The latter is likely to be affected directly by noticeable deterioration of air quality, media attention to air quality, or government funding for research in response to significant worsening of air quality. However, given that it takes time to produce and publish research output, we expect a lagged effect of air quality in China on academic publications. Conversely, it is possible that influential academic output attracts attention and leads to higher media coverage. We estimate a VAR model to study the lead-lag relationship between *APC* and academic output as follows. In Step 1, we measure academic output by first conducting a Google Scholar search based on the keywords “air pollution” and “China” for each year. The number of such publications, denoted as A1, is divided by the number of publications obtained from Google Scholar search only using the keyword “China” for each year (A2). Our measure of annual academic output associated with air pollution in China (APA) is calculated as the ratio of A1 to A2. In Step 2, we determine the order of the VAR model based on order-selection criteria, AIC, FPE, HQIC, LR and SBIC. Untabulated results suggest an order of 1 or 2. Hence, in Step 3, we estimate a VAR model of order 2 for *APC* and *APA*. Table 1 reports the results based on standardized *APC* and *APA*. We find that *APC* follows an AR(1) process and does not depend on *APA* in the past two years. *APA* also follows an AR(1) process, but depends on *APC* with a lag of two years. On average, *APA* increases by approximately 0.28 standard deviation (23.5% of the unconditional mean of *APA*) after an increase in *APC* by 1 standard deviation two years earlier.[18] Hence, academic research concerning air pollution in China generally responds to its news coverage and produces outputs with a time lag. This also suggests that *APC* likely captures significance of air pollution in China.

1.2 *Main dependent variables*

Next, we describe our dependent variables: Chinese cross-border moves, Chinese capital flight, international (U.S.) housing prices at the level of city (county and MSA), and employment in global metropolitan areas and U.S. MSAs.

Our measure inflows of individuals with Chinese nationality to foreign countries is sourced from the OECD (Organization for Economic Cooperation and Development) International Migration Database. The definition of inflow of foreigners is not uniform across different countries. Some countries only report the number of new residents (based on nationality). The length of the process required to obtain residency also varies (though for many countries, the period required is less than one year). In our regressions, we use country fixed effects to address such heterogeneity.

Chang and Dasgupta (2021) show that various aggregate measures of capital flight from China generally move in tandem. We use Cudddington's (1986) estimate, which contains the main component of different capital flight measures, namely, the balancing entry in the balance of payment, i.e., net errors and omissions (Claessens, Naude and Mundial (1993)).[19]

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[18] Table A1 provides summary statistics for estimating the economic significance in terms of original values.
[19] We obtain the data from Gunter (2017).

A major dependent variable is quarterly housing price growth of major cities worldwide, which we construct from the housing price indices of these cities, provided by the Knight Frank Group. For the U.S., we use real quarterly housing price growth at the Metropolitan Statistical Area (MSA) level. This is estimated from the Freddie Mac MSA Real Housing Price Index of Global Financial Data. We also use annual nominal housing price growth at the county level, based on the annual House Price Index of the counties, sourced from the U.S. Federal Housing Finance Agency (FHFA).

We also consider the effects on overseas metropolitan economies, in terms of employment growth We obtain total employment data of global metropolitan areas from the OECD Metropolitan Database. We obtain data of total employment and employment of the construction sector of U.S. Metropolitan Statistical Areas from the data website of the U.S. Bureau of Economic Analysis (https://www.bea.gov/data).

1.3 *Main conditioning variables*

We have three key conditioning variables: stock of China-born population in different countries, Chinese population in different regions of the U.S., the registered number of F1 visa approval by U.S. MSAs and the number of enrolled international students by U.S. states.

We measure the strength of a region's ethnic ties in terms of the number of Chinese in that region. For the international sample, we capture the strength of ethnic ties with China by the three-year-lagged stock of China-born population of the countries. However, it is possible that some regions enjoy stronger economic links with China, and are also more heavily populated by the Chinese. If higher air pollution in China reflects more economic activity in China and in regions in other countries China has stronger economic links with, property prices in these other regions could be spuriously correlated with air pollution in China. To mitigate this problem, we control for both current and realized future levels of economic activity in the country.

To further address this concern, we turn to the U.S., where county-level Chinese population data is available as early as 1870. Counties with higher Chinese population numbers as early as 1870 are less likely to reflect current economic ties with China; however, due to early Chinese settlement in these regions, ethnic ties could endure. Indeed, we find that the correlation between 1870 and 2010 Chinese population by county is 0.34.[20] We define counties as having stronger or weaker ethnic links to China depending on whether the Chinese population number in the county as of 1870 is above or below median in that year.[21]

Availability of data on the yearly number of visas/permits granted to Chinese students limits our analysis of the educational links to more recent years, from 1997. For our analysis of the effect of Chinese student inflows on property prices and employment in U.S. MSAs, we define MSAs as having strong or weak educational links to China based on information available from the "Global Cities Initiative" study conducted jointly by the Brookings Institute and JPMorgan Chase. The study provides MSA-level information on the number of F1 visas approved during the 2008-2012 period for the top 118 MSAs that had enrolled foreign students, accounting for 85% of the foreign students pursuing a bachelor's degree or above in the U.S. during that period. We also separately analyse the above effects in MSAs that are major student destinations in the top one-third states in terms of enrolled foreign students. To this end, we utilize the state-level enrolled international student numbers as of 2017, retrieved from the website of the Institute of International Education (IIE).[22]

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[20] Many of these counties of early Chinese settlement continue to be attractive to the Chinese because of the presence of a significant Chinese community and amenities that are attractive to the Chinese. Indeed, the correlation coefficient between the dummy for more populated Chinese counties based on 1870 population and that based on 2010 population is 0.65. The correlation coefficient between the dummy for counties with within-MSA above-median Chinese population based on 1870 population and that based on 2010 population is 0.78.

[21] Since many counties are without any recorded Chinese population as of 1870, the median is based on counties with Chinese population. The "below-median" counties are pooled with the counties without any recorded population in the "weaker ties" group because many of these have very small Chinese population numbers.

[22] The IIE data covers all states. IIE previously provided fact sheets for each state that could be downloaded from its Open Doors® data website. We use 2017 fact sheets for each state for our results. However, such state fact sheets are no longer available. Instead, IIE provides fast fact sheets that show the top 10 states hosting international students each year over 2010-2020. https://opendoorsdata.org/fast_facts/fast-facts-2020/. Retrieved June 19, 2021.

As for control variables, we calculate China's political risk in relation to the U.S. or another country (RPR or RPRc) (Badarinza and Ramadorai (2018), Chang and Dasgupta (2021)) based on the International Country Risk Guide (ICRG) indexes of political risk ratings of China, the U.S., and other countries, compiled by the PRS Group.[23] Other important control variables are economic growth and population growth. For the U.S., we obtain personal income and population of MSAs and counties from the data website of the U.S. Bureau of Economic Analysis (https://www.bea.gov/data). To match the real housing price growth of the MSAs, we obtain MSA deflators to convert nominal personal income to real personal income. For the global cities, we source quarterly GDP data of different countries in which these cities are located from Datastream.

To address the concern that "the demand side effect" may explain our results associated with influx of Chinese students driven by significant air pollution, we control for economic links with China. For the international analysis, yearly trade data of each foreign country with China is retrieved from the website of the National Bureau of Statistics of China (http://www.stats.gov.cn/) whereas the total yearly trade data of these countries are obtained from the OECD (http://data.oecd.org/). For the U.S. analysis, we source data of freight with China and all countries in the world of all air carriers from the website of the Bureau of Transportation Statistics of the United States (https://www.transtats.bts.gov/).

We winsorize all growth variables at the 1% and 99% to minimize the influence of outliers or errors in data. For ease of comparison of economic significance, in our regressions, we standardize all continuous variables.

2. Empirical Results

[23] The residual RPR from an AR(1) model has a correlation coefficient of 0.10 with the contemporary residual APC and 0.24 with the lagged residual APC.

In this section, we first examine whether international migration of Chinese citizens, and Chinese capital flight respond to significant deterioration of air pollution in China. We then study the effects of China's air pollution news on housing prices of metropolitan cities around the world and U.S. counties with varying degrees of Chinese connections. Finally, we investigate the effects of influx of Chinese students, driven by air pollution, on housing price appreciation and employment growth using both US and international data.

2.1 *China's air pollution news and cross-border moves of Chinese*

Chen, Oliva and Zhang (2017) document that when air pollution worsens 10% in a county in China, it loses 2.7% population to other counties with better air quality. Here, our interest is in cross-border migration of Chinese citizens in response to air pollution in China.

One challenge in identifying the effect of air pollution or other environmental factors on migration is that there would be some variable time lag between migration decisions (which we do not observe) and when migration actually happens. This may depend on the channels through which cross-border migration occurs, such as via sponsorship by family members, job search and applications. Our study is further complicated by the fact that available international migration data over for different countries are not consistent in their definitions of who are considered migrants ("foreign inflows"). For some countries, notably the U.S., the migration statistics only count those attaining permanent resident status. Related, the processing time for applications to migrate also varies across countries and the channel through which it occurs. We include country fixed effects to address the country-specific heterogeneity in data definitions, processing time, as well as other time-invariant factors that could affect Chinese migration to that country. In one of our specifications, we also include two lags of our key independent variable RAPC, the residual of air pollution news on China, to capture lagged effects attributable to gaps between decision/application time and eventual migration. Specifically, we estimate the following two models:

$$Y_{j,t} = a + b_0 RAPC_t + b_1 L1.APC_t + Controls + \delta_j + \epsilon_{j,t} \qquad (1)$$

$$Y_{j,t} = a + c_0 RAPC_t + c_1 L1.RAPC_t + c_2 L2.RAPC_t + Controls + \delta_j + \epsilon_{j,t} \qquad (2)$$

where Y_{jt} denotes Chinese migration to country *j* in year *t*. In model (1), the coefficient b_0 captures the contemporaneous effect of air pollution news surprise, while b_1 captures the lagged effect of air pollution news. In model (2), we assume that migration mainly responds to current or lagged surprise in air pollution news about China, and we let the model (i.e., the coefficients c_0, c_1, c_2) tell us at what lag migration decisions manifest in migration outcomes. Following Badarinza and Ramadorai (2018) and Chang and Dasgupta (2021), we incorporate China's political risk relative to country j's political risk, based on ICRG political risk ratings, of the previous year ($L1.RPR_{j,t}$) as our control variable. We also do our tests by excluding the U.S. from the sample countries. The results remain very similar, and are not reported separately.

