Local Effects of Global Capital Flows: A China Shock in the U.S. Housing Market*

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Abstract

This paper studies the real effects of foreign real estate capital inflows. Using transaction-level data, we document (i) a "China shock" in the U.S. housing market characterized by surging foreign Chinese housing purchases after 2008; and (ii) "home bias" in these purchases, as they concentrate in neighborhoods historically populated by ethnic Chinese. Exploiting their temporal and spatial variation, we find that these capital inflows raise local employment, with the effect transmitted through a housing net worth channel. However, they displace local lower-income residents. Our results show that real estate capital inflows can both stimulate the real economy and induce gentrification.

JEL Classification: F21, F38, E20, J21, R21

Keywords: Capital flows, employment, house price, displacement, China shock.

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1 Introduction

A nontraditional, opaque form of international capital flows—residential real estate capital flows—has become increasingly prominent. Ranging from 3 to 11 percent of gross capital inflows into the United States over the past decade, these flows possess characteristics of both foreign portfolio investment and foreign direct investment (FDI)—two traditional forms of international capital flows typically viewed as mutually exclusive.[1] Real estate capital flows are often contentious, as they are perceived to worsen housing affordability for domestic residents. In response, a number of countries have enacted regulations on purchases by foreign buyers.[2] Despite their unique characteristics and prominence as a policy concern, we still have a limited understanding of the economic significance of residential real estate capital flows. Whereas a few recent studies highlight their house price effects (e. g., Badarinza and Ramadorai 2018), this paper aims to provide causal evidence on the real effects of these capital flows.

In this paper, we quantify residential real estate capital inflows using transaction-level home purchase data and estimate the effects of these capital inflows on local employment. Using housing transaction data in California from 2001 to 2013, we document two salient phenomena: (i) a "China shock" in the U.S. real estate market characterized by an unprecedented surge in housing purchases by one particular group of foreigners, the Chinese, after 2008; and (ii) "home bias" in foreign Chinese housing purchases—namely, that these purchases tend to be concentrated in ZIP codes historically populated by ethnic Chinese.[3] Exploiting the temporal and spatial variation of real estate capital inflows from China, we show that they have a strong

[1] Estimates of the share of residential real estate capital inflows in gross capital inflows are based on data published by the International Monetary Fund Balance of Payments and the National Association of Realtors (NAR). However, it is unclear how these flows are recorded in the official balance of payments statistics, making them opaque and little understood.

[2] Regulations are often in the form of stamp taxes or additional duties. Multiple national and local governments around the world, including Singapore, Australia, New Zealand, Hong Kong, London, Vancouver, and Toronto, have implemented or are considering laws to curb foreign investment in local housing markets. For example, in 2011, the Singaporean government introduced an additional buyer's stamp duty of 10 percent of the purchase price to foreigners who buy residential property and increased it to 20 percent of the purchase price by 2018. In 2016, the British Columbia provincial government in Canada imposed an additional property transfer tax of 15 percent on all residential property purchased by foreign buyers.

[3] In this paper, "foreign Chinese" refers to non-resident Chinese, and "ethnic Chinese" refers to Chinese who regularly reside in the United States.

positive effect on local employment. The effect is driven by two competing forces—a housing net worth channel and a displacement channel. On the one hand, the capital inflows increase local house prices, which raises housing net worth and hence demand for non-tradable goods. On the other hand, these inflows displace local residents, lowering the demand for non-tradable goods. Our results reveal that the housing net worth channel plays a dominant role, as foreign Chinese real estate capital inflows significantly increase non-tradable-sector employment. Further, we find that these capital inflows displace local residents, especially low-income ones, suggesting that these inflows may give rise to adverse distributional consequences.

Though foreign Chinese housing purchases in the United States have grabbed many headlines in the popular press over the past decade, our paper is the first to provide a formal quantification of the phenomenon and directly estimate the elasticities of real economic outcomes with respect to these purchases.[4] A key difficulty in studying this issue lies in the lack of detailed data on real estate capital inflows. To overcome the challenge, we turn to housing transaction data to identify foreign homebuyers. Even though information on the origin of buyers is often unavailable because of legal restrictions, we devise a three-step algorithm to impute the amount of foreign housing purchases. First, we identify the ethnicities of buyers by applying the ethnic name-matching technique from Kerr (2008a) to *both* their first and last names. We keep only transactions made by buyers belonging to one of eight non–Anglo-American ethnic groups with a probability of one. Second, we keep only transactions that are made in *all cash*, as foreigners have limited access to U.S. mortgage markets. Third, we adjust our measures to keep only transactions made by *non-resident* foreigners. Using the algorithm, we construct two measures of foreign housing purchases for each of the eight foreigner groups, foreign housing transaction value and foreign housing transaction count, which capture the intensive and ex-

[4] Examples of media coverage of the surge in foreign Chinese housing purchases in the United States include "Chinese buying up California housing," 25 Nov. 2013, *CNBC*; "Chinese take lead among foreign buyers of U.S. homes," 18 Jun. 2015, *Financial Times*; and "Chinese cash floods U.S. real estate market," 28 Nov. 2015, *The New York Times*. According to the NAR, Chinese have taken the lead among all foreign buyers of U.S. real estate by a wide margin in both value and quantity. Foreign Chinese buyers spent $28.6 billion on residential property in the United States in 2014—a 30 percent increase from the previous year and more than two and a half times the amount spent by Canadians, the next biggest group of foreign buyers of real estate in the United States.

tensive margins of residential real estate capital inflows, respectively.

Using these measures, we document two salient phenomena. First, we observe a China shock in the California real estate market: Housing purchases by foreign Chinese buyers began to surge in 2008 and soared as much as 30- to 40-fold in terms of transaction share by value and count over the period from 2008 to 2013, reaching 3.5 percent of total housing transactions. We provide evidence suggesting that China's policies of loosening capital controls and imposing housing purchase restrictions (HPRs) to control housing price inflation since late 2007 are the primary drivers of the persistent surge in U.S. housing purchases by foreign Chinese buyers. Second, housing purchases by foreign Chinese buyers exhibit a form of home bias, as they are concentrated in locations historically populated by ethnic Chinese. Housing purchases by foreign Chinese buyers make up around 7 percent of total housing transactions in ZIP codes in the top decile of historical ethnic Chinese population shares and less than 0.5 percent in ZIP codes in the bottom decile.[5] These two facts reveal variations in these purchases in both the time-series and cross-sectional dimensions, which we exploit to estimate the employment effects of Chinese capital flows.

To guide our empirical analysis, we develop a conceptual framework to understand the employment effects of foreign housing purchases. Our model improves upon existing frameworks such as the one in Mian and Sufi (2014) by explicitly dissecting the forces driving local employment, including a housing net worth channel and a displacement channel. The model predicts that foreign real estate capital inflows push up local employment. On the one hand, the employment effect is driven by a housing net worth channel, as foreign capital inflows increase local house prices, which raises housing net worth and hence demand for non-tradable goods. On the other hand, greater foreign housing demand displaces local residents because of higher living costs, and this displacement channel lowers the demand for non-tradable goods and thereby non-tradable-sector employment. Our simulation shows that the housing net worth

[5] This stylized fact verifies the "home bias abroad" assumption in Badarinza and Ramadorai (2018) and echoes the documented pattern in Burchardi et al. (2019), which shows that the number of residents with ancestry from a given foreign country in U.S. counties strongly predicts the probability that local firms engage in FDI with that country.

channel is likely the dominating force, predicting that foreign housing demand increases non–tradable-sector employment. Directed by this framework, we test the effects of the Chinese shock on local employment, house prices, displacement, and employment by sector.

The challenge in establishing a causal relationship between foreign Chinese capital inflows and local economic conditions stems from an issue of endogeneity: There may be unobserved factors that influence both foreign Chinese housing purchases and local economic conditions.[6] To alleviate potential bias due to omitted variables, we apply an instrumental variables (IV) approach, where the foreign Chinese housing transaction value (count) is instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the historical ethnic Chinese population share at the ZIP code level, a strategy that exploits the home bias stylized fact. The exclusion restriction relies on the assumption that, conditioning on our ZIP code-level controls and county-year fixed effects, the historical ethnic Chinese population distribution is uncorrelated with factors that influence changes in local economic outcomes after the China shock in the U.S. real estate market.[7] Our subsequent analysis supports the exclusion restriction assumption and shows that our IVs have strong predictive power for measures of foreign Chinese housing purchases. In addition, our main specification adapts a difference-in-differences (DID) framework in which a China shock indictor variable is included to allow for a possible regime change, thus capturing the China shock stylized fact. The combination of a DID framework and an IV approach enhances identification relative to a traditional time-series analysis in estimating the economic effects of international capital flows.[8]

[6] Examples of such factors include the crowding out of domestic home buyers from ZIP codes that experience large Chinese capital inflows and the growth potential of the targeted neighborhoods.

[7] We include county-year fixed effects in the regressions to rely exclusively on within-county cross-ZIP code variation for identification, which relieves concerns about confounding factors such as heterogeneous land policy or county-level economic conditions (e. g., the tech boom in Silicon Valley). We also control for ZIP code-level characteristics that may systematically affect local economic conditions, including pre-sample period population, population density, education, and pre-trends of income and of the respective outcome variable.

[8] The international finance literature traditionally employs aggregate time-series analysis to study the effects of capital flows, which suffers from simultaneity: The timing of capital inflows is rarely exogenous and often coincides with unobserved factors that influence the economy concurrently. This empirical challenge partly explains the conflicting viewpoints on whether the effect of capital flows is beneficial (Fischer, 1997; Summers, 2000; Harrison et al., 2004; Tong and Wei, 2010), detrimental (Stiglitz, 2002; Aizenman and Jinjarak, 2009; Gourinchas and Obstfeld, 2012), or negligible for recipient countries (Rodrik, 1998).

Our results show that foreign Chinese housing purchases have a significant and positive effect on local employment. A one-standard-deviation difference in exposure to real estate capital inflows from China explains 21 percent of the cross-ZIP code variation in local employment.[9] The elasticity of employment to housing net worth implied by our estimates is consistent with that in Mian and Sufi (2014), confirming the external validity of our results.

We further dissect the channels underlying the employment effect of real estate capital inflows from China, as guided by our conceptual framework. First, we test for the role of a housing net worth channel. We find that foreign Chinese housing purchases significantly increase local house prices. A one-standard-deviation difference in exposure to real estate capital inflows from China, as measured by transaction value, explains 27 percent of the cross-ZIP code variation in local house prices, which is equivalent to $93,031, or 17 percent of the average home price across ZIP codes. Second, we find that a displacement channel also underlies the employment effect: Foreign Chinese real estate capital inflows induce displacement of local residents.

Between the two opposing forces, we find that the housing net worth channel plays a dominant role, as real estate purchases by foreign Chinese significantly increase non-tradable-sector employment on net. In addition, we show that foreign Chinese house purchases displace local low-income residents in particular, suggesting that foreign real estate capital inflows may contain adverse distributional consequences, in contrast to their positive employment effect.

This paper contributes to a growing literature on the local effects of foreign housing purchases. Recent studies show that they push up house prices in large cities in the United Kingdom (Sa, 2016; Badarinza and Ramadorai, 2018) and the United States (Gorback and Keys, 2020). While these papers are mostly based on reduced form evidence using discrete proxies of foreign house purchases, we directly estimate elasticities of specific outcomes with respect to these purchases. We also go beyond the asset price effects and study their real effects. In doing so, this paper adds to the line of research exploring the link between the housing market

[9] We also conduct a series of tests to assess the validity of the research design, including parallel pre-trend and reverse causality tests, and the robustness of the baseline results to alternative specifications or controlling for factors that capture neighborhoods' differential ability to withstand the financial crisis.

and the real economy (Green, 1997; Case, 2000; Glaeser and Parker, 2000).[10] Mian et al. (2013) and Mian and Sufi (2014) argue that the deterioration in household balance sheets due to the housing market crash during the 2007–09 financial crisis induced a sharp decline in U.S. consumption and employment. Our paper provides evidence supporting such a housing net worth channel, but in the context of a positive housing price effect driven by foreign capital inflows. Moreover, our paper adds to the research on the distributional consequences of foreign housing purchases, such as Favilukis and Van Nieuwerburgh (2021). Our findings on the real and distributional impacts of foreign housing purchases bring a new perspective to ongoing policy debates on the need for government regulations to curb foreign housing purchases.

In addition, our study contributes to the literature on the external impacts of China's integration into the global economy. Existing research mainly focuses on the effects of rising Chinese import competition on foreign labor markets, showing that Chinese imports have negative effects on local economies abroad (Autor et al. 2013; Acemoglu et al. 2016; Balsvik et al. 2015).[11] While China's role in international trade has been notable, China has also been increasingly integrated into global finance. This paper is the first to probe into the local economic effects of a China shock on the finance side—the surge of residential real estate capital inflows from China to the United States.[12] In contrast to prior studies, we find that this particular China shock has a positive real effect but contains potentially adverse distributional consequences.

2 Foreign Residential Real Estate Capital Inflows

We begin by quantifying the amount of residential home purchases by foreigners in the United States, which captures the extent of foreign residential real estate capital inflows. A key challenge in measuring these purchases is that U.S. county offices do not collect data on homebuy-

[10] See Davis and Van Nieuwerburgh (2015) for an overview.

[11] Besides labor market effects, subsequent papers find that rising Chinese import competition affects innovation (Autor et al., 2020), elections (Autor et al., 2020), and the marriage market (Autor et al., 2019).

[12] Our work is partly related to a few recent papers in international finance pointing out hidden capital coming out of China, including Horn et al. (2019) and Coppola et al. (2021). In some sense, the foreign Chinese real estate capital we study in this paper is another source of hidden capital from China.

ers' country of origin because of legal restrictions. The only available data are aggregate estimates published annually by the NAR based on voluntary survey responses from realtors, but the response rate tends to be extremely low (e. g., 3 percent in 2016). To overcome the data limitation, we use transaction-level data and devise a three-step algorithm to impute the amount of foreign real estate purchases. We show that the foreigner group that most significantly increased real estate purchases in the United States over the sample period from 2001 to 2013 is the Chinese. In particular, we document two new stylized facts—a China shock in the U.S. real estate market and home bias of foreign Chinese home purchases. Given the dominance of the Chinese as the key foreign buying group, we focus our study on the real effects of their real estate purchases in the subsequent analysis.

2.1 Real Estate Transaction Data

Our main data source is housing transaction records from DataQuick, which contain detailed purchase information collected from County Register of Deeds and Assessor Offices throughout the United States. These records cover both resident and non-resident initiated transactions. For each home sale, the data include the sales price, the closing date, the precise address of the home, home characteristics, information on home financing, and names of the buyers and sellers. In our analysis, we focus on housing transactions in the three largest core-based statistical areas in California (Los Angeles, Long Beach, Riverside; San Jose, San Francisco, Oakland; and San Diego, Carlsbad, San Marcos), comprising 17 counties and 773 ZIP codes. We restrict our sample to single-family residential homes. The final dataset contains 1,796,669 residential housing transactions over the period from 2001 to 2013.

2.2 Three-Step Imputation Algorithm

Using the housing transaction data, we develop a three-step algorithm to impute the amount of foreign residential real estate purchases. We construct two measures to capture the intensive and extensive margins of real estate capital inflows for seven foreigner groups: foreign housing transaction value ($fHTV$) and foreign housing transaction count ($fHTC$). We provide an overview of the algorithm below and relegate the details to Appendix A.

Step One. We identify the ethnicities of the homebuyers in our sample based on their first *and* last names using the ethnic name-matching algorithm from Kerr (2008a), Kerr (2008b), and Kerr and Lincoln (2010).[13] The algorithm applies the ethnic-name database from the Melissa Data Corporation and manually codes any remaining unmatched names.[14] Exploiting the fact that certain names are unique to one ethnicity or prevalent across multiple ethnicities, this algorithm assigns each homebuyer a probability of belonging to a specific ethnicity based on their first and last names, with the probabilities summing up to one. If a name is unique to one ethnicity, the buyer will be assigned to the respective ethnicity with a probability of one. For names common among multiple ethnicities, the technique uses the demographic breakdown in the metropolitan statistical area (MSA) where the property is located for assigning probabilities. For example, a person with the name Jia Li would be assigned to the Chinese ethnicity group with a probability of one. Someone with the name John Lee, which could be of Chinese, Korean, or American ethnicity, would be assigned to each of the three ethnic groups with probabilities based on the proportion of Chinese, Korean, and Americans in the MSA where the purchase took place. In total, eight ethnicities are distinguished by the name-matching technique: Anglo-Saxon/English, Chinese, European, Hispanic, Indian, Japanese, Korean, and Russian.[15] The match rate on the names from the housing transaction data is 97 percent.

As the first step of constructing measures of foreign housing transactions, we keep only transactions made by buyers belonging to one of the seven non–Anglo-American ethnic groups with a probability of *one*.[16]

[13] We thank William Kerr for running the buyer names from our sample with his ethnic name-matching algorithm.

[14] See Kerr (2008b) and Kerr (2008a) for details on the name-matching process and descriptive statistics from their matching exercises. Kerr (2008b) originally created the algorithm to identify the ethnicity of inventors granted patents by the U.S. Patent and Trademark Office. Kerr and Lincoln (2010) use it to investigate the impact of H-1B visa reforms on Chinese and Indian inventors and patents.

[15] A number of recent academic papers use similar ethnic name-matching algorithms to impute individuals' race or ethnicity, e. g., Diamond et al. (2019).

[16] Continuing with the example of Jia Li and John Lee, the first step of our algorithm would keep Jia Li's housing

Step Two. We keep only *all-cash* housing transactions made by non–Anglo-Americans.

This step is motivated by the fact that foreigners have limited access to the U.S. mortgage market: Non-U.S. citizens without lawful residency in the United States are not eligible for Fannie Mae, Freddie Mac, or Federal Housing Administration home loans, and financing homes through private lenders is difficult for them.[17] Furthermore, the NAR reports that most non-resident foreign buyers make all-cash home purchases, while a much smaller fraction of resident foreign buyers pay all cash. According to the "2014 Profile of International Activity in U.S. Residential Real Estate" published by the NAR, 76 percent of non-resident foreign buyers made all-cash purchases, while merely 33 percent of resident foreign buyers paid all cash. We recognize that our measures may be on the conservative side of the true magnitude as a result of this filtering because they do not reflect purchases made by foreigners who manage to get mortgages from U.S. private lenders. However, focusing on cash-only transactions allows us to identify foreign purchases more accurately, especially considering the opacity of the mortgage market for non-resident foreigners. Moreover, given the small size of non-all-cash transactions made by non-resident foreigners, they likely play a minor role in driving aggregate housing prices and real economic conditions.

Step Three. Restricting the sample to all-cash purchases by non–Anglo-Americans is a necessary but insufficient criterion for identifying foreign real estate transactions, as the sample may still include purchases by resident non–Anglo-Americans—those who normally reside in the United States. We thus adjust our measures to keep only *non-resident* transactions.[18]

Each non-resident non–Anglo-American foreign group's all-cash housing transaction value (or count) is constructed as the difference between its total all-cash housing transaction value (or count) and that of the corresponding U.S. resident population. Our estimates of all-cash home purchases by resident non–Anglo-Americans are based on the assumption that their

purchase in our sample but drop John Lee's purchase given the ambiguity of his ethnicity.

[17] Mortgages for foreigners through private lenders carry high interest rates and require borrowers to make large down payments in the range of 30 to 50 percent.

[18] While the overall real effects may be driven by both resident and non-resident purchases, we focus on non-resident transactions to identify capital inflows and isolate their effects on local economies.

propensity to make all-cash purchases is similar to that of Anglo-Americans. This assumption is motivated by the fact that all lawful residents in the United States have similar access to domestic home loans. We also observe evidence in support of this assumption in the data. As shown in Appendix Figure A.8, most non–Anglo-American foreign ethnic groups behave similarly to Anglo-Americans in their propensity for making all-cash real estate purchases, as measured by both value and count.[19]

Given the three-step imputation algorithm, the formula for constructing the total (adjusted) housing transaction value ($fHTV$) of each foreigner group f at ZIP code z and year t is

$$fHTV_{zt} = \left[HTV^{\text{cash}}_{fzt} - \frac{HTV^{\text{cash}}_{Azt}}{HTV_{Azt}} \times HTV_{fzt}\right] \frac{HTV_{Azt}}{HTV_{Azt} - HTV^{\text{cash}}_{Azt}}. \tag{1}$$

where HTV^{cash}_{fzt} denotes unadjusted all-cash housing transaction value of foreigner group f at ZIP code z and year t, and A denotes the Anglo-American ethnic group. The first term in equation (1) adjusts each foreigner group's total housing transaction value by the proxy for transactions made by its U.S. resident population; the second term is a re-scaling factor. The formula for constructing $fHTC$ is analogous. Details on the derivation of the formulas are presented in Appendix A.

