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Keywords: Capital Flight, housing prices, employment, deposits, ethnic ties, educational links, Spillovers

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Capital Inflows and Property Prices: Ethnicity, Education, and Spillovers[*]

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1. Introduction

Over the last five decades, flows of capital and people across borders have occurred at a faster pace than ever before. Not surprisingly, the U.S. and several European countries have been major destinations of both capital and labor from the developing economies, especially from Asia. The ethnic map of the developed world has changed rapidly, and asset ownership has also changed in tandem.

Residential property is one of the main asset classes that changes ownership when outflow of capital follows that of labor. Surprisingly, evidence on the significance and determinants of capital inflows from the developing economies on the residential property markets of the developed world has been scarce. An exception is a recent paper by Badarinza and Ramadorai (2018), who examine the effect of increase in political risk in other countries on property prices in the city of London. They find that increase in political risk in a particular country is associated with increases in property prices in areas of London with a high concentration of residents who have ethnic ties to that country.[1]

In this paper, we examine the effects of capital inflows on residential housing prices and the real economy, in the U.S. as well as major global cities, that are associated with capital flight from China—the most important source of capital outflow among developing countries over the last two decades.[2] Our analysis builds on that of Badarinza and Ramadorai (2018) by highlighting not only the importance of ethnic ties to China as a determinant of a region's exposure to Chinese political risk and the associated flight of capital from China to that region, but also the role of educational ties. To the best of our knowledge, ours is the first paper to

[1] Based on cash transaction data over the period 2001-2013, Li, Shen, and Zhang (2020) report significant increases in housing prices and employment in ZIP codes in California with high Chinese population over the period 2007-2013, driven by foreign Chinese housing purchases.
[2] The terms "capital outflow" and "capital flight" are used interchangeably in the rest of this paper. While the broad concept is similar, capital flight has been defined in alternative ways by researchers. One such definition is "…an outflow of funds from a country motivated by an adverse change in the country's economic, political or social environment." (Gunter, (2008), p. 434), which is essentially capital flight.

examine how property prices at international student destinations have been affected due to capital flight from China.[3] In addition, because we consider a large country like the U.S., we are also able to show that there are significant spillover effects on property prices in regions that do not have recorded ethnic Chinese residents but are adjacent to such areas. Finally, we demonstrate that capital outflows from China not only affect residential prices but also the real economy by creating employment growth and savings growth in regions with a high concentration of Chinese population and international student links with China.

Kar and LeBlanc (2013) document that China has by far the largest accumulated capital flight among the top 15 developing countries. Even though it is difficult to obtain accurate data on China's capital outflows (Taplin (2019); Wong (2017); Cheung, Steinkamp, and Westermann (2016)), several papers argue that the outflows have been increasing and are significant (see Gunter (2017) and Wong (2017)). For example, Gunter (2017) estimates that capital flight from China in 2014 was equivalent to 17% of its exports and almost twice its current account balance that year. Capital flight from China in 2014 was 165% of inward foreign direct investment (FDI), and exceeded inward FDI every year in the past decade.

Anecdotal evidence, reports in the popular press, global investment outlook blogs of real estate companies, and industry reports indicate that one of the important destinations of capital flight from China is foreign housing markets. These reports suggest that global Chinese offshore investment in real estate has increased rapidly and, in particular, that Chinese investors have been making significant investments in the real estate markets of countries such as the U.S., the U.K., Canada, and Australia. In the U.S., Chinese investment in real estate has been associated with surging residential housing markets in San Francisco and Los Angeles. Similar associations have been made for other global cities, such as London and Paris. However, the

[3] Yang (2018) finds that banks more recognized by Chinese university students experience more deposit growth associated with the influx of Chinese students, and these banks increase credit supply to local small business borrowers and second lien mortgagors in the U.S. She also documents that counties with more Chinese students have higher employment and more establishments in the same state-year.

extent of the impact Chinese real estate investment has had on the U.S. property market remains unclear. First, it is possible that any impact, if present, remains limited to certain Metropolitan Statistical areas Areas (MSAs), especially on the U.S. West Coast.[4] Second, the quantitative importance of Chinese real estate investment in the U.S. property market is unclear. 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.[5] These numbers suggest, at best, a modest impact of Chinese investment in the U.S. residential market. Therefore, even though by all accounts the inflows have been substantial and a significant fraction of these inflows are supposed to have been invested in the real estate market, the quantitative significance of Chinese residential investment for the overall U.S. residential market remains an empirical question.[6]

Although some estimates of capital outflows from China are available, it is challenging to obtain estimates of capital inflows to specific regions, even at the country level. This makes it problematic to relate these outflows to housing price changes in MSAs (or counties) in the U.S., or in global metropolitan cities, on a yearly basis. To circumvent this problem, we adopt several strategies, based on Badarinza and Ramadorai's (2018) observation that the perception of higher political risk is a major determinant of capital outflow that follows ethnic links from a domestic country to "safe heaven" destinations – in their case, the city of London. First, we identify two instances of significant capital flight from China associated with increased perception of political risk in that country. The two instances occurred in 1997 and 2011. The post-1997 episode of large capital outflows from China has been linked to an increase in uncertainty subsequent to the death of Deng Xiaoping in 1997, and the post-2011 episode has

[4] According to the National Association of Realtors, one third of Chinese residential investment in 2016-17 was in California.
[5] China overtook Canada as the top foreign country investing in U.S. residential real estate in 2014-2015.
[6] These figures classify only non-resident individuals and those who have been residents in the U.S. for less than two years (including temporary visa holders) as foreign buyers.

been linked to the bursting of the Chinese property market bubble and Xi Jinping's anti-corruption campaign (launched in 2012).[7] Figure 1 illustrates the time trends of capital outflows from China estimated using different methodologies, and the surges subsequent to 1997 and 2011 are quite evident. Figure 2 shows the time trend of the ratio of an index of China's political risk to that of the U.S. It is noticeable that the ratio peaks after 1997 and again increases after 2011. We argue that regions with stronger ethnic ties to China would attract significantly higher capital inflows from China after these events than before, compared to regions with weaker ethnic ties. Thus, we compare, in a difference-in-differences setting, residential property price growth in regions having stronger Chinese ties with those having weaker Chinese ties over five-year periods before and after two major instances that saw significantly increased capital flight from China.

Second, we use the annual measure of relative political risk (*RPR*) of China and the U.S. in "reduced form" regressions as a possible instrument for Chinese capital inflow to the U.S. (*CINFC*) and examine whether regions with stronger ethnic ties to China experience higher appreciation in residential property prices when *RPR* is higher. The *RPR* series can be constructed for 1985-2016. To validate the premise that *RPR* is a determinant of *CINFC*, we take advantage of a relatively short time series of estimated *CINFC* from Ferrantino, Liu, and Wang (2012) which is available for 1995-2008. We find that the two series are highly correlated (with a correlation coefficient of 0.53), shown in Figure 2, and both the index of China's political risk as well as that of the U.S. separately explain annual variation in *CINFC*. Finally, we also create a series of "imputed *CINFC*" using the method of multiple imputations based on *RPR* and use this variable to capture Chinese capital flight to the U.S. during 1990-2016. We validate our main results using the imputed *CINCF* series as a measure of capital inflow from China to the U.S.

[7] See Gunter (2004); Zhu, Li, and Epstein (2005); Cheung and Qian (2010), and Gunter (2017). Kar and Spanjers (2014) indicate that China registered a particularly large increase in capital outflow in 2011 ($162.8 billion) and 2012 ($249.6 billion).

Our first set of tests examines whether regions with stronger ethnic ties to China (and hence likely to attract more capital fleeing China) experience greater residential property price appreciation when *CINFC* is higher. To identify regions with stronger ethnic ties to China, following the work of Badarinza and Ramadorai (2018) for the city of London, we utilize the distribution of Chinese population in the U.S. However, one potential concern is that the regions with higher Chinese population during our period of study may not be randomly assigned. It is possible that these regions have economic characteristics that caused housing prices to grow faster, especially in a period of recovering or generally rising housing prices. We mitigate this concern in several ways. First, our classification of U.S. MSAs and counties as having stronger versus weaker ethnic ties to China is based on Chinese population distributions as of the year 1880 when we classify MSAs based on state population, and the year 1870 when we classify counties based on county population. We argue that these early distribution patterns persist over time,[8] and also attract new immigrant Chinese populations over the years for reasons that are less relevant for *current* economic prospects of these regions.[9] We also verify that prior to the two events of 1997 and 2011, the economic characteristics of the regions with high and low Chinese population are generally similar. In our regressions, we also control for MSA or county fixed effects or MSA×year fixed effects (e.g., when we compare high and low China-linked counties within the same MSA) to absorb regional characteristics that could affect property prices independently of variations in *CINFC*. In addition, we include in our regressions several control variables that vary over time to ensure that our results are not driven by omitted economic factors that could influence current property

[8] The correlation of county-level Chinese population in 1870 and that in 2000 and 2010 is 0.38 and 0.34, respectively. We provide further details in Section 3.C.

[9] We do not claim that early Chinese population distribution over different regions is random. It is possible that any early population distribution is determined by regional characteristics that persist over long periods and potentially bias our results. However, we show that when regions are classified as highly or sparsely populated based on early overall U.S. population distribution, we do not get results similar to those for classifications based on Chinese population. Thus, for our results to be attributable to non-random selection, the regional characteristics would have to be relevant not for human settlement in general, but *only* for early Chinese settlement, and persist for long periods. We also show that proximity to coastal areas (where significant early Chinese settlement occurred and which have thrived economically) does not explain our results.

prices. Finally, since Chinese capital is widely reported to have entered the residential markets of the burgeoning metropolitan districts in California, Washington, and New Jersey in recent decades, we repeat our tests by excluding the top 10 percent of MSAs in terms of recent Chinese population distribution, or by excluding California completely.

Our baseline results show that following the 2011 (1997) event, MSAs in states in the top quartile of the 1880 Chinese population distribution have about 1.1 percent (0.4 percent) per quarter higher residential property price growth compared to the MSAs in states in the bottom quartile. When we exclude the top 10 percent of Chinese-populated MSAs (based on 2010 Chinese population distribution), these magnitudes are, respectively, 1.0 percent per quarter for the 2011 event and 0.2 percent per quarter for the 1997 event. If we exclude the state of California, the largest Chinese-populated state, the magnitudes are, respectively, 0.7 percent per quarter for the 2011 event and 0.2 percent per quarter for the 1997 event. These magnitudes thus appear to be economically significant, and the effect of Chinese capital inflows is not limited to a few areas of high concentration of Chinese population.[10] In reduced form regression specifications that use the *RPR* as a possible instrument for *CINFC*, the interaction of *RPR* and an indicator variable for high Chinese-populated MSAs is positive and significant; however, as we cannot recover the structural parameters, we cannot quantify the effect of *CNIFC* on MSA-level residential property prices. We find similar results for county-level property price growth when counties are classified as having high or low Chinese ties based on 1870 population.

Chinese population distribution within MSAs is less likely to be related to a region's economic conditions or prospects than across MSAs, since economic shocks are likely to spill

[10] Badarinza and Ramadorai (2018) report that following elevated levels of political risk in a foreign country, the spread in housing prices in the city of London between wards that have high and low numbers of residents from the foreign country increases by 1.41 percent in two years. This estimate is lower than our MSA-level estimates, but comparable to within-MSA price differentials between high and low Chinese-populated counties, discussed below. Favilukis and Van Nieuwerburgh (2020) find that an inflow of out-of-town real estate investors (purchasing 10% of the housing in the city center and 5% in the suburbs) causes an increase in the house prices in short run (the first period) by 6.3% and in long run (the steady state) by 4.8%.

over more readily to nearby counties in the same MSA than across MSAs in different states. We therefore examine within-MSA comparisons. To do so, we compare annual property price growth in counties that had high and low Chinese population (as of the year 1870) within an MSA. We verify that these two groups of counties are generally not different in terms of key economic characteristics prior to the two events, suggesting that current economic conditions are not systematically related to the early distribution of Chinese population across counties.[11] Our results reveal a statistically significant difference in housing price growth between the high and low Chinese-populated counties in an MSA following the 1997 episode (about 1.2 percent per year), irrespective of whether we include the top 10 percent of Chinese-populated MSAs. Interestingly, the effect for the 2011 event is weaker when the top 10 percent Chinese MSAs are *not* excluded, and also weaker than for the 1997 event, which may appear surprising given that capital outflow from China was more significant following the 2011 event. We discuss this further below. We get consistent results from the reduced firm regressions based on *RPR*.

One possible reason why the results based on within-MSA comparisons are weaker following the 2011 event when the most densely Chinese populated MSAs are not excluded is spillover effects from the more heavily Chinese-populated counties to adjacent and less Chinese-populated counties. These spillover effects are likely to be more important if the heavily Chinese-populated counties experience more significant property price appreciation—as is likely to have happened after 2011—and could weaken the within-MSA differences between counties in the same MSA. To further document the spillover effect, we examine the potential effect of Chinese capital inflows to the U.S. for counties that have no recorded Chinese population as of 2010. We compare such counties in states with high state-level Chinese population and those in states with low state-level Chinese population. We find that after both the 2011 and 1997 events, counties without any recorded Chinese population in states

[11] Low and high Chinese-populated counties do differ significantly in terms of the employment-to-population and labor-to-population ratio, which is higher for low Chinese populated counties.

with high Chinese population experience between 1.1 to 1.6 percent per year higher property price growth than such counties in states with low Chinese population. We also document that the spillover effect decays as the distance (average distance) of a non-Chinese-populated county from the most densely Chinese-populated county (counties) in the same state increases.

We next examine the real economic effects of *CINFC*. Favilukis and Van Nieuwerburgh (2020) develop and calibrate a general equilibrium model to study the effects of property purchases by out-of-town buyers on property prices, rents, sectoral employment, and social welfare in major cities. In their model the local labor market clears, so there are no aggregate employment effects. However, they show that there is likely to be significant increase in residential construction in response to an out-of-town demand that constitutes 10 percent of city housing demand. We follow an empirical approach similar to that for our study of the impact of *CINFC* on residential property prices, and find that the growth rate of MSA-level annual employment increases by 0.6 percent more in states with high 1880 Chinese population after both the 1997 and 2011 events. Consistent with Favilukis and Van Nieuwerburgh (2020), the construction sector experiences much higher employment growth (2.8 percent per year after the 2011 event and 1.8 percent per year after the 1997 event). We get qualitatively similar results from the reduced form regressions based on *RPR*. We also examine whether *CINFC* has any impact on bank deposit growth at the MSA level. As reported by the National Association of Realtors, two-thirds of Chinese foreign buyers make all-cash transactions, which are likely to be associated with deposit growth. We only have access to data on deposit growth from the year 2002. We find that post-2011 quarterly deposit growth at the MSA level increases by 1.1 percent more in states with high 1880 Chinese population. We get similar results from reduced-form regressions.

Next, we examine the possible effects of educational links, particularly the widely reported phenomenon that many Chinese parents invest in residential property when their children move to another country to study.[12] We use data on Chinese and overall international student movements. We compare the impact of Chinese and other international student inflows on housing price growth in above-median and below-median Chinese-populated MSAs in the same state. Since continuous time-series data on the number of international students is available only from 1999, we focus on the 2000-2016 time period as well as the pre- and post-2011Q2 period surrounding the 2011 event. Since we do not have time-series data on international student destinations at the U.S. regional level, we use cross-sectional data (as of 2017) on the number of international students in each state to classify states as among the top third of states and bottom third of states in terms of student destinations. We find that for the states in the top third, the change in the annual number of Chinese international students has a significantly larger positive effect on the difference in property price growth between greater and lesser Chinese-populated MSAs in the same state for the 2000-2016 period. There are no effects for the states in the bottom third. When we focus on the 2011 episode, we find that for the top hosting states, the change in the number of Chinese international students has a significantly higher coefficient in the post-event period than that in the pre-event period. This suggests that it is not only the inflow of students but inflow of more capital per student that drives property prices in the Chinese-populated MSAs of these top hosting states. We find no such effects for non-Chinese international students.

Finally, we turn to the effect of Chinese capital outflows on residential prices in a cross-section of global metropolitan cities. Data limitations allow us to examine only the impact of capital outflows from China for the 2011 event, and we have to pursue a somewhat different estimation strategy. In particular, we use Chinese population inflows (as a proportion of total population inflows) to a particular country in a particular year as an indicator of the likely destination of Chinese capital. We hypothesize that variation in the proportion of incoming

[12] See, for example, Bradsher and Searcey (2015) and Juwai (2016).

Chinese to a country would be more strongly related to variation in residential prices when capital flight picks up after the 2011 event. We examine whether year-to-year variations in the proportion of Chinese-to-total inflow has a stronger impact on median city housing price growth in a country in the five years after the 2011 event, compared to that in the five years before, after controlling for country fixed effects interacted with period fixed effects. We find evidence consistent with our hypothesis. We find similar effects on employment growth of global metropolitan areas as well.[13] These results also hold in our reduced-form regressions where the *RPR* of China with respect to the destination country is used to instrument for flight of Chinese capital to that country. We then examine the effect of Chinese student inflows (as a proportion of total international student inflows) on median city housing price growth around the world. Consistent with our results on the effect of Chinese population inflows on global city housing prices, we find that year-to-year variations in relative Chinese student inflows have a stronger effect on global city housing price growth after the 2011 event.