In addition to inflows of Chinese migrants, we examine whether the inflow of Chinese students is affected by unexpected change in air pollution news about China. Accordingly, our dependent variable is the number of student visas granted by country *j* in year *t*(STUVISA). To the best of our knowledge, there are no quotas on the number of student visas that can be granted in a given application year for the countries in our sample. However, data, with a reasonably "long" period, is only available for four countries (the U.K, the U.S., Canada, Germany) with the U.S. data being available for the longest time period.[24] Accordingly, we have a very small sample. The regression specification is the same as for equations (1) and (2).

[24] Our data sources of student visas/permits are as follows: https://travel.state.gov (the U.S.), https://www.gov.uk (the U.K.), https://open.canada.ca/data (Canada) and https://www-genesis.destatis.de (Germany). There was a sharp drop of U.S. student visas granted to international students from 2016, and this was especially significant for Chinese and Indian student visas. Some have argued that this had to do with stricter scrutiny of student visa applications by the Trump administration, as well as a change in policy for Chinese students that affected the duration over which a F-1 visa was valid. Our sample period ends in 2016 and is therefore not significantly affected by these changes.

The first two columns of Table 2A report the regression results for Chinese cross-border migration. The effect of both contemporaneous as well as lagged air pollution news is significantly positive on migration outcomes. Focusing on column (2), while the contemporaneous and one-period-lagged RAPC are significant, the two-period lagged RAPC has a very similar magnitude and is marginally insignificant. Collectively, a one-standard deviation increase in RAPC leads to 7 percent of one-standard deviation (equivalent to 2505 Chinese or 14.25% of the unconditional mean of Chinese inflow based on Table A1) increase in Chinese cross-border migration over a three-year period.

Next we study Chinese student cross-border moves. While cross-border migration decisions are major decisions and are likely to be costly for the individuals concerned, requiring a higher threshold for a "push" factor, the decision to send children abroad for studies is likely to require a lower threshold. Such moves not only reduce children's immediate exposure to worsening air pollution, but also provide them with opportunities to migrate in the future if air pollution continues to worsen. It is also an outcome that is likely to show up immediately, since foreign educational institutions have been very willing to admit international students in recent decades. Finally, while inflows of Chinese citizens to other countries could reflect "demand-side" factors (e.g., more air pollution in China might reflect more trade between China and other countries, and possibly a higher demand for Chinese employees), such possibilities exist to a much lesser degree for student inflows out of China.

In columns (3) and (4) of Table 2A, we report our results with the number of student visas granted as the dependent variable. As noted, the sample size is small since we are only able to get the required data for four countries for a meaningful length of time. The number of student visas granted responds very strongly to air pollution news – a one-standard deviation increase in RAPC leads to 18.2 percent of one-standard deviation increase in the granted visa number and a slightly smaller increase in the following year (a total of 22,537 Chinese students for the two-year period, based on Table A1). Since there do not appear to be any factors such as admission or visa quotas for student visas, we interpret these as mainly effects driven by parents' willingness to invest in their children's education abroad in response to worsening air pollution in China.

Finally, in Table 2B, we take advantage of city-level air quality measures available to us from 2000-2015. We check whether outflows of passengers from airports in the four cities, Beijing, Shanghai, Guangzhou and Shenzhen, are more sensitive to the city's air quality than the average air quality in all other cities. To this end, we generate residuals of the annual average of the daily air quality measures for each city (AQI) from an AR(1) specification, and a corresponding one based on the average of the other three cities (OAQI). These residuals are denoted RAQI and ROAQI, respectively. We pool the observations for all these cities, and in column 1, regress the annual passenger outflow on RAQI and the first lag of AQI, as well as ROAQI and the first lag of OAQI. In an alternative version in column 2, we include RAQI and its two lags as well as ROAQI and the latter's two lags. Only RAQIs are significant in our regressions.

2.2 *China's air pollution news and capital flight*

Capital is likely to move when people move. However, capital can move across borders more quickly than people. Badarinza and Ramadorai (2018) find that following a shock to political risk in a particular country, capital flight from that country drives up housing prices in London city wards with high concentration of ethnic groups representative of the country as early as in the next quarter. Chang and Dasgupta (2021) document that Chinese capital flight occurs in periods of high political risk and pushes up foreign property prices in regions with stronger Chinese ties. If air pollution triggers migration decisions, such an effect is likely to show up in decisions to move capital abroad – in some case, even before the migration actually happens. Moreover, as discussed, spikes in air pollution can erode trust in government, and lead to capital flight.

We study how China's capital flight (CKOUT) changes when RAPC changes. We estimate models similar to equations (1) and (2) with CKOUT as the dependent variable. We replace country-specific relative political risk with China's political risk, L1.CPR. The last two columns of Table 2A report the regression results, based on robust standard errors. All the coefficients of the variables capturing China's air pollution news are positive, but only that of RAPC is statistically significant (at the 1% level). The magnitude is large – a one-standard deviation increase in RAPC leads to an increase of 35.7 percent of one-standard deviation of the dependent variable, i.e., approximately $21.7 billion (using statistics from Table A1) increase in Chinese capital flight. Though not significant, the magnitude is also large at a one-period lag, but thereafter the effect dies off quickly. Hence, China's capital flight reacts strongly and quickly to air pollution surprise.

2.3 *China's air pollution news and housing price growth of major cities around the world*

As Badarinza and Ramadorai (2018) and Chang and Dasgupta (2021) show, capital flight results in property price appreciation in regions where there are stronger ethnic ties with the source country. Based on the evidence presented above on how air pollution news affects outflow of people and capital, we predict more appreciation of housing prices, associated with China's capital inflows, in foreign regions with stronger ethnic ties to China.

To begin with, we estimate

$$MHPG_{j,t} = a + b * L3.CSTK_{jt} * RAPC_t + c * L3.CSTK_{jt} + d * RAPC_t + Controls + e_{j,t} \quad (3)$$

MHPG is the mean quarterly housing price growth of the major cities in a foreign country. L3.CSTK is the stock of China-born people in that foreign country in year t-3, the proxy for the strength of ethnic ties. RAPC is defined as above. We predict the parameter "b" in Equation

(3) to be positive. We include lagged China's political risk relative to that of the country in which the city is located (L1.RPR) as well as contemporaneous quarterly GDP growth of country j in which a city is located and the average of this variable for the next 20 quarters or remaining quarters for which the data are available, as additional control variables. We incorporate country fixed effects in the regression. We report results both without and with quarter fixed effects. RAPC and its lags, as well as L1.RPR, are dropped in the latter specification.

The first two columns of Table 3 report the results. Consistent with the expectation, the estimated coefficient of L3.CSTK*RAPC is statistically significantly positive. Hence, when the innovation of China's air pollution news is larger, Chinese capital flows, possibly associated with concurrent or planned cross-border moves, and demand for housing in major foreign cities with stronger ethnic ties to China increase rapidly and push up housing prices in these cities.

Certain major cities (that we have referred to as "global cities") have a higher proportion of Chinese residents among those cities in our sample, and therefore enjoy stronger ethnic ties with China. On the other hand, possibly because these are larger cities, the influence of Chinese capital inflow and cross-border migration could also be smaller. Hence, it is interesting to examine the corresponding effect on housing prices of these cities. As noted, we consider Los Angeles, San Francisco, Seattle, New York, Toronto, Vancouver, London, Paris, Sydney, and Melbourne as "global cities" that are typically major destinations of Chinese immigrants and students. The dependent variable becomes the quarterly housing price growth of a global city. We replace country fixed effects by city fixed effects and re-run the regression specified in column (1) and (2) of Table 3 for these global cities. We find similar results, shown in columns (3) and (4) in the same table. Moreover, consistent with Badarinza and Ramadorai (2018) and Chang and Dasgupta (2021), our results in columns (1) and (3) also show that there is housing price appreciation in these cities following an increase in China's political risk relative to the country to which the city belongs.

We can consider the "global" status of these major cities as natural proxies for stronger ethnic ties with the Chinese. To assess the incremental effect of air pollution news for these global cities (and hence Chinese ties) over that for all other cities in our sample, we create an indicator G for these global cities, interact it with each explanatory variable, and then estimate

$$HPG_{j,t} = a + b * G_j * RAPC_t + c * G_j * L1.APC_t + Controls + e_{j,t} \tag{4a}$$

$$HPG_{j,t} = a + b * G_j * RAPC_t + c * G_j * L1.RAPC_t + d * G_j * L2.RAPC_t + Controls + e_{j,t} \tag{4b}$$

HPG is the quarterly housing price growth of a city. The other variables are defined as above. We include city fixed effects. Table 4 reports the results. We find that the effect of RAPC on the housing price growth of these global cities is two to three times as large as that for all other cities in our sample. The incremental effect corresponds to a 0.58 - 0.92 percent appreciation in the housing prices in a year and is also statistically significant – the interaction of G and RAPC is significant at the 1 percent level when quarter fixed effects are included. Hence, China's air pollution surprises have much stronger effects on housing price appreciation of global cities which are likely to have stronger ethnic ties to China, compared to other major cities in our sample. Consistently, we also find the interaction of G and China's relative political risk (RPR) to be positive and highly significant. Together, our results suggest that these global cities indeed attract Chinese capital inflows when air pollution or political risk worsens in China.

2.4 *China's air pollution news, ethnic ties, and housing prices of U.S. counties*

Given that the U.S. is a major destination of Chinese migration and capital flows and county-level data for the U.S. are widely available, we consider the impact of air pollution in China on housing prices in U.S. counties. We use Chinese population of the counties in the

U.S. to gauge the strength of their Chinese ties. As discussed in section 1.4, we draw on early Chinese settlement to mitigate the concern that recent Chinese population concentration in a particular region could reflect the strength of the region's economic ties with China. If high air pollution levels in China are associated with more economic activity, which in turn affects U.S. regions with stronger economic ties and property prices in these regions, we could be capturing a spurious effect of Chinese air pollution on U.S. home prices. We use the county-level Chinese population as of 1870 to determine whether a county has strong or weak Chinese ties. When the 1870 county-level Chinese population of a county, by number, is above the median of all counties, we consider the county as having strong Chinese ties and assign a value of 1 for a high Chinese dummy (HC). We then interact HC with the key variables of interest and estimate the following models:

$$HPG_{j,t} = a + b * HC_j * RAPC_t + c * HC_j * L1.APC_t + Controls + e_{j,t} \tag{5a}$$

$$HPG_{j,t} = a + b * HC_j * RAPC_t + c * HC_j * L1.RAPC_t + d * HC_j * L2.RAPC_t + Controls + e_{j,t} \tag{5b}$$

HPG is the annual nominal housing price growth of county *j* for year *t*. As above, a key control variable is China's political risk relative to the U.S.'s of the previous year (L1.RPR). We also interact it with HC. The other control variables are annual growth of county-level personal income and annual growth of county-level population, for the contemporaneous year and for the next five years. The regressions include county fixed effects. We report results both without and with year fixed effects – in the latter case, we drop variables that only exhibit time-series variation. The robust standard errors are now based on clustering at the year level.