Discussion. Our algorithm provides a quantification of foreign housing purchases in the United States. While previous studies often divide neighborhoods into binary groups based on the "home bias abroad" assumption that foreign groups are more likely to buy into areas with more pre-existing source-country residents (see, e. g., Badarinza and Ramadorai 2018 and Gorback and Keys 2020), the measures from our algorithm reveal the intensity of foreign housing purchase, which enables an estimation of the elasticity of house prices or employment with respect to foreign capital inflows. Moreover, the measures allow us to verify the home bias abroad as-

[19] The only exception is the Chinese after 2008, when their share of all-cash housing transactions surged relative to those of Americans and all other groups. Given reports from the NAR about foreign Chinese becoming the fastest-growing buyer group (see e. g., "2013 Profile of International Activity in U.S. Residential Real Estate"), we conjecture that the divergence is driven by purchases by non-resident foreign Chinese.

sumption from Badarinza and Ramadorai (2018).

Nevertheless, our algorithm might not perfectly capture home purchases by all foreigners.[20] The ideal data to generate such measures would directly contain reliable information on the nationality of the buyers (e. g., the data used in Cvijanović and Spaenjers 2020 on housing transactions in France). Without such data for the United States, however, this algorithm provides a trackable estimate from available data: It uses information contained in both first and last names (to identify national origin), information derived from all-cash purchasing behavior (to distinguish foreigners, who generally cannot take out U.S. mortgages), and information from purchasing behavior of local residents (to avoid counting resident foreigners).

2.3 Patterns of Foreign Real Estate Capital Inflows

Using the measures $fHTV$ and $fHTC$, we examine home-purchasing behavior by each foreigner group f in the United States over time and across neighborhoods.

Fact 1: A China shock in the U.S. real estate market. We begin by examining the evolution of housing purchases made by foreigners in the Californian real estate market over the sample period. Figure 1(a) illustrates the share of total housing transactions, as measured by dollar value, made by seven foreigner groups: Chinese, European, Hispanic, Indian, Japanese, Korean, and Russian. While purchases by six of the seven groups appear negligible over the entire period, those by foreign Chinese increased sharply from 2008 to 2013. The percentage of housing trans-

[20] The algorithm does not account for residential real estate purchases by foreigners through corporations (e. g., for tax avoidance), a consideration in Badarinza and Ramadorai (2018) about the London housing market. However, this issue should not be significant in our context because we focus on single-family homes, and such purchases tend to be concentrated in high-end properties. Our context also differs from that of Badarinza and Ramadorai (2018), who highlight that a nontrivial amount of foreign purchases in London can be traced to offshore vehicles likely because they originate from politically unstable countries. In our case, purchases by foreign Chinese make up the majority of foreign home purchases, and they do not have much incentive to hide their names, as many of them aim to use the home for obtaining green card or as a base for their children's education in the future. Indeed, less than 6 percent of transactions in our sample originate from business entities. Therefore, measurement error arising from not accounting for foreign housing purchases through corporations is likely small in our case. Moreover, our subsequent results show that the effects using housing transaction count are just as strong, if not stronger than, those using housing transaction value, which indicates that our results are not driven by purchases of high-end properties.

actions by foreign Chinese, while comparable with the other groups before 2008, soared in 2008 and stayed persistently high thereafter, reaching 3.5 percent of total housing transaction value and count in California. That is more than a 30-fold increase in transaction value.

Figure 1(b) plots the share of housing transactions by count made by the seven foreigner groups. It shows a similar pattern as Figure 1(a). The fact that the pattern holds regardless of whether we examine housing transactions by value or count suggests that foreign Chinese buyers have been purchasing residential real estate across a full spectrum of housing types, not only high-end real estate.

Figure 1 reveals that foreign Chinese residential real estate capital inflows have been persistent during both economic decline and growth in the United States. The non-cyclical nature of this type of capital inflows differentiates them from traditional forms of international capital flows, which tend to be pro-cyclical (Kaminsky et al. 2004, Avdjiev et al. 2022).

In sum, we document a China shock in the U.S. real estate market in 2008, and that the surge has persisted thereafter. This observation is consistent with report from the NAR that the Chinese have become the leading group of foreign buyers in the U.S. real estate market (see "2015 Profile of International Activity in U.S. Residential Real Estate"). Moreover, the timing of the shock in 2008 is consistent with initial reports of increasing foreign Chinese home purchases by the NAR and of anecdotes of such activities in the media.[21]

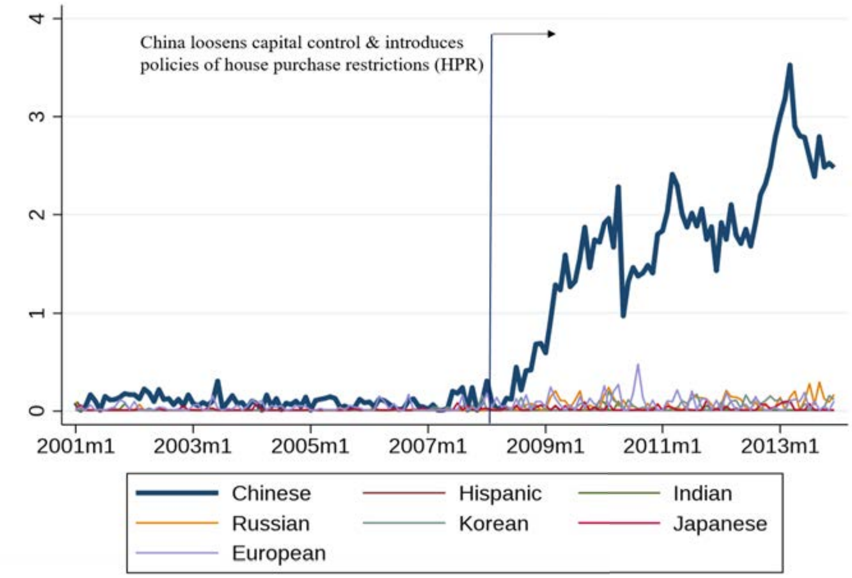
What factors potentially contributed to the China shock? In Appendix B.1, we discuss how the relaxation of capital controls and a series of HPRs introduced by the Chinese government in late-2007 likely played a key role.

Fact 2: Home bias of foreign Chinese housing purchases. We next examine the spatial distribution of these home purchases by foreign Chinese buyers. Figure 2(a) and (b) dissects Figure 1(a) and (b), respectively, by zooming in on the difference in foreign home purchases between ZIP codes in the top two deciles of the ethnic Chinese population based on data from the 2000

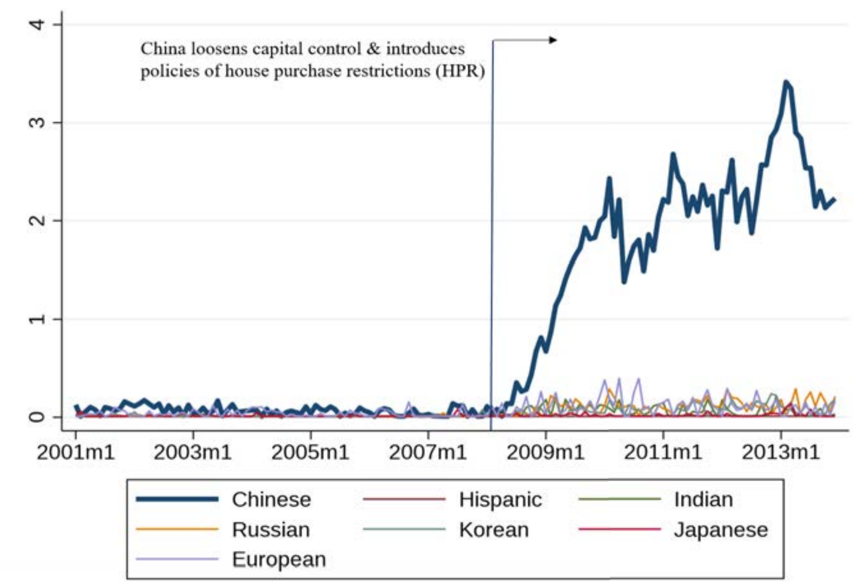
[21] For instance, multiple news articles in 2008 report that waves of cash-rich Chinese formed tour groups to house-hunt in the United States. See "Chinese tourists' hot souvenir: U.S. homes," 7 Dec., 2008, *Los Angeles Times*; "Chinese arriving to buy bargain U.S. homes," 12 Feb., 2009, *Daily Bulletin*.

Figure 1. Foreign Home Purchases in the Californian Real Estate Market

(a) Foreign Housing Transaction Value



(b) Foreign Housing Transaction Count



Note: Panel (a) plots the share of housing transactions by dollar value made by seven groups of foreigners in the three largest core-based statistical areas (CBSAs) in California. Panel (b) plots the share of housing transactions by count. The vertical line marks the timing of China's policies of capital control loosening and housing purchase restrictions. The sample period runs monthly from 2001 to 2013. Source: DataQuick and authors' calculations.

Census Bureau survey and those in other deciles. For foreign Chinese housing transactions, the difference amounts to 6 percent of the total real estate transaction value and count by 2013.[22] This reveals a form of home bias: Housing purchases made by foreign Chinese tend to be concentrated in areas historically populated by ethnic Chinese.[23]

We further examine the cross-sectional correlation of foreign Chinese housing purchases and the historical ethnic Chinese population share. To that end, we plot foreign Chinese housing transaction value and count, normalized by total housing transaction value and count, respectively, from 2008 to 2013 as a function of the historical ethnic Chinese population share. As shown in Figure 3(a) and (b), ZIP codes that historically had a higher concentration of ethnic Chinese population witnessed significantly more housing purchases by foreign Chinese, as measured by value and count. In particular, foreign Chinese housing purchases in the 9th and 10th deciles of the historical ethnic Chinese population share are about two and four times higher, respectively, than the 8th decile.[24]

The overall pattern is consistent with the idea of the "preferred habitats" theory in finance, which contends that heterogeneous investors prefer different subsets of assets within a broader asset class. Moreover, this stylized fact verifies the "home bias abroad" assumption in Badarinza and Ramadorai (2018).[25] Recent literature have proposed explanations that could potentially explain such kind of clustered house purchase behavior including preferences for neighborhood amenities (Bayer et al. 2007; Wong 2013) as well as lower information and contractual frictions due to trust or cultural affinity (Chaney 2014; Badarinza et al. 2021). We explore whether these factors influence the home bias observed in our context. We find that foreign

[22] In absolute terms, foreign Chinese housing transactions make up around 7 percent of the total housing transaction value and count in the top-quintile neighborhoods.

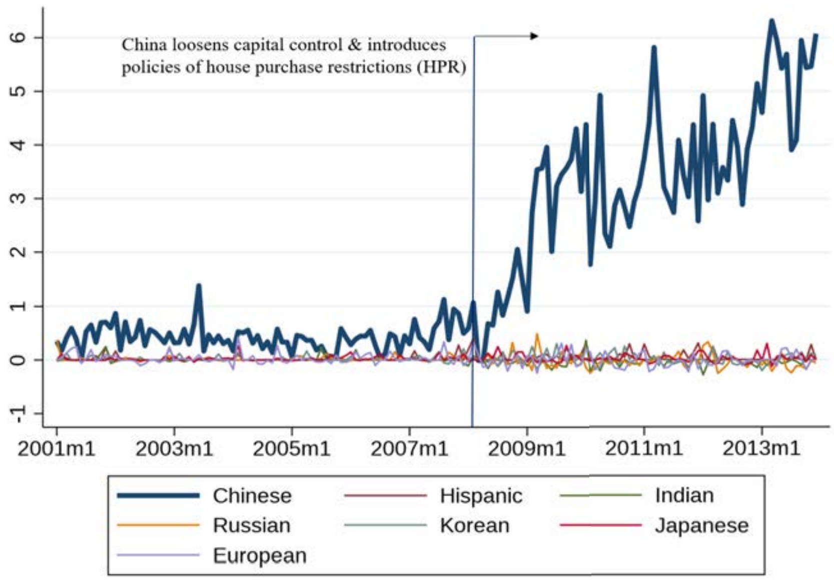
[23] This pattern of home bias in foreign Chinese housing purchases is also evident on the map. Appendix Figure A.9 illustrates housing purchases by foreign Chinese in the Los Angeles region from 2010 to 2013. Foreign Chinese home purchases tend to cluster in ZIP codes historically populated by ethnic Chinese (in darker shades of blue).

[24] We have run a test to identify whether there exists a structural break in foreign Chinese housing purchases, using a bootstrap dataset (sampled 1,000 times with replacement). The test shows that a structural break, as reflected by a significant jump in the slope of the fitted regression line, occurs at the 8th decile of the historical ethnic Chinese population.

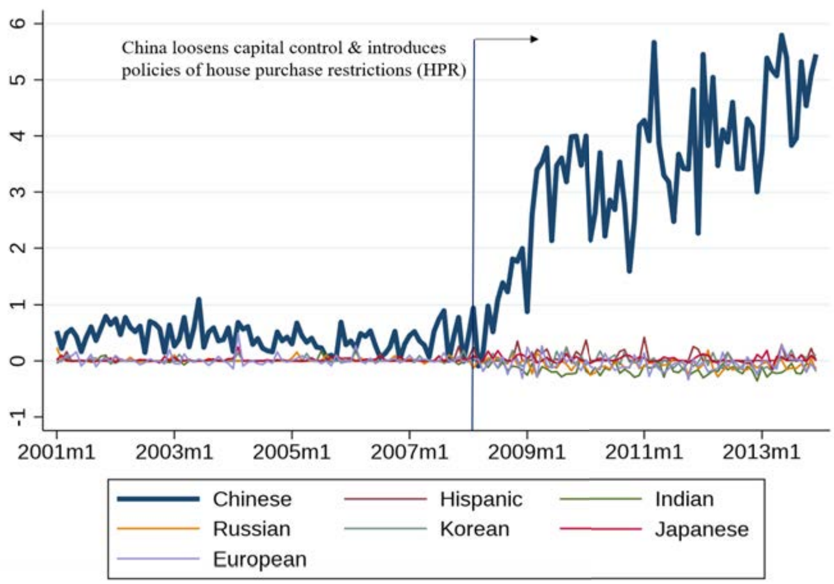
[25] The stylized fact also resonates with the finding in Burchardi et al. (2019) that the ancestry composition of U.S. counties strongly predicts the direction of FDI.

Figure 2. Foreign Home Purchases in the Californian Real Estate Market: Difference between ZIP Codes in Top Two versus Other Deciles of the Ethnic Chinese Population Share

(a) Foreign Housing Transaction Value



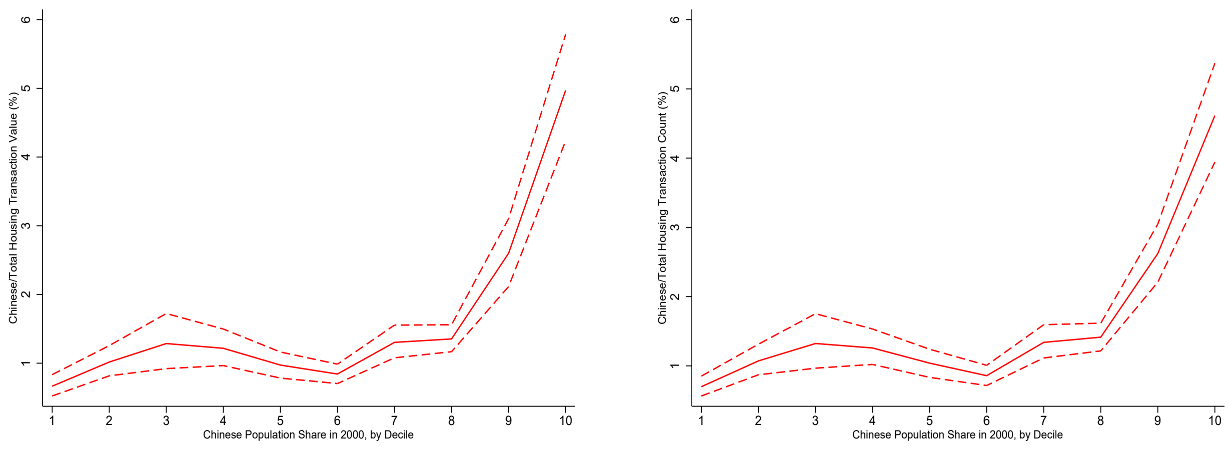
(b) Foreign Housing Transaction Count



Note: Panel (a) plots the difference in the shares of foreign housing transaction value between ZIP codes in the top two and other deciles of the ethnic Chinese population based on the 2000 Census Bureau survey in the three largest core-based statistical areas (CBSAs) in California, for seven foreigner groups. Panel (b) plots the analogue for housing transaction shares by count. The vertical line marks the timing of China's policies of capital control loosening and housing purchase restrictions. The sample period runs monthly from 2001 to 2013. Source: DataQuick; authors' calculations.

Figure 3. Foreign Chinese Housing Purchases versus Historical Ethnic Chinese Population

(a) Foreign Chinese House Transaction Value **(b)** Foreign Chinese House Transaction Count



Note: The left panel shows foreign Chinese housing transaction share, as measured by value, between 2008 and 2013 by deciles of historical ethnic Chinese population based on the 2000 Census Bureau Survey. The right panel shows the foreign Chinese housing transaction share, as measured by count. The dotted lines denote the 95% confidence intervals based on 1,000 bootstrap samples.

Chinese tend to buy into neighborhoods with better school quality and greater Chinese restaurant presence, and they are more likely than non-Chinese buyers to buy from ethnic Chinese sellers. Therefore, the spatial distribution of foreign Chinese housing purchases is plausibly influenced by both preferences for specific neighborhood amenities and lower frictions due to cultural affinity. Appendix Section B.2 provides the details of our analysis.

Given the dominance of home purchases by foreign Chinese buyers relative to all other foreigner groups, we focus on the real effects of foreign Chinese housing purchases in the subsequent analysis. The main regressors in the empirical specifications are Chinese housing transaction value ($CHTV$) and Chinese housing transaction count ($CHTC$), based on equation (1) where $f = C(hinese)$.

3 Conceptual Framework

In this section, we present a stylized framework to conceptualize the real effects of foreign real estate capital inflows on local economies and guide the subsequent empirical analysis. Our model builds upon Mian and Sufi (2014) and extends it in three key dimensions: We introduce a housing sector, allow mobility in cross-regional commuting, and formalize an explicit housing net worth channel.

3.1 Environment and Initial Equilibrium

Consider an economy composed of two regions, $z \in \{0,1\}$. Each region produces two types of goods, tradable (denoted with superscript T) and non-tradable (denoted with superscript N), and has a fixed housing stock (H_z). The tradable good can be freely traded across regions, but residents in each region must consume the non-tradable good produced in that region.[26] Workers are allowed to both commute between regions (i. e., work in one region and reside in another) and switch between sectors within a region. For simplicity, we assume that space is a divisible good; as such, equilibrium housing prices are determined by the interaction between local workers' demand for space and the fixed supply of housing.[27]

Let D_z denote the nominal income in each region, which consists of wage and rental income (rebated to local workers). Workers residing in region z have Cobb-Douglas preferences over the tradable good (C_z^T), non-tradable good (C_z^N), and housing (C_z^H), with prices $P^T = 1$, P_z^N, and P_z^H, respectively.[28] The consumption of the tradable good, non-tradable good, and housing can be expressed as $C_z^T = \beta D_z$, $P_z^N C_z^N = \alpha D_z$, and $P_z^H C_z^H = (1-\alpha-\beta) D_z$, respectively, where α, β, and $1-\alpha-\beta$ are the income shares on the respective goods.

Suppose that production is governed by a constant returns technology with employed labor,

[26] This assumption, which follows Mian and Sufi (2014), is meant to capture the fact that consumption of non-tradable goods depends on local demand, while consumption of tradable goods relies more diffusely on national demand.

[27] The assumption that housing is divisible implies that there is no utility penalty from down-sizing into a smaller unit. Accounting for non-divisible housing consumption would require modelling the dynamic decision of renting or owning houses, which we do not do in order to maintain the tractability of the model and highlight the key mechanisms driving the real effects of foreign real estate capital inflows.

[28] All regions face the same price for the tradable good because we assume that the good is traded across regions without friction. This assumption simplifies the model, allowing it to focus on the key channels through which a shock in real estate capital inflows affects the real economy. In contrast, the price of the non-tradable good is region-specific because non-tradable good must be consumed locally. In our model, the tradable good serves as the numeraire.

e, as the sole input. Outputs of the non-tradable and tradable good are then given by $y_z^N = ae_z^N$ and $y_z^T = be_z^T$, respectively, where a and b are productivity parameters.

Total employment in each region is normalized such that $e_z^T + e_z^N = 1$. Wages in the two sectors are given by $w_z^N = aP_z^N$ and $w_z^T = bP^T = b$. Free mobility of labor across sectors means that wage is equal across sectors, $w_z = w = b$, and the price of the non-tradable good is independent of the region, $P_z^N = \frac{b}{a}$.