To summarize, our paper makes several contributions. First, we show that ethnic ties between China and other regions have been important determinants of the destination of capital outflows from China. Capital flight associated with greater political uncertainty in China can have non-trivial impact on residential prices in the destination regions, and can also have real economic consequences by affecting employment growth and bank deposit growth in the destination regions. Overall, these results shed light on the question of the quantitative significance of Chinese capital outflows and real estate investment in U.S. residential property markets. This issue has remained unresolved because adequate data on capital outflows and their destinations are not readily available. Our results show that this effect is economically quite significant in regions more heavily populated by the Chinese, and also important enough to cause spillovers to other regions without an obvious ethnic link. Second, using educational

[13] The magnitude of the effect on employment (0.007) in relation to that on housing (0.010) for our global samples is highly comparable to that (0.011 and 0.006, respectively) for our U.S. samples.

migration patterns for identification, we confirm the relevance of pure capital transfers as a transmission channel, above and beyond the role of population movement. Finally, we study the effects of capital flight from China to other non-U.S. destinations and find similar effects on residential prices and employment.

The rest of the paper is organized as follows. Section 2 discusses our data, defines the key variables, and provides some descriptive statistics. Section 3 outlines our empirical methodology. Sections 4-7 present our main results, and Section 8 discusses some additional tests on the robustness of our results. Section 9 concludes.

2. Data, Descriptions, and Key Variables

We exploit variation in the geographical distribution of Chinese population in the U.S. for our identification strategy. We obtain population data from the U.S. Census and the U.S. Bureau of Economic Analysis. We principally use data on both early Chinese settlement in the U.S., available for the years 1870 (U.S. counties) and 1880 (U.S. states). Some of our tests require data on more recent Chinese population distribution, for which we use data as of the year 2010.

For global city-level analysis, we do not have comparable Chinese population data. However, we obtain data on annual Chinese and total population inflows to the corresponding countries from the Organisation for Economic Cooperation and Development (OECD) for 2000-2017. List 5 of Table SA1 in the Supplementary Appendix provides the list of cities constituting the sample for the analysis of Chinese population inflows and global city housing price growth.

Real or nominal housing price growth is one of the main dependent variables in our study.[14] We examine this at the MSA and county levels. We construct a time series of quarterly real housing price growth at the MSA level from Freddie Mac MSA Real Housing Price Index of Global Financial Data. We estimate the annual nominal housing price growth of counties based on the annual House Price Index of the counties downloaded from the website of the U.S. Federal Housing Finance Agency (FHFA).[15]

Our tests also require various economic variables at the state, MSA, and county levels. We source personal income, employment, and labor data from the data website of the U.S. Bureau of Economic Analysis (https://www.bea.gov/data) and the statistics website of the U.S. Bureau of Labor (https://www.bls.gov/data/). We calculate the quarterly deposit growth of the MSAs based on the deposit data of FFIEC CDR (Central Data Repository) Call Bulk Schedule of the U.S. Federal Financial Institutions Examination Council (FFIEC).[16] However, the deposit data is available only from the year 2001. To match the real housing price growth of the MSAs, we obtain MSA deflators to convert nominal personal income to real personal income.

Our quarterly housing price growth data for major cities around the world are based on the housing price indices of these cities, complied by the Knight Frank Group. For global metropolitan areas, we obtain the employment data from the OECD. GDP data for the countries in which these cities are located are obtained from Datastream.

We use China's political risk relative to the U.S. or another country (*RPR* or RPR_c) as a determinant of the capital flight from China to the U.S. (or another country). We use the

[14] All growth variables are winsorized at the 1% and 99% to minimize the influence of outliers and errors in the data.
[15] https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx
[16] Please see https://cdr.ffiec.gov/public/PWS/DownloadBulkData.aspx.

International Country Risk Guide (ICRG) indexes of political risk ratings of China, the U.S. and other countries from the PRS Group.

As children's education is a frequently mentioned consideration for Chinese overseas property purchases, we study whether the capital outflows from China have a more important effect on housing prices in regions that attract more foreign students. We obtain the number of tertiary international students in each of the U.S. states (as of 2017) from the website of the the Institue of International Education (IIE).[17] List 4 of Table SA1, in our Supplementary Appendix, presents the number of the tertiary international students by state. The top three states are California, New York, and Texas. The list also indicates which of these states do not have any of the top Chinese-populated MSAs in List 2 of Table SA1. Among these latter states, the top three hosting states are Ohio, Michigan, and Missouri. Except for Texas, Chinese students account for about 30-40 percent of international students in each of these top hosting states. We also obtain time series of the numbers of total and Chinese international students for the countries with the city housing data from the UNESCO Institute of Statistics. List 6 of Table SA1 indicates cities comprising the sample for our analysis of Chinese student inflows and global housing price growth.

3. Empirical Methodology

As argued in Badarinza and Ramadorai (2018), ethnic links are likely to be a significant determinant of destinations of capital outflows, especially for residential property investment, for a number of reasons. First, social links with relatives, friends, or friends of friends 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

[17] IIE previously provided state fact sheets that could be downloaded from its Open Doors® data website. 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 January 21, 2021.

understand their requirements. Second, 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. Third, as documented by Agarwal, Choi, He, and Sing (2019), ethnicity-specialized real estate agents can also facilitate sales of residential units at a later point of time.

A. Identifying Capital Inflow from China (CINFC)

Estimates of capital flight from China to specific destinations are not available for long time periods. For inflows to the U.S., Ferrantino et al. (2012) provide estimates for 1995-2008 based on the idea that capital flight from China to the U.S. is reflected in the under-invoicing of Chinese exports to the U.S. or over-invoicing of U.S. imports from China. We extend this time series using the method of multiple imputation, based on the time series for *RPR*, which is available for 1985-2016. Figure 2 shows both (standardized) time series. The two series exhibit significant correlation for 1995-2008, a period for which we have estimates from Ferrantino et al. (2012), which is consistent with the idea that capital flight is motivated by an increase in perceived relative political risk (Badarinza and Ramadorai (2018)). When we regress *CINFC* on *RPR* for the 1995-2008 period, we get a positive coefficient on *RPR* of 0.37 (significant at the 1 percent level), with an R^2 of 28 percent. Ferrantino et al. (2012) also suggest that the first-differenced *CINFC* captures capital flight from China to the U.S. after removing time trends in mis-invoicing. When we regress the first difference of *CINFC* on *RPR*, the coefficient on the latter is 0.50 (significant at the 1 percent level) and a regression R^2 of 48 percent. We use *RPR* as a proxy for *CINFC* in reduced-form regressions as part of our empirical design. We also create a measure of change in relative political risk by subtracting from *RPR* its past three-year average (*DRPR*). Our reduced-form results are qualitatively similar but less significant when we use this variable instead of *RPR*. However, a dummy variable that equals 1 when *DRPR* is above the 90^{th} percentile produces significant results in our reduced-form specifications.

B. Two Events

Estimates of capital flight from China (but not specific to any particular destination) are available for 1984-2014 from Gunter (2017), who provides three estimates of Chinese capital flight. Figure 1, based on methods discussed in Gunter (2017), shows the five-year moving averages of three estimates: Gunter's adjusted balance of payments (BOP) estimate based on Cuddington (1986), Cuddington's BOP estimate, and an estimate based on the BOP balancing entry "net errors and omissions."[18]

Even though these estimates are not specific to the U.S. or any particular country, it is quite evident that capital flight from China accelerated immediately after 1997 and again after 2011. From Figure 2, it can also be seen that these episodes of surges in capital outflow coincided with corresponding increases in *RPR*. In both instances, the increase in *RPR* is driven by the numerator, i.e., China's political risk. One can relate both episodes to events in China that appear exogenous to the external economies for which we study the impact of these surges in capital outflows. The 1997 episode occurred immediately after Deng Xiaoping's death in the first quarter of that year, and the 2011 episode occurred after the bursting of the Chinese property bubble (second quarter in 2011) and the subsequent launch of the anti-corruption drive in China (fourth quarter of 2012).

For the 1997 event, Gunter (2017) notes that even though capital flight appears to have *declined* according to Cuddington's (1986) method after 1998 when decade-long capital controls were imposed, the two residual methods create a very different picture. Gunter (2017) argues that tighter controls can represent the government's (unsuccessful) attempt to reign in capital flight or can hasten capital flight through creative channels in anticipation of the

[18] Cuddington's (1986) method essentially defines capital flight as "hot money" that leaves the country in response to perceived small changes in risk or return, and is calculated as the sum of short-term capital exports by the non-bank sector and errors and omissions (the balancing entry, which is supposed to reflect unrecorded short-term capital flows). Gunter (2017) further adjusts Cuddington's estimate by subtracting the change in foreign financial assets held by residents in China, reported by People's Bank of China. See Gunter (2017) for details.

government's repressive intent. Moreover, capital controls can reduce capital reparations, and such capital can be reinvested in assets abroad. Finally, Gunter (2017) links the post-2011 capital flight to the anti-corruption campaign, a sharp increase in income inequality in China, lower transaction costs of moving capital out of China, and a desire to migrate for educational, economic, political, social, or environmental reasons,[19] which may have been triggered by a softening of capital controls after 2009 to internationalize the RMB.

We argue that even though capital flight to the U.S. or any specific destination cannot be accurately measured, capital inflow from China to the regions with strong ethnic ties to China is likely to have significantly increased during these episodes. In our empirical analysis, we focus on five-year periods immediately before and after the two episodes. For ease of discussion, we refer to the years 1997 and 2011 (1997Q1 and 2011Q2) as "event years" ("event quarters") associated with the start of each of the two episodes of increased capital outflows.[20]

C. Empirical Strategy

For the U.S., we have Chinese population settlement data as early as 1870 for counties and 1880 for states.[21] We use this early settlement data to determine regions with strong ethnic ties and weak ethnic ties to China. Similar classifications based on more recent data could correlate with regional characteristics that attract both Chinese population and increase property prices, and drawing on early settlement data mitigates this concern. We provide evidence below that these early Chinese population distribution patterns are fairly persistent, and the regions classified as having stronger ethnic ties to China have significantly more

[19] See Gunter (2017), Section 6.

[20] These two years (quarters) are excluded from our empirical analysis. Our results are also robust to defining the launch of the anti-corruption drive as the relevant event for the second episode.

[21] We have 1870 county Chinese population data for 62% of the states. Therefore, we do not aggregate 1870 county Chinese numbers to estimate state Chinese numbers.

Chinese population, both in numbers and in terms of percentage of Chinese, as of the year 2010.

For the two events of 1997 and 2011, our empirical strategy is to examine whether the regional housing price growth is higher in the five-year period immediately after each of the events compared to the five-year period immediately before, for regions that have stronger ethnic ties to China compared with those that have weaker ties.

We conduct our analysis both at the level of MSAs as well as counties. For MSAs, we utilize quarterly data on housing prices, while for counties our data is at an annual frequency. When the analysis is done at the MSA level, we use MSA fixed effects and cluster standard errors by quarter.

For counties, we conduct three types of analysis. Similar to our regressions at the MSA-level, we run regressions at the county level using county fixed effects and cluster standard errors by year. For regressions involving within-MSA comparisons between counties with stronger and weaker Chinese ethnic ties, we incorporate MSA×year fixed effects and cluster standard errors at the state level. For our analysis of spillover effects of Chinese capital inflows, our unit of analysis is a county without any recorded Chinese population as of the year 2010. Here, we use county and year fixed effects, and cluster standard errors by state.

Thus, our empirical specifications take the following form:

$$HPG_{jt} = a + b * POST + c * HCT_{jt} * POST + d * X_{jt} + FE + \epsilon_{jt} \qquad (1)$$

where subscripts j and t index region and time, respectively. The dependent variable is the housing price growth (*HPG*) per quarter or per year. *POST* is an indicator variable that has a value of 1 if the unit of observation occurs for a time period in the five-year window after the event, and a value of 0 if it occurs in the five-year window before the event. *HCT* is an indicator variable that has a value of 1 if the unit of observation pertains to a region that is considered to have stronger ethnic ties to China, and a value of 0 if the region is considered to have weaker ethnic ties to China.

For our reduced-form regressions, we replace *POST* with lagged *RPR*. The sample period is 1986Q1-2016Q4 for MSA-level analysis and 1986-2016 for country-level analysis.

$$HPG_{jt} = a + b * RPR_{t-1} + c * HCT * RPR_{t-1} + d * X_{jt} + FE + \epsilon_{jt} \qquad (2)$$

We next discuss how the *HCT* dummy is constructed. For MSA-level analysis, we assign to each MSA the population number in its state as of 1880. MSAs that are in the top quartile of the resulting distribution are classified as MSAs with strong ethnic ties to China (*HCT*=1), whereas those in the bottom quartile are classified as having weak ties to China (*HCT*=0).[22] As shown in Panel A of Table 1, the Chinese population distribution is quite persistent over time. Using MSA-level Chinese population data for the year 2010, we find that the mean Chinese population number in *HCT*=1 MSAs was 17,784 and the Chinese population percentage was 0.7 percent, and the corresponding numbers for *HCT*=0 MSAs were 2,501 and 0.2 percent, respectively.

For our within-MSA county-level analysis, counties in the same MSA are classified as having stronger (*HCT*=1) ethnic ties to China if they are above the MSA median in terms of the number of Chinese in the county as of the year 1870. The remaining counties are classified as having weaker (*HCT*=0) ethnic ties to China.[23] The data shows remarkable persistence in terms of the distribution of Chinese population across counties from 1870 to 2010. As indicated in Panel A of Table 1, as of 2010, the mean number of Chinese in the *HCT*=1 counties was 47,505 and the mean Chinese population percentage was 3.9 percent, compared to 6,109 and

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[22] For states with an MSA at the margin of the 75th (25th) percentile threshold, all MSAs are included in *HCT*=1 (*HCT*=0) groups.

[23] 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 *HCT*=0 group because many of these have very small Chinese population numbers.

0.7 percent, respectively, in the *HCT*=0 counties. Finally, for our analysis of the spillover effect of *CINFC* to counties without any recorded Chinese population as of 2010, *HCT*=1 if the state had above median Chinese population (in terms of number or proportion), and *HCT*=0 otherwise.

We check whether the regions classified as *HCT*=1 and *HCT*=0 differ, prior to the two events of 1997 and 2011, in terms of key economic characteristics. Panel B of Table 1 gives a list of the characteristics as of the year before each event, as well as the statistically significant p-values for the pairwise comparison of subsample means. The p-values indicate that the subsamples are homogeneous with respect to most of the characteristics. The only exceptions are that *HCT*=0 MSAs experience higher growth of labor per capita and employment per capita and the *HCT*=0 counties have higher labor per capita and employment per capita in 1996 (prior to the first event). To the extent that these differences suggest more robust economic activity in the regions with weaker Chinese ties, they are unlikely to explain our results.

Finally, to further ensure that our results are not due to differences in regional demographic or economic prospects between greater and lesser Chinese-populated regions, in addition to region or region interacted with year fixed effects, we saturate the model with many time-varying control variables. These include contemporaneous per capita income growth, contemporaneous population growth, rolling past five-year regional income growth, and future average income growth and population growth.

4. Chinese Capital Inflow and Housing Prices

A. MSA-level Quarterly Housing Price Growth

Our first set of results are from regressions where the dependent variable is quarterly housing price growth at the MSA level. To create a balanced sample of high and low Chinese-populated MSAs based on the 1880 Chinese population, each MSA is assigned the corresponding state's 1880 population and the MSAs are then grouped into top and bottom quartiles. The high Chinese population dummy *HCT* has a value of 1 if the MSA is in the highest quartile, and a value of 0 if it is in the lowest quartile. MSAs that are in the two middle quartiles are excluded. List 1 in Table SA1 of the Supplementary Appendix shows the states that contain the MSAs in the top (Panel A) and bottom (Panel B) quartiles.

The results for the two events are reported in columns (1) and (2) of Table 2. We find that the residential prices in the MSAs with high state-level Chinese population (as of 1880) increased about 1.1 percent more per quarter after the 2011 event than those with low state-level Chinese population. This effect therefore is economically highly significant. The economic magnitude of the same effect after the 1997 event is smaller: about 0.4 percent per quarter, which is consistent with the perception from Figure 1 that the capital outflow after the 1997 event was more modest. The contemporaneous control variables for real personal income growth and population growth at the MSA level are all highly statistically significant, suggesting that they absorb the effects of real economic activity and demographic changes on property prices well. Past five-year growth has a significantly positive effect on property prices around the 1997 event. The *POST* dummy itself is highly significant for the 2011 event, which is consistent with property prices falling in the pre-event period which includes the financial crisis. For the future growth variables, future MSA real personal income growth and population growth—to the extent that they proxy for expected future growth—have a significantly positive impact on residential prices in all regressions. All our results are also robust to the exclusion of either or both of these future growth variables.