Columns (1) – (4) of Table 5A report the results. As expected, the estimated coefficients of interaction term between HC and RAPC are positive and statistically significant at the 1% level. This suggests that when there is abnormally high volume of air pollution news about China, U.S. counties with strong Chinese ties experience stronger housing price appreciation, compared with those counties with weak Chinese ties. The magnitude of this incremental effect is also economically significant – based on column (3) of Table 5A, a one-standard deviation increase in RAPC increases housing price growth by 26 percent of one-standard deviation more (about 1.3 percent per year based on Table A1) in a county with strong Chinese ties than in counties with weak Chinese ties. The coefficient of L1.APC in column (3) is also noticeably positive and significant at the 5 percent level, and those of L1.RAPC and L2.RAPC in column (4) are positive, though marginally insignificant. However, their interactions with the HC dummy are insignificant. The economic magnitude of a one-standard deviation increase in L1.APC translates to a 0.7 percent increase in annual housing prices in all counties. L1.APC is high if RAPC has been high in the recent past, so its coefficient (as well as those of L1.RAPC and L2.RAPC) likely captures a gradual response of property prices to recent capital inflows. However, these lagged effects are similar whether the region has strong or weak Chinese ties. As we discuss further below, these results may suggest a gradual slowdown in the rate of property price appreciation in regions with stronger Chinese ties and some spillover to other regions without significant ties in response to increases in RAPC.

Differences across counties may be driven by differences in development in broader areas such as those at the MSA or the state level. Therefore, comparison among counties in the same MSA is likely to be less susceptible to the problem of omitted variables. We thus redefine HC as follows. When the 1870 county-level Chinese population of a county, by number, is above (not above) the median in its MSA, we consider the county as having strong (weak) Chinese ties, and assign a value of 1 (0) of HC to it. We then replace the county fixed effects by MSA×year fixed effects. The robust standard errors are now based on clustering at the state level. With these changes, we re-run the regressions of the housing price growth of the U.S. counties.

Columns (5) and (6) of Table 5A report the within-MSA results. The sample size for this set of results is much smaller, mainly because we have to leave out counties in MSAs that had no recorded Chinese population as of 1870 and those counties not in an MSA. The estimated coefficients of the key interaction term of interest HC*RAPC remain positive and statistically highly significant. However, their magnitude is only ⅕ – ¼ as before (in Columns (3) – (4)), i.e., an extra 0.3 percent price appreciation annually per one-standard deviation increase in RAPC. This is consistent with Chang and Dasgupta (2021), who suggest that spillovers to adjacent regions could occur relatively quickly. The authors argue that the difference in housing price growth between a county with strong Chinese ties and one with weak Chinese ties will be smaller when both are in the same MSA due to spillover effects of higher housing prices in the former spreading to the latter, as compared to a situation where the county with weak Chinese ties is not near any county with strong Chinese ties.

For the same regressions, in columns (5) and (6), the ones with stronger Chinese ties continue to experience slightly higher property price appreciation in the following year, as evidenced by the significantly positive coefficient of HC*L1.APC. The interactions of the HC dummy with lagged values of RAPC in column (6), though not statistically significant, are also positive. Together with the results reported in columns (3) and (4), these results suggest that spillovers to more distant counties with weak ties take longer than those to nearby counties with weak ties.

In Table 5B, we run our regressions separately on two sub-periods – before and after the year 2000. Since air quality in China has worsened steadily over time, we expect that the sensitivity of individual decisions to sharp increases in air pollution to be stronger in the latter period, when worsening air pollution reaches a more alarming level. In Table 5B, we report the subsample results corresponding to columns (1) and (5) in Table 5A. In columns (1) and (2) of Table 5B, we find that the effect of RAPC on property prices in high Chinese populated counties is only significant in the post-2000 period. The within-MSA comparisons reported in columns (3) and (4) show that the within-MSA high Chinese populated countries experience more rapid property price growth in both sub-periods. While the economic magnitude of the contemporaneous effect is larger for the pre-2000 sub-period, the effect of lagged APC is significant only for the latter period. These results are consistent with a stronger spillover effect to nearby low Chinese populated counties and a more sustained appreciation in the high Chinese population counties in the latter period, as also seen in Table 5A.[25]

The state of California has been historically important for Chinese migration, and anecdotal evidence suggests that Chinese capital inflows have boosted property prices in that state. Our results hold if we exclude California from our sample. We find that the estimated coefficients of HC*RAPC corresponding to columns (3) and (5) in Table 5A remain positive and significant. The former (latter) has a coefficient with 61% (similar) magnitude of that in the original samples with California. These results are reported in Appendix Table A2.

We also check the robustness of our results when the air pollution news time series is based on a broader set of keywords, as discussed in section 1.1. Appendix Table A3 presents the results corresponding to those reported in tables 3 and 5, but now for which the air pollution news time series is based on the broadest set of keywords. The results remain.

Finally, as noted, for the shorter sample period of 2000-2015, we have daily air quality measures for major cities. We average the daily measures for each city for each year to obtain an annual measure, and average the measure across cities. We repeat all the tests using this AQI measure the residual RAQI extracted from an AR(1) model. These tests are reported in Table A4. All our results hold despite weaker statistical significance for the U.S. county results.

2.5 *China's air pollution news, educational links, housing prices and employment*

[25] The coefficient of L1.APC is actually larger in the pre-2000 period, but it is estimated imprecisely and is thus insignificant.

China overtook Canada as the top foreign country investing in U.S. residential real estate in 2014-2015. According to the National Association of Realtors, while Chinese foreign buyers were the top buyers in terms of both volume and number, accounting for 20 percent of the total foreign buyer volume, the dollar volume of all foreign purchases in the U.S. accounted for 10 percent of the dollar volume of existing home sales in 2016-2017 (Chang and Dasgupta, 2021). A major driver of the increasing influence of Chinese home purchases abroad are related to Chinese students studying in other countries. As discussed in the introductory section, Chinese parents are increasingly accompanying their children when the latter go to study abroad. For these parents, buying overseas property is generally preferred to renting. According to Juwai Data,[26] 70% of Chinese property buyer enquiries in 2015 for the U.S. – the #1 investment destination for Chinese buyers – was tied to education. Accordingly, we expect Chinese air-pollution induced student inflows to have a stronger effect on property prices and economic activity in areas that are major destinations of Chinese students.

We focus on student inflows to the U.S. because the U.S. data at the level of MSAs enables within-state comparisons. However, we report similar results for within-country comparisons of global cities versus other major cities.

Specifically, for the U.S., we examine whether residential property price growth and employment growth are higher in MSAs that are major destinations of international students ("high student" or "HS" MSAs) compared to other MSAs in the same state ("low student" or "LS" MSAs) when the predicted Chinese student visas granted by the U.S., instrumented by air pollution news in China, is higher. This is conducted via two-stage least squares estimation. In the first stage, we predict the total number of Chinese students receiving students U.S. student visas, STUVISA, based on the variables corresponding to air pollution news in China, RAPC and one-year lagged APC, as in column (3) of Table 2A, including state fixed effects.

[26] "6 Reasons Why Education Underpins Chinese Overseas Property Investment" (November 2016), Juwai.com.

For the second stage, we first divide MSAs into the HS and LS groups based on available estimates of international student numbers for 118 MSAs that account for 85% of all international students studying for bachelor degrees or above in the U.S. between 2008-2012, as discussed in section 1.4. Based on such data, we identify HS (LS) MSAs as those with (without) above median estimated international student numbers among all MSAs in the same state.[27]

In Stage 2, the dependent variable is ΔREAL_HPG, ΔTOTAL_EMPG, or ΔCONST_EMPG, the within-state difference in the average of the growth rate between the HS and LS groups in terms of quarterly real housing prices, annual total employment, or annual employment of the construction sector. To mitigate the possibility that air pollution in China is correlated with the intensity of economic exchange between China and the U.S. state in question and such effect may be more pronounced among the MSAs in the HS group, we include in the second stage the ratio of the contemporaneous state-level freight with China to the contemporaneous state-level total freight with all countries around the world (FREIGHT) as a control variable. The other control variables include the difference between the HS and LS groups in the average MSA total population of the previous calendar year (ΔL1.POP), in the average contemporaneous real MSA personal income growth of the current calendar year (ΔRPIG0Y), in the average contemporaneous MSA population growth of the current calendar year (ΔPOPG0Y), in the average ΔRPIG of the next five calendar years or remaining years for which data are available, and in the average ΔPOPG of the next five calendar years or remaining years for which data are available. Finally, China's political risk relative to the U.S.'s, based on ICRG political risk ratings, of the calendar year t-1 (L1.RPR) is also included as an explanatory variable.

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[27] We obtain similar results when we alternatively identify HS (LS) MSAs as those with a positive (zero) estimated international student number.

We report our results for all states, as well as for the top-third U.S. states in terms of their importance as destinations of international students. The regression results for the two samples are reported in columns (1)-(3) and (4)-(6) of Table 6, respectively. In columns (1) and (4), the dependent variable is ΔREAL_HPG, while in columns (2) and (5) [(3) and (6)], it is ΔTOTAL_EMPG [ΔCONST_EMPG]. The coefficient of the predicted student visa number, E(STUVISA), is positive and significant in all columns. Not surprisingly, the economic magnitudes are larger (approximately 2.12 – 2.59 times) when we restrict attention to the top-third states, since the HS MSAs in these states attract much larger number of international students. These results show that air-pollution driven inflow of Chinese students to the U.S. not only affect residential property prices, but also real economic activity, as reflected in overall employment growth and employment growth in the construction sector. In fact, the effect on the latter sector is much larger in magnitude than for overall employment (approximately 0.9 percent vs. 0.3 percent per year) when we restrict attention to the top-third states.