We first solve the model under a set of symmetric assumptions: In the initial state, both regions have the same housing stock $H_z = H_0$, the economy achieves full employment, and all workers work at the location of their residence.[29] The solutions for prices, wage, output, and employment are as follows, where superscript (*) denotes the initial steady state:

$$\begin{aligned}
\text{Prices:} \quad & P_z^{*N} = \frac{b}{a}; \qquad P^{*T} = 1; \qquad P_z^{*H} = \frac{1-\alpha-\beta}{\alpha+\beta}\frac{b}{H_0}; \\
\text{Wage:} \quad & w_z^{*N} = w_z^{*T} = b \equiv w; \\
\text{Nominal income:} \quad & D_z^* = w + P_0 H_0 = b + \frac{1-\alpha-\beta}{\alpha+\beta} b = \frac{b}{\alpha+\beta}; \\
\text{Employment:} \quad & e_z^{*N} = \frac{\alpha}{\alpha+\beta}; \qquad e_z^{*T} = \frac{\beta}{\alpha+\beta}.
\end{aligned}$$

3.2 Equilibrium under a Real Estate Capital Inflow Shock

Suppose now that Region 1 faces an exogenous increase in housing demand from a group of foreigners, inducing a surge in real estate capital inflows:

$$H_0 = C_1^H + C_{\text{f}}^H,$$

[29] We assume a fixed housing stock both for simplicity and to highlight the core mechanism of the model. This assumption is not unreasonable given our empirical setting because i) our data focus on housing transactions in California, which imposes one of the most stringent requirements on residential housing permits in the country, and ii) our analysis is at the ZIP code level at annual frequency, and there is likely little fluctuation in the stock of single-family homes at this level of variation. If the model was extended to incorporate a housing supply function, the key insights of the model would stay the same as long as housing supply is not perfectly elastic.

where C_1^H denotes housing demand by local workers, and C_f^H denotes housing demand by the foreigner group f.[30]

We proceed to solve for the new equilibrium of the model. Notably, we allow for commuting: Some workers, $\bar{e}$ (≥ 0), may choose to live in Region 0 and commute to Region 1 for work, but have to pay an individual-specific commuting cost, ϕ_i, that takes on distribution $\phi_i \sim F(\phi)$ and is proportional to wage.[31] We further allow a fraction of the commuters, λ, to consume at the location of residence, and the rest at the location of employment. As such, the number of workers that consume locally is $1 - \lambda\bar{e}$ in Region 1 and $1 + \lambda\bar{e}$ in Region 0.

In the new equilibrium, nominal income for goods consumption in Region 1 and Region 0 is $D_1 = b(1 - \lambda\bar{e}) + P_1^H H_0$ and $D_0 = b(1 + \lambda\bar{e}) + P_0^H H_0$, respectively.[32] Housing market clearing conditions are $H_0 = (1-\alpha-\beta)\frac{b(1-\bar{e})+P_1^H H_0}{P_1^H} + C_f^H$ for Region 1 and $H_0 = C_0^H = (1-\alpha-\beta)\frac{b(1+\bar{e})+P_0^H H_0}{P_0^H}$ for Region 0, which can be rewritten as

$$\text{Region 1: } P_1^H = \frac{(1-\alpha-\beta)b(1-\bar{e})}{(\alpha+\beta)H_0 - C_f^H}; \tag{2a}$$

$$\text{Region 0: } P_0^H = \frac{(1-\alpha-\beta)b(1+\bar{e})}{(\alpha+\beta)H_0}. \tag{2b}$$

A worker will choose to commute if her real wage conditional on commuting is higher:

[30] We treat a real estate capital inflow shock as a housing demand shock, an approach also adopted by contemporaneous studies such as Gorback and Keys (2020), Cvijanović and Spaenjers (2020), and Favilukis and Van Nieuwerburgh (2021).

[31] Our assumption that commuting costs are heterogeneous across workers is motivated by both convention in spatial models and empirical evidence. On the theory side, papers such as Desmet and Rossi-Hansberg (2013) model commuting costs as a function of commuting distance, which differ across workers based on their locations of work and residence. Moreover, Monte et al. (2018) show that commuting plays a key role in determining the heterogeneous response of local employment to local labor demand shock. On the empirical side, the U.S. Census Bureau's American Housing Survey (Table 13B "2017 California–Annual Commuting Costs by Type of Commuter") and Roberto (2008) report that commuting costs vary by demographics and transportation mode. Le Barbanchon et al. (2021) find that commuting distance differs substantially across workers.

[32] We assume that foreign buyers do not physically move into the purchased properties, which gives rise to vacancy in Region 1. This assumption is motivated by anecdotal evidence and empirical evidence from the existing literature such as Cvijanović and Spaenjers (2020) that foreign buyers tend to act as "absentee landlords." It is also consistent with our finding from Section 5.2 that foreign Chinese housing purchases are not accompanied by a significant inflow of immigrants. Given this assumption, foreign buyers do not demand local goods.

$\frac{w}{(P_1^N)^\alpha (P_1^H)^{1-\alpha-\beta}} < \frac{w(1-\phi_i)}{(P_0^N)^\alpha (P_0^H)^{1-\alpha-\beta}}$, or

$$P_1^H > P_0^H \left(\frac{1}{1-\phi_i}\right)^{\frac{1}{1-\alpha-\beta}}. \tag{3}$$

If the housing price in Region 1 is too high, some workers will be forced to commute. Substituting equations (2a), (2b) into (3) yields the cutoff commuting cost:

$$\phi_i < 1 - \left[\left(1 - \frac{C_f^H}{(\alpha+\beta)H_0}\right)\left(\frac{1+\bar{e}}{1-\bar{e}}\right)\right]^{1-\alpha-\beta}. \tag{4}$$

Let this (endogenous) cutoff be denoted by $\bar{\phi}$. Workers with a commuting cost $\phi_i < \bar{\phi}$ will choose to commute, and the equilibrium number of commuters is $\bar{e} = F(\bar{\phi})$.

We can solve for $\bar{\phi}$ with

$$1 - \left[\left(1 - \frac{C_f^H}{(\alpha+\beta)H_0}\right)\left(\frac{1+F(\bar{\phi})}{1-F(\bar{\phi})}\right)\right]^{1-\alpha-\beta} = \bar{\phi}. \tag{5}$$

Since $\partial\bar{\phi}/\partial C_f^H \geq 0$, $\partial\bar{e}/\partial C_f^H \geq 0$.[33] That is, a rise in foreign housing demand shock increases the number of commuters.[34] Equations (2a), (2b), and (5) jointly determine the equilibrium house prices, P_0^H and P_1^H, and the number of commuters, $\bar{e}$.[35]

[33] This condition is derived from applying the implicit function theorem to equation (5).

[34] Consider a simple case where commuting costs are homogeneous across workers, i. e., $\phi_i = \phi \; \forall i$. We can solve for the equilibrium number of commuters by setting equation (4) to equality and obtain:

$$\bar{e} = \frac{(\alpha+\beta)H_0 - \left(\frac{1}{1-\phi}\right)^{\frac{1}{1-\alpha-\beta}}[(\alpha+\beta)H_0 - C_\mathrm{f}^H]}{(\alpha+\beta)H_0 + \left(\frac{1}{1-\phi}\right)^{\frac{1}{1-\alpha-\beta}}[(\alpha+\beta)H_0 - C_\mathrm{f}^H]}.$$

The solution shows that a foreign housing demand shock leads to an increase in the number of commuters.

[35] The model suggests that a positive foreign housing demand shock could both raise local house prices and drive out local residents, with the latter force potentially moderating the former. The size of the house price effect depends on the distribution of commuting costs. In an extreme case where $\phi = 1$ for all workers, there would be no commuting, and all the house price effects would be absorbed by Region 1. If the house price effect dominates, Region 1 would have higher house prices than Region 0. This prediction is supported by findings in the literature, including Badarinza and Ramadorai (2018) and Gorback and Keys (2020). Note that house prices will also increase in Region 0 because of demand from the commuters who are driven out of Region 1, although the increase will be smaller than in Region 1.

Employment effect. Given our interest in understanding the real effects of foreign housing purchases, we focus on the effect of a foreign housing demand shock on local employment and the underlying channels. Total employment in the two regions is determined by the number of commuters: $1+\bar{e}$ in Region 1 and $1-\bar{e}$ in Region 0. As the number of commuters increases in response to a positive foreign housing demand shock, the total employment in Region 1 increases, while that in Region 0 declines.

Local employment in the non-tradable sector in equilibrium is pinned down by the demand for the non-tradable good:

$$e_1^N = \frac{\alpha D_1}{aP_1^N} = \frac{\alpha b(1-\lambda\bar{e}) + \alpha P_1^H H_0}{b} = \underbrace{\frac{\alpha}{b} P_1^H H_0}_{\text{housing net worth channel}} + \underbrace{\alpha(1-\lambda\bar{e});}_{\text{displacement channel}} \tag{6a}$$

$$e_0^N = \frac{\alpha D_0}{aP_0^N} = \frac{\alpha b(1+\lambda\bar{e}) + \alpha P_0^H H_0}{b} = \underbrace{\frac{\alpha}{b} P_0^H H_0}_{\text{housing net worth spillover}} + \underbrace{\alpha(1+\lambda\bar{e}).}_{\text{displacement spillover}} \tag{6b}$$

Equation (6a) shows that an increase in foreign housing demand affects local non-tradable-sector employment in Region 1 through two opposing forces. On the one hand, greater foreign housing demand increases local house prices, which raises local housing net worth and hence demand for the local non-tradable good, driving up local non-tradable-sector employment—a *housing net worth channel*. On the other hand, the resulting higher living costs in Region 1 drive out local residents, lowering the demand for local non-tradable goods—a *displacement channel*.[36] Equation (6a) also shows that the housing net worth channel strengthens as the share of commuters consuming at the location of employment increases (i. e., as λ decreases).[37]

Local employment in the tradable sector can be determined by taking the difference be-

[36] Equation (6b) shows that a positive foreign Chinese housing demand shock affects local non-tradable-sector employment in Region 0 through two spillover channels. First, because of the displacement effect in Region 1, house prices in Region 0 are pushed up, which raises local housing net worth, the demand for the local non-tradable good, and thereby non-tradable-sector employment—a housing net worth spillover channel. Second, some of the commuters who are driven out of Region 1 now consume in Region 0, which also pushes up demand for the Region 0's non-tradable good and non-tradable-sector employment—a displacement spillover channel.

[37] Figure A.7 in Appendix C illustrates the simulated effects of positive foreign housing demand as the parameter λ varies.

tween total employment and employment in the non-tradable sector:

$$e_1^T = 1 + \bar{e} - e_1^N = 1 - \alpha - \frac{\alpha}{b} P_1^H H_0 + (1 + \alpha\lambda)\bar{e}; \tag{7a}$$

$$e_0^T = 1 - \bar{e} - e_0^N = 1 - \alpha - \frac{\alpha}{b} P_0^H H_0 - (1 + \alpha\lambda)\bar{e}, \tag{7b}$$

where we have substituted in equations (6a) and (6b) to arrive at the second equality. Equation (7a) shows that an increase in foreign housing demand also affects local tradable-sector employment in Region 1 through two opposing forces. On the one hand, the increased labor demand in the non-tradable sector in Region 1 due to the housing net worth channel would lower the amount of available labor to produce the tradable good there. On the other hand, the commuters to Region 1 would constitute extra supply of labor and contribute to the production of the tradable good.[38] The overall effect on tradable-sector employment depends on which of the two forces dominates, which in turn depends on the size of the foreign demand shock.

We calibrate the model and provide detailed discussions of the simulation results in Appendix C. To summarize the main takeaways, Figure 4 provides a stylized illustration of the impact of a positive foreign housing demand shock on the local (total, non-tradable-sector, and tradable-sector) employment, house prices, and number of commuters. As shown, our model predicts that a positive shock increases local non-tradable-sector employment, as the housing net worth channel tends to dominate the displacement channel, while the effect on tradable-sector employment is ambiguous.

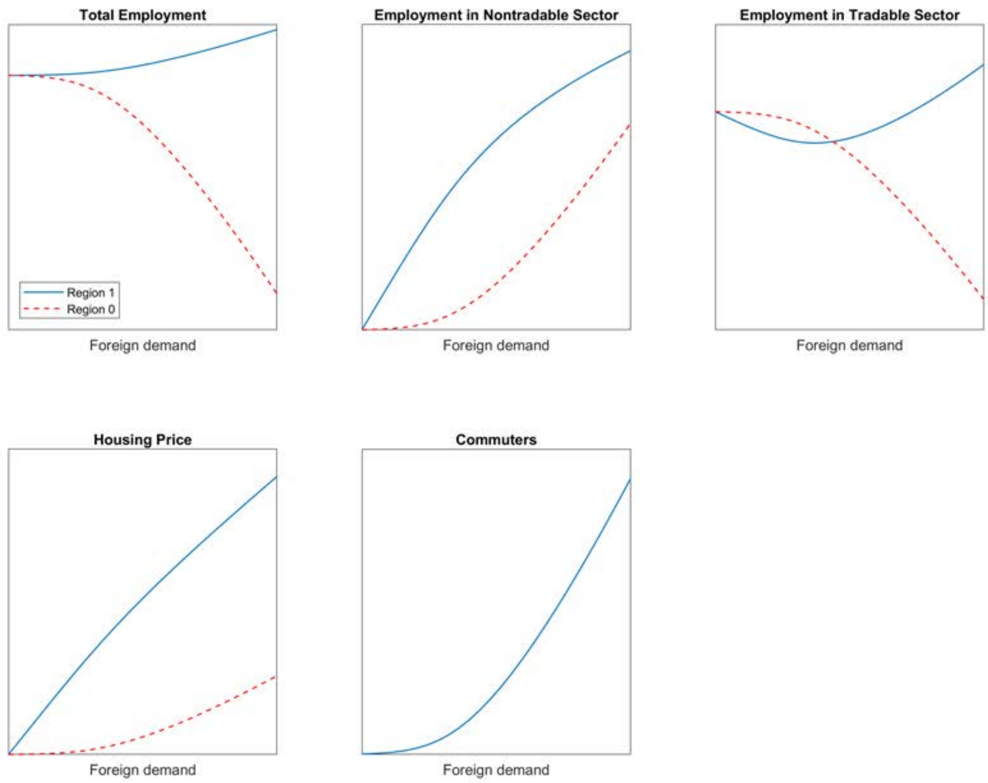
Model predictions. Taken together, the model yields the following predictions on the effects of a positive foreign housing demand shock on the local economy:

1. A positive shock in foreign housing demand increases total employment in the directly-impacted region.

2. The employment effect is partly driven by a housing net worth channel. As such, an increase in foreign housing demand leads to a rise in local housing prices.

[38] In Region 0, these two forces work in the same direction to lower employment in the tradable sector.

Figure 4. Local Effects of A Positive Foreign Housing Demand Shock, Stylized Diagram



Note:: This figure provides a stylized illustration of the effects of a positive foreign housing demand shock on the local economy, including local total employment, non-tradable-sector employment, tradable-sector employment, housing price, and number of commuters.

3. The employment effect is also affected by a displacement channel. As such, an increase in foreign housing demand leads to a rise in displacement of local residents.

4. The employment effect is concentrated in the non-tradable sector, driven by the housing net worth channel as the dominant force.

Directed by the conceptual framework, we proceed to empirically test the employment effect of the positive foreign Chinese housing demand shock and study the underlying roles of the housing net worth and the displacement channels.

4 Empirical Framework

We are interested in studying the effects of the China shock in the U.S. real estate market—the surge in foreign Chinese real estate capital inflows documented in Section 2.3 as the first stylized fact—on various local economic outcomes, including employment, house prices, and displacement. To that end, we estimate an empirical model of the following general form:

$$\ln(Y_{zt}) = \alpha + \theta \ln(CHTV_{zt}) + \beta \ln(CHTV_{zt}) \times \mathbb{I}\{t \geq 2008\} + \gamma X_{z,0} + \eta_{ct} + \varepsilon_{zt} \tag{8a}$$

$$\ln(Y_{zt}) = \tilde{\alpha} + \tilde{\theta} \ln(CHTC_{zt}) + \tilde{\beta} \ln(CHTC_{zt}) \times \mathbb{I}\{t \geq 2008\} + \tilde{\gamma} X_{z,0} + \tilde{\eta}_{ct} + \tilde{\varepsilon}_{zt} \tag{8b}$$

where Y_{zt} denotes the outcome variables of interest in ZIP code z and year t; $CHTV_{zt}$ denotes the foreign Chinese housing transaction value measure based on equation (1); $CHTC_{zt}$ denotes the foreign Chinese housing transaction count measure based on equation (A.4b); $\mathbb{I}\{t \geq 2008\}$ is an indicator variable that takes the value 1 if the year is 2008 or later and 0 otherwise, intended to capture the China shock in the U.S. real estate market; $X_{z,0}$ is a vector of ZIP code-level socioeconomic and geographic controls, including population, population density, and education (measured as the share of the population with bachelor's degrees) from the pre-sample year 2000, an indicator variable for whether there is a college within a five-mile distance, and pre-trends of income (calculated as the change in income between 1998 and 2001) and of the respective dependent variable (calculated as its change between 1996 and 2000); η_{ct} and $\tilde{\eta}_{ct}$ are county-year fixed effects; and ε_{zt} and $\tilde{\varepsilon}_{zt}$ are disturbance terms.[39]

Our coefficients of interest, β and $\tilde{\beta}$, measure the extent to which ZIP codes that received more foreign Chinese real estate capital inflows (i. e., faced a greater China shock) experienced a greater change in economic conditions after 2008—when policies of capital control loosening and HPR were introduced in China and foreign Chinese housing purchases in the United States surged. We are able to directly estimate the elasticity of real outcomes with respect to these

[39] We use the year 2008 as the shock period because policies of capital control loosening and HPR were introduced in late 2007, and there likely was a lag between policy introduction in China and real estate purchases in the United States.

inflows because we have carefully quantified their magnitudes, which is a key contribution of our analysis, as existing studies have mostly relied on reduced form evidence based on discrete proxies of foreign capital (e. g., evidence of differential trends of housing prices across locations with high versus low prevalence of foreigners).

We include county-year fixed effects in the regressions to rely exclusively on within-county cross-ZIP code variation for identification, which relieves concerns about confounding factors such as heterogeneous county-level economic developments (e. g., the tech boom in Silicon Valley). We also control for ZIP code-level characteristics that may systematically affect local labor and housing markets. We condition the effects on the post-shock period because of the clear trend break in capital inflows from China to the U.S. real estate market shown in Figures 1 and 2. A specification with such an interaction term allows for more flexibility in the estimation because it accounts for potentially different effects in the two regimes and identify the effects of foreign Chinese housing purchases off of the trend break.[40]

However, ordinary least squares (OLS) estimates of equations (8a) and (8b) may be affected by omitted variables bias. There may be unobserved factors that both correlate with foreign Chinese housing capital inflows and affect the local economic conditions, such as the crowding out of domestic home buyers from ZIP codes that experience large Chinese capital inflows and the growth potential of the targeted neighborhoods.[41] These factors could lead to either

[40] Essentially, this specification applies a generalized difference-in-differences framework with continuous treatment: We are comparing economic outcomes of locations that witnessed large amounts of foreign Chinese housing purchases with those with few foreign Chinese purchases before and after the China shock. This empirical strategy is similar to that in Berger et al. (2020), which studies the effects of a housing market stimulus policy. Moreover, we show in Appendix Table A.5 that our results remain qualitatively the same using a specification unconditioned on the post-shock period. Nevertheless, one does not know ex-ante whether the conditioning matters. Therefore, a specification that compares pre-post differences in economic conditions between regions with high versus low foreign Chinese housing purchases tends to be more flexible and more conservative.

[41] Increased foreign Chinese housing demand in specific neighborhoods could crowd out domestic buyers from these neighborhoods and shift their focus to the surrounding ones. This could have a positive effect on the employment and home prices of the latter set of ZIP codes and, in turn, damp the relative impact of Chinese capital inflows on the real economy of the targeted ZIP codes. This scenario would lead to negative bias in OLS estimates of equations 8a and 8b. The growth potential of neighborhoods may be another unobserved factor that could result in omitted variable bias. On the one hand, foreign Chinese may seek neighborhoods with better prospects of house price appreciation and employment opportunities, leading to positive bias in OLS estimation. On the other hand, they may buy in locations where interest and demand by local residents have already peaked and house prices have plateaued, which would lead to negative bias in OLS estimation (Cvijanović and Spaenjers, 2020).

negative or positive bias in OLS estimates.