To address the concern that results could be driven by Chinese capital inflow in certain MSAs where the Chinese population is most concentrated, for the results reported in columns (3) and (4) of Table 2 we first remove the MSAs that are in the top 10 percent in terms of Chinese population as of 2010, and then identify the top and bottom quartiles of the remaining

MSAs based on their 1880 state-level Chinese population. In Table SA1 of the Supplementary Appendix, List 2 gives a list of the MSAs that are removed, and the last column of List 3 indicates which states remain in the sample. The results, reported in columns (3) and (4) of Table 2, are qualitatively similar, although the economic magnitude for the 1997 event is smaller than that for the full sample.[24]

Figures 3 and 4 show that the parallel trends assumption holds for our difference-in-differences methodology. The solid line denotes the difference in the annual average of the quarterly housing price growth between the *HCT*=1 and *HCT*=0 MSAs, and the dashed lines show the 95 percentile confidence intervals. The difference is not significant at the 5 percent level in the pre-event period, and only becomes significantly positive in the post-event period, for both events.

One caveat with the analysis in Table 2 is that, especially during the 1997 event period which coincided with the Asian financial crisis, capital outflow to the U.S. also took place from several Asian countries such as Thailand and South Korea, and is also likely to have followed ethnic links with the corresponding U.S.-based population. Since there was some degree of overlap between these population groups and the Chinese, we use 2010 population information to control for non-Chinese Asian population number at the MSA level. The results are reported in Appendix Table A1. We find that MSAs with high Chinese population experience faster property price growth after both events. For the 1997 event, regions with higher non-Chinese Asian population also experience higher property price growth after the event. However, these regions actually experience significantly lower property price growth after the 2011 event,

[24] In section 8.B, we show that when regions are classified based on early overall U.S. population distribution (as opposed to the distribution of Chinese population), we do not find similar results around the two events. This mitigates the concern that classifications based on early population distributions are associated with regional characteristics that persist over long periods and potentially bias our results.

which could reflect a decrease in capital inflow from other Asian countries after the financial crisis.

Finally, in columns (5) and (6) of Table 2, we report results for reduced form regressions involving *RPR*. An increase in *RPR* in general has a marginally significant positive effect on the following year's residential prices in MSAs without strong ties according to our classifications,[25] but this effect is magnified in *HCT*=1 MSAs.

B. County-level Annual Housing Price Growth

Our data on county-level housing price growth is available to us only in nominal terms and at an annual frequency. We first conduct similar analysis as in the previous section at the county level. Here, *HCT*=1 if a county has above-median Chinese population as of 1870, and *HCT*=0 if the country has no recorded Chinese population in that year.[26] The results are reported in Appendix Table A2. The regressions include county fixed effects and county-level economic variables such as contemporaneous and past five-year (nominal) personal income growth and population growth. The coefficient of *HCT*×*POST* is positive and significant for both the 1997 and 2011 events, and the implied magnitudes are very close to those from the MSA-level analysis.

Figures 5 and 6 show that the housing price changes in *HCT*=1 and *HCT*=0 counties do not differ significantly prior to each event; however, the difference becomes significant after each event, validating our difference-in-differences methodology.

C. Within-MSA Housing Price Growth and Spillovers

[25] This could reflect the strongly positive significant effect of *POST* in Table 2 for the 2011 event, during which RPR also reached higher values due to higher political risk in China.

[26] Such a classification is convenient given that in 1870 there were many counties without any recorded Chinese population. Our results are similar for alternative definitions of HCT, such as the top 25th and bottom 25th percentile among counties with recorded Chinese population.

In Table 3, we compare property price growth before and after the two events in counties with above MSA median Chinese population and the remaining counties within the same MSA, based on population data as of 1870. Within-MSA comparisons are likely less susceptible (than comparisons between MSAs located in different states) to the issue that other factors such as local economic activity may be correlated with Chinese population presence, since economic shocks can spill over more easily to adjoining counties than across states. The regressions include MSA interacted with year fixed effects, which implies that the coefficient estimate of *HCT* captures within-MSA differences between high and low Chinese populated counties.

Results in the first four columns in Table 3 show that after both events, the housing price growth is higher for *HCT*=1 counties than for *HCT*=0 counties within the same MSA. For the 2011 event, the difference is about 0.5 percent per year in nominal terms, but marginally insignificant at conventional levels. It is about 1.1 percent per year for the 1997 event.

In the last two columns of Table 3, we present results from reduced-form regressions using *RPR*. The effect of *RPR* is significantly higher for *HCT*=1 counties than for *HCT*=0 counties.

An interesting aspect of the results is that the effects are quantitatively weaker for the 2011 event when all the MSAs with Chinese population are kept in the sample (first column in Table 3), compared to the corresponding regression for the 1997 event (Column (3)) or when counties from the top 10 percent Chinese MSAs are excluded from the sample (Column (2)). In fact, compared to the MSA-level results in Table 2 or the county-level results in Appendix Table A2, the within-MSA results for counties in Table 3 are quantitatively weaker. We hypothesize that this has to do with the fact that counties in the same MSA experience more similar property price growth than MSAs in different states, irrespective of population distribution. An important reason for this is that spillover effects are likely to be more important across counties within the same MSA than across MSAs. Since the post-2011 outflows were more significant, the property price increases in the high Chinese-populated counties were more substantial, which spilled over to the low Chinese-populated counties. This reduced the between-county differences within the same MSA.

To investigate the presence of spillover effects, in Table 4 we consider counties with no reported Chinese population as of 2010. We examine whether property price appreciation in these counties was higher in the post-event periods when their states had greater Chinese population (as of 2010). With more recent population data, we can report results based on both the number of Chinese and the proportion of Chinese in the state population. Consistent with spillover effects, we find that when all states are considered for both events, the property price growth in the post-period increased for non-Chinese counties in high Chinese population states by about 1.5 percent per year more than in non-Chinese counties in low Chinese population states. However, as shown in the last two columns in Table 4, there was no such effect after the 1997 event when states with at least one major (top 10 percent) Chinese-populated MSA are excluded. The absence of spillover for the states without a significant Chinese-populated MSA after the 1997 event is consistent with the fact that capital outflows from China to the U.S. in the earlier period were geographically more concentrated in states with significant Chinese presence.

Spillover effects are expected to decay as a non-Chinese populated county is farther away from the main destination(s) of *CINFC*. To test this hypothesis, we first identify the top 20 percent Chinese populated counties in the U.S., based on 2010 population. Next, we calculate the average distance of a non-Chinese county (in any state that includes a top 20 percent Chinese populated county) from the top 20 percent counties located in that state. Non-Chinese counties in states that do not include a top 20 percent Chinese county are not included in the sample. If there are multiple top 20 percent counties in the same state, we construct both a simple average distance as well as a weighted-average distance based on the Chinese population numbers. Table 5 reports results for regressions that include state×year fixed effects. The coefficient of the interaction of *POST* and the logarithm of average distance (weighted-average distance) is significantly negative, suggesting that the spillover effect to non-Chinese counties dampens with distance from the counties with significant Chinese population.

5. MSA-level Annual Employment Growth and Deposit Growth

Capital inflows are likely to have significant employment effects for the regional economies. This can happen not only via the creation of more jobs in the real estate sector, but also indirectly, via deposit creation at local banks and increased bank lending. Industry reports have suggested that many Chinese banks have become a major source of debt capital in the U.S. and Chinese developers became very active in commercial real estate development after the year 2011. Favilukis and Van Nieuwerburgh (2020) develop a calibrated general equilibrium model to estimate the effect of out-of-town (OOT) home buyers who buy but do not rent out housing units in metropolitan cities. Their model implies economically significant effects of OOT capital inflows to the residential markets on rentals and sectoral employment, which spill over to suburbs.

Not surprisingly, the construction sector is one of the major beneficiaries of such OOT inflow to the residential sector. The model, however, assumes that the labor market clears, so there are no aggregate employment effects. We follow an empirical approach similar to that for our analysis of *CINFC* on residential prices, and document significant employment effects not only in the construction sector, but also for all other sectors combined. The results for the two events appear in Table 6. Columns (1) and (2) present results for overall MSA-level employment, columns (3) and (4) present results for the construction sector, and columns (5) and (6) present results for all non-construction sectors combined. The results show that *POST*HCT* has a significant positive effect on employment growth for the 2011 event. For the

1997 event, while the coefficient is positive, it is significant at conventional levels only for the construction sector.[27]

The quantitative effect on the construction sector is three to five times as large as for overall employment, for both the 1997 and the 2011 events. The difference-in-differences coefficient *HCT*POST* capturing the effect of *CINFC* on the growth rate of construction sector employment is larger following the 2011 event (2.8 percent higher in *HCT*=1 MSAs than *HCT*=0 MSAs) than for the 1997 event (1.8 percent higher). This is also the case for employment growth in all non-construction sectors combined. These results are consistent with the observation that the unemployment rate in the U.S. economy was about 6 percent in 1996, but about 10 percent in 2010 following the financial crisis.

We also replicate the MSA-level employment analysis reported in Table 6 at the county level, using county and year fixed effects. Results are qualitatively the same (not reported in a table).

Capital inflows can stimulate the local economy not only via creation of more jobs in the real estate sector, but also indirectly via deposit creation at local banks and increased bank lending. Since information on MSA-level deposits is available only from the year 2002, in the last column of Table 6 we report results for the 2011 event, for which quarterly deposit growth is the dependent variable. The coefficient of *HCT*POST* is highly significant, and the magnitude of the coefficient suggests that deposit growth in the MSAs with strong Chinese ties is more than 4 percent higher than in MSAs with weak Chinese ties.

Reduced-form regressions are reported for both employment growth and bank deposit growth in Table 7. In the first two columns in Table 7, overall MSA-level employment growth is the dependent variable, while in the third and fourth columns, it is the growth rate of

[27] The results (not reported) are similar when we exclude the top 10 percent Chinese MSAs.

construction sector employment. Finally, in the last two columns, we consider deposit growth at the MSA level (the annual average of all quarters). In columns 2, 4, and 6, we also include lagged residential price growth (annual average of all quarters) to examine whether the impact on the real economy is a direct outcome of the capital flow, or an indirect implication of developments in the housing market. Our hypothesis is that any impact that works through the housing price channel will be reflected in a positive significant effect of lagged housing price growth on the variable of interest; however, if housing prices do not directly affect the variable, but the inflow does, then only the interaction of lagged *RPR* and *HCT* will be significant. To ensure a meaningful comparison, the sample period is 2002-2016 (for which MSA-level deposit information is available) in each regression.

In columns (1) and (3), we find that the coefficient of *HCT***RPR* is positive for overall employment growth as well as for the construction sector. While it is marginally insignificant for the construction sector, the magnitude is three times that for overall employment. However, both coefficients become insignificant when lagged housing price growth is included in the regression, as seen in columns (2) and (4). Lagged housing price growth itself is significant at the 1 percent level. These findings suggest that the housing sector plays a significant role in the process of employment creation and the effect of CINFC on employment works mainly through this sector. In contrast, as we see from columns (5) and (6), for deposit growth, the coefficient of *RPR***HCT* remains positive and significant irrespective of whether lagged housing price growth is included. Lagged housing price growth itself is significant at the 10 percent level in Column (6), but its inclusion has little effect on the coefficient of *RPR***HCT*. These results are consistent with the idea that deposit growth mainly responds to capital inflows.

6. Educational Links and Property Price Growth

It has been widely reported in the media that Chinese families that have sent children to study abroad have invested heavily in the residential markets of these countries. They do so partly as an investment to finance their children's education, and also to find a place for them to stay (sometimes both, in separate locations). Moreover, familiarity with a region is likely to develop when they visit their children, and investment in residential property could follow. In this section, we examine whether such educational links determine the destinations of capital outflows from China and affect the residential prices in these regions.

Our annual international student enrolment data is for the U.S. as a whole, and begins in the year 1999. To capture the strength of educational links, we rank states based on international student numbers in these states as of 2017. We then estimate the following model separately for the top one-third and bottom one-third of hosting states based on international student numbers in 2017. [28] For 2000-2016, we estimate the following model:

$$\overline{HPG}_{HC,s,t} - \overline{HPG}_{LC,s,t} = a + +b * \Delta CHINSTU_t + c * \Delta NCHINSTU_t + d * (\overline{X_{HC,s,t}} - \overline{X_{LC,s,t}}) + \gamma_s + \epsilon_{s,t} \quad (3)$$

For the 2011 event, we estimate the following model:

$$\overline{HPG}_{HC,s,t} - \overline{HPG}_{LC,s,t} = a + b * POST + c * \Delta CHINSTU_t * POST + d * \Delta NCHINSTU_t * POST + e * \Delta CHINSTU_t + f * \Delta NCHINSTU_t + g * (\overline{X_{HC,s,t}} - \overline{X_{LC,s,t}}) + \gamma_s + \epsilon_{s,t} \quad (4)$$

Here, the dependent variable is the difference in the average housing price growth in above-median (HC) and below-median (LC) Chinese-populated MSAs in state *s* in each

[28] In the Supplementary Appendix, List 4 in Table SA1 gives the 2017 international student numbers for each state. We obtain the state-level international student numbers from the Institute of International Education and the country-level yearly total and Chinese international student numbers from UNESCO Institute of Statistics. The annual change in the number of the non-Chinese international students ($\Delta NCHINSTU_t$) is the change in the difference between the total and Chinese international student numbers from year *t*-1 to year *t*.

quarter. $\Delta CHINSTU_t$ is the change in the number of Chinese international students in the U.S, in the year corresponding to quarter *t*, and $\Delta NCHINSTU_t$ is the change in the number of non-Chinese international students. $POST$ is an indicator variable equal to 1 for any of the quarters after the event-quarter (2011Q2), and 0 otherwise. The regressions control for the difference in the average of MSA-level economic variables between above-median and below-median Chinese populated MSAs in state *s*, well as state fixed effects.

We are restricted to the 2011 event because international student data is not available for the early 1990s. We also estimate reduced-form regressions with RPR replacing $POST$ in Eqn. (4).

We expect that the impact of an increase in student numbers would be mainly confined to the top third of hosting states, and if Chinese capital inflows and investment in residential property follow Chinese international students, then they are more likely to be invested in MSAs with higher Chinese population that in those with lower Chinese population within those states. Thus, for Eqn. (3), we would expect the coefficient of the change in Chinese student numbers to be positive and significant for the top third of hosting states, but not for the bottom third of hosting states. Further, the inflow of Chinese capital per student should be higher after the 2011 event than before. Hence the coefficient of $\Delta CHINSTU_t * POST$ should be significantly positive for the top third of hosting states. Similarly, in our reduced-form regressions for 2000-2016, the coefficient of $\Delta CHINSTU_t * RPR$ should be significantly positive.

The results reported in the first two columns of Table 8 show that, for the top one-third of hosting states, the change in the number of Chinese international students in the U.S. has a significantly positive effect on the difference in property price increase between high and low Chinese MSAs. There is also a similar positive effect of the change in the number of non-Chinese international students in the U.S.; however, the corresponding coefficient is about 50 percent lower. We find no effect for the bottom one-third of hosting states. In Column (3), we examine whether the effect of the change in the number of Chinese international students (for the top one-third of hosting states) is stronger in the post-2011Q2 period than the period before. We find that this is indeed the case. The post-period effect associated with a change in Chinese student numbers is slightly more than twice that of the pre-period effect. However, we find no such effect in the post-2011 period for the inflow of non-Chinese international students. Similarly, in Column (4), we find that when *RPR* is higher, the inflow of Chinese international students has a significantly larger effect on the difference in property prices of above median and below median MSAs for the top third of hosting states. We find no significant results when we repeat the exercises in the last two columns on the bottom third of hosting states (these results are not reported).

7. Global Cities, Chinese Population and Student Inflows, Housing Prices and Employment

Our results discussed above are for U.S. residential property markets. However, Chinese capital flight is likely to reach other countries as well, although precise magnitudes are not readily available. Therefore, to strengthen the plausibility and to establish the external validity of our analysis, we extend our event-based and relative political risk-based analysis to examine the effect of Chinese capital inflow on a cross-section of global metropolitan cities.

While we do not have a snapshot of Chinese population distribution from a single source for regions outside the U.S. to do tests similar to those reported in Tables 2 and 8, we do have more reliable data on annual population inflow, including Chinese population inflow, as well as on international (including Chinese) student inflow, to various countries for 2000-

2017.[29] However, this data availability restricts us to a shorter time period and only to the 2011 event.

We use the ratio of Chinese population inflow to total population inflow to a country in a calendar year as an indicator of the destination of capital outflow from China. The flow data is at the country level, but our property price data are for major global cities. We calculate the median of the quarterly housing price growth of all cities for each country-quarter as the dependent variable of interest.[30] We run weighted least square (WLS) regressions to adjust for the fact that the influence of a population inflow at the country level will be more relevant for its major cities if the population size in the country is smaller.