Next, we conduct an alternative two-stage least squares estimation, with state fixed effects, as a robustness check. In particular, we instrument an estimate of the number of new Chinese students at the level of each MSA. This estimate ($STUVISA_{MSA}$) is the product of the following three terms: the yearly total number of student visas granted by the U.S. to Chinese students, the state's proportion of Chinese students in the U.S., and the MSA's proportion of foreign student visas in the state (MSW). In the first stage, $STUVISA_{MSA}$ is predicted based on explanatory variables RAPC, L1.APC, MSW, MSW*RAPC and MSW*L1.APC, where MSW is the MSA's proportion of the number of F1-visas in the state. In the second stage, we use the predicted $STUVISA_{MSA}$ to explain real residential property price growth, overall employment growth and employment growth of the construction sectors for U.S. MSAs. Table A5 presents the results. We find the coefficient of E($STUVISA_{MSA}$) remains positive and significant, with economic magnitude larger than those in Table 6, especially for employment growth.

Last, we turn to the effect of student inflows on housing prices in cities and employment in metropolitan areas beyond the U.S. As for the U.S., we examine how predicted student inflow to a country affects the difference in property price growth between a global city and other cities in the same country. Given the limited availability of data, to increase the power of the test, we do pairwise comparisons, with the dependent variable being the difference in property price growth in the global city *g* in country *i* and another major city *k* in country *i*. We include pair fixed effects for pair (*gi*, *ki*) to control for time invariant heterogeneity that could be associated with differences in property price growth, as well as a number of control variables in the second stage of our two-stage least squares estimation. The latter include: the ratio of the country's contemporaneous trade with China to the country's contemporaneous total trade with all countries of the world (TRADE), China's political risk relative to that of the country in which a city is located, based on ICRG political risk ratings, of the calendar year t-1 (L1.RPR), the estimated difference between the global city and the non-global major city's population of the previous calendar year (ΔL1.POP), the estimated difference in the contemporaneous annual real GDP growth (ΔRGDPG) and in the estimated contemporaneous annual population growth (ΔPOPG). We also examine the effect of predicted Chinese student inflow on employment growth in the same way. Table 7 presents the results. We find that higher predicted student inflows are associated with higher property price growth and higher employment growth in the global cities compared to other major cities in the same country.[28]

2.6 *Time-period effects*

One concern with the interpretation of our results could be that extreme air pollution years are becoming more common over time, and what we are capturing is not sensitivity to extreme air pollution but rather a concurrent time period effect that reflects the per capita GDP

[28] We check whether our results on the impact of student movements on prices and employment hold if we instrument student inflows with the air quality measures. The results, reported in Appendix tables A6 and A7, are very similar.

of China crossing some threshold beyond which the upper middle class considers living in foreign countries attractive and affordable – but not necessarily because they have become particularly sensitive to air pollution. This could drive the real estate prices in regions with more connection with China. Controlling GDP per capita would not necessarily solve the problem, as this effect could be nonlinear in GDP per capita. To address this issue, we lag all our air pollution news variables by two additional periods. We find no significant results, suggesting that we are not simply capturing a time-period effect. These (non-) results are available on request.

2.7 *Other types of pollution*

It is important, however, to recognize that while GDP-per-capita of economic well-being alone cannot explain our results, it is quite likely that costly economic decisions such as migration or sending children abroad in response to pollution may be only possible at a sufficiently high standard of living, and a larger fraction of the Chinese population is reaching this threshold over time. While awareness of air pollution among Chinese citizens is a recent phenomenon, triggered by the wider availability of air quality data, especially satellite-based and official data on particulate matter (PM2.5), concern about water pollution dates back much earlier. We construct a water pollution news time series in a way similar to the air pollution news series. Appendix Figures A1 and A2 show the time series of water and air pollution news together, as well as those of the residuals from an AR(1) model. However, as seen from the figure, the importance of water pollution news and especially news innovation remains stable over our time period. We do not find any evidence that water pollution news surprise affects migration or capital flight from China; nor is there any effect of water pollution news surprises on global property prices. This suggests that economic well-being alone does not trigger the type of effects we observe – the level of attention to the particular type of pollution matters.

3. Conclusion

How quickly individuals revise their beliefs about the salience of environmental risks is likely to be a key determinant of the success of efforts towards arresting climate change. Such belief revision is easier to detect in countries that are major contributors to emissions, and where individual economic decisions are likely to be more responsive to exposure to these risks. China has been one of the major contributors to emissions and Chinese citizens have reached a standard of living where, for a significant percentage of the population, environmental and climate issues are important considerations for the quality of living. How they respond to indicators of worsening climate and environmental conditions, and what the likely economic implications of such response are, therefore is an important issue to study. In this paper, we construct a time series of news coverage about air pollution in China. We find that when news coverage is unexpectedly high, more Chinese citizens leave the country, and capital flight from China picks up. Student enrolments in foreign countries increases. We find that regions in other countries with stronger ethnic links to China experience faster increases in residential property prices. More Chinese parents send their children abroad to study when Chinese air pollution is more in the news, and appear to spend more on residential property purchases in regions where the children study. We find that residential prices and employment increase faster in regions that are major destinations of foreign students. Overall, the results suggest that environmental issues are increasingly shaping individual decisions in China and having cross-border repercussions in terms of relocation of capital and labor.

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Figure 1. APC and AQI

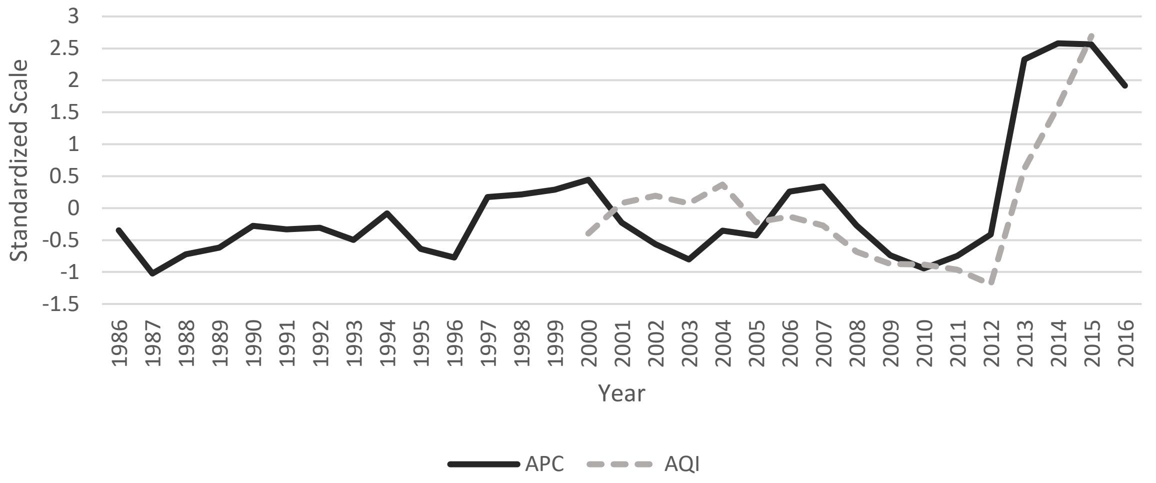

Figure 1. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China. AQI is the average of the average daily air quality indices of Beijing, Shanghai, Guangzhou and Shenzhen.

Figure 2. Residual APC (RAPC) and Residual AQI (RAQI)

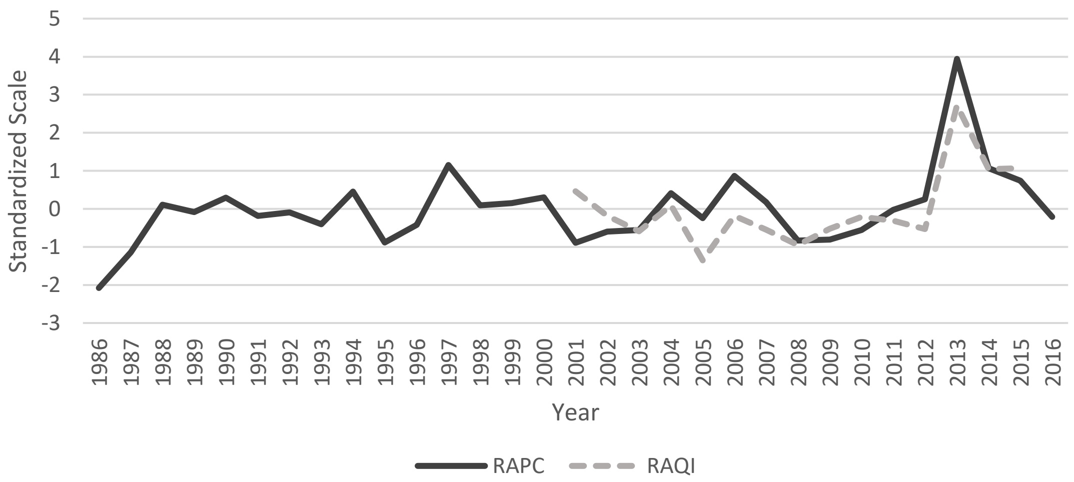

Figure 2. Both RAPC and RAQI are residuals of AR(1) models. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China. AQI is the average of the average daily air quality indices of Beijing, Shanghai, Guangzhou and Shenzhen.

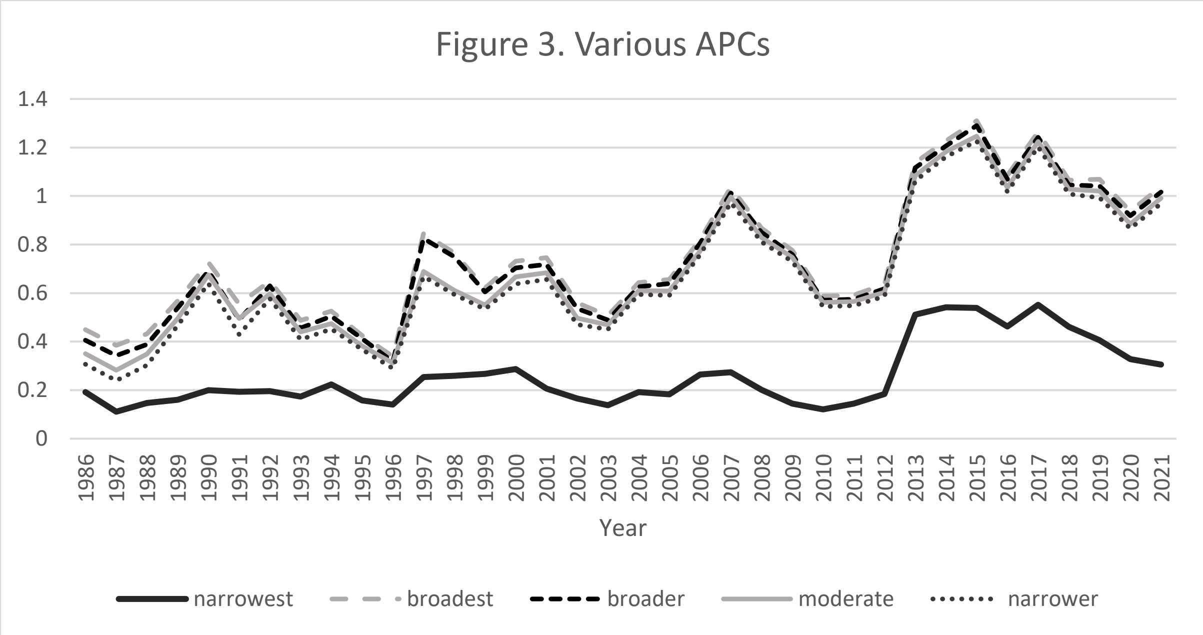

Figure 3. Broadest APC is the number of articles based on Factiva search using the broadest set of keywords "(air pollutants OR air pollution OR air quality OR toxic air OR carbon dioxide emissions OR smog OR soot OR toxic emissions OR particulate OR haze OR clean air) AND China". Broader APC excludes "soot" from the broadest set. Moderate APC excludes "haze" from the broadest set. Narrower APC excludes both "soot" and "haze" from the broadest set. Narrowest APC is the number of articles based on Factiva search using the keywords "air pollution AND China". All APCs are measured as a proportion of the number of articles based on Factiva search only using the keyword "China".