To address the concern, we implement an IV approach by exploiting the second fact, i. e., home bias in foreign Chinese housing purchases. We utilize cross-ZIP code variation in the concentration of historical ethnic Chinese to identify differential exposure to real estate capital inflows from China. We instrument foreign Chinese housing transaction value ($CHTV$) and count ($CHTC$) by the aggregate foreign Chinese housing transaction value and count in California, respectively, weighted by pre-existing shares of ethnic Chinese population at the ZIP code level. Specifically, our instrumental variables are $CHShare_{z,0} \times CHTTV_t$ and $CHShare_{z,0} \times CHTTC_t$, where $CHShare_{z,0}$ is the ethnic Chinese population share in ZIP code z from the pre-sample year 2000 and $CHTTV_t$ ($CHTTC_t$) is a time-varying measure of the total housing transaction value (count) by foreign Chinese in California.[42]

The approach is numerically equivalent to that of a Bartik (1991) instrument, whose underlying identification lies in cross-sectional variation (Goldsmith-Pinkham et al., 2020). In this case, our IV strategy fundamentally uses cross-sectional variation in local ethnic Chinese population share to identify foreign Chinese housing demand.[43] Similar approaches that exploit the spatial variation of historical immigrant distribution have been applied to study the effects of immigrants on the labor markets (Card, 2001), the effects of ancestral composition on FDI (Burchardi et al., 2019), and, similar to our context, the effects of foreigners' house purchases on house prices (Badarinza and Ramadorai 2018 and Sakong 2020).[44]

Our research design essentially combines an IV approach with a DID framework. This com-

[42] We take the logarithm of the instrumental variables to address the skewness of their distribution, illustrated in Figure 3.

[43] A typical Bartik instrument is constructed by taking the product of ex-ante regional industry shares and industry-level aggregate shocks, making the instrument varying at the regional level. In our context, the parallel to "industry" is foreigner group, and we focus on one group—the foreign Chinese. When the instruments are applied to equations (8a) and (8b), the time-varying component of the IVs, total foreign Chinese housing transaction value or count in California ($CHTTV_t$ or $CHTTC_t$), is absorbed by the county-year fixed effects.

[44] Our IVs are similar to the instrument used in Sakong (2020), who also studies the effects of foreign Chinese house purchases on U.S. house prices. The only difference is that we exploit cross-sectional variation from the historical ethnic *Chinese* population share, and Sakong (2020) uses the historical *Asian* population share. Another instrument that Sakong (2020) uses in his study to predict foreign Chinese housing demand is the opening and closing of flight routes between cities in China and the United States. However, this instrument does not contain enough variation for the setting of our study (California), as flight routes between China and major cities in California have been in operations for decades and do not vary during the sample period.

bination enhances identification over the traditional time-series analysis on the effect of capital inflows because it makes use of both cross-sectional and time-series variation in capital flows in the estimation. The exclusion restriction relies on the assumption that, conditioning on ZIP code-level characteristics and county-year fixed effects, the historical ethnic Chinese population shares do not systematically influence changes in local economic conditions including employment and house prices except through higher Chinese real estate capital inflows (i. e. via "home bias abroad").[45] We recognize that, unconditionally, the historical ethnic Chinese population may be correlated with certain local characteristics, such as income and education, that could affect local conditions. We thus control for such characteristics, including pre-sample period population, education, the income trend, and trends in the outcome variable of interest. We also include population density and proximity to universities as urban controls. There may be concerns that the exclusion restriction is violated because our instruments may be related to a few other demand- or supply-side factors that may in turn affect local real outcomes. On the demand side, the ethnic Chinese population is conceivably related to the immigration inflow from China. However, our subsequent analysis suggests that real estate capital inflows from China are not accompanied by an inflow of immigrants. This is not surprising given the studies that show foreign Chinese tend to leave their houses abroad vacant (Rosen et al., 2017; Simons et al., 2016).[46] Also, data from the Yearbook of Immigration Statistics published by the U.S. Department of Homeland Security show that there was not a significant jump in the aggregate admissions of immigrants from China after the China shock. In fact, the number declined slightly: the number of new Chinese who obtained permanent residence in the United States was 87,307 in 2006, decreased to 64,238 in 2009, and reverted back to 71,798 in 2013. Appendix Figure A.10 illustrates the full time-series pattern.

On the supply side, one may wonder whether a productivity boom or land regulation in the

[45] Because the ethnic Chinese population distribution varies at the ZIP code level, we do not control for ZIP code fixed effects in the regressions, as doing so would absorb the useful variation we leverage for identification. In Appendix E, we apply a standard difference-in-differences specification in which ZIP code fixed effects are included, and our results remain robust.

[46] Rosen et al. (2017) and Simons et al. (2016) find that foreign Chinese real estate buyers tend not to use their purchased properties in the United States as primary residences or rental properties.

United States confounds the estimated effects from real estate capital inflows from China. For example, if locations with higher ethnic Chinese population density happened to experience an employment boom in the technology sector after 2008 (e. g., the Silicon Valley tech boom), this would contaminate the estimated employment and house price effects. Another potential concern is that these locations may impose stricter land regulation and hence have more restrictive housing supply, which would drive up house prices. Given our identification relies on variation at the ZIP code level with county-year fixed effects, we control for shocks at the county level, which ameliorates worries about differential technology booms and land policy driving the results. Moreover, we later show that the positive employment effect is concentrated in the non-tradable sectors, which further abates concerns related to confounding effects from technology-led jobs.[47]

Summary statistics of key variables To estimate equations (8a) and (8b), we obtain various zip-code-level data for the outcome and control variables, in addition to the real estate transaction data described in Section 2 for imputing foreign Chinese housing capital inflows. Our two key sets of outcome variables are ZIP code-level employment and house prices. Employment data are from ZIP Codes Business Patterns collected by the Census Bureau. These annual statistics for businesses with paid employees at the ZIP code level are categorized by two- through six-digit North American Industry Classification System (NAICS) code. For house prices, we use the Zillow Home Value Index for single-family homes, which is a smoothed, seasonally adjusted measure of the median estimated home value in a given ZIP code. In addition to the outcome variables, we also collect information on ZIP code-level population, education (measured as the share of the population with bachelor's degrees, from the Census Bureau), and income from the Internal Revenue Service (IRS) to use as control variables.

[47] We conduct a series of analysis in Section 6.1 to further test the validity of our identification strategy and the robustness of our results.

TABLE 1. Summary Statistics, by ZIP Code-Year

	All periods (2001–13)		Pre-shock period (2001–07)					Post-shock period (2008–13)				
	Mean	SD	Mean	SD	p(10)	p(50)	p(90)	Mean	SD	p(10)	p(50)	p(90)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Foreign Chinese trans.												
Value ($)	1.92M	4.82M	1.01M	1.51M	0.12M	0.52M	2.22M	3.05M	5.78M	0.19M	1.25M	7.30M
Log value	13.71	1.42	13.19	1.16	11.73	13.17	14.61	13.98	1.47	12.17	14.04	15.80
Counts	4.45	10.33	1.60	2.21	0.36	0.96	3.17	7.25	12.45	0.60	2.73	17.93
Log counts	0.71	1.34	0.11	0.88	-0.75	-0.83	1.18	1.13	1.34	-0.44	1.04	2.90
Total Housing trans.												
Value ($)	140.96M	99.58M	189.23M	120.06M	57.54M	166.90M	344.73M	113.60M	73.84M	33.65M	98.50M	211.44M
Counts	302.83	221.40	371.60	247.50	121.00	310.00	690.00	270.13	203.00	77.00	226.00	498.00
Log total emp.	9.21	0.94	9.30	0.90	8.03	9.40	10.37	9.15	0.96	7.90	9.28	10.23
Log non-tradable emp.	8.11	0.89	8.20	0.85	6.92	8.33	9.24	8.06	0.97	6.83	8.19	9.09
Log tradable emp.	5.96	1.93	6.16	1.94	3.50	6.48	8.47	5.84	1.92	3.18	6.03	8.18
Log establishment num.	6.53	0.76	6.59	0.70	5.63	6.69	7.42	6.51	0.79	5.53	6.64	7.40
Zillow SF home price	0.55M	0.36M	0.62M	0.38M	0.26M	0.54M	1.02M	0.67M	0.48M	0.25M	0.55M	1.18M
Log SF home price	13.05	0.58	13.20	0.55	12.47	13.20	13.83	13.22	0.61	12.44	13.22	13.98
Household income	77,517	67,124	73,450	56,400	34,374	59,862	115,003	78,410	71,901	35,145	61,048	133,592

Note: This table presents the summary statistics of the key variables in the dataset at the ZIP code-year level. Columns (1)–(2) shows annual means and standard deviations across ZIP codes for the whole sample period (2001–13). Columns (3)–(7) show the summary statistics for the pre-China shock period (2001–07), and columns (8)–(12) for the post-China shock period (2008–13). Foreign Chinese housing transaction value and counts are constructed using the three-step imputation algorithm described in Section 2.2, for transactions of single-family residential homes. *Source:* DataQuick, Zillow, Census Bureau, Internal Revenue Service, and authors' calculations.

Table 1 shows the summary statistics of the key variables at the ZIP code-year level. The top panel shows the dollar value and count of housing transactions by foreign Chinese buyers and by all buyers in the sample.[48] Columns (1) and (2) of Table 1 show the means and standard deviations of the variables for 2001 to 2013. Note the per-unit housing transaction value of foreign Chinese buyers is comparable with that of the average buyer in the sample, which suggests that the results in this study are not skewed by high-end real estate purchases.

To give a sense of the evolution of foreign Chinese house purchases in the United States, we also present the summary statistics of the key variables for the two sub-periods—the pre-China shock period of 2001 to 2007 and the post-China shock period of 2008 to 2013—in columns (3)–(7) and columns (8)–(12), respectively. Housing transactions by foreign Chinese increased dramatically after 2007. On average, while each ZIP code witnessed 1.6 housing transactions by foreign Chinese for a total value of $1.01 million per year between 2001 and 2007, these figures jumped to 7.25 transactions and $3.05 million, respectively, from 2008 to 2013. Compared with the pre-China-shock period, the share of Chinese transactions in all housing transactions in California in terms of value and count also increased from 0.53 percent to 2.68 percent and from 0.43 percent to 2.68 percent, respectively, during the post period. It is interesting to note that foreign Chinese housing transactions in value and count surged at a time when overall transactions dropped from pre-China shock levels.

The bottom panel of Table 1 shows summary statistics of the variables related to U.S. local economic conditions in the dataset. Home prices, tradable and non-tradable-sector employment, income, and the number of establishments appear similar across the two sub-periods. There is, nonetheless, considerable heterogeneity across ZIP codes, which we exploit to estimate the real effects of foreign Chinese house purchases on local economies.

[48] In aggregate over the sample period of 2001 to 2013, there were almost 1.5 million residential housing transactions, amounting to approximately $692 billion. Foreign Chinese made 21,842 house purchases with a total value of $9.43 billion, making up 1.4 percent and 1.5 percent of the total transaction value and count, respectively.

5 Real Effects of Foreign Chinese House Purchases

In this section, we present the main results on the employment effect of foreign Chinese house purchases and, guided by our theoretical framework, delve into the roles of the housing net worth and displacement channels.

5.1 Employment Effect

To test the model prediction on the employment effect of foreign Chinese house purchases (prediction 1 from Section 3), we estimate equations (8a) and (8b) with ZIP code-level employment size as the outcome variable and report the results in columns (1)–(2) of Table 2. Results from specifications using $CHTV$ as the main regressor are shown in odd-numbered columns, while those using $CHTC$ are shown in even-numbered columns.

The results show that foreign Chinese home purchases have a positive and significant effect on the local labor market. A one percent increase in housing demand by foreign Chinese, as measured by transaction value and count, raises local employment by 0.140 percent and 0.236 percent, respectively. The finding that the marginal effect of one additional unit of foreign Chinese purchase is greater than that of one additional dollar indicates that the employment effect is not driven by purchases of higher-end homes. In terms of economic magnitude, a one-standard-deviation difference in exposure to foreign Chinese real estate capital inflows (as measured by log $CHTV$) explains 21 percent of the cross-sectional variation in total employment.[49] These findings support the prediction from our theoretical framework on the employment effect of foreign real estate capital inflows.

The corresponding first-stage regression F-statistics, reported at the bottom of Table 2, range from 27 to 41, indicating that our instrumental variables have strong predictive power for foreign Chinese housing purchases, consistent with Figure 3. More detailed first-stage results are shown in Panel A of Appendix Table A.1. In addition, the coefficients on *CHTV* and *CHTC* cap-

[49] The corresponding calculation is 0.140 (coefficient)*1.42 (standard deviation of log CHTV)/0.94 (standard deviation of log total employment)=0.21.

ture any pre-existing differences in economic conditions between neighborhoods with high and low Chinese housing purchases before the China policy shock, providing a natural pre-trend test. These coefficients are small in magnitude and insignificant statistically, indicating that our results are driven by the China shock.

We dive deeper into the employment effect by exploring the extensive margin of adjustment: Namely, did foreign Chinese capital inflows increase total employment size by inducing new establishments? As shown in columns (3) and (4) of Table 2, we find that there is a significant positive adjustment on this extensive margin. A one percent increase in housing demand by foreign Chinese, as measured by transaction value and count, increases the number of local establishments by 0.144 percent and 0.238 percent, respectively. In terms of economic magnitude, a one-standard-deviation difference in exposure to foreign Chinese real estate capital inflows (as measured by log $CHTV$) explains 27 percent of the cross-sectional variation in the number of establishment.[50]

5.2 Channels Underlying the Employment Effect

Next, we turn to dissect the channels underlying the employment effect of foreign Chinese housing demand. Specifically, we test the model prediction on the role of the housing net worth channel versus the displacement channel in driving the effect (predictions 2–3) and assess whether the former channel dominates the latter (prediction 4).

Housing net worth channel. The housing net worth channel posits that higher foreign housing demand increases local employment through its positive effect on local house prices: Higher house prices raise local housing net worth and hence demand for the local non-tradable good and local employment in the non-tradable sector. To test these predictions, we first estimate the effect of the surge in foreign Chinese housing purchases on local house prices.

We estimate regression equations (8a) and (8b) with house prices as the outcome variable.

[50] The corresponding calculation is 0.144 (coefficient)*1.42 (standard deviation of log CHTV)/0.76 (standard deviation of log number of establishment)=0.27.

TABLE 2. Foreign Chinese Housing Demand and Total Employment

	Total Employment		Number of Establishments	
	(1)	(2)	(3)	(4)
ln(CHTV)*Post	0.140***		0.144***	
	(0.066)		(0.050)	
ln(CHTV)	0.026		-0.031	
	(0.103)		(0.078)	
ln(CHTC)*Post		0.236***		0.238***
		(0.094)		(0.074)
ln(CHTC)		-0.015		-0.083
		(0.112)		(0.086)
Controls	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
First-stage F-stat.	41	27	42	28
Obs.	4272	4336	4272	4336

Note: This table reports regression results from equations (8a) and (8b). The dependent variables are log total employment size (columns (1)–(2)) and log number of establishments (columns (3)–(4)). $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction value (count) instrumented by the aggregate housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. $Post$ is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. All regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, and pre-trends of income (1998–2001) and of the outcome variable (1996–2000). Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1, p < 0.05,$ and $p < 0.01$.

Columns (1)–(2) of Table 3 show results using (log) Zillow Single-Family Home Value Index as the outcome variable, and Columns (3)–(4) use housing transaction prices from DataQuick as the outcome variable. The results show that real estate capital inflows from China significantly increase local house prices, which supports the housing net worth channel prediction. A one percent increase in housing demand by foreign Chinese, as measured by transaction value and count, increased local home prices by 0.111 percent and 0.195 percent, respectively. In terms of economic magnitude, the former estimate implies that a one-standard-deviation increase in exposure to foreign Chinese real estate capital inflows (as measured by log $CHTV$) explains 27 percent of the cross-sectional variation in Zillow Home Value Index and raises the home price in an average ZIP code by $93,946, or 17 percent of the mean Zillow Home Value Index over the sample period ($0.55M).[51] Similarly, a one-standard-deviation increase in foreign Chinese housing purchase count explains 45 percent of the cross-sectional variation in Zillow Home Value Index and raises the home price in an average ZIP code by $164,326 or 30 percent.[52] The finding that foreign Chinese housing purchase count induces a greater marginal effect than volume also supports the role of the housing net worth channel: Higher quantity of foreign purchases likely reduces the housing stock available for local residents to a greater degree than higher volume; therefore, it goes with our expectation that a one percent increase in $CHTC$ drives up local house prices—and hence local housing net worth—more than a one percent increase in $CHTV$.

In addition to using the Zillow Home Price Index as a measure for house prices, we estimate equation (8a) using housing transaction prices from DataQuick as the dependent variable. This set of regressions allows us to study the effects of Chinese capital inflows on local house prices through the lens of newly-transacted houses. For these regressions, we control for ZIP code averages of the hedonic characteristics of the houses, including the number of bathrooms, square footage, and the age of the home, in addition to the baseline controls. The results, shown in columns (3)–(4) of Table 3, are slightly larger than those using Zillow Home Price Index as the dependent variable: A one percent increase in the housing demand by foreign Chinese, as measured by transaction value and count, increases local home transaction prices by 0.151 percent and 0.250 percent, respectively.

Overall, our results on the positive house price effect of foreign Chinese housing purchases are consistent with findings in the existing literature such as Badarinza and Ramadorai (2018) and Gorback and Keys (2020). We contribute to the literature by going beyond the asset price ef-

[51] The calculation to arrive at 27 percent of cross-sectional variation is 0.111 (coefficient)*1.42 (standard deviation of log CHTV)/0.58 (standard deviation of log Zillow Home Price Index)=0.27. The calculation for the latter statistics is $e^{13.05+0.58^2/2+1.42*0.111} - e^{13.05+0.58^2/2} = 93,946$, which is 17 percent of the mean Zillow Home Value Index over the sample period ($0.55M). It applies the expectation formula for a lognormal distributed variable and summary statistics from Table 1.

[52] The calculation to arrive at 45 percent of the cross-sectional variation is 0.195 (coefficient)*1.34 (standard deviation of log CHTC)/0.58 (standard deviation of log Zillow Home Price Index)=0.45. The calculation for the latter statistics is $e^{13.05+0.58^2/2+1.34*0.195} - e^{13.05+0.58^2/2} = 164,326$, which is 30 percent of the mean Zillow Home Value Index over the sample period ($0.55M).

TABLE 3. Foreign Chinese Housing Demand, Local Home Prices, and Displacement

	Home Prices (Zillow)		Home Prices (Transactions)		Number of Tax Returns	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(CHTV)*Post	0.111^{***}		0.151^{***}		-0.038^{***}	
	(0.022)		(0.021)		(0.014)	
ln(CHTV)	-0.031		-0.065^{**}		0.024	
	(0.029)		(0.026)		(0.019)	
ln(CHTC)*Post		0.195^{***}		0.250^{***}		-0.060^{***}
		(0.041)		(0.044)		(0.022)
ln(CHTC)		-0.082^{**}		-0.125^{***}		0.038
		(0.039)		(0.038)		(0.024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat.	42	23	45	24	36	20
Obs.	3995	4053	4258	4322	4021	4075

Note: This table reports regression results from equations (8a) and (8b). The dependent variables are log Zillow Single-Family Home Value Index in columns (1)–(2), log housing transaction values from DataQuick in columns (3)–(4), and log number of tax filers in columns (5)–(6). $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction value (count) instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. $Post$ is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. All regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, and pre-trends of income (1998–2001) and of the outcome variable (1996–2000). Columns (3)–(4) additionally controls for home characteristics, including the number of bathrooms, the square footage, and age of the home. *, **, and *** denote $p < 0.1$, $p < 0.05$, and $p < 0.01$.

fect and showing that house prices serve as a mechanism through which foreign Chinese housing demand shocks are transmitted to the local real economy.

Displacement channel. Besides the housing net worth channel, our conceptual framework points out that a competing channel—a displacement channel—could also be at play underlying the employment effect of foreign Chinese real estate capital inflows: Foreign housing demand could drive out local residents and lower demand for local non-tradable goods, leading to a decline in non-tradable sector employment.

We consider this channel as a component of a broader mechanism related to migration. Besides displacement, it is conceivable that foreign Chinese real estate capital inflows could accompany in-migration and thereby higher non-tradable-sector employment: Foreign Chinese may be moving into the neighborhoods in which they purchased houses, and their consumption would directly push up local non-tradable employment. Relatedly, these buyers could rent out the houses to local workers, whose demand for local goods could also push up employment. If the displacement channel dominates, we would observe that foreign Chinese housing purchases are associated with a net decline in the number of local residents. On the other hand, if the immigration or local rental channel dominates, we would observe a net increase.

To test this mechanism, we examine how foreign Chinese housing transactions affect the number of income tax returns at the ZIP code level, which has been used as a proxy for the number of local residents in the literature (see e. g., Greenland et al. 2019).[53] The income tax returns data are based on administrative records of individual income tax returns (Forms 1040) from the IRS. The presence of all Chinese who earned income or studied in the United States should be reflected in the tax returns data. Foreign Chinese without the appropriate work or student visa can only stay in the United States on a temporary basis (typically less than six months), and are unlikely to drive the employment results. While the change in the number of tax filers is not a perfect measure of migration, it provides a reasonable approximation.