There are several concerns with the use of population flow data. One is that because capital and population flows are likely to be highly correlated, it may not be straightforward to discern the effect of capital inflow on property prices from that of population inflow. A related concern is that population flow could be endogenous to country-wide factors that drive city property prices and at the same time attract Chinese and other population groups. To address such concerns, we examine whether the effect of Chinese population inflow (relative to overall population inflow) on major cities' property prices becomes stronger after the 2011 event. The idea is that variation in the proportion of incoming Chinese to a country would be more strongly related to variation in residential prices when capital flight – and per capita capital inflow from China – picks up after the 2011 event. To absorb any country-specific metropolis-level factors that could affect property price growth before and after 2011 differently, we include in our regression specification country interacted with post-2011 and pre-2011 dummy fixed effects. Thus, we test whether within-country yearly fluctuation in the ratio of Chinese population inflow to total population inflow has a stronger effect on city property prices in the post-2011

[29] Canada and the U.S. have data as early as 1980. However, comprehensive coverage of countries begins in 2000.
[30] The results are essentially the same when we replace the median by the mean or by the most-populated city.

period compared to the pre-2011 period, relative to the mean property price growth in each subperiod. We expect an interaction of a post-2011Q2 indicator variable and relative Chinese population inflow to have a positive and significant effect on quarterly city property price growth.

The results for this regression are in Column (1) of Table 9. We report Weighted Least Square (WLS) regression results, where the weight is the inverse of a country's yearly urban population, obtained from the World Bank. We include among our independent variables contemporaneous GDP growth of the country as well as GDP growth over the next 20 quarters, to control for future expectations of growth affecting property prices. Both variables have significantly positive effects. The main variable of interest—the interaction of the logarithm of the ratio of Chinese population inflow to total population inflow to a country in which a city is located and an indicator variable for the post-2011 period—has a positive and significant coefficient in both regressions.[31] The coefficient indicates that the increase in the city property price growth is 1 per cent per quarter in the post-2011 period when the relative Chinese population inflow increases by 1 per cent, compared with that in the pre-2011 period.

In columns (2)-(4), *HCHPINF* is an indicator variable that takes the value of 1 if Chinese population inflow as a proportion of overall population inflow to the country to which a city belongs is in the upper *x* fraction of all countries in our sample for that year, and 0 if it is in the lowest x fraction, where x= ½ in Column (2), ⅓ in Column (3), and ⅕ in Column (4). The key variable of interest is the interaction of *HCHPINF* and RPR_c, where the latter variable represents the relative political risk of China and the country in which the city is located. WLS estimates indicate that the coefficient of $HCHPINF \times RPR_c$ is significantly positive in all columns, and it monotonically increases from Column (2) to Column (4) as the difference

[31] We consider the logarithm of the relative Chinese population inflow to reduce the impact of skewness of the distribution.

between *HCHPINF=1* and *HCHPINF=0* widens. This evidence suggests that when Chinese capital inflows increase, city residential prices increase more in countries that attract more Chinese.

Finally, we examine whether Chinese student inflows affect property prices in global cities, using the international student inflow data for the countries in which the cities are located. However, since we do not have data on Chinese population distribution within regions in a country to match the regions for which we have city housing price data, we do not conduct a within-country comparison between high and low Chinese-populated regions as we do for the U.S. in Table 8. Instead, we follow the same approach as that for our analysis of Chinese population inflow. In a regression specification identical to that reported in Colum (1) of Table 9, we replace the yearly country-level ratio of Chinese population inflow to total population inflow with the yearly country-level ratio of Chinese student inflow to total foreign student inflow.

Column (5) of Table 9 reports WLS regression results. The weight of the WLS is the yearly country-level ratio of total foreign student inflow to the total urban population. The results are qualitatively the same as those of Chinese population inflow. The key variable of interest—the interaction of relative Chinese student inflow and an indicator variable for the post-2011 period—has a significantly positive coefficient in both regressions. In particular, when the relative Chinese student inflow increases by 1 percent, the growth of the global city property prices increases 1.6 percent per quarter in the post-event period. It is worth noting that the un-interacted Chinese student inflow is also positive and statistically significant at the 10 percent level, suggesting existence of a positive effect on the global city housing price growth before the 2011 event.

In Table 10, we examine the association of Chinese capital inflow and employment growth in metropolitan areas of a country. The specification in columns (1) and (2) are similar to that in Column (1) of Table 9, and include country fixed effects interacted with *POST* and 1-*POST*. We find that the interaction of the proportion of Chinese population inflow to total population inflow and *POST* is positive and significant after the 2011 event, suggesting that more capital inflow per capita increases metropolitan employment after the 2011 event. In columns (3) and (4), we report reduced-form regressions. *HCHINF* is an indicator variable that takes the value of 1 if the proportion of Chinese population inflow to overall population inflow is in the upper third of all countries for which we have data, and 0 if it is in the lower third. Countries in the middle third are dropped. The interaction of *HCHINF* and RPR_C is significantly positive in Column (3). However, it becomes insignificant in Column (4) when we control for lagged residential price growth, consistent with our findings in Table 7, suggesting that the capital flow into the housing market is a major driver of the employment growth.

8. Additional Results

In this section, we address several issues relating to the robustness of our results.

A. Excluding California

The state of California is the most Chinese-populated state in the U.S., with a Chinese population of 1.185 million as of 2010, which is about two times greater than that of New York, the second most Chinese-populated state. While Chinese population in the U.S. has become more widely distributed over time, California remains the leading Chinese-populated state. As shown in List 2 of Table SA1, it has a third of the top 10 percent of MSAs in terms of Chinese population as of 2010. It has at least 16 Chinatowns, including the oldest and one of the largest and most prominent ones in San Francisco. It is quite possible, therefore, that the state attracts a large share of the Chinese capital inflow to the U.S., and the question then arises whether our results hold if we leave California out.

We exclude California and re-run our main regressions. In Table A3 in the Appendix, we report the coefficient estimates of *HCT**POST* for the two events. The coefficient remains statistically significant (except for the within-MSA county regression corresponding to Table 3, Column (1)), and the economic magnitudes of the estimated effects of *CINFC* subsequent to the two events, though somewhat smaller when California is excluded, remain quantitatively important. For example, when California is included, the *HCT*=1 MSAs experience 1.1 percent and 0.4 percent per quarter higher property price appreciation in the post-event period than the *HCT*=0 MSAs for the 2011 and 1997 events, respectively; the corresponding numbers when California is excluded are 0.7 percent and 0.2 percent. These results therefore reinforce the results on samples that exclude the top 10 percent of Chinese MSAs reported throughout the paper; while California and the major Chinese-populated MSAs seem to contribute significantly to the overall impact of *CINFC* on U.S. housing prices, Chinese population in the country is now spread out enough that there are significant effects on other regions as well. We should note here that the spillover results documented in Tables 4 and 5 also imply that the effect of *CINFC* is not confined to counties that are more heavily populated by the Chinese.

B. Classifications Based on Overall Population, and Controlling for Coastal Regions

For our classification of regions with stronger Chinese ties versus weaker Chinese ties, we have relied on early Chinese population distributions. Panel A of Table 1 shows that regions with more Chinese settlement 140-150 years ago have significantly more Chinese population in the period of our analysis than those with fewer Chinese settlement. However, early population distributions—whether of the Chinese population or the overall U.S. population – are also likely non-random, and there could be a concern that regions with a higher early population have some unique advantages that persist in recent times. If this is the case, our results could be affected by selection bias (although as Table 1 shows, the *HCT*=1 and *HCT*=0 regions in our sample are essentially similar in terms of many economic characteristics, which mitigates this concern). Since Chinese population remains a relatively small fraction of overall U.S. population, the above argument applies even more to the early distribution of overall U.S. population. Accordingly, we classify U.S. MSAs and counties as high total population (*HT*=1) and low population (*HT*=0) regions based on total population (as of 1880 and 1870, respectively) in the same way as we classify regions based on early Chinese population. The upper panel of Table A4 in the Appendix shows that *POST*HT* is either of the wrong sign or is insignificant in all but one of the regressions.[32] The lower panel shows that inclusion of *POST*HT* does not have any meaningful effect on the coefficients of *POST*HCT*.

Thus, while it is possible that early population distribution across regions is associated with regional characteristics that persist over long periods, for such factors to explain our results, this would have to be the case *only* for regions that were associated with early *Chinese* settlement. The coastal states in the West and New York in the East experienced significant early Chinese settlement, and it could be argued that coastal states have historically thrived relative to other parts of the country and could be associated with persistent regional effects. However, it is worth noting that our within-MSA county-level results in Table 3, our within-state results based on educational links in Table 8, and those for global metropolitan cities in Tables 9 and 10, cannot be attributed to coastal state effects.

To further explore whether location in coastal states explain some of our remaining results, in Table A5, we include an interaction term *POST*COAST*, where the latter variable is an indicator variable that takes the value of 1 for an MSA or county located in a coastal state, and 0 otherwise. For the county-level regressions in the middle two columns, instead of within-MSA results, we report results for county-level regressions analogous to Table A2. Using

[32] The exception occurs for the within-MSA county-level property price result for the 1997 event. The upper panel of Table SA2 in the Supplementary Appendix shows that *HT*=1 regions have higher Chinese population and percentage of Chinese than *HT*=0 regions, especially for counties. This could potentially explain why, for the within-MSA county-level regressions, residential prices increase more for the 1997 event for *HT*=1 counties than for *HT*=0 counties (recall that, consistent with spillover, the within-MSA results are stronger for high Chinese counties for the 1997 event as well, compared to the 2011 event).

county and year fixed effects. *POST*COAST* is significant for housing price growth post-1997 and for employment growth post-2011. However, *POST*HCT* remains positive, with almost the same magnitude, and significant in all regressions.

C. Supply Elasticities

Property prices may respond more to capital inflows to residential markets or other demand shocks if supply elasticities are lower. It is possible that *HCT*=1 regions are associated with tighter regulation of residential construction relative to *HCT*=0 regions. To see if this could be driving our results, we re-run our main housing regressions by additionally controlling for a composite regulatory index (*LURI*). *LURI* is a standardized measure of residential land use regulatory restrictiveness, based on a 2018 survey of communities across nationwide metropolitan areas in the U.S.[33] The index is the first factor of a factor analysis of a dozen subindexes that capture the different components of the local regulatory environment (Gyourko, Hartley and Krimmel, 2019). The results are reported in Appendix Table A6. *POST*LURI* has positive and significant coefficients for MSA level regressions, suggesting that supply elasticities do contribute towards the impact of *CINFC* on residential property prices. However, the coefficients of *POST*HCT* remains positive and highly significant in all regressions.

D. Relative Political Risk Revisited

In our reduced-form regressions, we used *RPR* to proxy for *CINFC*. We choose the level, rather than the change, in *RPR* because capital flight may not immediately reach an equilibrium level when a major change in *RPR* occurs. For example, if *RPR* declines only slightly following a large increase, capital flight is likely to continue. To see whether our results hold when we accommodate lagged response to significant changes in *RPR*, we construct a

[33] Gyourko, Hartley and Krimmel (2019) suggest that regulatory tightening across housing markets do not generally differ significantly over time.

measure of change in risk (*CRPR*) as the difference between last-period's *RPR* and the mean *RPR* of the previous three years. *DRPR* is a dummy variable that equals 1 when *CRPR* is above the 90th percentile in either the current year or the previous year, and 0 otherwise. The results in Table A7 in the Appendix show that the interaction of *DRPR* and *HCT* is significant in our main specifications. Results are similar when we extend *DPRP* to cover one more post-event year.

E. Imputed CINFC

Since we have data from Ferrantino et al. (2012) on capital flight from China to the U.S. for a relatively short time period (1995-2008), we construct a longer time series using the method of multiple imputation based on the ratio of U.S. to China ICRG political risk rating (*RPR*).[34] Figure 2 shows this series, and in Appendix Table A8 we replicate our main results based on this imputed *CINFC* (*ICINFC*). The interactions of *ICINFC* and *HCT* are positive and significant for our main results.

F. Synthetic Matching

We replicate our main results for the U.S. on synthetically matched samples of *HCT*=1 and *HCT*=0 MSAs and counties. These results are reported in Appendix Table A9.[35] Our main conclusions remain.

[34] The method of multiple imputation is outlined in https://www.stata.com/bookstore/multiple-imputation-reference-manual/

[35] The synthetic control method creates a synthetic version of treated units by weighting variables and observations in the control group. In other words, a synthetic control MSA, which does not necessarily exist, is a weighted average of various MSAs in the control group. We explain this method with reference to the MSA housing analysis. For each treated MSA (MSA with *HCT*=1), the synthetic control MSA is formed by searching for a weighted average of MSAs in the control group (with *HCT*=0) whose predicted housing price growth over the pre-event period, based on our MSA housing model, matches closest to that of the treated MSA. See Abadie, Diamond, and Hainmueller (2015).

9. Conclusion

Available evidence indicates that capital flight from China increases when political risk in China increases relative to that in other countries, for example, after 1997 following Deng Xiaoping's death, and then more substantially after the bursting of the property bubble in China in 2011 and the launch of Xi Jingping's anti-corruption drive soon thereafter. The exact magnitude or destinations of such capital outflows, and their impact on international property markets, have not been established. In this paper, we attempt to provide some answers by examining whether residential property prices and real economic activity are affected in regions with stronger ethnic and student links to China compared with those with weaker links. Our results confirm that ethnic and educational links play an important role in determining the destinations of the capital outflows and their impact on foreign residential property markets and local economies. We also document spillover effects to nearby regions that do not have strong ethnic ties and are thus unlikely to be destination of Chinese capital flight. We show that the impact of the Chinese capital outflows, especially in recent years, has been quite substantial. Chinese capital outflows have not only played an important role in the recovery of the U.S. property market subsequent to the financial crisis, but have also contributed to employment creation and bank deposit growth.

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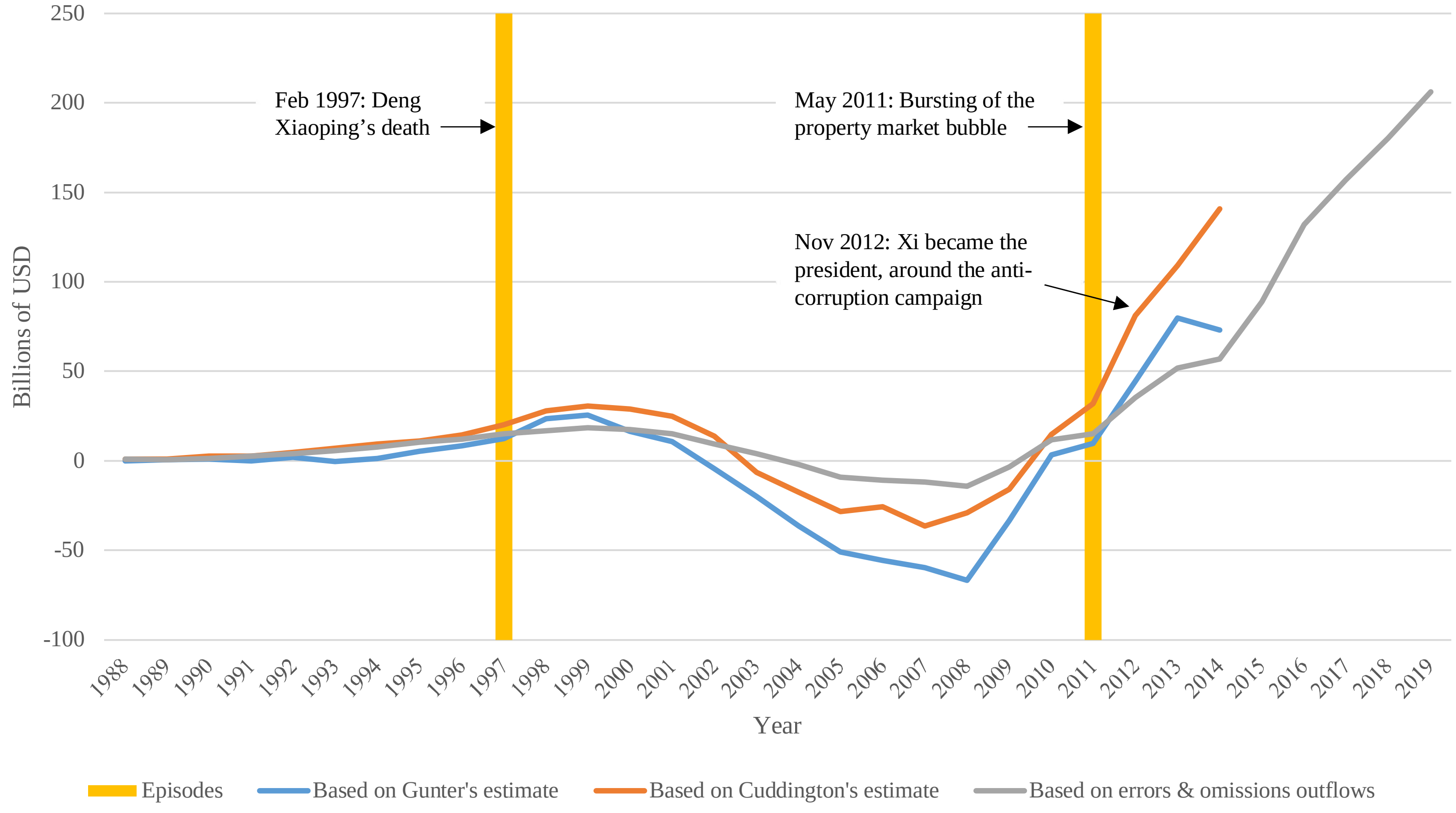
Figure 1. 5-Year Moving Average Chinese Capital Flight