Table 1. VAR for APC and APA

This table reports the estimates of the vector autoregression model of order 2 for APC and APA. The sample period is between 1986 and 2019. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. APA is the yearly ratio of the number of articles based Google Scholar search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. Both APC and APA are standardized by subtracting from mean and then dividing by standard deviation. L1.APC is APC lagged once. L2.APC is APC lagged twice. L1.APA is APA lagged once. L2.APA is APA lagged twice. The estimated coefficients and the standard errors (in parentheses) are reported. *** and ** indicate the 1% and 5% levels of significance, respectively.

	(1)	(2)
	APC	APA
L1.APC	0.852***	-0.117
	(0.167)	(0.136)
L2.APC	-0.216	0.277**
	(0.166)	(0.135)
L1.APA	-0.000	0.804***
	(0.209)	(0.170)
L2.APA	0.369	0.250
	(0.246)	(0.200)
Constant	0.098	0.170**
	(0.094)	(0.077)
Observations	32	32
R^2	0.752	0.836

Table 2A. China's air pollution news and Chinese cross-border flows

This table shows the effect of China's air pollution news on Chinese cross-border flows. The sample periods are 2000-2016, 1996-2017, and 1986-2014 in Columns (1)-(2), (3)-(4), and (5)-(6), respectively. $CINFLOW_j$ is the inflow of people with Chinese nationality (by number) to country j in year t. STUVISA is the number of study visa/permits granted to people with Chinese nationality by country j in year t. CKOUT is the sum of short-term capital exports by the non-bank sector and the balance-of-payment balancing entry (net errors and omissions) of China in year t, based on Cuddington's (1986) capital flight estimate. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. RAPC is residual APC of an AR(1) model for year t. L1.RAPC is RAPC lagged once. L2.RAPC is RAPC lagged twice. $L1.RPR_j$ is China's political risk relative to country j, based on ICRG political risk ratings, of the previous year. L1.CPR is China's political risk, based on ICRG political risk ratings, of the previous year. All variables are standardized. In Columns (1)-(4), country fixed effects are included; standard errors are based on clustering at the year level. The estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$CINFLOW_j$	$CINFLOW_j$	STUVISA	STUVISA	CKOUT	CKOUT
RAPC	0.034***	0.027**	0.227**	0.182*	0.410***	0.357***
	(0.011)	(0.011)	(0.108)	(0.100)	(0.104)	(0.084)
L1.APC	0.034*		0.256		0.247	
	(0.016)		(0.202)		(0.325)	
L1.RAPC		0.025**		0.170*		0.196
		(0.010)		(0.094)		(0.227)
L2.RAPC		0.019		0.146		0.049
		(0.014)		(0.137)		(0.169)
$L1.RPR_j$	-0.023	-0.016	0.114	0.187		
	(0.032)	(0.034)	(0.196)	(0.136)		
L1.CPR					0.270#	0.273#
					(0.192)	(0.200)
Constant	-0.000	-0.000	-0.000	-0.000	0.122	0.096
	(0.021)	(0.021)	(0.127)	(0.122)	(0.187)	(0.164)
Observations	410	410	45	45	30	30
R^2	0.898	0.898	0.352	0.367	0.258	0.264

Table 2B. China's air pollution news and Chinese cross-border flows

This table shows the effect of China's air pollution news on Chinese cross-border flows. The sample period is 2001-2015. PASSENGER is the number of passengers flying from city k in China to the U.S. in year t, where k is Beijing, Shanghai, Guangzhou or Shenzhen. AQI is the average of the daily air quality index of city k in year t. RAQI is residual AQI of an AR(1) model for year t. L1.RAQI is RAQI lagged once. L2.RAQI is RAQI lagged twice. L1.AQI is AQI lagged once. OAQI is the average of AQI of the other three cities in the sample. ROAQI, L1.OAQI, L1.ROAQI and L2.ROAQI are constructed in the same way as those based on AQI, but based on OAQI. All variables are standardized. City fixed effects are included; standard errors are based on clustering at the year level. The estimated coefficients and the robust standard errors (in parentheses) are reported. ***, ** and * indicate the 1%, 5% and 10% levels of significance, respectively.

	(1) PASSENGER	(2) PASSENGER
RAQI	0.236*	0.245**
	(0.121)	(0.096)
L1.AQI	0.125	
	(0.304)	
L1.RAQI		0.230***
		(0.060)
L2.RAQI		0.154*
		(0.076)
ROAQI	0.052	0.012
	(0.055)	(0.053)
L1.OAQI	-0.031	
	(0.109)	
L1.ROAQI		-0.044
		(0.056)
L2.ROAQI		-0.103**
		(0.037)
Constant	-0.064	0.009
	(0.087)	(0.077)
Observations	60	52
R^2	0.650	0.810

Table 3. China's air pollution news and housing price growth in metropolitan cities worldwide

This table shows the effect of China's air pollution news on housing price appreciation of major cities worldwide. The sample period is between 2001 and 2016. In Columns (1) – (2), the dependent variable is the average quarterly housing price growth of all major cities in country j (MHPG). The sample for columns (3) & (4) only includes "Global Cities", i.e., Los Angeles, San Francisco, Seattle, New York, Toronto, Vancouver, London, Paris, Sydney, and Melbourne. In these columns, the dependent variable is the quarterly housing price growth of a global city (HPG). L3.CSTK is the stock of China-born population in country j in year t-3. RAPC is residual APC of an AR(1) model for year t, where APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.RPR is China's political risk relative to country j in which a city is located, based on ICRG political risk ratings, of the previous calendar year. GDPG0Q is the contemporaneous quarterly GDP growth of the country. FUTURE_GDPG20Q is the country-level average GDP growth of the next 20 quarters or remaining quarters for which data are available. All variables are standardized. The robust standard errors are based on clustering at the quarter level. The estimated coefficients and the robust standard errors (in parentheses) are reported. ***, ** and * indicate the 1%, 5% and 10% levels of significance, respectively.

	Country Mean (1)	Country Mean (2)	Global Cities (3)	Global Cities (4)
	MHPG	MHPG	HPG	HPG
RAPC	0.006		0.190***	
	(0.048)		(0.049)	
L3.CSTK*RAPC	0.164***	0.133***	0.121***	0.172***
	(0.023)	(0.022)	(0.043)	(0.045)
L3.CSTK	-0.799***	-0.252	-0.719***	-1.262*
	(0.119)	(0.155)	(0.170)	(0.656)
L1.RPR	0.179***		0.429***	
	(0.060)		(0.109)	
GDPG0Q	0.228***	0.097**	0.256***	0.118
	(0.047)	(0.042)	(0.082)	(0.104)
FUTURE_GDPG20Q	0.093**	0.015	-0.155	-0.264
	(0.046)	(0.056)	(0.170)	(0.214)
Constant	0.001	1.459***	-0.066	0.829**
	(0.052)	(0.101)	(0.090)	(0.399)
Country/city fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	No	Yes	No	Yes
Observations	677	677	408	408
R^2	0.174	0.333	0.305	0.546

Table 4. China's air pollution news and incremental housing price growth for global cities (G)

This table shows the incremental effect of China's air pollution news on housing price appreciation for global cities. The sample period is between 1986 and 2016. The dependent variable is the quarterly housing price growth of a major city. G is an indicator for Los Angeles, San Francisco, Seattle, New York, Toronto, Vancouver, London, Paris, Sydney, and Melbourne. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. RAPC is residual APC of an AR(1) model for year t. L1.RAPC (L2.RAPC) is RAPC lagged once (twice). L1.RPR is China's political risk relative to country j in which a city is located, based on ICRG political risk ratings, of the previous calendar year. GDPG0Q is the contemporaneous quarterly GDP growth of the country. FUTURE_GDPG20Q is the country-level average GDP growth of the next 20 quarters or remaining quarters for which data are available. All variables are standardized. The robust standard errors are based on clustering at the quarter level. The estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
		Incremental effects for global cities		
G*RAPC	0.050*	0.071***	0.064**	0.082***
	(0.027)	(0.024)	(0.025)	(0.022)
G*L1.APC	0.005	-0.010		
	(0.029)	(0.026)		
G*L1.RAPC			-0.042	-0.038
			(0.034)	(0.032)
G*L2.RAPC			0.001	-0.016
			(0.027)	(0.026)
G*L1.RPR	0.144***	0.237***	0.152***	0.246***
	(0.042)	(0.046)	(0.041)	(0.046)
G*GDPG0Q	0.255***	0.136***	0.249***	0.132***
	(0.055)	(0.049)	(0.055)	(0.050)
G*FUTURE_GDPG20Q	-0.236***	-0.093*	-0.242***	-0.099**
	(0.059)	(0.049)	(0.058)	(0.049)
		Baseline effects for all cities		
RAPC	0.030#		0.034#	
	(0.023)		(0.024)	
L1.APC	-0.048*			
	(0.024)			
L1.RAPC			-0.024	
			(0.019)	
L2.RAPC			-0.038#	
			(0.024)	
L1.RPR	0.163***		0.164***	
	(0.044)		(0.045)	
GDPG0Q	0.247***	0.159***	0.247***	0.159***
	(0.034)	(0.020)	(0.033)	(0.020)
FUTURE_GDPG20Q	0.060**	0.075***	0.059*	0.075***
	(0.030)	(0.025)	(0.030)	(0.025)
Constant	-0.012	-0.542***	-0.013	-0.542***
	(0.030)	(0.054)	(0.030)	(0.054)
Fixed effects	City	City & Quarter	City	City & Quarter
Observations	8,067	8,067	8,067	8,067
R^2	0.151	0.244	0.152	0.244

Table 5A. China's air pollution news and housing price growth in U.S. counties (Full sample period)

The dependent variable is the county-level annual nominal housing price growth for year t. The sample period is between 1986 and 2016. In Columns (1)-(4), HC is a dummy variable that has a value of 1 if the 1870 county-level Chinese population, by number, is above the median, and 0 if not reported. In Columns (5)-(6), HC is a dummy variable that has a value of 1 if the 1870 county-level Chinese population (by number) is above the median in its MSA, and 0 otherwise. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. RAPC is residual APC of an AR(1) model for year t. L1.RAPC is RAPC lagged once. L2.RAPC is RAPC lagged twice. L1.RPR is China's political risk relative to the U.S.'s, based on ICRG political risk ratings, of the previous year. PIG0Y is the contemporaneous county-level annual nominal personal income growth. POPG0Y is the contemporaneous county-level annual population growth. FUTURE_PIG5Y is the county-level average annual nominal personal income growth of the next five years or remaining years for which data are available. FUTURE_POPG5Y is the county-level average annual population growth of the next five years or remaining years for which data are available. All variables are standardized. In Columns (1)-(4), standard errors are based on clustering at the year level. In Columns (5)-(6), standard errors are based on clustering at the state level. The estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% levels of significance, respectively.