[53] A more direct measure for the outcome variable for this test would be migration inflow and outflow counts. However, to our knowledge, migration data are not collected at the ZIP code level.

The regression results are shown in columns (5) and (6) of Table 3. We find a significantly negative relationship between foreign Chinese housing transactions and the number of tax filings, which suggests that foreign Chinese house purchases drive out local residents as a whole. A one percent increase in foreign Chinese housing demand, as measured by transaction value and count, lowers the number of tax filings by 0.038 percent and 0.060 percent, respectively. This result is consistent with the displacement channel and implies that real estate capital inflows from China did not induce a significant immigration wave.

The observation that foreign Chinese housing purchases are not accompanied by a significant inflow of immigrants can be reconciled with anecdotal evidence that foreign Chinese tend to leave their houses abroad vacant.[54] Studies by Rosen et al. (2017) and Simons et al. (2016) find that foreign Chinese real estate buyers tend to use their purchased properties in the United States as neither primary residences nor rental properties. In some cases, their housing purchases are positively related to the number of Chinese investors in the EB-5 Immigrant Investor Visa Program, who are primarily interested in obtaining green cards for their children instead of gaining actual returns on their real estate investments. The tendency of foreign Chinese real estate buyers to leave housing properties vacant is not surprising in light of a similar practice in China: Glaeser et al. (2017) show that housing vacancy rates in China are much higher than in the United States, reaching more than 20 percent in major Chinese cities in 2012. Cvijanović and Spaenjers (2020) find a similar pattern using data on non-resident real estate purchases in Paris. They show that few properties bought by non-residents are rented out, which echoes reports about foreign Chinese real estate owners acting as "absentee landlords."

In summary, we show that foreign Chinese real estate capital inflows displace local residents. While we cannot not definitively rule out any forces that might induce an inflow of population such as immigration, such forces, if they exist, appear to be dominated by the displacement of local residents.

[54] Relatedly, if foreign Chinese rented out their houses, the number of tax returns should not drop as observed in the data.

Housing net worth versus displacement channel. To assess the relative importance of the housing net worth versus the displacement channel, we examine the effect on local non-tradable-sector employment, as guided by our theoretical framework. If the housing net worth channel is the dominant mechanism, we conjecture an increase in non-tradable-sector employment in response to higher foreign Chinese housing purchases, and vice versa if the displacement channel is dominant. In addition, we study the effect of foreign Chinese housing purchases on tradable-sector employment, on which our model predicts an ambiguous effect.

To test these predictions, we re-estimate the baseline regression equations using non-tradable-sector and tradable-sector employment as the dependent variables. We categorize the sectors using the four-digit industry classification in Mian et al. (2013). An industry is defined as tradable if its sum of imports plus exports exceeds \$10,000 per worker, or if the total at the NAICS four-digit industry exceeds \$500 million, while non-tradable industries include the retail sector, restaurants, and sectors related to construction, real estate, or land development. Appendix Table A.2 lists the non-tradable industries.

Table 4 reports the regression results. Housing purchases by foreign Chinese have a positive and significant effect on the local non-tradable-sector employment but do not appear to strongly affect tradable-sector employment. A one percent increase in $CHTV$ and $CHTC$ raises ZIP code-level non-tradable-sector employment by 0.190 percent and 0.284 percent, respectively (columns (1) and (2)). These results are consistent with the model prediction of a housing net worth channel as a dominant mechanism driving the employment effect of Chinese real estate capital inflows.[55] The insignificant results on tradable-sector employment is also consistent with the model prediction.

One may wonder whether the strong relationship between foreign Chinese housing purchases and non-tradable-sector employment is driven by an increase in construction-sector employment since higher house prices could stimulate housing construction projects. We test

[55] Also, as in Table 2, the coefficients on *CHTV* and *CHTC* are statistically insignificant before the China shock and turn positive and significant in the post-shock period, which indicate that the increase in non-tradable employment in the post period is unlikely driven by pre-existing trends.

TABLE 4. Foreign Chinese Housing Demand, Employment by Sector, and Average Income

	Nontradable		Tradable		NT excl. Const.		Average Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(CHTV)*Post	0.190**		0.008		0.129*		0.082***	
	(0.066)		(0.149)		(0.067)		(0.025)	
ln(CHTV)	-0.085		0.370*		-0.037		-0.094**	
	(0.104)		(0.223)		(0.106)		(0.039)	
ln(CHTC)*Post		0.284***		0.085		0.210**		0.111***
		(0.090)		(0.209)		(0.088)		(0.032)
ln(CHTC)		-0.137		0.372		-0.083		-0.120***
		(0.108)		(0.248)		(0.110)		(0.043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat.	40	27	40	27	40	27	36	20
Obs.	4270	4334	4203	4267	4270	4334	4021	4075

Note: The dependent variables are log non-tradable-sector employment (columns 1–2), log tradable-sector employment (columns 3–4), log non-tradable non-construction-sector employment (columns 5–6), and log average household income (columns 7–8). $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction value (count) instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. $Post$ is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. All regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, and pre-trends of income (1998–2001) and the outcome variable (1996–2000). Columns show results for employment in non-tradable (with and without construction) and tradable sectors. Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1$, $p < 0.05$, and $p < 0.01$.

this conjecture by re-running the regressions excluding the construction sector from non-tradable-sector employment. The results are reported in columns (5) and (6) of Table 4. We still find a positive and significant link between foreign Chinese housing purchases and non-tradable-sector employment. While the magnitude of coefficients is smaller, these results show that most of employment effect is concentrated in the non-tradable and non-construction sectors, which further supports the housing net worth channel.

While the housing net worth channel appears to be the dominant mechanism driving the employment effect, the displacement of local residents in response to foreign Chinese housing purchases could also affect local employment through a change in the composition of local population in terms of household income. If displacement results in higher average income, demand for local non-tradable goods and thereby employment could increase with endogenous response in neighborhood amenities catered to higher-income households—a channel demonstrated in Almagro and Domınguez-Iino (2021).[56] To explore this relationship, we study whether foreign Chinese housing purchases affect average household income across ZIP codes. As shown in columns (7) and (8) of Table 4, the average income of households in the neighborhoods that experienced a surge in foreign Chinese housing purchases significantly increases. A one percent increase in these purchases as measured by transaction value and count is associated with a 0.08 percent and 0.111 percent increase in average income, respectively. This result suggests that endogenous adjustment in neighborhood amenities resulting from displacement effect may be an additional avenue through which Chinese real estate capital inflows impact local employment.[57]

6 Robustness and Discussion

In this section, we first conduct additional analyses to test the validity of our identification strategy and assess the robustness and external validity of our results. We then provide a discussion of the implication of the results, highlighting their distributional consequences.

6.1 Validation and Robustness

Event study and parallel trends. A key assumption underlying our estimation is that of parallel trends, which stipulates that in the absence of the surge in real estate capital inflows from China, house prices and employment between the more ethnic-Chinese-concentrated neighborhoods and others would have similar trajectories, conditioning on our ZIP code-level controls and county fixed effects. To test the validity of this assumption, we estimate the event-study versions of regressions (8a) and (8b), in which we interact $CHTV$ and $CHTC$ with a series of year dummies, controlling for the set of standard ZIP code-level controls and fixed effects.

[56] Using Dutch data, Almagro and Domınguez-Iino (2021) show that consumption amenities such as restaurants, cafes, and bars respond to changes in the demographic characteristics of the local population.

[57] Our conceptual framework from Section 3 does not contain predictions on local income, which would require a more full-fledged model and could be explored in future research.

Specifically, we run the following regressions:

$$\ln(Y_{zt}) = \alpha + \theta \ln(CHTV_{zt}) + \sum_{k=2001}^{2013} \beta_k \ln(CHTV_{zt}) \times \mathbb{I}\{t = k\} + \gamma X_{z,0} + \eta_{ct} + \varepsilon_{zt} \tag{9a}$$

$$\ln(Y_{zt}) = \tilde{\alpha} + \tilde{\theta} \ln(CHTC_{zt}) + \sum_{k=2001}^{2013} \tilde{\beta}_k \ln(CHTC_{zt}) \times \mathbb{I}\{t = k\} + \tilde{\gamma} X_{z,0} + \tilde{\eta}_{ct} + \tilde{\varepsilon}_{zt}, \tag{9b}$$

where $\mathbb{I}\{t = k\}$ are indicator variables for the various sample years (k). The coefficients β_k and $\tilde{\beta}_k$ estimate the dynamic effects of the China shock, with 2007 used as the reference year (i. e., the coefficients for that year are set to zero). For the parallel trend assumption to hold, these time-varying coefficients on the interaction terms should be significantly different from zero only for the post-China shock years.

Figure 5 plots the estimated coefficients on the dynamic effects of the China shock on total employment (Panels (a) and (b)), non-tradable-sector employment (Panels (c) and (d)), and tradable-sector employment (Panels (e) and (f)). Plots on the left panel are based on $CHTV$ as the main regressor, and those on the right panel are based on $CHTC$. Focusing first on the effect on total employment, we find that the key coefficients are not statistically different from zero before the China shock in 2008, which indicate that the employment conditions of neighborhoods of varying ethnic Chinese concentration exhibit parallel pre-trends, conditioned on the controls. The coefficients turn positive and significant in the post-shock period from the specification with $CHTC$ as the main regressor, while the post-shock effect using $CHTV$ are not significant. Estimating the coefficients dynamically year by year comes at the expense of reduced statistical power given the lower degree of freedom, resulting in relatively wide confidence intervals. Our baseline specifications improve the statistical power of the estimation by comparing the pooled effects from the pre-shock years to the post-shock years.

For the dynamic effects of the China shock on non-tradable-sector employment, we find that the key coefficients are not statistically different from zero before the China shock in 2008 and turn positive and significant in the post-shock period. For tradable-sector employment, the estimated coefficients for the post-China shock period are statistically indistinguishable from those for the pre-shock period. These results also support the parallel trend assumption and are consistent with our findings on the housing net worth channel from Section 5.2.[58]

Reverse causality and balance tests. To further examine whether neighborhoods that attracted more real estate capital from China had systematically different economic conditions from other neighborhoods, we conduct a reverse causality test. We test whether foreign Chinese have been targeting neighborhoods that systematically differ in pre-existing employment opportunities and income, using the following regression specification:

$$\Delta(Y_{\text{pre},z}) = \alpha_0 + \beta_0 \ln(CHTV_{08-13,z}) + \gamma_0 X_z + \eta_c + \epsilon_z \tag{10a}$$

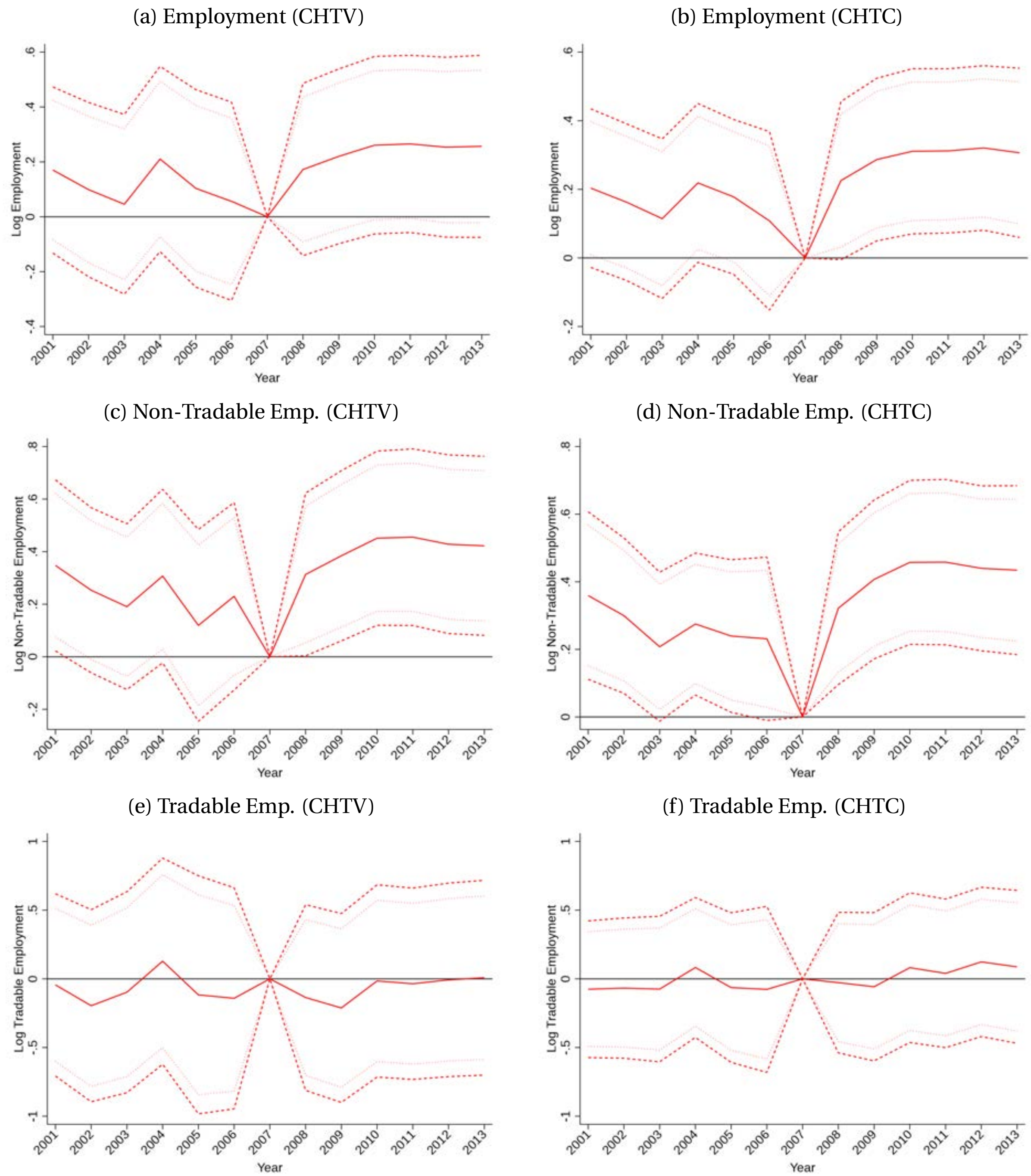
$$\Delta(Y_{\text{pre},z}) = \tilde{\alpha}_0 + \tilde{\beta}_0 \ln(CHTC_{08-13,z}) + \tilde{\gamma}_0 X_z + \tilde{\eta}_c + \tilde{\epsilon}_z, \tag{10b}$$

where $Y_{\text{pre},z}$ denotes variables capturing local economic conditions in two pre-shock periods in ZIP code z: employment size and household income during 2001–07 (pre-China capital control and HPR policy shock) and 1996–2000 (pre-sample period), $CHTV_{08-13,z}$ denotes foreign Chinese housing transaction value between 2008 and 2013 for ZIP code z, X_z denotes a set of ZIP code-level control variables—including population and education, and η_c denotes county fixed effects. The coefficient of interest is β_0. If the ZIP codes that attracted more foreign Chinese capital inflows had systematically better economic conditions, β_0 would be positive and significant. Panel (a) of Table 5 shows the regression results. The estimates of β_0 are statistically and economically insignificant, indicating that ex-post foreign Chinese capital inflows are not correlated with ex-ante local employment and household income, after controlling for local population and education. In other words, it does not appear that neighborhoods that attracted more foreign Chinese capital inflows after 2008 had better economic conditions before the shock.[59]

[58] Appendix Figure A.11 illustrates the estimated coefficients on the dynamic effects of the China housing demand shock on local home prices. They also support the parallel trend assumption and the findings from Section 5.2.

[59] As we mentioned in Section 5.1, another way to examine whether there is a systemic divergence in economic conditions across neighborhoods with varying Chinese capital inflows is checking the estimated coefficients θ and

Figure 5. The Dynamic Effects of Foreign Chinese Housing Demand on Local Employment



Note: This figure plots the coefficients on the interaction terms between foreign Chinese housing transaction value ($CHTV$) or foreign Chinese housing transaction count ($CHTC$) and a series of year dummies from regressions equations (9a) and (9b). The regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), and pre-trends of income (1998-2001) and the outcome variable (1996-2000) and county-year fixed effects, with 2007 used as the reference period. Plots on the left panels show the effects on total employment and by-sector employment using $CHTV$ as the key measure, and those on the right panels show the effects using $CHTC$ as the key measure. The 95 percent and 90 percent (in lighter color) confidence intervals are drawn based on standard errors clustered at the ZIP code level.

In addition to the reverse causality test, we perform a balance test to detect any potential violation of the exclusion restriction in the cross sectional variation of our IV prior to the China shock, following the proposal from Goldsmith-Pinkham et al. (2020). We conduct this test both statistically and graphically. First, we regress employment and income from either the pre-China shock or pre-sample period on the fundamental cross-sectional variation behind our instrument—the ethnic Chinese population distribution in 2000, measured in shares and percentiles, using specifications similar to equations (10a) and (10b). Reassuringly, panel (b) of Table 5 shows that the pre-period ethnic Chinese population distribution is uncorrelated with the pre-period outcomes. Next, we illustrate these regression results graphically by displaying scatter plots of residualized pre-shock period employment and income (with the control variables and county fixed effects from regression equations (10a) and (10b) partialled out) against the ethnic Chinese population distribution by percentile in 2000. Appendix Figure A.12 shows a flat slope in the fitted lines, with the zero horizontal line contained within the 95% confidence intervals. These findings from the balance test further attest to the validity of the exclusion restriction of our instrument.

Financial crisis. Despite the observation that ZIP codes with a higher ethnic Chinese concentration are not systematically different from other ZIP codes before the China shock, we are still concerned that the differences in their real outcomes after 2008 may be driven by factors other than foreign Chinese housing capital inflows. In particular, given that the timing of the initial surge in capital inflows coincided with the global financial crisis of 2007–08, one may worry that the neighborhoods populated by more ethnic Chinese were affected by the crisis differently than other neighborhoods. For instance, these neighborhoods may have weathered the crisis better and thus experienced smaller declines in employment and house prices.

We take several steps to address this concern. First, we analyze the employment and house

$\tilde{\theta}$ on $CHTV$ and $CHTC$ from equations (8a) and (8b): These coefficients capture any pre-existing differences in economic conditions between these neighborhoods. As shown from the baseline regression tables, they appear small and mostly statistically insignificant, which offers additional evidence of parallel pre-trends.

TABLE 5. Reverse Causality and Balance Tests

Panel (a): Reverse Causality Test

	Pre-policy shock: 2001–2007				Pre-sample: 1996–2000			
	Employment		Income		Employment		Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\text{CHTV}_{08\text{-}13})$	0.014		-0.005		-0.016		0.008	
	(0.012)		(0.004)		(0.012)		(0.009)	
$\ln(\text{CHTC}_{08\text{-}13})$		0.016		-0.006		-0.018		0.010
		(0.013)		(0.005)		(0.013)		(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat.	154	127	154	127	156	129	155	127
Obs.	639	628	639	628	640	629	638	627

Panel (b): Balance Test

	Pre-policy shock: 2001–2007				Pre-sample: 1996–2000			
	Employment		Income		Employment		Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CHShare	-0.0259		-0.0789		-0.0496		0.0630	
	(0.1215)		(0.0543)		(0.1290)		(0.0468)	
CHPercentile		-0.0002		-0.0001		0.0002		0.0005
		(0.0005)		(0.0002)		(0.0005)		(0.0005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8,320	8,320	8,320	8,320	8,333	8,333	8,307	8,307

Note: This table reports regression results from a reverse causality test in panel (a) and a balance test in panel (b). The dependent variables are log change in total employment size and income in two pre-shock periods: 2001–07 and 1996–2000. $CHTV_{08-13}$ ($CHTC_{08-13}$) denotes the log change in the foreign Chinese housing transaction value (count) between 2008 and 2013 instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. $CHShare$ and $CHPercentile$ measure the distribution of Chinese population in shares and percentiles, respectively. All regressions control for ZIP code-level population, population density, education, an indicator variable for whether there is a college within a five-mile distance, and county fixed effects. Education is measured as the population share with bachelor's degrees. Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1, p < 0.05,$ and $p < 0.01$.

price effects of foreign Chinese real estate capital inflows for the post-crisis period of 2012–13.[60] The results, reported in columns (1)–(2) of Table 6, are in line with our baseline results in both magnitude and significance. These results are also reflected in the event study plots in Figure 5. The fact that our results hold for both the crisis and post-crisis periods alleviates concern about potential confounds due to the financial crisis.