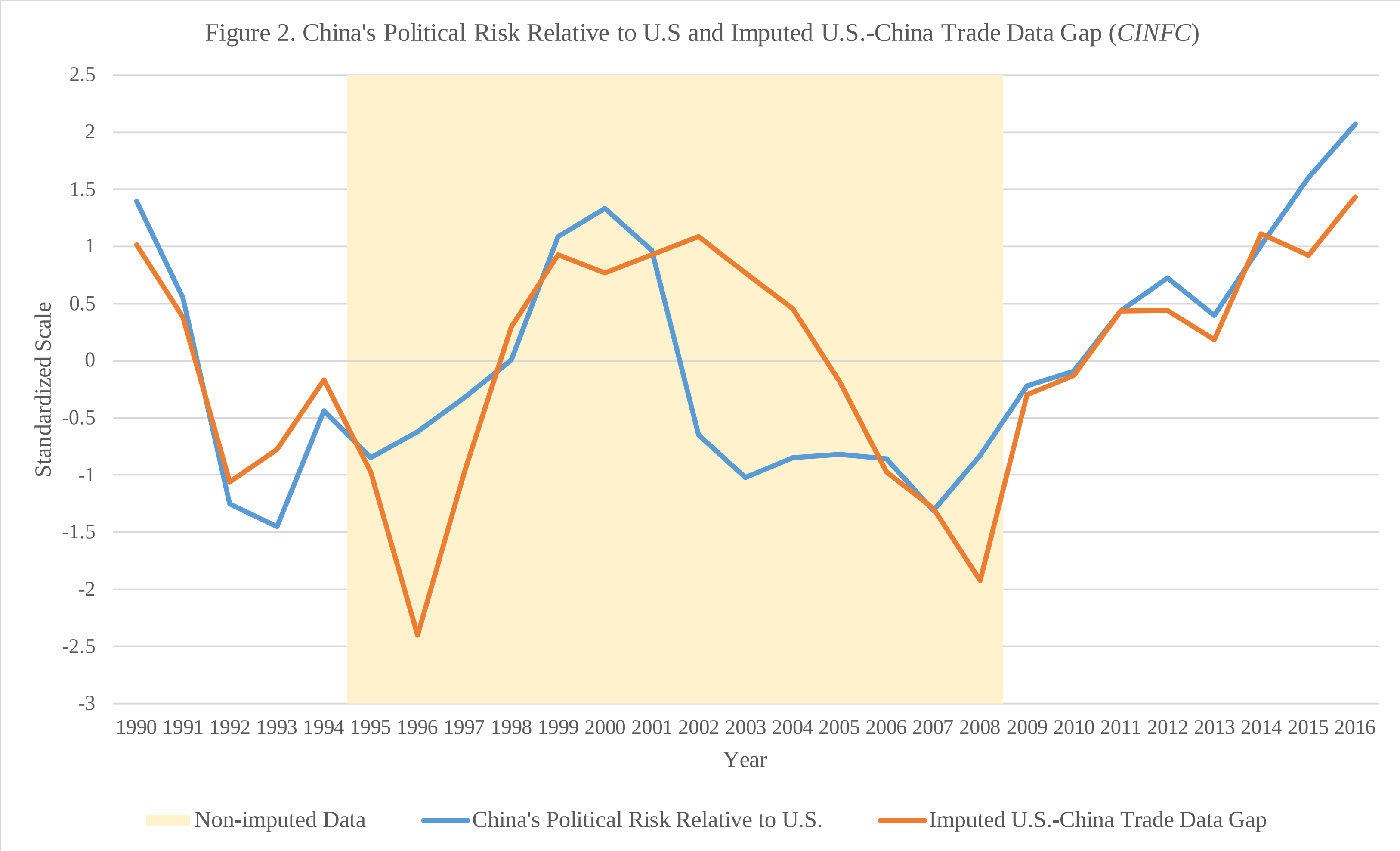


Figure 2. China's Political Risk Relative to U.S and Imputed U.S.-China Trade Data Gap (*CINFC*)
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
Standardized Scale
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
Year
Non-imputed Data
China's Political Risk Relative to U.S.
Imputed U.S.-China Trade Data Gap

Figures 3-6. Difference in Housing Price Growth Around 1997 and 2011 events in *HCT*=1 and *HCT*=0 U.S. MSAs (upper panel) and counties (lower panel). The events are the bursting of the Chinese property market bubble in 2011 (the left panel) and Deng Xiaoping's death in 1997 (the right panel). The dashed lines show the 95% confidence intervals (CI) of the difference (solid line).

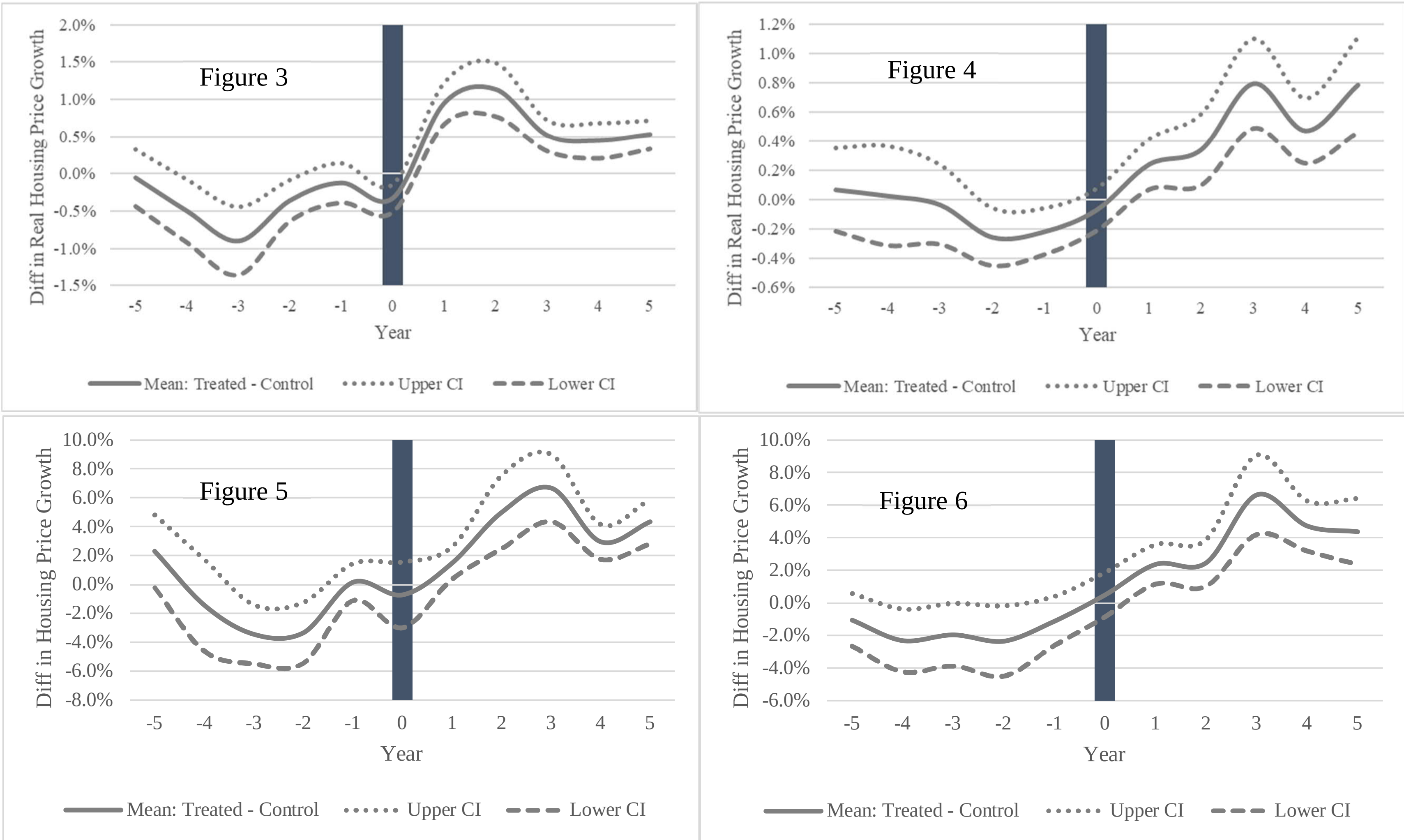


Table 1. Pre-Event Characteristics of High and Low Chinese-populated MSAs and Counties

This table compares the mean statistics of HIGH CHINESE (*HCT*=1) and LOW CHINESE (*HCT*=0) counties and MSAs in our regression samples of Tables 2 and 3 for the years 1996 and 2010 (i.e., immediately before the 1997 and 2011 events, respectively). ***, **, and * indicate a statistically higher mean of a two-sided *t*-test of the null hypothesis that the means of HIGH CHINESE and LOW CHINESE counties/MSAs are the same, at the 1%, 5%, and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)
	MSAs	MSAs	Counties	Counties
Year	2010	1996	2010	1996
Panel A: Chinese population				
2010 Chinese population				
HIGH CHINESE	17784*		47505**	
LOW CHINESE	2501		6109	
2010 Chinese percent				
HIGH CHINESE	0.7**		3.9**	
LOW CHINESE	0.2		0.7	
Panel B: Key economic characteristics				
Personal income per capita (dollars)				
HIGH CHINESE	36372	22370	50510	27085
LOW CHINESE	35363	21986	44447	26417
Growth of personal income per capita				
HIGH CHINESE	0.0185	0.0428	0.0308	0.0561
LOW CHINESE	0.0183	0.0439	0.0266	0.0634
Labor-to-population ratio				
HIGH CHINESE	0.4916	0.4945	0.5148	0.4937
LOW CHINESE	0.4875	0.5064	0.5123	0.5169*
Growth of labor-to-population ratio				
HIGH CHINESE	-0.0156	-0.0002	0.0071	0.0037
LOW CHINESE	-0.0125	0.0063***	-0.0078	0.0029
Employment-to-population ratio				
HIGH CHINESE	0.4399	0.4601	0.4627	0.4634
LOW CHINESE	0.4428	0.4837	0.4668	0.4915*
Growth of employment-to-population ratio				
HIGH CHINESE	-0.0262	0.0026	0.0010	0.0062
LOW CHINESE	-0.0157	0.0081**	-0.0133	0.0060
Bank deposit per capita (thousands of dollars)				
HIGH CHINESE	9.93	—	84.32	—
LOW CHINESE	17.77	—	49.53	—
Growth of bank deposit per capita				
HIGH CHINESE	-0.0521	—	-0.0029	—
LOW CHINESE	-0.0337	—	0.0266	—

Table 2. Chinese Capital Inflow and Real Housing Price Growth in U.S. MSAs

In columns (1)-(4), the sample periods of the 1997 and 2011 events are 1992Q1-2002Q1 and 2006Q2-2016Q2, but excluding the event quarters, respectively. In columns (5) and (6), the sample period is 1986Q1-2016Q4. We consider only those MSAs that are in the bottom or top quarter of MSAs based on state-level Chinese population in the year 1880. For columns (3), (4) and (6), the top 10% high Chinese-populated MSAs based on 2010 Chinese population distribution (in List 2 in Supplementary Appendix) are excluded. *HCT* is a dummy variable that has a value of 1 for the MSAs in the top quarter Chinese populated group, and 0 for the MSAs in the bottom quarter Chinese populated group. The dependent variable is the MSA-level quarterly real housing price growth. *POST* is the post-event dummy that has a value of 1 for 1997Q2 (2011Q3) or after for the 1997 (2011) event, and 0 otherwise. *RPR* is China's political risk relative to the U.S. based on ICRG political risk ratings of the previous calendar year. *RPIG0Y* is the MSA-level real annual personal income growth of the current calendar year. *POPG0Y* is the MSA-level annual population growth of the current calendar year. *LAGGED SRPIG20Q* is the state-level average real personal income growth of the past 20 quarters. *FUTURE RPIG5Y* is the MSA-level average real personal income growth of the next five calendar years or remaining calendar years for which data are available. *FUTURE POPG5Y* is the MSA-level average population growth of the next five calendar years or remaining calendar years for which data are available. MSA fixed effects are included. The robust standard errors are based on clustering at the quarter level. Estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Sample:	Full	Full	No-top-CN	No-top-CN	Full	No-top-CN
Event:	2011	1997	2011	1997	—	—
	(1)	(2)	(3)	(4)	(5)	(6)
*POST*HCT*	0.011***	0.004***	0.010***	0.002**		
	(0.002)	(0.001)	(0.001)	(0.001)		
POST	0.015***	0.001	0.015***	0.001		
	(0.003)	(0.002)	(0.003)	(0.002)		
*RPR*HCT*					0.019***	0.018***
					(0.005)	(0.005)
RPR					0.011	0.011
					(0.009)	(0.009)
RPIG0Y	0.102**	0.080***	0.102***	0.063***	0.168***	0.157***
	(0.039)	(0.020)	(0.037)	(0.018)	(0.023)	(0.022)
POPG0Y	0.093***	0.373***	0.088***	0.334***	0.301***	0.288***
	(0.021)	(0.035)	(0.020)	(0.035)	(0.041)	(0.039)
LAGGED SRPIG20Q	0.067	1.229***	0.087	1.166***	0.272	0.238
	(0.460)	(0.202)	(0.446)	(0.210)	(0.216)	(0.216)
FUTURE RPIG5Y	0.126*	0.088***	0.115*	0.094***	0.136**	0.130**
	(0.063)	(0.031)	(0.061)	(0.028)	(0.054)	(0.053)
FUTURE POPG5Y	0.578***	0.274***	0.578***	0.299***	0.080	0.119*
	(0.096)	(0.076)	(0.095)	(0.076)	(0.066)	(0.067)
Observations	7,025	7,520	6,790	7,120	23,524	22,168
Adjusted R^2	0.374	0.311	0.364	0.278	0.139	0.131

Table 3. Chinese Capital Inflow and Nominal Housing Price Growth in U.S. Counties, within MSA-Year Comparison

In columns (1)-(4), the sample periods of the 1997 and 2011 events are 1992-2002 and 2006-2016, excluding the event years, respectively. In columns (5) and (6), the sample period is 1986-2016. For "No-top-CN" samples, the top 10% Chinese-populated MSAs (in List 2 in Supplementary Appendix) are excluded. The dependent variable is the county-level annual nominal housing price growth. *HCT* 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. *POST* is the post-event dummy that has a value of 1 if it is in 1998 (2012) or after for the 1997 (2011) event, and 0 otherwise. *RPR* is China's political risk relative to the U.S. based on ICRG political risk ratings of the previous calendar 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 average county-level nominal personal income growth of the next five years or remaining years for which data are available. *FUTURE POPG5Y* is the average county-level population growth of the next five years or remaining years for which data are available. MSA fixed effects interacted with year fixed effects are included. The robust standard errors are based on clustering at the state level. Estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Sample:	Full	Full	No-top-CN	No-top-CN	Full	No-top-CN
Event:	2011	1997	2011	1997	—	—
	(1)	(2)	(3)	(4)	(5)	(6)
*POST*HCT*	0.005	0.013***	0.012**	0.011**		
	(0.005)	(0.005)	(0.005)	(0.005)		
*RPR*HCT*					0.021***	0.020***
					(0.008)	(0.006)
HCT	0.012*	-0.004*	0.003	-0.005***	-0.021**	-0.023**
	(0.007)	(0.002)	(0.003)	(0.002)	(0.009)	(0.009)
PIG0Y	0.045**	0.031	0.035*	0.025	0.041***	0.034**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.013)	(0.013)
POPG0Y	0.125***	0.072	0.125***	0.034	0.108***	0.107***
	(0.012)	(0.085)	(0.008)	(0.068)	(0.013)	(0.012)
FUTURE PIG5Y	0.072	0.069***	0.030	0.078**	0.059**	0.046*
	(0.054)	(0.023)	(0.038)	(0.031)	(0.028)	(0.026)
FUTURE POPG5Y	-0.101	-0.186*	-0.083	-0.137*	-0.191***	-0.152***
	(0.061)	(0.100)	(0.059)	(0.079)	(0.056)	(0.056)
Observations	8,214	8,050	6,887	6,731	25,332	21,175
R^2	0.933	0.834	0.935	0.817	0.917	0.912