	All Counties	All Counties	All Counties	All Counties	Within MSA	Within MSA
	(1)	(2)	(3)	(4)	(5)	(6)
HC*RAPC	0.279***	0.241***	0.260***	0.233***	0.054≈***	0.056≈***
	(0.081)	(0.077)	(0.077)	(0.073)	(0.021)	(0.022)
HC*L1.APC	-0.028		-0.045		0.048***	
	(0.104)		(0.101)		(0.014)	
HC*L1.RAPC		0.081		0.054		0.013
		(0.110)		(0.119)		(0.021)
HC*L2.RAPC		-0.112		-0.110		0.031
		(0.089)		(0.088)		(0.022)
RAPC			0.088	0.066		
			(0.068)	(0.071)		
L1.APC			0.147**			
			(0.070)			
L1.RAPC				0.095#		
				(0.065)		
L2.RAPC				0.072		
				(0.064)		
HC*L1.RPR	0.221*	0.230*	0.198*	0.202*	0.020	0.028
	(0.123)	(0.114)	(0.115)	(0.107)	(0.020)	(0.021)
L1.RPR			-0.045	-0.021		
			(0.084)	(0.083)		
HC					0.138**	0.139**
					(0.053)	(0.054)
PIG0Y	0.120***	0.121***	0.169***	0.163***	0.029***	0.029***
	(0.015)	(0.015)	(0.056)	(0.055)	(0.009)	(0.009)
POPG0Y	0.187***	0.187***	0.225***	0.224***	0.042***	0.042***
	(0.048)	(0.048)	(0.054)	(0.055)	(0.005)	(0.005)
FUTURE_PIG5Y	-0.027	-0.027	0.091*	0.094*	0.025**	0.025**
	(0.026)	(0.026)	(0.052)	(0.053)	(0.012)	(0.012)
FUTURE_POPG5Y	0.120***	0.119***	0.217***	0.209***	-0.055***	-0.055***
	(0.039)	(0.039)	(0.065)	(0.064)	(0.016)	(0.016)
Fixed effects	County & Year	County & Year	County	County	MSA×Year	MSA×Year
Observations	65,831	65,831	65,831	65,831	25,332	25,332
R^2	0.361	0.361	0.161	0.160	0.917	0.917

Table 5B. China's air pollution news and housing price growth in U.S. counties (Subperiods)

The dependent variable is the county-level annual nominal housing price growth for year t. The sample period is between 1986 and 2016. In Columns (1)-(2), HC is a dummy variable that has a value of 1 if the 1870 county-level Chinese population, by number, is above the median, and zero if not reported. In Columns (3)-(4), HC is a dummy variable that has a value of 1 if the 1870 county-level Chinese population (by number) is above the median in its MSA, and 0 otherwise. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. RAPC is residual APC of an AR(1) model for year t. L1.RAPC is RAPC lagged once. L2.RAPC is RAPC lagged twice. L1.RPR is China's political risk relative to the U.S.'s, based on ICRG political risk ratings, of the previous year. PIG0Y is the contemporaneous county-level annual nominal personal income growth. POPG0Y is the contemporaneous county-level annual population growth. FUTURE_PIG5Y is the county-level average annual nominal personal income growth of the next five years or remaining years for which data are available. FUTURE_POPG5Y is the county-level average annual population growth of the next five years or remaining years for which data are available. All variables are standardized. In Columns (1)-(2), standard errors are based on clustering at the year level. In Columns (3)-(4), standard errors are based on clustering at the state level. The estimated coefficients and the robust standard errors (in parentheses) are reported. ***, ** and * indicate the 1%, 5% and 10% levels of significance, respectively.

Sample	All Counties	All Counties	Within MSA	Within MSA
Period	≤ 2000	> 2000	≤ 2000	> 2000
	(1)	(2)	(3)	(4)
HC*RAPC	0.109	0.309**	0.063**	0.033*
	(0.108)	(0.122)	(0.030)	(0.019)
HC*L1.APC	-0.263	0.015	0.063	0.017**
	(0.170)	(0.146)	(0.039)	(0.007)
HC*L1.RPR	0.282***	0.149	0.022	0.044**
	(0.080)	(0.220)	(0.024)	(0.018)
HC			0.052*	0.226***
			(0.030)	(0.069)
PIG0Y	0.173***	0.089***	0.060***	0.018**
	(0.037)	(0.013)	(0.015)	(0.008)
POPG0Y	0.310***	0.158***	0.030	0.046***
	(0.044)	(0.047)	(0.023)	(0.004)
FUTURE_PIG5Y	-0.025	-0.037	0.029***	0.020
	(0.039)	(0.035)	(0.010)	(0.014)
FUTURE_POPG5Y	0.125**	0.179***	-0.073***	-0.037**
	(0.043)	(0.042)	(0.020)	(0.017)
Fixed effects	County & Year	County & Year	MSA×Year	MSA×Year
Observations	25,401	40,430	12,197	13,135
R^2	0.215	0.449	0.849	0.950

Table 6. China's air pollution news, influx of Chinese students, and growth of housing prices and employment (U.S.)

This table reports two-stage-least-squares (2SLS) regression results to examine the effect of influx of Chinese students, associated China's air pollution news, on the difference in growth of housing prices and employment between high- and low-foreign-student MSAs in the same state. The sample consists of all states in Columns (1)-(3) and the top-third states ranked in terms of foreign student numbers as of 2017 in Columns (4)-(6). The sample period is 1997-2016. For each state, we partition its MSAs into two groups— High (above-median, denoted HS) and Low (median-or-below, denoted LS) number of student visa grants —based on the median MSA-level number of registered F1-visa approval in the 2008-2012 period. We then compute the difference in growth of average quarterly real housing prices (ΔREAL_HPG), annual overall employment (ΔTOTAL_EMPG), and annual employment of the construction sector (ΔCONST_EMPG) between the HS and LS student groups. In the first stage of the 2SLS regressions, we estimate the predicted total number of student visas, STUVISA, granted to Chinese students by the U.S., based on explanatory variables RAPC and L1.APC, and state fixed effects. RAPC is residual APC of an AR(1) model for year t, where APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. 1. The second stage regresses ΔREAL_HPG, ΔTOTAL_EMPG, or ΔCONST_EMPG on the predicted STUVISA (E(STUVISA)) and control variables. The control variables include the following variables: the ratio of the contemporaneous quarterly/yearly state-level freight with China to the contemporaneous state-level total freight with all countries around the world (FREIGHT), China's political risk relative to the U.S.'s, based on ICRG political risk ratings, of the calendar year t-1 (L1.RPR), the difference between the average of all MSA of the high and that of low Chinese groups in total population of the previous calendar year (L1.Δ POP), in the contemporaneous real MSA personal income growth of the current calendar year (ΔRPIG0Y), in the contemporaneous MSA population growth of the current calendar year (ΔPOPG0Y), in the average ΔRPIG of the next five calendar years or remaining years for which data are available, and in the average ΔPOPG of the next five calendar years or remaining years for which data are available. All variables are standardized. The estimated coefficients and the standard errors (in parentheses) of the second stage are reported. ***, **, * and # indicate the 1%, 5%, 10% and one-sided 10% levels of significance, respectively.

The difference in mean between high- and low-foreign student MSAs in the same state						
	All states			Top ⅓ foreign student hosting states		
	ΔREAL_HPG	ΔTOTAL_EMPG	ΔCONST_EMPG	ΔREAL_HPG	ΔTOTAL_EMPG	ΔCONST_EMPG
	(1)	(2)	(3)	(4)	(5)	(6)
E(STUVISA)	0.112***	0.130**	0.133*	0.237***	0.291***	0.345***
	(0.043)	(0.058)	(0.074)	(0.071)	(0.095)	(0.118)
FREIGHT	0.097***	0.025	0.022	-0.178***	-0.271***	-0.247**
	(0.020)	(0.034)	(0.044)	(0.033)	(0.079)	(0.097)
L1.Δ POP	-0.774***	0.118	-0.000	-1.913***	0.754***	0.000
	(0.292)	(0.169)	(0.000)	(0.437)	(0.205)	(0.000)
ΔRPIG0Y	0.113***	0.287***	0.118***	0.173***	0.262***	0.145**
	(0.018)	(0.031)	(0.039)	(0.027)	(0.050)	(0.060)
ΔPOPG0Y	0.213***	0.407***	0.162***	0.183***	0.231***	0.041
	(0.023)	(0.042)	(0.053)	(0.032)	(0.065)	(0.084)
FUTURE_ ΔRPIG5Y	0.066***	-0.080**	-0.089**	0.034	-0.134**	-0.139*
	(0.020)	(0.034)	(0.043)	(0.033)	(0.064)	(0.075)
FUTURE_ ΔPOPG5Y	0.023	-0.011	0.130**	0.025	0.088	0.061
	(0.028)	(0.052)	(0.064)	(0.043)	(0.069)	(0.087)
L1.RPR	0.073***	-0.022	0.053	0.219***	0.032	0.167**
	(0.022)	(0.037)	(0.049)	(0.033)	(0.058)	(0.070)
Constant	-0.000	-0.030	0.057	0.000	-0.000	-0.104
	(0.017)	(0.029)	(0.197)	(0.025)	(0.046)	(0.359)
Observations	3,004	716	713	1,324	339	315
Prob > χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Table 7. China's air pollution news, influx of Chinese students, and growth of housing prices and employment (Global)