Second, we include an additional set of control variables that plausibly capture neighborhoods' differential ability to withstand the financial crisis in our regressions: (i) the share of foreclosed homes in each ZIP code, as neighborhoods that experienced more foreclosures were likely more affected by the financial crisis (Campbell et al. 2011 and Mian et al. 2015); (ii) the share of all-cash house transactions in each ZIP code, as neighborhoods that saw more all-cash house transactions were likely more insulated from the crisis; and (iii) the share of employment in the financial sector in each ZIP code, as neighborhoods more exposed to the financial sector—the hardest-hit sector—were likely more affected by the crisis. The results, shown in columns (3)–(8) of Table 6, are generated from regressions that include these variables as time-varying controls. The results shown in Appendix Table A.3 are from regressions that include these variables as pre-sample period controls, to further relieve endogeneity concerns. Both sets of results are qualitatively and quantitatively similar to our baseline results, alleviating our concern about potential confounding effects from the financial crisis.

Additional robustness analyses. We conduct additional analyses to check the robustness of the baseline results. We present the key takeaways below and relegate the details on the regression specifications and related discussions to Appendix E.

First, we apply a standard difference-in-differences empirical design to provide a simple estimate of the differential employment and house price effects between ZIP codes with more and less historical ethnic Chinese population (i. e., ZIP codes divided into treated and control group). Consistent with our baseline findings, Appendix Table A.4 shows that after the China

[60] We consider 2012–13 to be the post-crisis period because house prices in California was on a declining trend until 2012Q1 based on the California House Price Index from the U.S. Federal Housing Finance Agency.

TABLE 6. Foreign Chinese Housing Demand, Employment, and House Prices: Controlling for Financial Crisis Confounding Factors

Panel (a): Total Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(CHTV)*Post	0.152**		0.183***		0.131*		0.148**	
	(0.075)		(0.069)		(0.069)		(0.066)	
ln(CHTV)	0.030		-0.017		0.041		0.009	
	(0.112)		(0.098)		(0.110)		(0.104)	
ln(CHTC)*Post		0.218**		0.287***		0.226**		0.240**
		(0.100)		(0.104)		(0.094)		(0.094)
ln(CHTC)		0.029		-0.081		0.005		-0.030
		(0.117)		(0.115)		(0.118)		(0.111)
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	–	–	Foreclosure	Foreclosure	All-cash Transactions	All-cash Transactions	Financial Sector	Financial Sector
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post period	2012–13	2012–13	2008–13	2008–13	2008–13	2008–13	2008–13	2008–13
First-stage F-stat.	34	28	40	22	44	27	41	28
Obs.	2482	2510	3974	4038	4272	4336	4269	4333

Panel (b): Home Prices (Zillow)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(CHTV)*Post	0.121***		0.075***		0.105***		0.111***	
	(0.023)		(0.021)		(0.022)		(0.022)	
ln(CHTV)	-0.017		-0.015		-0.021		-0.033	
	(0.030)		(0.027)		(0.031)		(0.029)	
ln(CHTC)*Post		0.194***		0.126***		0.187***		0.196***
		(0.041)		(0.034)		(0.039)		(0.042)
ln(CHTC)		-0.050		-0.046		-0.066		-0.084**
		(0.037)		(0.035)		(0.041)		(0.040)
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	–	–	Foreclosure	Foreclosure	All-cash Transactions	All-cash Transactions	Financial Sector	Financial Sector
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post period	2012–13	2012–13	2008–13	2008–13	2008–13	2008–13	2008–13	2008–13
First-stage F-stat.	34	23	43	20	45	23	42	23
Obs.	2320	2343	3995	4053	3995	4053	3995	4053

Note: The dependent variables are log total employment size in panel (a) and log Zillow Single-Family Home Value Index in panel (b). $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction value (count) instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. $Post$ is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. All regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, and pre-trends of income (1998–2001) and of the outcome variable (1996–2000). Columns (1)–(2) show the results for the post-global financial crisis period of 2012–13. Columns (3)–(4) additionally control for the share of foreclosed homes in each zip code. Columns (5)–(6) additionally control for the share of all-cash house transactions in each zip code. Columns (7)–(8) additionally control for the size of the financial sector, measured as the share of finance sector employment in each zip code. All the additional controls are time-varying. Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1, p < 0.05,$ and $p < 0.01$.

shock in 2008, employment and house prices in treated ZIP codes are significantly higher than the control ZIP codes, conditioning on either ZIP code-level characteristics or ZIP code and time fixed effects.

Second, we run a version of equations (8a) and (8b) without the post-China shock period interaction, which gives the average effects of foreign Chinese housing purchases for the entire sample period. Appendix Table A.5 shows that foreign Chinese home purchases have a positive and significant effect on local labor and housing market on average, again consistent with the baseline results.

Third, we assess the robustness of the main results to the imputation algorithm for constructing measures of foreign Chinese housing transactions. Details of the analysis are provided in Appendix E. In sum, we find that (i) the second step of algorithm—keeping only all-cash housing transactions by ethnic Chinese—is unlikely to generate bias in the estimation results; (ii) our results are not sensitive to the third step of the imputation algorithm distinguishing resident versus foreign Chinese homebuyer; and (iii) it is unlikely that our baseline results are affected by purchases by non-Chinese foreigners.

External validation. Finally, we assess the external validity of our estimation results by comparing the elasticity of employment to housing net worth implied by our estimates to those in the existing literature. Based on data from the 2010 Survey of Consumer Finances on the asset and debt holdings associated with the primary residence across age groups, we obtain a range of 1.5–6.4 for leverage ratios.[61] A back-of-the-envelope calculation based on our baseline results yields a range of 0.20–0.82 for the elasticity of total employment with respect to housing net worth.[62] The corresponding elasticity estimates are 0.27–1.14 for non-tradable-sector

[61] Based on the 2010 Survey of Consumer Finances, the average amounts of asset holding associated with the primary residence for the age groups of less than 35, 35–44, 45–54, 55–64, 65–74, and 75 or more are \$170,400, \$238,100, \$294,300, \$306,100, \$271,400, and \$233,200, respectively. The average amounts of debt holding for the corresponding age groups are \$143,700, \$178,700, \$172,100, \$147,400, \$122,900, and \$79,600, respectively. The leverage ratio is calculated as asset over equity. As expected, the leverage ratio is higher for younger households as they tend to be new home owners who have built up less equity.

[62] Our housing price results imply that a one percent increase in foreign Chinese real estate capital inflows induces a 0.111 percent increase in house prices, or a range of 0.17–0.71 percent increase in housing net worth in the

employment, and 0.18–0.77 for non-tradable non-construction-sector employment. The lower end of the estimated range is in line with the estimates of 0.2–0.5 from Mian and Sufi (2014), although we obtain higher estimates at the upper end. Our estimates may be higher for two reasons. First, our analysis is at the ZIP code level while that of Mian and Sufi (2014) is at the county level. As a result, we capture the employment effect that arises from commuters across ZIP codes, which may not be present across counties. Second, our sample period covers both economic booms and busts, while Mian and Sufi (2014) focus on the Great Recession period when the labor market was sluggish.

6.2 Distributional Consequences

Finally, we consider the implications of our findings. Despite the positive real effects of foreign Chinese real estate capital inflows, do these flows potentially carry adverse distributional consequences? The house price effect of foreign Chinese housing purchases suggests that these purchases worsen local housing affordability, and the displacement effect suggests that foreign Chinese real estate capital inflows contain implications for gentrification. We further explore the potential distributional consequences by studying whether the displacement effect is concentrated in a particular segment of the income distribution.

Specifically, we assess the effect of foreign Chinese housing purchases on the displacement of low-income households and high-income households separately. As in Section 5.2, we use the number of income tax returns to proxy for the number of local residents. We divide the income tax returns into two groups based on household income: Households with annual income less than \$50,000 are categorized as low-income households, and those with more than \$50,000 are categorized as high-income households. We run equations (8a) and (8b) using the number of low-income and high-income tax filers as the outcome variables.

local economy. Our baseline employment results show that a one percent increase in foreign Chinese real estate capital inflows leads to 0.140 percent increase in total employment. The elasticity of total employment with respect to housing net worth is calculated as the ratio of the coefficient on total employment and the increase in housing net worth.

TABLE 7. Foreign Chinese Housing Demand and Displacement of Residents by Income

	No. of Low-Income Tax Returns (under $50,000)		No. of High-Income Tax Returns (above $50,000)	
	(1)	(2)	(3)	(4)
ln(CHTV)*Post	-0.067***		-0.031	
	(0.016)		(0.034)	
ln(CHTV)	0.031		0.136***	
	(0.021)		(0.048)	
ln(CHTC)*Post		-0.109***		0.005
		(0.028)		(0.050)
ln(CHTC)		0.059**		0.130**
		(0.028)		(0.058)
Controls	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
First-stage F-stat.	37	20	36	20
Obs.	4021	4075	4021	4075

Note: The dependent variables are log number of income tax returns by households with income less than $50,000 (columns 1–2) and greater than $50,000 (columns 3–4). $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction value (count) instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. $Post$ is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. All regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, and pre-trends of income (1998–2001) and of the outcome variable (1996–2000). Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1$, $p < 0.05$, and $p < 0.01$.

The results, presented in Table 7, show that the displacement effect is concentrated in the low-income resident group. A one percent increase in foreign Chinese housing transactions, as measured by transaction value and count, lowers low-income household count by 0.067 percent and 0.109 percent, respectively (columns (1) and (2)). The magnitudes of the estimated coefficients are nearly twice as large as those from the full-sample regressions shown in columns (5)–(6) of Table 3. By contrast, the effect on the number of high-income households is statistically insignificant (columns (3) and (4) of Table 7). Our results suggest that foreign Chinese housing purchases have driven out low-income households in particular.[63]

[63] Given that the low-income households are more likely to be renters, our results imply that foreign real estate capital inflows likely have induced displacement of local renters in particular. We do not study the effects of foreign Chinese housing purchases on rent or migration by tenancy status because, to our knowledge, no reliable data are

7 Conclusion

In this paper we study the real effects of foreign real estate capital inflows—a nontraditional and opaque form of international capital flows. Using transaction-level housing purchase data, we document two salient phenomena: (i) a China shock in the U.S. real estate market as characterized by a surge of foreign Chinese housing purchases after 2008; and (ii) home bias in these purchases as they are concentrated in ZIP codes historically populated by ethnic Chinese. We exploit the temporal and spatial variation of real estate capital inflows from China and find that they significantly increase employment in the local economy. We present evidence that the employment effect is mainly transmitted through a housing net worth channel: These capital inflows increase local house prices, raising local housing wealth and, in turn, demand for local non-tradable goods and non-tradable-sector employment. At the same time, foreign Chinese housing purchases drive out local residents, especially those of lower-income brackets, and thus induce gentrification.

Our analysis highlights both the positive real effects and potentially adverse distributional consequences of foreign real estate capital flows. However, it is worth noting a few limitations of this study. First, our estimates represent the local general equilibrium effects of foreign capital inflows on the local labor and housing markets and may understate the true magnitude of the impact, as they do not capture the aggregate effects across all U.S. regions. Second, we have not thoroughly examined the welfare implications of foreign purchases on homeowners and renters. Potential negative effects on domestic homeownership and gentrification have ignited intense policy debates on whether and how to control real estate capital flows from foreign countries. More research on the aggregate effects and welfare consequences of real estate capital flows will help inform optimal policies on this issue.[64]

available to capture these outcomes at the ZIP code level.

[64] Another limitations of our study is its scope in terms of geographical and housing type coverage. For future research, our algorithm to impute the amount of foreign housing purchases and empirical methodology could be applied to a larger cross-section of geographical areas and house types.

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For Online Publication

Local Effects of Global Capital Flows: A China Shock in the U.S. Housing Market

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Appendix A Additional Details on Measures of Real Estate Capital Inflows

In this section, we provide additional details on the derivation of the two measures of real estate capital inflows—foreign housing transaction value ($fHTV$) and housing transaction count ($fHTC$)—based on three-step imputation algorithm described in Section 2.2.

Given the second step of the imputation algorithm that *all-cash* housing transactions are used identify foreign purchases, our measures of $fHTV$ and $fHTC$ are equivalent to all-cash housing transaction value ($fHTV^{\text{cash}}$) and count ($fHTC^{\text{cash}}$), respectively, for each non–Anglo-American foreign ethnic group (f):

$$fHTV \equiv fHTV^{\text{cash}}, \tag{A.1a}$$

$$fHTC \equiv fHTC^{\text{cash}}. \tag{A.1b}$$

For the third step of the algorithm, we estimate the amount of all-cash housing purchases made by *resident* non–Anglo-Americans and adjust our measures downward accordingly to keep only *non-resident* transactions. As noted in the main text, each non–Anglo-American foreign ethnic group f's (all-cash, adjusted) housing transaction value (and count), $fHTV$ ($fHTC$), is the difference between its total (all-cash, unadjusted) housing transaction value (and count), HTV_f (HTC_f), and those of its U.S. resident population, $RHTV_f$ ($RHTC_f$); equivalently:

$$fHTV = HTV_f - RHTV_f, \;\; fHTV^{\text{cash}} = HTV_f^{\text{cash}} - RHTV_f^{\text{cash}}; \tag{A.2a}$$

$$fHTC = HTC_f - RHTC_f, \;\; fHTC^{\text{cash}} = HTC_f^{\text{cash}} - RHTC_f^{\text{cash}}. \tag{A.2b}$$

Our estimates of housing purchases by resident non–Anglo-American foreign ethnic groups (f) are based on the assumption that their propensity to make all-cash purchases is similar to

Anglo-Americans (A):

$$\frac{RHTV_f^{\text{cash}}}{RHTV_f} = \frac{HTV_A^{\text{cash}}}{HTV_A}; \tag{A.3a}$$

$$\frac{RHTC_f^{\text{cash}}}{RHTC_f} = \frac{HTC_A^{\text{cash}}}{HTC_A}. \tag{A.3b}$$

Given the conditions specified in equations (A.2a), (A.2a) and (A.3a), we derive the formulas for estimating $fHTV$ and $fHTC$ for each foreigner group f at ZIP code z in year t, taking advantage of the granularity of our data:

$$fHTV_{zt} = \left[HTV_{fzt}^{\text{cash}} - \frac{HTV_{Azt}^{\text{cash}}}{HTV_{Azt}} \times HTV_{fzt}\right] \frac{HTV_{Azt}}{HTV_{Azt} - HTV_{Azt}^{\text{cash}}}, \tag{A.4a}$$

$$fHTC_{zt} = \left[HTC_{fzt}^{\text{cash}} - \frac{HTC_{Azt}^{\text{cash}}}{HTC_{Azt}} \times HTC_{fzt}\right] \frac{HTC_{Azt}}{HTC_{Azt} - HTC_{Azt}^{\text{cash}}}. \tag{A.4b}$$

The first term in equations (A.4a) adjusts each foreigner group's total housing transaction value and count, respectively, by the proxy for transactions made by its U.S. resident population; the second term is a re-scaling factor.

As discussed in Section 2.3, foreign Chinese dominate all other foreigner groups in housing purchases in the United States; we thus focus on the real effects of foreign Chinese housing in the our analysis. As such, the main regressors in our empirical specifications are Chinese housing transaction value ($CHTV$) and Chinese housing transaction count ($CHTC$), as defined in equations (A.4a) for $f = C(hinese)$.

Appendix B Determinants of Foreign Chinese Real Estate Capital Inflow Patterns

In this section, we explore determinants driving the patterns of foreign Chinese real estate capital inflows summarized in the two stylized facts in Section 2.3. While a rigorous study is out of the scope of this paper, we provide a discussion of the potential drivers of a China shock in the U.S. real estate market and home bias of foreign Chinese housing purchases.

B.1 Potential Causes of a China Shock

We show that relaxation of capital controls and a series of house purchase restrictions (HPR) introduced by the Chinese government in late-2007 likely played a key role in inducing the surge in foreign Chinese housing purchases in the United States since then.

Capital control loosening and "smurfing." In the second half of 2007, the Chinese government introduced several policies of capital control relaxation to soften economic problems generated by its record trade surplus and encourage money outflows. The timing of these policies coincides with the initial sharp surge in foreign Chinese housing purchases in the United States, as denoted by the solid vertical line in Figure 1.

In late 2007, the State Administration of Foreign Exchange (SAFE) increased the limit on how much Chinese citizens can exchange yuan to other currencies from \$20,000 to \$50,000 per person annually (SAFE No. 1 [2007]). Around the same time, the government also expanded the Qualified Domestic Institutional Investor (QDII) scheme, which allows financial institutions to invest in overseas capital markets including equity and bonds. For example, SAFE introduced a pilot program in late 2007 that allows domestic individual investors to convert an unlimited amount of yuan into foreign currency and invest it in Hong Kong. Since Hong Kong did not impose limits on capital outflows, this program significantly lowered frictions to moving capital abroad. In early 2008, the China Banking Regulatory Commission and the U.S. Securities and Exchange Commission reached and agreement to enable Chinese individuals to invest in the U.S. equity market.

In the subsequent years leading up to the inclusion of the Chinese yuan into IMF's special drawing rights (SDR) basket in 2016, the Chinese government introduced additional policies to loosen capital control and demonstrate its determination to reforming its financial system. For example, it implemented a pilot program in Wenzhou to allow wealthy local residents to invest overseas in 2012. The continuation of these policies of capital control loosening can explain the persistence of foreign Chinese housing purchases over the sample period.

Moreover, these policies particularly aid a popular technique for moving capital abroad for real estate buying purposes, known as "smurfing." Smurfing entails a group of people (family, friends, and neighbors) lending their foreign currency quotas to a single individual by wiring money to one overseas bank account. Once enough foreign currency has been accumulated in the account, an overseas investment, such as real estate, can be made. This approach of pooling foreign exchange quotas has been difficult for the Chinese authorities to detect and thus widely used by individuals to circumvent the official capital control, especially for the purpose of purchasing real estate overseas.

The Chinese government has tried to curb the practice of smurfing. In November 2009, SAFE issued a notice (SAFE No. 56 [2009]) to identify potential instances of smurfing, using the following criteria: 1) five or more individuals convert Chinese yuan to foreign currency and transfer the money to the same person or institution overseas on the same day or in consecutive days; 2) an individual withdraws close to $10,000 (the daily foreign currency withdrawal quota) five or more times within seven days from one account; or 3) an individual transfers money to five or more direct relatives, who then apply their foreign exchange quota to conduct foreign exchange transactions within the year. Furthermore, if a client is suspected of being involved in smurfing, banks are ordered to request additional verification or deny her foreign exchange application.

While these measures make it more difficult to move capital out of China, Chinese residents still find creative ways to get around them, including pooling foreign exchange quota among friends instead of relatives, spreading out the pace of currency exchange, using underground money lenders through Hong Kong, and even physically moving cash through traveling. There are numerous anecdotal evidence in media reports about how Chinese, through these means, move capital abroad to invest in real estate.[65]

Given Chinese residents' persistence efforts to circumvent existing measures of smurfing prevention, the Chinese authorities continuously escalated their monitoring and punishment schemes. In 2011, SAFE started compiling a watchlist of people suspected of practicing smurfing (No. 41 [2011]). People on the watchlist are not allowed to exchange foreign currencies electronically and, without clearance from additional investigation, are banned from conducting foreign exchange transactions for two years. In 2017, SAFE began explicitly banning foreign currency exchange for the purpose of real estate investment, allowing that only for expenses related to "education, visiting relatives, medical bills, or purchasing non-investment insurance or consulting services."[66] The authorities also established policies to punish violators, including banning their use of the foreign exchange quota for two years and recording such violation in personal credit reports, which would affect their future borrowing capacity. The fact that the Chinese authorities have had to keep escalating monitoring and punishment measures over time reflect the fact that Chinese residents continue to find ways to circumvent existing regulations and move capital abroad.

Housing purchase restrictions. The Chinese housing market witnessed surging demand and skyrocketing prices in the decade after the government commercialized real estate transactions for the first time in the country's history in 1998. Concerned about house price inflation, the Chinese government began implementing a series of policies to rein in speculative housing demand in late 2007.[67] The People's Bank of China and the China Banking Regulatory Com-

65 See, e. g., "Smurfs' Beat Cash Controls, Sending Real Estate Soaring." 2 Nov., 2015, *Bloomberg News*, and "Chinese Start to Lose Confidence in Their Currency." 13 Feb., 2016 *New York Times*.

66 Prior to then, foreign exchange for the purpose of real estate investment was not explicitly banned, only implicitly discouraged. People's Bank of China Notice No. 2006-3 Item 22 allowed foreign currency exchange for the purpose of housing purchases as long as the money source and foreign exchange transaction meet the regulatory requirements.

67 Before 1998, the Chinese government controlled the distribution of real estate, providing it only to employees of state-owned enterprises as part of the employment benefits. In 1998, the government introduced a reform to commercialize real estate, allowing unrestricted buying and selling of properties for the first time in the country's

mission jointly issued the No. 359 [2007] Notice to "strengthen the management of residential real estate credit loans." The new regulation increased the mortgage down-payment restriction for second homes to 40 percent, bounded the interest rate on mortgage loans to be at least 10 percent higher than the prevailing market rate, and capped the maximum monthly payment-to-income ratio at 50 percent.