Table 4. Spillover Effects of Chinese Capital Inflows: Housing Price Growth in U.S. Counties without Chinese Population – 1997 and 2011 Events

The sample periods for the 1997 and 2011 events are 1992-2002 and 2006-2016, respectively. The event years are excluded. We consider only counties that have no recorded Chinese population as of 2010. The dependent variable is the county-level annual nominal housing price growth. *HCT* is the dummy variable that has a value of 1 if the 2010 state-level Chinese population (by number or proportion) is above the median of the sample and 0 otherwise. For "No top-CN" samples, *states* with a top 10% Chinese-populated MSA (in List 3 in Supplementary Appendix) are excluded. *POST* is the post-event dummy that has a value of 1 if it is in 1998 (2012) or after for the 1997 (2011) event, and 0 otherwise. *PIG0Y* is the contemporaneous county-level annual nominal personal income growth. *POPG0Y* is the contemporaneous county-level annual population growth. *FUTURE PIG5Y* is the average county-level nominal personal income growth of the next five years or the remaining years for which data are available. *FUTURE POPG5Y* is the average county-level population growth of the next five years or the remaining years for which data are available. County and year fixed effects are included. The robust standard errors are based on clustering at the state level. Estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Sample:	Full	Full	Full	Full	No top-CN	No top-CN	No top-CN	No top-CN
Event:	2011	2011	1997	1997	2011	2011	1997	1997
HIGH CHINESE	Proportion	Number	Proportion	Number	Proportion	Number	Proportion	Number
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*POST*HCT*	0.016***	0.014≈***	0.011**	0.014***	0.016**	0.013**	1.7e-4	4.9e-4
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
HCT	-0.012***	-0.012***	-0.007*	-0.009**	-0.013***	-0.013***	0.003	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
PIG0Y	0.099***	0.095***	0.073***	0.075***	0.071***	0.069***	0.044**	0.044**
	(0.021)	(0.021)	(0.017)	(0.017)	(0.022)	(0.023)	(0.017)	(0.017)
POPG0Y	0.239***	0.242***	0.379***	0.373***	0.222**	0.224**	0.400***	0.400***
	(0.088)	(0.089)	(0.058)	(0.058)	(0.085)	(0.088)	(0.066)	(0.066)
FUTURE PIG5Y	-0.038	-0.048	-0.033	-0.021	-0.095*	-0.118***	-0.062	-0.063
	(0.049)	(0.051)	(0.036)	(0.034)	(0.049)	(0.041)	(0.040)	(0.045)
FUTURE POPG5Y	0.540***	0.556***	-0.006	-0.019	0.665***	0.706***	0.061	0.060
	(0.094)	(0.095)	(0.060)	(0.058)	(0.119)	(0.117)	(0.069)	(0.069)
Observations	23,538	23,538	17,761	17,761	14,998	14,998	11,020	11,020
R^2	0.380	0.378	0.172	0.175	0.360	0.358	0.215	0.214

Table 5. Spillovers and Distance-decay: Housing Price Growth in Non-Chinese Counties – 1997 and 2011 Events

The sample periods of the 1997 and 2011 events are 1992-2002 and 2006-2016, but exclude the event years. We consider only counties that have no recorded Chinese population as of 2010. We first identify the top 20% Chinese populated counties in the U.S., based on the Census 2010 population. Next, we calculate the distance (average distance) of a non-Chinese county (in any state that includes a top 20% Chinese populated county) from the top 20% county (counties) located in that state. Non-Chinese counties in states that do not include a top 20% Chinese county are not included in the sample. In columns (1) and (3), *LN(DIST)* is the logarithm of the simple average distance, while in columns (2) and (4), it is the logarithm of the weighted average distance, where the weight is the number of Chinese in the top Chinese counties in the state. The dependent variable is the county-level annual nominal housing price growth. *POST* is the post-event dummy that has a value of 1 if it is in 1998 (2012) or after for the 1997 (2011) event, and 0 otherwise. *PIG0Y* is the contemporaneous county-level annual nominal personal income growth. *POPG0Y* is the contemporaneous county-level annual population growth. *FUTURE PIG5Y* is the average county-level nominal personal income growth of the next five years or the remaining years for which data are available. *FUTURE POPG5Y* is the average county-level population growth of the next five years or the remaining years for which data are available. State interacted with year fixed effects are included. The robust standard errors are based on clustering at the county level. Estimated coefficients and the robust standard errors (in parentheses) are reported. *** indicates the 1% level of significance.

Event:	2011	2011	1997	1997
Distance from top 20% Chinese populated counties (DIST):	Weighted average	Simple average	Weighted average	Simple average
	(1)	(2)	(3)	(4)
*POST*LN(DIST)*	-0.030***	-0.030***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.001)	(0.001)
LN(DIST)	0.022***	0.023***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
PIG0Y	0.066***	0.066***	0.075***	0.075***
	(0.016)	(0.016)	(0.020)	(0.020)
POPG0Y	0.362***	0.367***	0.229***	0.229***
	(0.063)	(0.063)	(0.053)	(0.053)
FUTURE PIG5Y	0.111***	0.110***	0.001	0.001
	(0.036)	(0.035)	(0.037)	(0.037)
FUTURE POPG5Y	-0.138	-0.142	-0.078	-0.081
	(0.088)	(0.088)	(0.072)	(0.072)
Observations	9,234	9,234	7,439	7,439
Adjusted R^2	0.600	0.601	0.288	0.288

Table 6. Chinese Capital Inflow and Employment and Deposit Growth in U.S. MSAs – 1997 and 2011 Events

The sample periods of the 1997 and 2011 events are 1992Q1-2002Q1 and 2006Q2-2016Q2, but exclude the event years, respectively. We consider only those MSAs that are in the bottom or top quarter of the 1880 state-level Chinese population of all MSAs. In columns (1)-(2), the dependent variable is the MSA-level annual overall employment growth. In columns (3) and (4), the dependent variable is the MSA-level annual employment growth of the construction sector. In columns (5) and (6), the dependent variable is the MSA-level annual employment growth of the non-construction sector. In Column (7), the dependent variable is the MSA-level quarterly deposit growth. *HIGH CHINESE* is the dummy variable that has a value of 1 for the MSAs in the top quarter Chinese populated group, and 0 for the MSAs in the bottom quarter Chinese populated group. *POST* is the post-event dummy that has a value of 1 for 1998 (2012) or after for the 1997 (2011) event, and 0 otherwise. *LAGGED SRPIG20Q* is the state-level average real personal income growth of the past 20 quarters. MSA fixed effects are included. The robust standard errors are based on clustering at the year or quarter level. 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.

Dependent variable:	Overall employment growth		Construction employment growth		Non-construction employment growth		Deposit growth
Event:	2011	1997	2011	1997	2011	1997	2011
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*POST*HCT*	0.006***	0.006#	0.028**	0.018*	0.005≈**	0.004	0.011**
	(0.002)	(0.004)	(0.010)	(0.010)	(0.002)	(0.004)	(0.004)
POST	0.011	-0.014*	0.054*	-0.033*	0.009	-0.011*	-0.005
	(0.009)	(0.006)	(0.027)	(0.015)	(0.008)	(0.005)	(0.005)
LAGGED SRPIG20Q	0.581	0.409	1.231	3.821*	0.582	0.204	1.518**
	(0.670)	(0.557)	(2.215)	(2.012)	(0.575)	(0.630)	(0.671)
Observations	2,030	1,850	1,732	1,684	1,990	1,850	7,271
Adjusted R^2	0.141	0.252	0.181	0.054	0.093	0.168	0.014

Table 7. Transmission Channel: Chinese Capital Inflows, Relative Political Risk, and Employment and Deposit Growth

The sample period is 2002-2016. We consider only those MSAs that are in the bottom or top quarter of the 1880 state-level Chinese population of all MSAs. In columns (1) and (2), the dependent variable is the MSA-level annual overall employment growth. In columns (3) and (4), the dependent variable is the MSA-level annual employment growth of the construction sector. In columns (5) and (6), the dependent variable is the average of the MSA-level quarterly deposit growth in a year. *HCT* is a dummy variable that has a value of 1 for the MSAs in the top quarter Chinese populated group, and 0 for the MSAs in the bottom quarter Chinese populated group. *RPR* is China's political risk relative to the U.S. based on ICRG political risk ratings of the previous calendar year. The dependent variable is the MSA-level quarterly deposit growth. *LAGGED REAL HOUSING PRICE GROWTH* is the average of the MSA-level quarterly real housing price growth, as a percentage, of the previous calendar year. *LAGGED SRPIG20Q* is the state-level average real personal income growth, as a percentage, of the past 20 quarters. MSA fixed effects are included. The robust standard errors are based on clustering at the year level. Estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Dependent variable:	Overall employment growth		Construction employment growth		Deposit growth	
	(1)	(2)	(3)	(4)	(5)	(6)
*RPR*HCT*	0.025***	0.010	0.076*	0.036*	0.033*	0.029**
	(0.008)	(0.011)	(0.041)	(0.021)	(0.019)	(0.013)
RPR	-0.004	-0.003	0.066	0.038	-0.032*	-0.037*
	(0.029)	(0.018)	(0.095)	(0.061)	(0.018)	(0.020)
LAGGED REAL HOUSING PRICE GROWTH		0.006***		0.027***		0.003*
		(0.001)		(0.004)		(0.001)
LAGGED SRPIG20Q	-0.002	-0.010	0.011	-0.025	0.021**	0.015
	(0.006)	(0.006)	(0.027)	(0.022)	(0.008)	(0.009)
Observations	3,184	2,655	2,747	2,452	2,748	2,613
Adjusted R^2	0.088	0.360	0.001	0.406	0.059	0.073

Table 8. Chinese Student Inflows and U.S. Housing Prices.

In Column (1) [(2)-(4)], the sample consists of the bottom [top] one-third hosting states, in terms of the 2017 foreign student number. For the 2011 event, the sample period is 2006Q2-2016Q2, excluding the event quarter. For each state, we partition its MSAs into two groups—high and low Chinese population—based on the median 2010 MSA-level Chinese population. The dependent variable is the difference in average real MSA quarterly housing price growth between the high and low Chinese groups. *ΔCHINSTU* (*ΔNCHINSTU*) is the change in the number of the Chinese (non-Chinese) international students in the U.S., in millions, from the previous calendar year to the current calendar year. *POST* is the post-event dummy for the 2011 event that has a value of 1 if it is in 2011Q3 or after, and 0 otherwise. *RPR* is China's political risk relative to the U.S. based on ICRG political risk ratings of the previous calendar year. *ΔRPIG0Y* is the difference in the average contemporaneous real MSA personal income growth of the current calendar year between the high and low Chinese groups. *ΔPOPG0Y* is the difference in the average contemporaneous MSA population growth of the current calendar year between the high and low Chinese groups. *FUTURE ΔRPIG5Y* is the average *ΔPRIG* of the next five calendar years or remaining years for which data are available. *FUTURE ΔPOPG5Y* is the average *ΔPOPG* of the next five calendar years or remaining years for which data are available. State fixed effects are included. Estimated coefficients and the robust standard errors (in parentheses) are reported. *** and ** indicate the 1% and 5% levels of significance, respectively.

Hosting states:	Bottom ⅓	Top ⅓	Top ⅓	Top ⅓
Sample period:	2000-2016	2000-2016	2011 event	2000-2016
	(1)	(2)	(3)	(4)
ΔCHINSTU	0.031	0.059***	0.069***	-0.366**
	(0.026)	(0.010)	(0.025)	(0.144)
ΔNCHINSTU	0.000	0.030***	0.080***	0.304***
	(0.013)	(0.004)	(0.025)	(0.101)
*POST*ΔCHINSTU*			0.154≈***	
			(0.063)	
*POST*ΔNCHINSTU*			-0.019	
			(0.031)	
POST			-0.003	
			(0.002)	
*RPR*ΔCHINSTU*				0.285***
				(0.110)
*RPR*ΔNCHINSTU*				-0.217***
				(0.073)
RPR				0.012***
				(0.002)
ΔRPIG0Y	0.065***	0.005	0.007	-0.004
	(0.021)	(0.012)	(0.014)	(0.012)
ΔPOPG0Y	0.193***	0.094***	0.011	0.032
	(0.066)	(0.030)	(0.030)	(0.030)
FUTURE ΔRPIG5Y	0.160***	-0.014	-0.160***	-0.067***
	(0.054)	(0.024)	(0.034)	(0.023)
FUTURE ΔPOPG5Y	0.072	0.123**	0.218***	0.130***
	(0.097)	(0.052)	(0.076)	(0.050)
CONSTANT	-0.001	-0.001***	-0.003***	-0.015***
	(0.001)	(0.000)	(0.001)	(0.002)
Observations	496	1,116	720	1,054
Adjusted R^2	0.0913	0.140	0.284	0.193

Table 9. Chinese Capital Inflow and Housing Prices in Global Metropolitan Cities

The dependent variable is the median of the quarterly housing price growth of all major cities of a country. In columns (1) and (5), the sample period covers 2006Q2-2016Q2, but excludes 2011Q2. In columns (2) – (4), the sample period is 2000-2016. *POST* is the post-event dummy that has a value of 1 for 2011Q3 or after, and 0 for the other quarters. *CHPINF* (*CHSTUINF*) is the logarithm of the ratio of a country's contemporaneous annual Chinese population (student) inflow to overall foreign (foreign student) inflow. The sample in columns (2)-(4) consists of the extreme top and bottom x of *CHINF* (by year), where x = ½, ⅓, and ⅕, respectively. *HCPINF* has a value of 1 for countries in the top x, and 0 for countries in the bottom x. RPR_C is China's political risk relative to country *C* 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. In columns (1) and (5), country fixed effects interacted with *POST* and country fixed effects interacted with (1 – *POST*) are included. In columns (2)-(4), country fixed effects are included. The robust standard errors are based on clustering at the quarter level. This table reports the results of the weighted least square regressions, where the inverse of the contemporaneous annual country-level urban population is the weight in columns (1)-(4) and the contemporaneous annual country-level ratio of the total foreign student number to the urban population is the weight in Column (5). Estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Extreme x% Chinese inflow by proportion	—	x = ½	x = ⅓	x = ⅕	—
	(1)	(2)	(3)	(4)	(5)
*POST*CHPINF*	0.010***				
	(0.003)				
CHPINF	-0.006**				
	(0.003)				
RPR_C**HCHPINF*		0.016**	0.044***	0.055***	
		(0.007)	(0.010)	(0.011)	
RPR_C		0.002	0.001	0.020	
		(0.027)	(0.024)	(0.025)	
*POST*CHSTUINF*					0.016***
					(0.004)
CHSTUINF					0.004*
					(0.002)
GDPG0Q	0.630***	0.456***	0.218**	0.416**	0.669***
	(0.157)	(0.142)	(0.099)	(0.160)	(0.119)
FUTURE GDPG20Q	1.556**	1.041*	0.639	1.674**	1.214**
	(0.714)	(0.524)	(0.554)	(0.655)	(0.467)
Observations	1,010	1,522	1,016	669	1036
R^2	0.234	0.162	0.253	0.353	0.260

Table 10. Chinese Capital and Population Inflows and Employment Growth in Global Metropolitan Areas

The dependent variable is the median of the annual employment growth of major metropolitan areas of a country. In columns (1) and (2), the sample period covers 2006-2016, but excludes 2011. In Columns (3) & (4), the sample period covers 2002-2017. *POST* is the post-event dummy for the 2011 event that has a value of 1 for 2012 or after, and 0 for the other years. *CHPINF* is the logarithm of the contemporaneous annual Chinese proportion of the country-level foreign population inflow. In columns (3) and (4), the sample consists only of those countries in the extreme top or bottom ⅓ *CHPINF* (by year). *HCHPINF* takes a value of 1 (0) for countries in the top (bottom) ⅓ of *CHPINF*. RPR_C is China's political risk relative to country *C* in which an area is located, based on ICRG political risk ratings of the previous calendar year. *LAGGED HOUSING PRICE GROWTH* is the quarterly average of the country's median city-level housing price growth of the previous calendar year. *FOREIGN OVERALL INFLOW* is the logarithm of 1 plus the contemporaneous annual foreign overall inflow of the country. In columns (1) and (2), country fixed effects interacted with *POST* and country fixed effects interacted with (1 – *POST*) are included. In columns (3) and (4), country fixed effects are included. The robust standard errors are based on clustering at the year level. Estimated coefficients and the robust standard errors (in parentheses) are reported. *** and ** indicate the 1% and 5% level of significance, respectively.