This table reports two-stage-least-squares (2SLS) regression results to examine whether the effects of influx of Chinese students, associated with China's air pollution news, on city housing price growth and metropolitan employment growth, are stronger for global cities than other major cities. The sample periods are 2002-2016 and 2005-2016 for regressions of housing prices and employment, respectively. The global cities consist of Los Angeles, San Francisco, Seattle, New York, Toronto, Vancouver, London, Berlin. Each global city is compared with every other major city in the same country. To do so, we first compute the difference in growth of quarterly housing prices (ΔHPG) and annual overall employment (ΔTOTAL_EMPG) between each global city and every other major city ("city-pair") in the same country. In the first stage of the 2SLS regression, the dependent variable is the number of study visas/permits, STUVISA, granted to Chinese students by a foreign country, which is regressed on explanatory variables RAPC and L1.APC, defined as follows. RAPC is residual APC of an AR(1) model for year t, where APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. The second stage regresses ΔHPG or ΔTOTAL_EMPG on the predicted STUVISA (E(STUVISA)) and control variables, including "city-pair" fixed effects. The control variables include the following variables: the yearly ratio of the country's contemporaneous trade with China to the country's contemporaneous total trade with all countries of the world (TRADE), China's political risk relative to country j in which a city is located, based on ICRG political risk ratings, of the calendar year t-1 (L1.RPR), and the estimated difference between the global city and the non-global major city in the population of the previous calendar year (L1.ΔPOP), in the contemporaneous yearly real GDP growth (ΔRGDPG) and in the contemporaneous yearly population growth (ΔPOPG). All variables are standardized. The estimated coefficients and the standard errors (in parentheses) of the second stage are reported. *** and ** indicate the 1% and 5% levels of significance, respectively.

The difference between a global city and a non-global major city in the same country		
	ΔHPG	ΔTOTAL_EMPG
	(1)	(2)
E(STUVISA)	0.791***	0.723***
	(0.213)	(0.205)
TRADE	-1.243***	-0.397***
	(0.243)	(0.108)
L1.Δ POP	2.088***	1.085*
	(0.355)	(0.623)
ΔRGDPG	0.227***	0.088***
	(0.023)	(0.027)
ΔPOPG	0.259***	0.482***
	(0.035)	(0.045)
L1.RPR_j	-0.113*	0.109**
	(0.069)	(0.045)
Constant	0.262***	-6.617*
	(0.043)	(3.814)
Observations	3,992	1,302
Prob > χ^2	0.00	0.00

Table A1. Summary statistics for regression samples

This table shows the summary statistics of the original key variables of interest (before standardization) that appear in the main tables. The variable definitions are given in the respective tables. All are yearly variables, except MSA and city housing price growth that is measured quarterly.

Table	Variable	Mean	Standard Deviation	Min	Max
Table 1	APC (%)	0.256	0.133	0.111	0.552
Table 1	APA (%)	1.130	0.948	0.112	4.251
Table 2A (1)	RAPC (%)	0.017	0.094	-0.073	0.309
Table 2A (1)	L1.APC (%)	0.263	0.144	0.121	0.541
Table 2A (1)	CINFLOW (number)	17573	35278	0	192858
Table 2A (3)	RAPC	0.031	0.097	-0.073	0.309
Table 2A (3)	L1.APC	0.280	0.150	0.121	0.541
Table 2A (3)	STUVISA (number)	62352	64026	11974	276503
Table 2A (5)	RAPC	-0.004	0.081	-0.163	0.309
Table 2A (5)	L1.APC	0.214	0.085	0.111	0.511
Table 2A (5)	CKOUT ($ millions)	24633	60789	-68836	196934
Table 3 (1)	RAPC	0.034	0.104	-0.073	0.309
Table 3 (1)	MHPG	0.010	0.025	-0.056	0.079
Table 3 (1)	L3.CSTK (number)	145498	341195	189	1651511
Table 3 (3)	RPAC	0.025	0.102	-0.073	0.309
Table 3 (3)	HPG	0.010	0.028	-0.071	0.072
Table 3 (3)	L3.CSTK (number)	816815	536285	75350	1651511
Table 4 (1)	RAPC	0.015	0.089	-0.163	0.309
Table 4 (1)	L1.APC	0.237	0.121	0.111	0.541
Table 4 (1)	HPG	0.012	0.029	-0.077	0.098
Table 5A (3)	RAPC	0.003	0.080	-0.163	0.309
Table 5A (3)	L1.APC	0.238	0.119	0.111	0.541
Table 5A (3)	HPG	0.027	0.050	-0.127	0.193
Table 5A (5)	RAPC	-0.001	0.078	-0.163	0.309
Table 5A (5)	L1.APC	0.234	0.114	0.111	0.541
Table 5A (5)	HPG	0.028	0.049	-0.127	0.193
Table 6	E(STUVISA|L1.RAPC, L2.APC)	85260	56900	22697	202499
Table 6 (1)	∆REAL_HPG (all states)	0.001	0.005	-0.013	0.015
Table 6 (2)	∆TOTAL_EMPG (all states)	0.004	0.010	-0.025	0.035
Table 6 (3)	∆CONST_EMPG (all states)	0.004	0.034	-0.097	0.093
Table 6 (4)	∆REAL_HPG (top ⅓ host states)	0.001	0.005	-0.010	0.013
Table 6 (5)	∆TOTAL_EMPG (top ⅓ host states)	0.005	0.009	-0.019	0.028
Table 6 (6)	∆CONST_EMPG (top ⅓ host states)	0.006	0.026	-0.063	0.075
Table 7	E(STUVISA|L1.RAPC, L2.APC)	66351	50092	17288	149587
Table 7	∆HPG	0.005	0.024	-0.061	0.066
Table 7	∆TOTAL_EMPG	0.007	0.016	-0.037	0.053

Table A2. Main housing results without California

This table reports the results for which we exclude California and re-run the main regressions of U.S. housing price growth. The sample period is between 1986 and 2016. In Column (1), HC is a dummy variable that has a value of 1 (0) if the 1870 county-level Chinese population, by number, is above the median (is not reported). In Column (2), HC is a dummy variable that has a value of 1 if the 1870 county-level Chinese population (by number) is above the median in its MSA, and 0 otherwise. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. RAPC is residual APC of an AR(1) model for year t. The other variable definitions and regression specifications are given in Table 5A. All variables are standardized. For brevity, we report only the results of the key variables of interest. The estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Reference Table (Column)	Table 5A (3)	Table 5A (5)
Sample	All Counties	Within MSA
	(1)	(2)
HC*RAPC	0.158***	0.050*
	(0.055)	(0.026)
HC*L1.APC	0.046	0.049**
	(0.060)	(0.020)
RAPC	0.089	
	(0.069)	
L1.APC	0.151**	
	(0.071)	
Observations	64,810	24,244
R^2	0.157	0.905

Table A3. Main housing results based on the broadest APC

This table reports the results for which we use an alternative APC measure, the broadest APC and re-run the main regressions of housing price growth. The sample period is between 1986 and 2016. In In Column (1), L3.CSTK is the stock of China-born population in country j in year t-3. In Column (2), HC is a dummy variable that has a value of 1 (0) if the 1870 county-level Chinese population, by number, is above the median (not reported). In Column (3), HC is a dummy variable that has a value of 1 if the 1870 county-level Chinese population (by number) is above the median in its MSA, and 0 otherwise. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. RAPC is residual APC of an AR(1) model for year t. The other variable definitions and regression specifications are given in the respective main tables. All variables are standardized. For brevity, we report only the results of the key variables of interest. The estimated coefficients and the robust standard errors (in parentheses) are reported. *** and ** indicate the 1% and 5% levels of significance, respectively.

Reference Table (Column)	Table 3 (1)	Table 5A (3)	Table 5A (5)
Sample	Country Mean	All U.S. Counties	Within U.S. MSA
	(1)	(2)	(3)
L3.CSTK*RAPC	0.093***		
	(0.031)		
HC*RAPC		0.249**	0.069***
		(0.097)	(0.023)
HC*L1.APC		-0.082	0.078***
		(0.111)	(0.026)
RAPC	0.053	0.114	
	(0.053)	(0.071)	
L1.APC		-0.001	
		(0.068)	
Observations	677	65,831	25,332
R^2	0.177	0.152	0.917

Table A4. Main housing results based on AQI

This table reports the results for which we use an air quality measure (AQI) and re-run the main regressions of housing price growth. The sample period is between 2001 and 2015. In Column (1), L3.CSTK is the stock of China-born population in country j in year t-3. In Column (2), HC is a dummy variable that has a value of 1 (0) if the 1870 county-level Chinese population, by number, is above the median (not reported). In Column (3), HC is a dummy variable that has a value of 1 if the 1870 county-level Chinese population (by number) is above the median in its MSA, and 0 otherwise. AQI is the average of the yearly average of daily air quality index of Beijing, Shanghai, Guangzhou and Shenzhen in year t. L1.AQI is AQI lagged once. RAQI is residual AQI of an AR(1) model for year t. The other variable definitions and regression specifications are given in the respective main tables. All variables are standardized. For brevity, we report only the results of the key variables of interest. The estimated coefficients and the robust standard errors (in parentheses) are reported. ***, ** and # indicate the 1%, 5% and one-sided 10% levels of significance, respectively.