While these policies only toughened lending standards, they were effective in reducing home purchase volume and flattening house price trends in major Chinese cities, as they negatively affected the future expected return of real estate in China. As such, it is conceivable that the policies made housing investment abroad comparatively more attractive.[68] Indeed, the timing of these HPRs in China coincides with the initial sharp surge in foreign Chinese housing purchases in the United States, as denoted by the solid vertical line in Figure 1.

The Chinese government introduced additional HPRs in the subsequent years, which can explain the intensification and persistence of foreign Chinese housing purchases. In mid-2010, the Chinese government stepped up its effort by imposing more stringent restrictions on home purchases. Based on the "National Ten" (*guoshitiao*) real estate market regulation, city residents who already own one house or condo can buy at most one more house or condo, and non-residents can buy at most one house or condo. Regardless of whether the second home was an upgrade, the down payment had to be at least 50 percent.[69] The restriction was first implemented in Beijing and soon got expanded to other major cities such as Shanghai, Guangzhou, and Shenzhen later that year. In 2011, a new set of "New National Eight" (*xin guobatiao*) regulations further increased the minimum down payment on second homes to 60 percent and introduced more tightening measures involving taxes, land transactions, and no mortgage beyond the second home. Sun et al. (2017) document that these stringent HPRs significantly lowered housing prices and transaction volume in China, further damping speculative demand and slowing home price inflation. The timing of this additional round of HPRs in mid-2010 corresponds to a new wave of foreign Chinese home purchases in the United States.

Other factors. Additional factors that may have played a role in inducing housing purchases by foreign Chinese in the United States include the appreciation of the yuan against the dollar and greater flow of information about the U.S. housing markets to potential buyers in China. The latter factor could have facilitated the intensification and persistence of foreign Chinese house buying in the United States since 2008.[70]

The collapse of U.S. house prices during the Great Recession may have also encouraged foreign investment in U.S. real estate. However, the influence is likely secondary given that

history. This, combined with high household savings, a lack of alternative investment opportunities, and a low down-payment requirement for mortgages (around 20 percent at the time) induced surging housing demand and skyrocketing house prices in the subsequent years. Worried about house price inflation, the Chinese government elevated house price stability as an official initiative by 2007.

[68] Deng et al. (2021) show that similar HPRs in selected Chinese cities in 2016–17 induced spillover effects on housing demand in neighboring non-regulated cities.

[69] If the first home was smaller than the average house size per person in a city, the second home was considered an upgrade. Before 2010, the down payment and mortgage requirements for buying such second homes were similar to those for first homes.

[70] Numerous Chinese websites that advise buying opportunities in the United States emerged during our sample period. One of the most popular is juwai, which was founded in 2010.

housing purchases by foreign Chinese in the United States were persistently high over the entire period of 2008–13 and even surged after 2011, when the U.S. housing market began to recover. Moreover, such persistent housing demand was not seen from other groups of foreigners.

B.2 Forces Influencing Home Bias of Foreign Chinese Housing Purchases

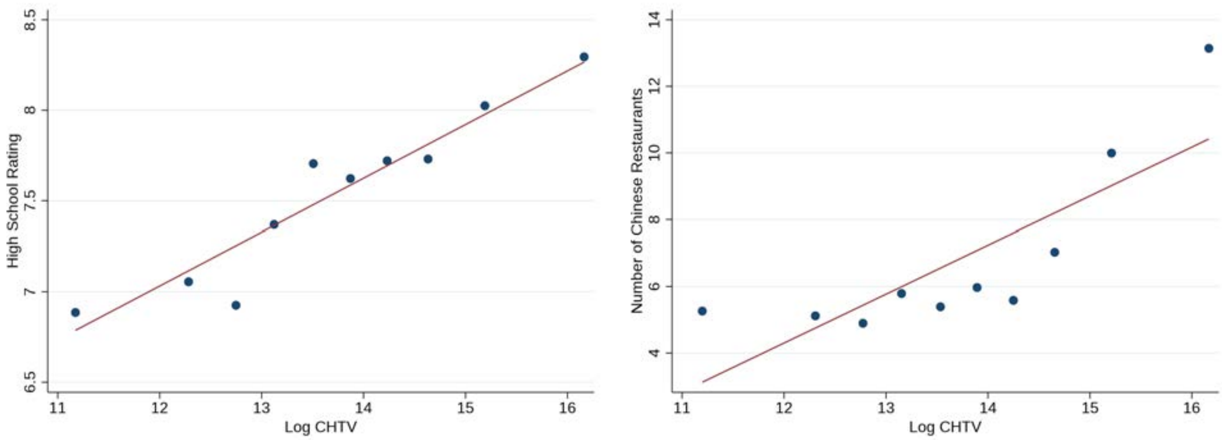
Why do foreign Chinese cluster their housing purchases in neighborhoods historically populated by ethnic Chinese—the second stylized fact documented in Section 2.3? The literature have proposed two possible forces for clustered housing purchases among heterogeneous households: preference for neighborhood amenities such as school quality (Bayer et al. 2007, Wong 2013), and cultural affinity and trust that results in lower information and contractual friction in purchase transactions (Chaney 2014, Badarinza et al. 2021). We conduct analyses to explore whether these two forces influenced the home bias behavior of foreign Chinese in the U.S. housing market.

First, we investigate whether their behavior is driven by preferences for specific amenities including school quality and ethnic food availability. To generate a measure of local school quality, we extract the ratings of high schools in each ZIP code from GreatSchools.org and compute an average rating. Panel (a) of Figure A.1 shows the relationship between (log) foreign Chinese housing transaction value (CHTV) and local school quality in a binned scatterplot. We observe a strong correlation, indicating that foreign Chinese tend to purchase houses in neighborhoods with better school quality. Similarly, we examine the relationship between CHTV and the presence of Chinese restaurants in each ZIP code, using data extracted from Yelp. As shown in Panel (b) of Figure A.1, we find that ZIP codes that attract more real estate capital from foreign Chinese tend to have more Chinese restaurants. Overall, this evidence indicates that the preference of foreign Chinese for specific amenities such as school quality and ethnic food availability is a plausible driving force for their home bias abroad behavior.

Next, we examine the potential role of cultural affinity and trust in influencing the home bias of foreign Chinese housing purchases. Recent literature such as Chaney (2014) and Badarinza et al. (2021) show that personal connections and counterparty affinity can determine patterns of export flows and cross-border investment flows through the reduction of information and contractual frictions. Motivated by these findings, we conduct a simple exercise to explore whether foreign Chinese buyers are more likely to buy from ethnic Chinese sellers, using the real estate transaction data. For each ZIP code decile by historical ethnic Chinese population, we compute the share of housing transactions by foreign Chinese buyers and non-Chinese buyers from ethnic Chinese sellers. As shown in Figure A.2, foreign Chinese buyers are more likely than non-Chinese buyers to buy from ethnic Chinese sellers across all ZIP codes. Overall, our evidence suggests that affinity or trust may also play a role in driving the home bias behavior of foreign Chinese in U.S. housing market.

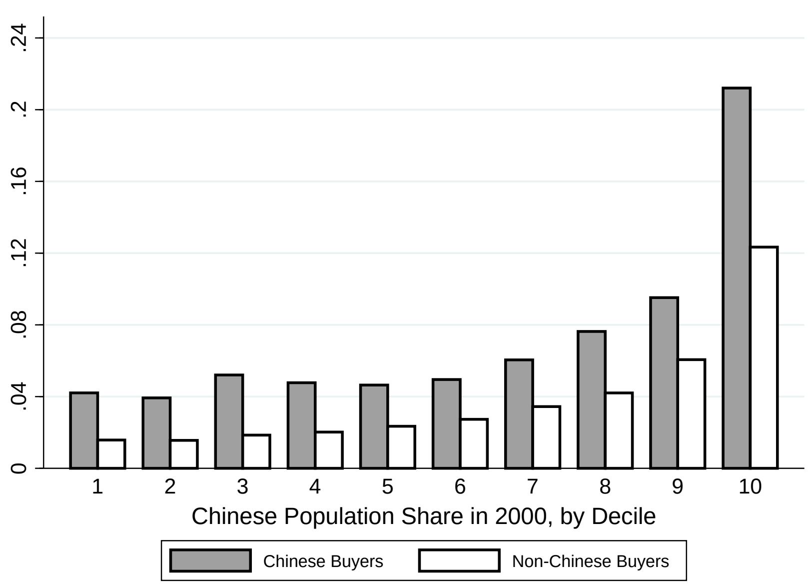
Figure A.1. Foreign Chinese Housing Purchases and Neighborhood Amenities

(a) High School Quality **(b)** Chinese Restaurant Presence



Note: Panel (a) shows the relationship between neighborhood high school quality and (log) foreign Chinese housing transaction value (CHTV) across ZIP codes over the period of 2007 to 2013 in a binned scatterplot (slope of fitted line: 0.30, with $t = 15.44$). The measure of neighborhood high school quality is based on the average rating of high schools in each ZIP code from GreatSchools.org. Panel (b) shows the relationship between Chinese restaurant presence, as measured by the number of Chinese restaurants in each ZIP code using data from Yelp, and (log) CHTV from 2007 to 2013 (slope of fitted line: 1.47, with $t = 14.59$).

Figure A.2. Purchases by Chinese and Non-Chinese Buyers from Ethnic Chinese Sellers



Note: This figure illustrates the share of housing transactions by foreign Chinese and non-Chinese buyers from ethnic Chinese sellers across ZIP code deciles by historical ethnic Chinese population, based on the 2000 Census Bureau Survey.

Appendix C Model Simulations

In this section, we calibrate the model presented in Section 3 and discuss the simulation results. In particular, we examine how the two opposing forces—the housing net worth channel and the displacement channel—govern the effects of a positive foreign housing demand shock on non-tradable and tradable sector employment. The parameter values we apply are based on established data sources and evidence from existing literature. For parameters whose values are potentially more varied or indeterminate, we apply several parameter configurations to gauge the implications of the modeling choice on our results.

Baseline Simulation. For our baseline simulation, we use $\alpha = 0.45$, $\beta = 0.2$ for consumption expenditure shares on tradable and non-tradable goods, respectively, based on data from the U.S. Department of Agriculture.[71] The housing stock is normalized with $H_0 = 1$. We apply a normal distribution to commuting costs, $\phi \sim \mathcal{N}(0.032, 0.008)$, with the parameters determined by data from the U.S. Census Bureau's 2017 American Housing Survey.[72] For the parameter on the share of commuters consuming at the location of residence, the data for which are not readily available at the ZIP code level to our knowledge. We choose $\lambda = 0.5$ as the baseline and subsequently explore how the outcomes vary with different values of λ.

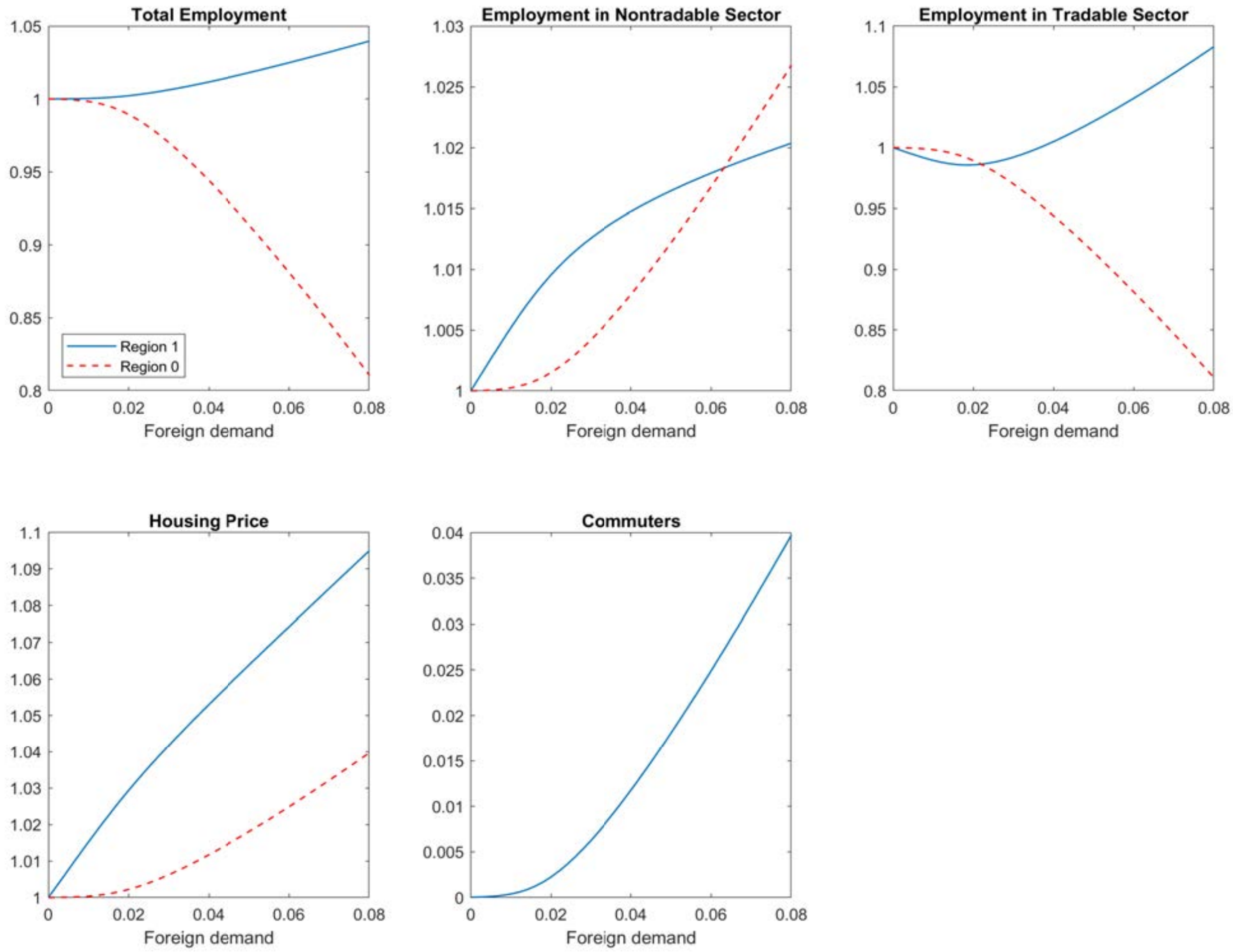
Appendix Figure A.3 shows the effects of positive foreign housing demand on (total, non-tradable-sector, and tradable-sector) employment, house prices, and number of commuters using the baseline parameter values. It shows that an increase in foreign housing demand raises employment in the non-tradable sector in Region 1 (the region experiencing the direct shock), which is driven by the housing net worth channel.[73]. Meanwhile, the number of commuters increases because of the displacement channel, which dampens the housing net worth channel and hampers the rise of non-tradable-sector employment in Region 1. Nevertheless, the housing net worth channel appears to dominate the displacement channel. As such, our model predicts that a positive foreign housing demand shock increases local non-tradable-sector employment. On the other hand, the effect of foreign housing demand on tradable-sector employment is less clear-cut, as shown by the non-monotonicity in the figure. The housing net worth channel initially pushes down tradable-sector employment in Region 1 and then raises it as foreign housing demand increases. The reason is that employment in the non-tradable sector cannibalizes tradable-sector employment at low levels of commuters, but as the number of commuters (and demand for tradable and non-tradable goods) increases, the extra labor supply raises employment in the tradable sector in Region 1. Therefore, the model prediction on the effect of foreign housing demand on tradable-sector employment is ambiguous.

[71] The data on consumption expenditure shares are collected by the U.S. Department of Labor, Bureau of Labor Statistics, and Consumer Expenditure Survey.

[72] According to data from the 2017 American Housing Survey conducted by the U.S. Census Bureau, the median annual total commuting costs in California are around \$2,504 (Table 13B "2017 California–Annual Commuting Costs by Type of Commuter"), which corresponds to 3.2 percent of household income in our sample. The range of distribution is in line with estimates from empirical studies such as Roberto (2008).

[73] Region 0 also experiences an increase in non-tradable employment because of the housing net worth spillover channel.

Figure A.3. Simulated Effects of Positive Foreign Housing Demand Shock, Baseline

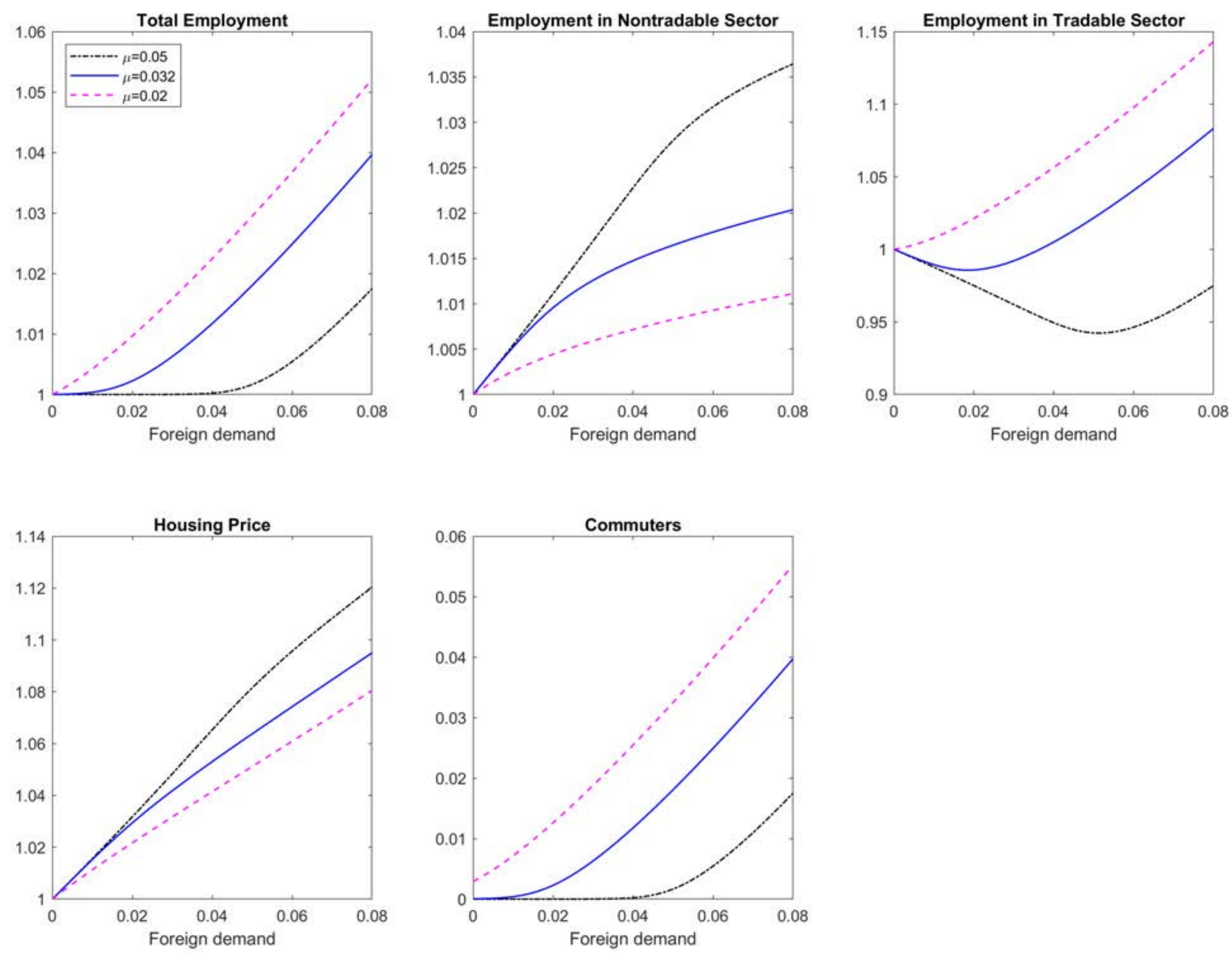


Note: This figure illustrates the simulated effects of a positive foreign housing demand shock on local total employment, non-tradable-sector employment, tradable-sector employment, housing price, and number of commuters. The parameter values for the simulation are $a = 1, b = 1,\ \alpha = 0.45,\ \beta = 0.2,\ H_0 = 1,\ \lambda = 0.5$, and $\phi \sim \mathcal{N}(0.032, 0.008)$. The parameter values on expenditure shares are based on data from the U.S. Department of Agriculture, and those on commuting costs are based on data from the American Housing Survey conducted by the U.S. Census Bureau.

Simulations with different distributions of commuting costs. To gauge the implications of the choice of the commuting cost distribution on our results and for completeness, we also calibrated the model to several other cost distributions.