	(1)	(2)	(3)	(4)
*POST*CHPINF*	0.007≈**	0.007**		
	(0.003)	(0.003)		
CHPINF	-0.005	-0.006**		
	(0.002)	(0.002)		
RPR_C**CHPINF*			0.013**	-0.017
			(0.005)	(0.049)
RPR_C			-0.015	-0.021
			(0.032)	(0.028)
LAGGED HOUSING PRICE GROWTH				0.537***
				(0.133)
FOREIGN OVERALL INFLOW		0.008	0.019***	0.022***
		(0.005)	(0.006)	(0.007)
Observations	255	255	236	161
R^2	0.316	0.326	0.238	0.526

Table A1. Chinese Capital Inflow and Real Housing Price Growth in U.S. MSAs, Controlling for Non-Chinese Asian Population

The sample periods of the 1997 and 2011 events are 1992Q1-2002Q1 and 2006Q2-2016Q2, but exclude the event quarters respectively. We consider only those MSAs that are in the bottom or top quarter of the 1880 state-level Chinese population of all MSAs. *HCT* is a dummy variable that has a value of 1 for the MSAs in the top quarter Chinese populated group, and 0 for the MSAs in the bottom quarter Chinese populated group. The dependent variable is the MSA-level quarterly real housing price growth. *POST* is the post-event dummy that has a value of 1 for 1997Q2 (2011Q3) or after for the 1997 (2011) event, and 0 otherwise. *NON-CHINESE ASIAN POPULATION* is the 2010 MSA-level non-Chinese Asian population in millions. *RPIG0Y* is the MSA-level real annual personal income growth of the current calendar year. *POPG0Y* is the MSA-level annual population growth of the current calendar year. *LAGGED SRPIG20Q* is the state-level average real personal income growth of the past 20 quarters. *FUTURE RPIG5Y* is the MSA-level average real personal income growth of the next five calendar years or remaining calendar years for which data are available. *FUTURE POPG5Y* is the MSA-level average population growth of the next five calendar years or remaining calendar years for which data are available. MSA fixed effects are included. The robust standard errors are based on clustering at the quarter level. Estimated coefficients and the robust standard errors (in parentheses) are reported. *** and ** indicate the 1% and 5% levels of significance, respectively.

Event:	2011	1997
	(1)	(2)
*POST*HCT*	0.011***	0.003***
	(0.002)	(0.001)
POST	0.015***	0.001
	(0.004)	(0.002)
*POST*NON-CHINESE ASIAN POPULATION*	0.004	0.031***
	(0.003)	(0.003)
RPIG0Y	0.104**	0.079***
	(0.040)	(0.019)
POPG0Y	0.088***	0.348***
	(0.020)	(0.036)
LAGGED SRPIG20Q	0.013	1.173***
	(0.477)	(0.220)
FUTURE RPIG5Y	0.114	0.097***
	(0.077)	(0.029)
FUTURE POPG5Y	0.577***	0.304***
	(0.092)	(0.071)
Observations	6,505	7,000
Adjusted R^2	0.382	0.342

Table A2. Chinese Capital Inflow and Nominal Housing Price Growth in U.S. Counties

In columns (1)-(4), the sample periods of the 1997 and 2011 events are 1992-2002 and 2006-2016, but exclude the event years, respectively. In columns (5) and (6), the sample period is 1986-2016. For "No-top-CN" samples, the top 10% Chinese-populated MSAs (in List 2 in Supplementary Appendix) are excluded. The dependent variable is the county-level annual nominal housing price growth. *HCT* 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). *POST* is the post-event dummy that has a value of 1 if it is in 1998 (2012) or after for the 1997 (2011) event, and 0 otherwise. *RPR* is China's political risk relative to the U.S. based on ICRG political risk ratings of the previous calendar 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 average county-level nominal personal income growth of the next five years or remaining years for which data are available. *FUTURE POPG5Y* is the average county-level population growth of the next five years or remaining years for which data are available. County fixed effects are included. The robust standard errors are based on clustering at the year level. Estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively. # indicates a p-value of 0.117.

Sample:	Full	Full	No-top-CN	No-top-CN	Full	No-top-CN
Event:	2011	1997	2011	1997	—	—
	(1)	(2)	(3)	(4)	(5)	(6)
*POST*HCT*	0.055**	0.040***	0.053**	0.036***		
	(0.021)	(0.008)	(0.021)	(0.009)		
POST	0.018	0.003	0.016	0.001		
	(0.016)	(0.005)	(0.016)	(0.005)		
*RPR*HCT*					0.102*	0.090[#]
					(0.055)	(0.056)
RPR					0.016	0.010
					(0.037)	(0.036)
PIG0Y	0.229**	0.084**	0.208**	0.074*	0.190**	0.172**
	(0.084)	(0.034)	(0.080)	(0.033)	(0.076)	(0.072)
POPG0Y	0.521***	0.589***	0.514***	0.551***	0.677***	0.669***
	(0.141)	(0.100)	(0.131)	(0.099)	(0.174)	(0.171)
FUTURE PIG5Y	0.191*	-0.118	0.157	-0.099	0.127	0.131
	(0.102)	(0.068)	(0.092)	(0.069)	(0.117)	(0.109)
FUTURE POPG5Y	1.952***	0.257**	2.009***	0.287**	0.808***	0.904***
	(0.593)	(0.102)	(0.577)	(0.104)	(0.275)	(0.271)
Observations	25,610	19,913	24,450	18,754	65,831	62,193
R^2	0.202	0.180	0.192	0.175	0.135	0.132

Table A3. Main Results without California

This table reports the results for which we exclude California and re-run the main regressions. *POST* is the post-event dummy. For the MSA regressions, *HCT* is the dummy variable that has a value of 1 (0) for the MSAs in the top (bottom) quintile of the 1880 state-level Chinese population of all MSAs. For the county regressions, *HCT* is the 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. The other variable definitions and regression specifications are given in the respective main tables. For brevity, we report only the results of the key variable of interest. 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 2 (1)	Table 2 (2)	Table 3 (1)	Table 3 (2)	Table 6 (1)	Table 6 (7)
	MSA housing	MSA housing	County housing	County housing	MSA employment	MSA deposit
Event:	2011	1997	2011	1997	2011	2011
	(1)	(2)	(3)	(4)	(5)	(6)
*POST*HCT*	0.007***	0.002*	0.005	0.016***	0.004**	0.011*
	(0.001)	(0.001)	(0.006)	(0.005)	(0.002)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	MSA	MSA	MSA×Year	MSA×Year	MSA	MSA
S.E. clustering	Quarter	Quarter	State	State	Year	Quarter
Observations	4,703	5,000	7,874	7,710	1,380	5,146
R^2	0.351	0.246	0.923	0.797	0.220	0.035

Table A4. Main Results for Regional Classifications Based on Overall Population

In the regressions reported in the upper panel below, we replace the high Chinese population dummy (*HCT*) by a high total (aggregate) population dummy (*HT*) and re-run the main regressions. In the bottom panel, we re-run our main regressions by additionally controlling for the interaction of *HT* and *POST*. *POST* is the post-event dummy. For the MSA regressions, *HT* is a dummy variable that has a value of 1 (0) for an MSA in the top (bottom) quartile of MSAs ranked on the basis of 1880 overall state-level population. *HCT* is a dummy variable that has a value of 1 (0) for an MSA in the top (bottom) quartile of MSAs ranked on the basis of 1880 state-level Chinese population. For the county regressions, *HT* is a dummy variable that has a value of 1 if the 1870 county-level aggregate population (by number) is above the median in its MSA, and 0 otherwise. *HCT* 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. The other variable definitions and regression specifications are given in the respective main tables. For brevity, we report only the coefficients of the key variable of interest. 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 2 (1)	Table 2 (2)	Table 3 (1)	Table 3 (2)	Table 6 (1)	Table 6 (7)
	MSA housing	MSA housing	County housing	County housing	MSA employment	MSA deposit
Event:	2011	1997	2011	1997	2011	2011
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
*POST*HT*	-0.010***	-0.001	0.002	0.004***	-0.006	-0.005
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	MSA	MSA	MSA×Year	MSA×Year	MSA	MSA
S.E. clustering	Quarter	Quarter	State	State	Year	Quarter
Observations	6,809	7,120	8,214	8,050	1,906	7,119
R^2	0.450	0.239	0.932	0.834	0.306	0.034
	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)
*POST*HCT*	0.012***	0.004***	0.004	0.011**	0.007***	0.011≈***
	(0.002)	(0.001)	(0.005)	(0.005)	(0.002)	(0.004)
*POST*HT*	-0.016***	0.001	0.001	0.003**	-0.013**	-0.006
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	MSA	MSA	MSA×Year	MSA×Year	MSA	MSA
S.E. clustering	Quarter	Quarter	State	State	Year	Quarter
Observations	6,905	7,520	8,214	8,050	2,030	7,151
R^2	0.406	0.329	0.933	0.835	0.234	0.040

Table A5. Main Results with Coastal States

We re-run our main regressions by further incorporating a dummy variable for coastal states (*COAST*). The results are reported below. *POST* is the post-event dummy. For the MSA regressions, *HCT* is the dummy variable that has a value of 1 (0) for the MSAs in the top (bottom) quarter of the 1880 state-level Chinese population of all MSAs. For the county regressions, *HCT* 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). For brevity, we report only the coefficients of the key variable of interest. 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 2 (1)	Table 2 (2)	Table A2 (1)	Table A2 (2)	Table 6 (1)	Table 6 (7)
	MSA housing	MSA housing	County housing	County housing	MSA employment	MSA deposit
Event:	2011	1997	2011	1997	2011	2011
	(1)	(2)	(3)	(4)	(5)	(6)
*POST*COAST*	0.001	0.007***	-0.003	0.028***	0.003***	-0.002
	(0.001)	(0.001)	(0.009)	(0.006)	(0.001)	(0.005)
*POST*HCT*	0.011***	0.004***	0.056**	0.030***	0.006***	0.011**
	(0.002)	(0.001)	(0.019)	(0.007)	(0.002)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	MSA	MSA	County	County	MSA	MSA
S.E. clustering	Quarter	Quarter	Year	Year	Year	Quarter
Observations	7,025	7,520	25,610	19,913	2,030	7,271
R^2	0.391	0.351	0.202	0.214	0.229	0.039

Table A6. Main Results with Residential Land Use Regulatory Index

We re-run our main housing regressions by additionally controlling for a composite regulatory index (*LURI*). The results are reported below. *LURI* is a standardized measure of residential land use regulatory restrictiveness, based on a 2018 survey of communities across nationwide metropolitan areas in the U.S. The index is the first factor of the factor analysis of a dozen subindexes that capture the different components of local regulatory environment (see Gyourko, Hartley and Krimmel 2019). For MSA regressions, *LURI* is the average of *LURI* of all the units in the same MSA. For county regressions, *LURI* is the average of *LURI* of all the units in the same county. *POST* is the post-event dummy. For the MSA regressions, *HCT* is the dummy variable that has a value of 1 (0) for the MSAs in the top (bottom) quarter of the 1880 state-level Chinese population of all MSAs. For the county regressions, *HCT* is the dummy variable that has a value of 1 if the 1870 county-level Chinese population, by number, is above the median, and 0 otherwise. *RPR* is China's political risk relative to the U.S. based on ICRG political risk ratings of the previous calendar year. For brevity, we report only the coefficients of the key variable of interest. Estimated coefficients and the robust standard errors (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	Table 2 (1)	Table 2 (2)	Table 3 (1)	Table 3 (2)	Table 2 (5)	Table 3 (5)
	MSA housing	MSA housing	County housing	County housing	MSA housing	County housing
	2011	1997	2011	1997	—	—
	(1)	(2)	(3)	(4)	(5)	(6)
*POST*LURI*	0.003***	0.002***	0.000	0.000		
	(0.001)	(0.000)	(0.001)	(0.001)		
*POST*HCT*	0.011***	0.003***	0.006*	0.011**		
	(0.002)	(0.001)	(0.003)	(0.005)		
*RPR*LURI*					0.005**	0.000
					(0.002)	(0.000)
*RPR*HCT*					0.018***	0.019**
					(0.005)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	MSA	MSA	MSA×Year	MSA×Year	MSA	MSA×Year
S.E. clustering	Quarter	Quarter	State	State	Quarter	State
Observations	5,418	5,880	5,180	5,149	18,312	16,332
R^2	0.412	0.383	0.963	0.920	0.155	0.952

Table A7. Main Reduced-form Results Based on an Indicator for Large Change in China's Political Risk Relative to U.S.

We replace China's political risk relative to U.S. (*RPR*) in the reduced-form regressions by an indicator variable for large change in *RPR*. We first compute *CRPR*(t) = *RPR*(t) – [*RPR*(t-1) + *RPR*(t-2) + *RPR* (t-3)]/3. We then identify the top 10% *CRPR* of the whole sample period. In the odd columns below, *DRPR* is a dummy that takes a value of 1 if *CRPR* is in the top 10% in either of the previous two years, and 0 otherwise. In the even columns, *DRPR* is a dummy that takes a value of 1 if *CRPR* is in the top 10% in any of the previous three years, and 0 otherwise. For the MSA regressions, *HCT* is the dummy variable that has a value of 1 (0) for the MSAs in the top (bottom) quarter of the 1880 state-level Chinese population of all MSAs. For the county regressions, *HCT* is the dummy variable that has a value of 1 if the 1870 county-level Chinese population, by number, is above the median, and 0 otherwise. The other variable definitions and regression specifications are given in the respective main tables. For brevity, we report only the results of the key variable of interest. 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 2 (5)	Table 2 (5)	Table 3 (5)	Table 3 (5)	Table 7 (1)	Table 7 (1)	Table 7 (5)	Table 7 (5)
Top 10% CRPR	t-1 or t-2	t-1, t-2, or t-3	t-1 or t-2	t-1, t-2, or t-3	t-1 or t-2	t-1, t-2, or t-3	t-1 or t-2	t-1, t-2, or t-3
	MSA housing	MSA housing	County housing	County housing	MSA employment	MSA employment	MSA deposit	MSA deposit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*DRPR*HCT*	0.003***	0.005***	0.011***	0.011***	0.006***	0.005***	0.005**	0.007≈***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	MSA	MSA	MSA×Year	MSA×Year	MSA	MSA	MSA	MSA
S.E. clustering	Quarter	Quarter	State	State	Year	Year	Year	Year
Observations	21,268	21,268	23,307	23,307	2,700	2,700	2,613	2,613
R^2	0.122	0.134	0.920	0.920	0.150	0.149	0.130	0.131

Table A8. Main Results Using Imputed *CINFC*

We construct a series for the imputed U.S.-China trade data gap (*ICINFC*), which captures capital flight from China to the U.S., end examine the effect of *ICINFC* on housing price growth, employment growth, and deposit growth. For "No-top-CN" samples, the top 10% Chinese-populated MSAs (in List 2 in Supplementary Appendix) are excluded. For the MSA regressions, *HCT* is the dummy variable that has a value of 1 (0) for the MSAs in the top (bottom) quarter of the 1880 state-level Chinese population of all MSAs. For the county regressions, *HCT* is the 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. The other variable definitions and regression specifications are given in the respective main tables. For brevity, we report only the results of the key variable of interest. 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 2 (5)	Table 2 (6)	Table 3 (5)	Table 3 (6)	Table 7 (1)	Table 7 (5)
Sample:	Full	No-top-CN	Full	No-top-CN	Full	Full
	MSA housing	MSA housing	County housing	County housing	MSA employment	MSA deposit
	(1)	(2)	(2)	(4)	(3)	(4)
*ICINFC**HCT*	0.047***	0.044***	0.006	0.042**	0.024**	0.058**
	(0.006)	(0.006)	(0.022)	(0.016)	(0.010)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	MSA	MSA	MSA×Year	MSA×Year	MSA	MSA
S.E. clustering	Quarter	Quarter	State	State	Year	Year
Observations	19,012	18,152	3,400	1,988	2,700	2,613
Model *F* statistics	15.91***	16.20***	50.44***	215.67***	3.24*	5.30**

Table A9. Main Results Using a Synthetic Control Method

We reconsider the main regressions using synthetically matched samples. Each (treated) *HIGH CHINESE* MSA/county is matched with a synthetic control MSA/county formed by a weighted average of the *LOW CHINESE* MSAs/counties, based on regression models over the pre-event period. For the MSA regressions, *HCT* is the dummy variable that has a value of 1 for the MSAs in the top quarter of the 1880 state-level Chinese population of all MSAs, and 0 for the synthetic control MSAs. For the county regressions, *HCT* is the 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 for the synthetic control counties. *POST* is the post-event dummy. The other variable definitions and regression specifications are given in the respective main tables. For brevity, we report only the results of the key variable of interest. Estimated coefficients and the robust standard errors (in parentheses) are reported. The last row reports the difference in the dependent variable between the treated group and the synthetic control group over the matching period. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Reference Table (Column):	Table 2 (1)	Table 2 (2)	Table 3 (1)	Table 3 (2)	Table 6 (1)	Table 6 (7)
	MSA housing	MSA housing	County housing	County housing	MSA employment	MSA deposit
Event:	2011	1997	2011	1997	2011	2011
	(1)	(2)	(3)	(4)	(5)	(6)
*POST*HCT*	0.010***	0.010***	0.014**	0.012≈**	0.009***	0.012**
	(0.001)	(0.002)	(0.006)	(0.005)	(0.003)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	MSA	MSA	State×Year	State×Year	MSA	MSA
S.E. clustering	Quarter	Quarter	State	State	Year	Quarter
Observations	6,560	3,720	300	300	1,970	6,960
R^2	0.409	0.404	0.969	0.937	0.208	0.043
Pre-event dependent variable: Treated – Synthetic Control	-0.0061***	0.0001	-0.0019	-0.0045	-0.0029*	-0.0075***

Supplementary Appendix

"Capital Inflows and Property Prices: Ethnicity, Education, and Spillovers" by Yuk Ying Chang and Sudipto Dasgupta

Table SA1. **Chinese Population by U.S. Regions, Chinese and International Student Number by U.S. States, and List of Global Cities**. List 1 provides a list of states that had the top (Panel A) and bottom (Panel B) quartile of MSAs based on the state-level 1880 Chinese population. The list also indicates which of these states contain one of the top 10 Chinatowns and at least one leading city of an MSA that is among the top 10% in terms of Chinese population in the year 2010. List 2 provides a list of the top 10% of MSAs in terms of Chinese population in 2010. List 3 indicates the states that have and do not have an MSA in List 2 and provides their Chinese population and percent of Chinese population in 2010. List 4 shows the number of tertiary international students and Chinese proportion of this number by states in 2017 (the latest available information when we started the analysis) and also indicates which states do not contain an MSA in List 2. List 5 provides the sample of the global cities for studying the effect of Chinese population inflows on housing price growth. List 6 provides the sample of the global cities for studying the effect of Chinese student inflows on housing price growth.