Reference Table (Column)	Table 3 (1)	Table 5A (3)	Table 5A (5)
Sample	Country Mean	All U.S. Counties	Within U.S. MSA
	(1)	(2)	(3)
L3.CSTK*RAQI	0.147***		
	(0.025)		
HC*RAQI		0.273#	0.033#
		(0.196)	(0.022)
HC*L1.AQI		0.305#	-0.015
		(0.212)	(0.019)
RAQI	0.044	0.145#	
	(0.054)	(0.088)	
L1.A		0.266**	
		(0.096)	
Observations	671	37,889	12,315
R^2	0.159	0.281	0.952

Table A5. The effect of influx of Chinese students (U.S. MSA Samples): Alternative Estimation

This table examines the effect of influx of Chinese students, associated China's air pollution news, on growth of housing prices and employment in MSAs in the U.S. The sample period is 1997-2016. $STUVISA_{MSA}$ is the product of the yearly total number of student visas granted by the U.S. to Chinese students, the state's proportion of Chinese students in the U.S. as of 2017, and the MSA's proportion of foreign student visas in the state over the period 2008-2012. We then conduct two-stage least squares estimation, with state fixed effects. In the first stage, we predict $STUVISA_{MSA}$, based on explanatory variables RAPC, L1.APC, MSW, MSW*RAPC and MSW*L1.APC, defined as follows. RAPC is residual APC of an AR(1) model for year t, where APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China" for year t. L1.APC is APC lagged once. MSW is the MSA's proportion of the number of F1-visas in the state. The second stage regresses growth of quarterly real housing prices (REAL_HPG), growth of annual overall employment (TOTAL_EMPG), or growth of annual employment of the construction sector (CONST_EMPG) on the predicted STUVISA ($E(STUVISA_{MSA})$) and control variables. The control variables include the following variables: the ratio of the contemporaneous quarterly/yearly state-level freight with China to the contemporaneous state-level total freight with all countries around the world (FREIGHT), the MSA-level total population of the previous calendar year (L1.POP), the contemporaneous real MSA personal income growth of the current calendar year (RPIG0Y), the contemporaneous MSA population growth of the current calendar year (POPG0Y), the average RPIG of the next five calendar years or remaining years for which data are available, the average POPG of the next five calendar years or remaining years for which data are available, and China's political risk relative to the U.S.'s, based on ICRG political risk ratings, of the calendar year t-1 (L1.RPR). All variables are standardized. The estimated coefficients and the standard errors (in parentheses) of the second stage are reported. *** and ** indicate the 1% and 5% levels of significance, respectively.

	REAL_HPG	TOTAL_EMPG	CONST_EMPG
	(1)	(2)	(3)
$E(STUVISA_{MSA})$	0.056***	0.343***	0.259***
	(0.021)	(0.038)	(0.053)
FREIGHT	-0.021**	-0.001	-0.131***
	(0.009)	(0.019)	(0.025)
L1.POP	-0.010	-0.178***	-0.147***
	(0.013)	(0.025)	(0.034)
RPIG0Y	0.189***	0.466***	0.373***
	(0.006)	(0.010)	(0.012)
POPG0Y	0.162***	0.339***	0.158***
	(0.008)	(0.014)	(0.018)
FUTURE_RPIG5Y	0.061***	-0.031***	-0.042***
	(0.007)	(0.011)	(0.014)
FUTURE_POPG5Y	0.085***	0.150***	0.174***
	(0.009)	(0.015)	(0.018)
L1.RPR	0.235***	0.046***	0.137***
	(0.006)	(0.010)	(0.013)
Constant	-0.000	0.006	0.001
	(0.006)	(0.010)	(0.012)
Observations	25,760	6,460	5,669
Prob > χ^2	0.00	0.00	0.00

Table A6. China's AQI, influx of Chinese students, and growth of housing prices and employment (U.S.)

This table reports the results for which we replace APC by an air quality measure (AQI) and re-run the U.S. regressions that examine the effect of influx of Chinese students, associated with China's air quality, as in Table 6. The sample period is 2001-2015. E(STUVISA) is the predicted total number of student visas granted to Chinese students by the U.S., based on explanatory variables RAQI and L1.AQI, and state fixed effects. AQI is the average of the yearly average of daily air quality index of Beijing, Shanghai, Guangzhou and Shenzhen in year t. L1.AQI is AQI lagged once. RAQI is residual AQI of an AR(1) model for year t. The regression specifications are as those in Table 6. All variables are standardized. For brevity, we report only the results of the key variable of interest. The estimated coefficients and the standard errors (in parentheses) are reported. ***, **, *, and # indicate the 1%, 5%, 10%, and one-sided 10% levels of significance, respectively.

	The difference in mean between high- and low-foreign student MSAs in the same state					
	All states			Top ⅓ foreign student hosting states		
	ΔREAL_HPG	ΔTOTAL_EMPG	ΔCONST_EMPG	ΔREAL_HPG	ΔTOTAL_EMPG	ΔCONST_EMPG
	(1)	(2)	(3)	(4)	(5)	(6)
E(STUVISA)	0.117#	0.191**	0.227*	0.456***	0.470***	0.656***
	(0.082)	(0.096)	(0.124)	(0.160)	(0.172)	(0.227)
Observations	2,248	533	531	988	254	234
Prob > χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Table A7. China's AQI, influx of Chinese students, and growth of housing prices and employment (Global)

This table reports the results for which we replace APC by an air quality measure (AQI) and re-run the global regressions that examine the effect of influx of Chinese students, associated with China's air quality, as in Table 7. The sample period is 2001-2015. E(STUVISA) is the predicted total number of student visas granted to Chinese students by a foreign country, based on explanatory variables RAQI and L1.AQI. AQI is the average of the yearly average of daily air quality index of Beijing, Shanghai, Guangzhou and Shenzhen in year t. L1.AQI is AQI lagged once. RAQI is residual AQI of an AR(1) model for year t. The regression specifications are those in Table 7. All variables are standardized. For brevity, we report only the results of the key variable of interest. The estimated coefficients and the standard errors (in parentheses) are reported. *** indicates the 1% level of significance.

	The difference between a global city and a non-global major city in the same country	
	ΔHPG	ΔTOTAL_EMPG
	(1)	(2)
E(STUVISA)	1.616***	0.053
	(0.292)	(0.115)
Observations	3,832	1,191
Prob > χ^2	0.00	0.00

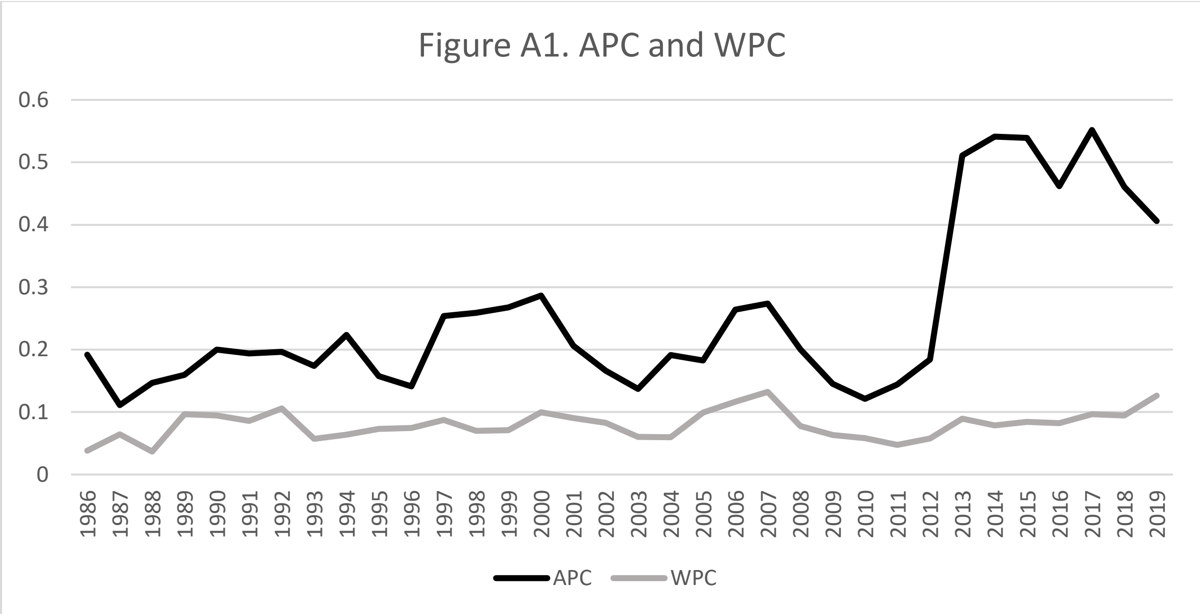

Figure A1. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China". WPC is the ratio of the number of articles based on Factiva search using the keywords "water pollution" and "China" to that only using the keyword "China".

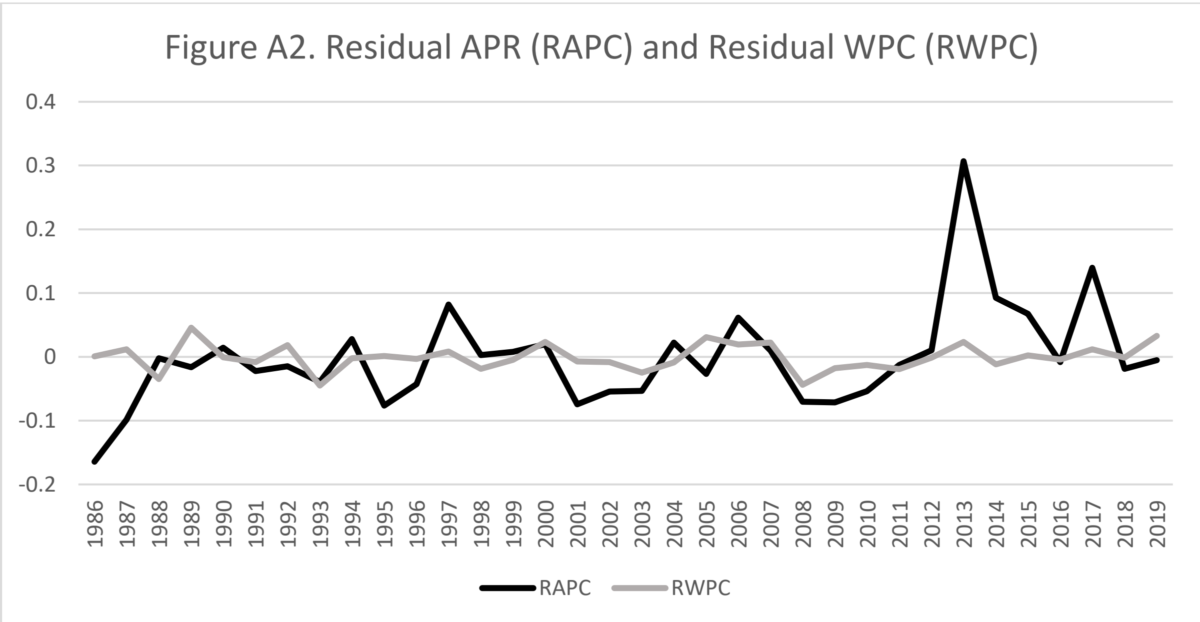

Figure A2. Both RAPC and RWPC are residuals of AR(1) models. APC is the ratio of the number of articles based on Factiva search using the keywords "air pollution" and "China" to that only using the keyword "China. WPC is the ratio of the number of articles based on Factiva search using the keywords "water pollution" and "China" to that only using the keyword "China".