List 1. States containing the top and bottom quartile of MSAs based on 1880 Chinese population

A. Top Chinese states	Chinese number	Chinese percent	Top 10 Chinatowns today	Contains leading city in a top 10% Chinese MSA (based on the 2010 population)
California	75132	8.69	2	✓
Oregon	9510	5.44		
Nevada	5416	8.70		
Idaho	3379	10.36		
Washington	3186	4.24	1	✓
Montana	1765	4.51		
Arizona	1630	4.03		✓
Wyoming	914	4.40		
New York	909	0.02	1	✓
Colorado	612	0.31		
Utah	501	0.35		
Louisiana	489	0.05		

List 1 (continued).

B. Bottom Chinese states	Chinese number	Chinese percent	Top 10 Chinatowns today	Contains leading city in a top 10% Chinese MSA (based on the 2010 population)
North Carolina	0	0.00		
Oklahoma	0	0.00		
Vermont	0	0.00		
Delaware	1	6.8e-4		
Alabama	4	3.2e-4		
Maryland	5	5.3e-4		
West Virginia	5	8.1e-4		
Virginia	6	4.0e-4		
Maine	8	1.2e-3		
North Dakota	8	0.02		
South Carolina	9	9.0e-4		
Kentucky	10	6.1e-4		
District of Columbia	13	7.3e-3	1	✓
New Hampshire	14	4.0e-3		
Wisconsin	16	1.2e-3		
Georgia	17	1.1e-3		✓

Source of Chinese population: U.S. Census Bureau
Sources of top Chinatowns today: USA Today, EscapeHere, Mercury News, Tripping

List 2. MSAs with the top 10% of 2010 Chinese population among MSAs with Chinese population (from the most Chinese populated to the least Chinese populated)

New York-Northern New Jersey-Long Island, NY-NJ-PA	*: New York City, NY
Los Angeles-Long Beach-Santa Ana, CA	*: Los Angeles, CA
San Francisco-Oakland-Fremont, CA	*: San Francisco, CA
San Jose-Sunnyvale-Santa Clara, CA	
Boston-Cambridge-Quincy, MA-NH	*: Boston, MA
Chicago-Joliet-Naperville, IL-IN-WI	*: Chicago, IL
Washington-Arlington-Alexandria, DC-VA-MD-WV	*: Washington DC
Seattle-Tacoma-Bellevue, WA	*: Seattle, WA
Houston-Sugar Land-Baytown, TX	*: Houston, TX
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	*: Philadelphia, PA
Honolulu, HI	*: Honolulu, HI
Sacramento-Arden-Arcade-Roseville, CA	
San Diego-Carlsbad-San Marcos, CA	
Dallas-Fort Worth-Arlington, TX	
Atlanta-Sandy Springs-Marietta, GA	
Riverside-San Bernardino-Ontario, CA	
Miami-Fort Lauderdale-Pompano Beach, FL	
Phoenix-Mesa-Glendale, AZ	

*: The top 10 Chinatowns today (sources: USA Today, EscapeHere, Mercury News, Tripping)
Source of Chinese population: the U.S. Census Bureau

List 3. States without an MSA in List 2 (indicated by ✓ below)

State	2010 Chinese pop.	2010 Chinese percent	Not in List 2
Alabama	9361	0.20	✓
Alaska	1916	0.28	✓
Arizona	34679	0.56	
Arkansas	3994	0.14	✓
California	1185064	3.23	
Colorado	24064	0.49	✓
Connecticut	29126	0.82	✓
Delaware	6358	0.72	
District of Columbia	5368	0.92	
Florida	66368	0.36	
Georgia	41333	0.44	
Hawaii	56594	4.24	
Idaho	3263	0.21	✓
Illinois	101536	0.80	
Indiana	21977	0.34	
Iowa	8331	0.28	✓
Kansas	11464	0.41	✓
Kentucky	8386	0.20	✓
Louisiana	9669	0.22	✓
Maine	3089	0.23	✓
Maryland	65363	1.15	
Massachusetts	120277	1.86	
Michigan	43726	0.44	✓
Minnesota	22373	0.43	✓
Mississippi	4665	0.16	✓
Missouri	18521	0.31	✓
Montana	1026	0.11	✓

List 3 (continued).

State	2010 Chinese pop.	2010 Chinese percent	Not in List 2
Nebraska	5432	0.30	✓
Nevada	29369	1.12	✓
New Hampshire	6172	0.47	
New Jersey	127926	1.47	
New Mexico	5898	0.29	✓
New York	554277	2.88	
North Carolina	30488	0.33	✓
North Dakota	1486	0.23	✓
Ohio	40135	0.35	✓
Oklahoma	8383	0.23	✓
Oregon	28239	0.75	✓
Pennsylvania	76762	0.61	
Rhode Island	7325	0.69	✓
South Carolina	9006	0.20	✓
South Dakota	1169	0.15	✓
Tennessee	15270	0.24	✓
Texas	144914	0.60	
Utah	11270	0.42	✓
Vermont	1732	0.28	✓
Virginia	57649	0.74	
Washington	89171	1.36	
West Virginia	2292	0.12	
Wisconsin	16530	0.29	
Wyoming	862	0.16	✓

List 4. The number of tertiary international students by state in 2017 (from the largest student number to the smallest student number)

State	International student number	Chinese student percent	Not in List 2
California	156879	38.4	
New York	118424	37.7	
Texas	85116	18.1	
Massachusetts	62926	33.6	
Illinois	52225	34.5	
Pennsylvania	51129	39.6	
Florida	45718	17.5	
Ohio	38680	39.9	✓
Michigan	34296	34.5	✓
Indiana	30600	35.6	
Washington	27801	36.8	
Missouri	23261	28.6	✓
New Jersey	22708	38.9	
Arizona	22670	36.4	
Georgia	21510	30.2	
Virginia	20400	28.1	
North Carolina	20112	29.4	✓
Maryland	19501	35.9	
Minnesota	15389	28.5	✓
Connecticut	14711	28.2	✓
Wisconsin	13220	39.3	
Oregon	13209	40.8	✓
Iowa	12488	42.6	✓
District of Columbia	12204	35.9	
Colorado	11527	30.9	✓
Kansas	10231	28.3	✓

List 4 (continued).

State	International student number	Chinese student percent	Not in List 2
Tennessee	9957	26.3	✓
Oklahoma	9789	22.3	✓
Alabama	9549	33.4	✓
Utah	8520	21.3	✓
Kentucky	7832	18.9	✓
Louisiana	7698	23.5	✓
South Carolina	6636	25.8	✓
Arkansas	6455	11.8	✓
Nebraska	6089	38	✓
Delaware	5664	46.4	
Rhode Island	5378	31.6	✓
New Hampshire	4671	27.7	
West Virginia	4192	11	
Hawaii	3855	10	
Mississippi	3765	15.2	✓
Idaho	3733	11.2	✓
New Mexico	3595	13.1	✓
Nevada	2901	28.7	✓
North Dakota	2393	19.6	✓
South Dakota	2108	10.2	✓
Vermont	1767	41	✓
Montana	1720	10.7	✓
Maine	1341	21.6	✓
Wyoming	1155	16.4	✓
Alaska	419	7.4	✓

Source: The Institue of International Education

List 5. Cities in the sample for studying the effect of Chinese population inflows on global city housing price growth.

Country	**City**	**Country**	**City**	**Country**	**City**
Australia	Adelaide	Israel	Haifa	Sweden	Gothenburg
Australia	Brisbane	Israel	Jerusalem	Sweden	Malmo
Australia	Canberra	Israel	Tel Aviv	Sweden	Stockholm
Australia	Darwin	Italy	Bologna	Switzerland	Bern
Australia	Hobart	Italy	Florence	Switzerland	Zurich
Australia	Melbourne	Italy	Genoa	U.K.	Aberdeen
Australia	Perth	Italy	Milan	U.K.	Birmingham
Australia	Sydney	Italy	Napoli	U.K.	Bristol
Austria	Vienna	Italy	Palermo	U.K.	Edinburgh
Belgium	Brussels	Italy	Rome	U.K.	Glasgow
Canada	Calgary	Italy	Trieste	U.K.	London
Canada	Edmonton	Italy	Turin	U.K.	Manchester
Canada	Halifax	Italy	Venice	U.K.	Nottingham
Canada	Hamilton	Japan	Tokyo	U.S.	Atlanta
Canada	Montreal	Latvia	Riga	U.S.	Boston
Canada	Ottawa Gatineau	Mexico	Mexico City	U.S.	Charlotte
Canada	Quebec	Netherlands	Amsterdam	U.S.	Chicago
Canada	Toronto	Netherlands	Hague	U.S.	Cleveland
Canada	Vancouver	Netherlands	Rotterdam	U.S.	Dallas
Canada	Victoria	Netherlands	Utrecht	U.S.	Denver
Canada	Winnipeg	New Zealand	Auckland	U.S.	Detroit
Chile	Santiago	New Zealand	Wellington	U.S.	Las Vegas
Denmark	Copenhagen	Norway	Oslo	U.S.	Los Angeles
Estonia	Tallinn	Portugal	Lisbon	U.S.	Miami
Finland	Helsinki	Portugal	Porto	U.S.	Minneapolis
France	Lille	Slovakia	Bratislava	U.S.	New York
France	Lyon	Slovenia	Ljubljana	U.S.	Phoenix
France	Marseille	South Korea	Seoul	U.S.	Portland
France	Paris	Spain	Barcelona	U.S.	San Diego
Greece	Athens	Spain	Madrid	U.S.	San Francisco
Greece	Thessaloniki	Spain	Malaga	U.S.	Seattle
Hungary	Budapest	Spain	Sevilla	U.S.	Tampa
Iceland	Reykjavik	Spain	Valencia	U.S.	Washington
Ireland	Dublin				

List 6. Cities in the sample for studying the effect of Chinese student inflows on global city housing price growth

Country	**City**	**Country**	**City**	**Country**	**City**
Australia	Adelaide	India	Ahmedabad	Spain	Madrid
Australia	Brisbane	India	Bengaluru	Spain	Malaga
Australia	Canberra	India	Chennai	Spain	Sevilla
Australia	Darwin	India	Delhi	Spain	Valencia
Australia	Hobart	India	Jaipur	Sweden	Gothenburg
Australia	Melbourne	India	Kanpur	Sweden	Malmo
Australia	Perth	India	Kochi	Sweden	Stockholm
Australia	Sydney	India	Kolkata	Switzerland	Bern
Austria	Vienna	India	Lucknow	Switzerland	Zurich
Belgium	Brussels	India	Mumbai	Turkey	Ankara
Brazil	Rio de Janeiro	Indonesia	Jakarta	Turkey	Istanbul
Brazil	Sao Paulo	Ireland	Dublin	Turkey	Izmir
Canada	Calgary	Israel	Haifa	U.K.	Aberdeen
Canada	Edmonton	Israel	Jerusalem	U.K.	Birmingham
Canada	Halifax	Israel	Tel Aviv	U.K.	Bristol
Canada	Hamilton	Italy	Bologna	U.K.	Edinburgh
Canada	Montreal	Italy	Florence	U.K.	Glasgow
Canada	Ottawa Gatineau	Italy	Genoa	U.K.	London
Canada	Quebec	Italy	Milan	U.K.	Manchester
Canada	Toronto	Italy	Napoli	U.K.	Nottingham
Canada	Vancouver	Italy	Palermo	U.S.	Atlanta
Canada	Victoria	Italy	Rome	U.S.	Boston
Canada	Winnipeg	Italy	Trieste	U.S.	Charlotte
Chile	Santiago	Italy	Turin	U.S.	Chicago
Colombia	Bogota	Italy	Venice	U.S.	Cleveland
Croatia	Zagreb	Japan	Tokyo	U.S.	Dallas
Cyprus	Larnaca	Latvia	Riga	U.S.	Denver
Cyprus	Limassol	Malaysia	Kuala Lumpur	U.S.	Detroit
Cyprus	Nicosia	Netherlands	Amsterdam	U.S.	Las Vegas
Denmark	Copenhagen	Netherlands	Hague	U.S.	Los Angeles
Estonia	Tallinn	Netherlands	Rotterdam	U.S.	Miami
Finland	Helsinki	Netherlands	Utrecht	U.S.	Minneapolis
France	Lille	Norway	Oslo	U.S.	New York
France	Lyon	Portugal	Lisbon	U.S.	Phoenix
France	Marseille	Portugal	Porto	U.S.	Portland
France	Paris	Russia	Moscow	U.S.	San Diego
Greece	Athens	Russia	St. Petersburg	U.S.	San Francisco
Greece	Thessaloniki	Slovakia	Bratislava	U.S.	Seattle
Hungary	Budapest	Slovenia	Ljubljana	U.S.	Tampa
Iceland	Reykjavik	Spain	Barcelona	U.S.	Washington

Table SA2. Pre-Event Characteristics of Heavily and Lightly Populated MSAs and Counties

This table compares the mean statistics of heavily populated ("HIGH POP" and *HTT*=1) and lightly populated ("LOW POP" and *HTT*=0) counties and MSAs for the years 1996 and 2010 (i.e., immediately before the 1997 and 2011 events, respectively). For MSAs, *HTT* is the dummy variable that has a value of 1 (0) for the MSAs in the top (bottom) quartile of the 1880 state-level aggregate population of all MSAs. For counties, *HTT* is the dummy variable that has a value of 1 if the 1870 county-level aggregate population (by number) is above the median in its MSA, and 0 otherwise. ***, **, and * indicate a statistically higher mean of a two-sided *t*-test of the null hypothesis that the means of HIGH POP and LOW POP counties/MSAs are the same, at the 1%, 5%, and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)
	MSAs	MSAs	Counties	Counties
Year	2010	1996	2010	1996
		Panel A: Chinese population		
		2010 Chinese population		
HIGH POP	12762		5349*	
LOW POP	4271		2776	
		2010 Chinese percent		
HIGH POP	0.49		0.56**	
LOW POP	0.33		0.30	
		Panel B: Key economic characteristics		
		Personal income per capita (dollars)		
HIGH POP	36921	23310	41272***	25319***
LOW POP	37888	23181	38597	23725
		Growth of personal income per capita		
HIGH POP	0.0228	0.0421	0.0265	0.0681***
LOW POP	0.0181	0.0429	0.0251	0.0600
		Labor-to-population ratio		
HIGH POP	0.4998	0.5088	0.5055**	0.5168***
LOW POP	0.4967	0.5018	0.4981	0.5061
		Growth of labor-to-population ratio		
HIGH POP	-0.0047**	0.0033**	-0.0017**	0.0036
LOW POP	-0.0162	-0.0018	-0.0104	0.0039
		Employment-to-population ratio		
HIGH POP	0.4526	0.4848	0.4587**	0.4932***
LOW POP	0.4503	0.4738	0.4521	0.4811
		Growth of employment-to-population ratio		
HIGH POP	-0.0037**	0.0049**	-0.0043***	0.0054
LOW POP	-0.0237	-0.0015	-0.0139	0.0063
		Bank deposit per capita (thousands of dollars)		
HIGH POP	15.70	—	73.64	—
LOW POP	53.89	—	112.90	—
		Growth of bank deposit per capita		
HIGH POP	-0.0530	—	-0.0133	—
LOW POP	-0.0537	—	0.0002	—