First, we run the simulations with the commuting costs modeled by normal distributions with different means from the baseline. As shown in Appendix Figure A.4, as average commuting costs increase, the number of commuters to Region 1 declines given the same level of foreign housing demand shock. Housing prices in the region are higher because of less dilution from commuters' housing demand, which leads to a greater positive effect on non-tradable-sector employment driven by a stronger housing net worth force. Moreover, non-tradable employment cannibalizes tradable employment more easily when commuting is more costly because there are fewer extra workers to provide labor to Region 1.

Figure A.4. Simulated Effects of A Positive Foreign Housing Demand Shock, Varying Means of Commuting Cost Distribution

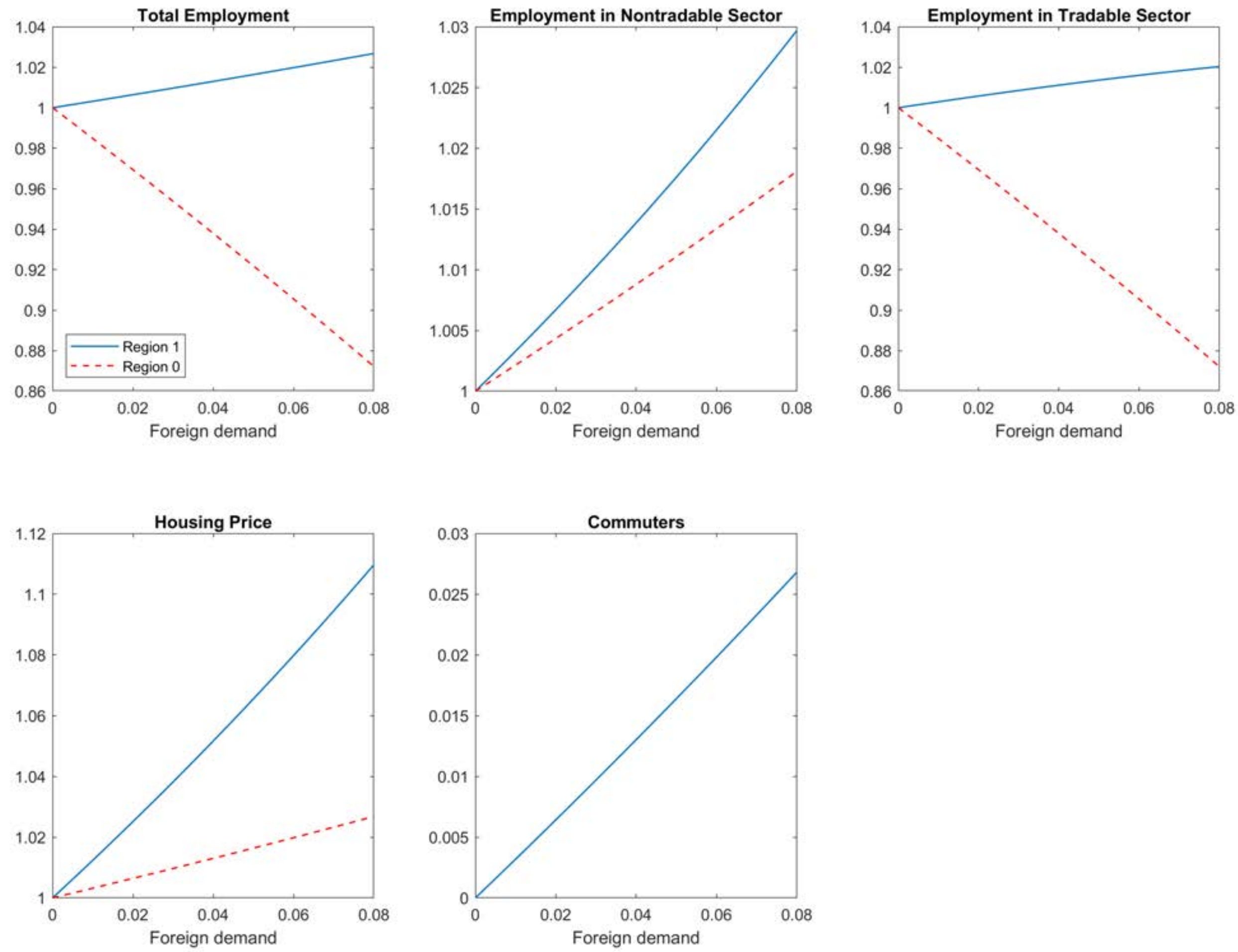


Note: This figure illustrates the simulated effects of a positive foreign housing demand shock on local total employment, non-tradable-sector employment, tradable-sector employment, housing price, and number of commuters, with three different means of the commuting cost distribution: $\phi \sim \mathcal{N}(0.02, 0.008)$, $\phi \sim \mathcal{N}(0.032, 0.008)$ (baseline), and $\phi \sim \mathcal{N}(0.05, 0.008)$. The other parameter values are $a = 1, b = 1$, $\alpha = 0.45$, $\beta = 0.2$, $H_0 = 1$, and $\lambda = 0.5$. The parameter values on expenditure shares are based on data from the U.S. Department of Agriculture.

Second, we explore how the effects of a positive foreign housing demand shock differ with a uniform distribution for commuting costs where $\phi \sim U(0, 1)$. The simulation results, shown in Appendix Figure A.5, are qualitatively similar to the case with normally-distributed commuting costs.

Third, we simulate the model with homogeneous commuting costs using $\phi = 0.032$, based on data from the 2017 American Housing Survey. As shown in Appendix Figure A.6, this specification leads to a threshold effect, as all workers would commute only if their real wage gain from moving to a location with lower housing prices exceeds the (homogeneous) commuting

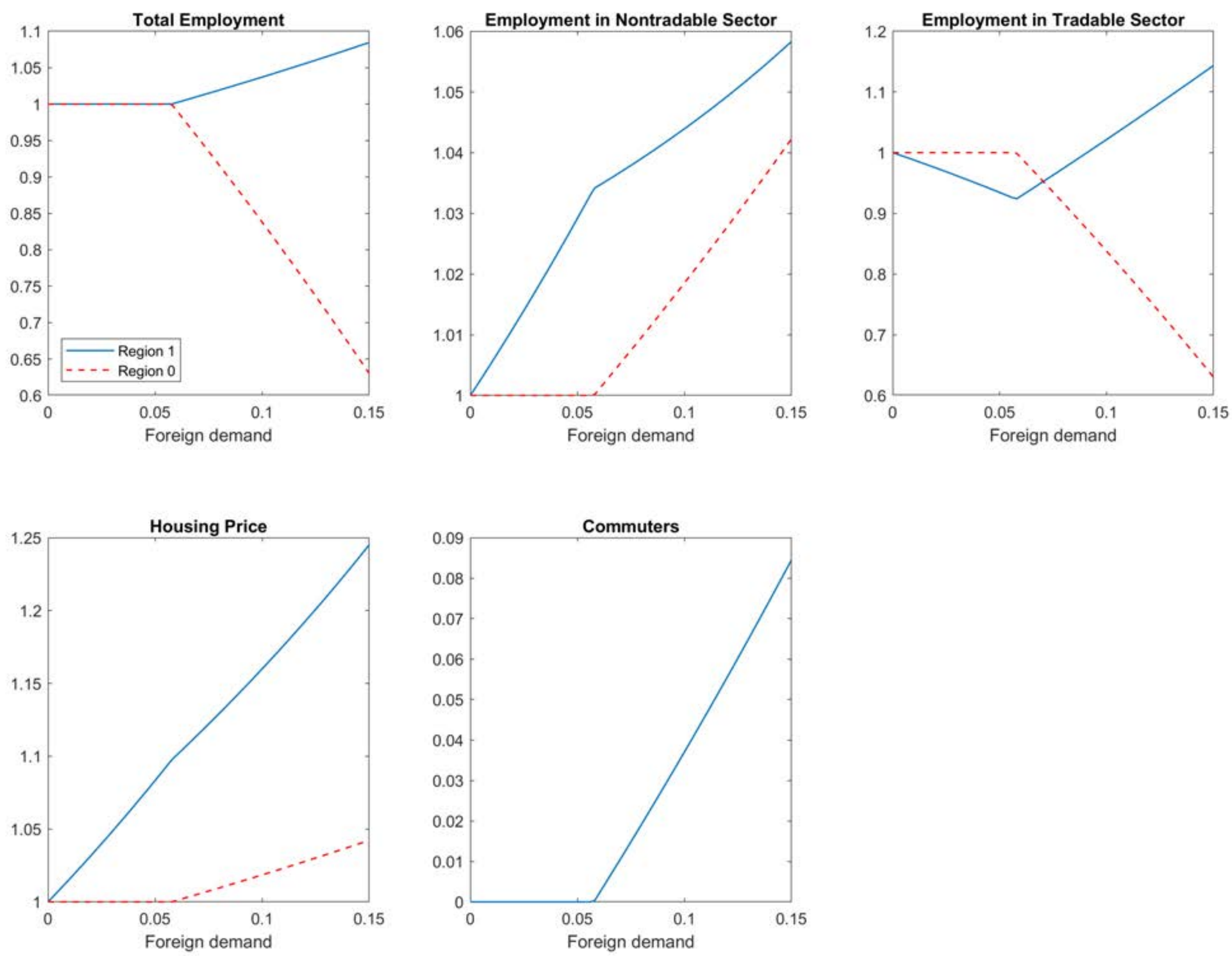
Figure A.5. Simulated Effects of A Positive Foreign Housing Demand Shock, Uniformly Distributed Commuting Costs



Note: This figure illustrates the simulated effects of a positive foreign housing demand shock on local total employment, non-tradable-sector employment, tradable-sector employment, housing price, and number of commuters, with uniformly distributed commuting costs where $\phi \sim U(0,1)$. The other parameter values are $a = 1, b = 1,\ \alpha = 0.45,\ \beta = 0.2,\ H_0 = 1,$ and $\lambda = 0.5$. The parameter values on expenditure shares are based on data from the U.S. Department of Agriculture.

costs. Initially, employment in the non-tradable sector in Region 1 rises as foreign housing demand increases because of the housing net worth channel. After foreign housing demand passes a certain threshold, the displacement force kicks in as the number of commuters increases, which slows down the increase in non-tradable-sector employment in Region 1. Nevertheless, the housing net worth channel still dominates the displacement channel, as in the baseline scenario. Also, the effect of foreign housing demand on tradable-sector employment remains ambiguous. As such, the simulated effects with homogeneous commuting costs are qualitatively similar to the baseline.

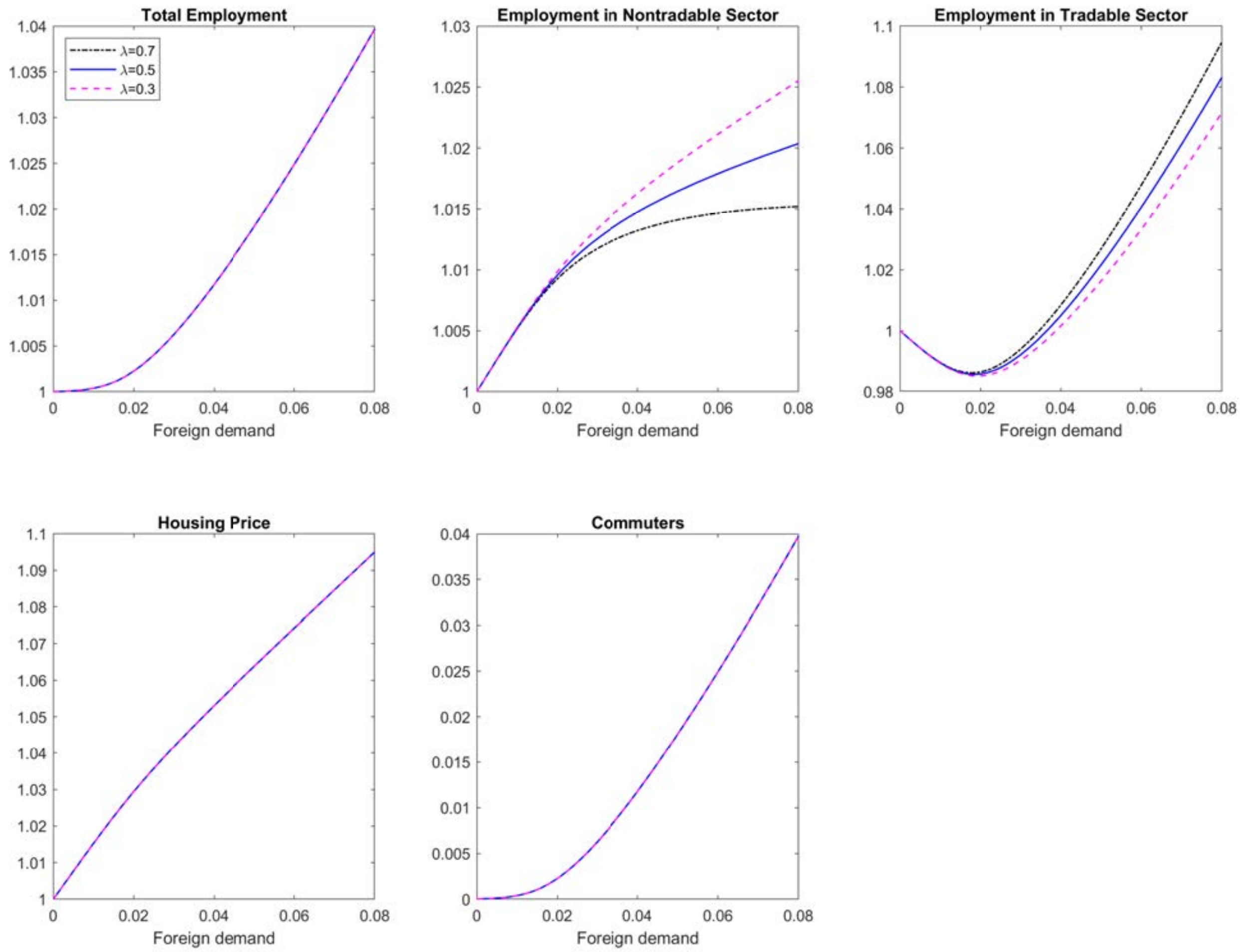
Figure A.6. Simulated Effects of A Positive Foreign Housing Demand Shock, Homogeneous Commuting Costs



Note: This figure illustrates the simulated effects of a positive foreign housing demand shock on local total employment, non-tradable-sector employment, tradable-sector employment, housing price, and number of commuters, with homogeneous commuting costs where $\phi = 0.032$. The other parameter values are $a = 1, b = 1, \alpha = 0.45, \beta = 0.2, H_0 = 1$, and $\lambda = 0.5$. The parameter values on expenditure shares are based on data from the U.S. Department of Agriculture, and those on commuting costs are based on data from the American Housing Survey conducted by the U.S. Census Bureau.

Simulations with varying λ. Finally, we simulate the model with varying parameter values for the share of commuters who consumes at the location of residence (λ). As shown in Figure A.7, as the share of commuters consuming at the location of work increases (λ decline), the impact of foreign housing demand shock on non-tradable-sector employment increases. This is driven by the strengthening of the housing net worth channel, as reflected in equation (6a).

Figure A.7. Simulated Effects of A Positive Foreign Housing Demand Shock, Varying λ

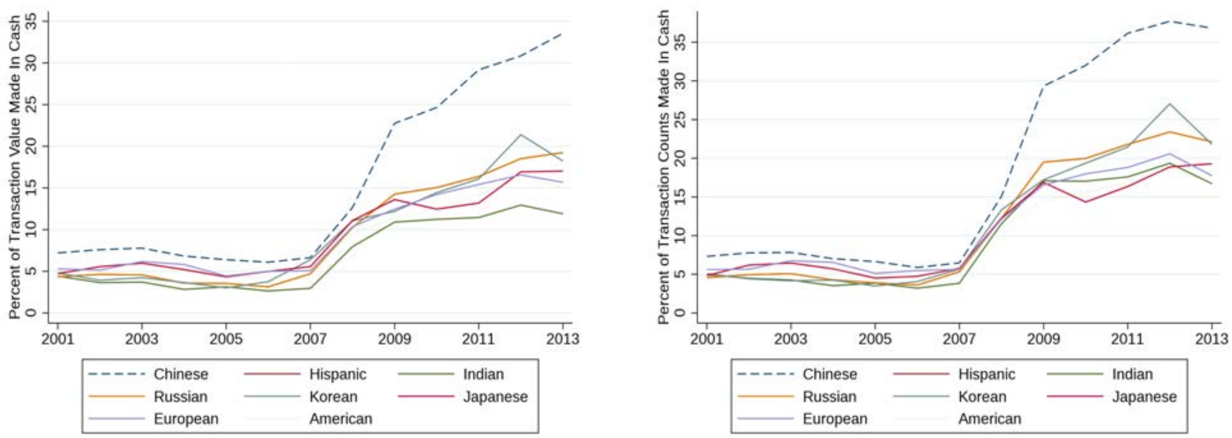


Note: This figure illustrates the simulated effects of a positive foreign housing demand shock on local total employment, non-tradable-sector employment, tradable-sector employment, housing price, and number of commuters, as the share of commuters consuming at the location of residence, λ, varies: $\lambda = 0.3$, $\lambda = 0.5$ (baseline), and $\lambda = 0.7$. The other parameter values are $a = 1, b = 1$, $\alpha = 0.45$, $\beta = 0.2$, $H_0 = 1$, and $\phi \sim \mathcal{N}(0.032, 0.008)$. The parameter values on expenditure shares are based on data from the U.S. Department of Agriculture, and those on commuting costs are based on data from the American Housing Survey conducted by the U.S. Census Bureau.

Appendix D Additional Figures and Tables

Figure A.8. Propensity for All-Cash House Purchases by Anglo-Americans and non–Anglo-American Ethnic Groups

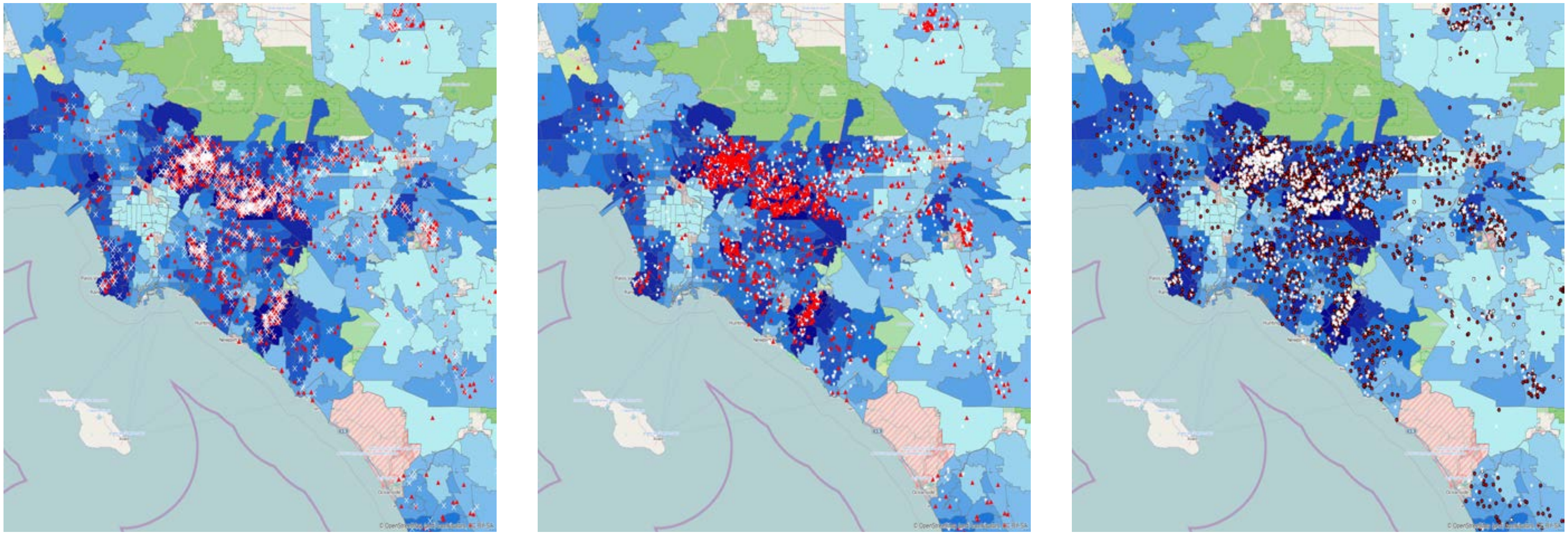
(a) Transaction Value **(b)** Transaction Count



Note: Panel (a) plots the percentage of all-cash housing purchases as measured by transaction value by Anglo-Americans and non-Anglo-American ethnic groups between 2001 and 2013. Panel (b) plots the percentage of all-cash housing purchases as measured by transaction count by Anglo-Americans and non-Anglo-American ethnic groups between 2001 and 2013. The ethnicity assignments are made based on ethnic name-matching technique of Kerr (2008a). A buyer is considered to be a particular ethnicity if the technique assigns that ethnicity to the buyer with a probability of one. Source: DataQuick and authors' calculations.

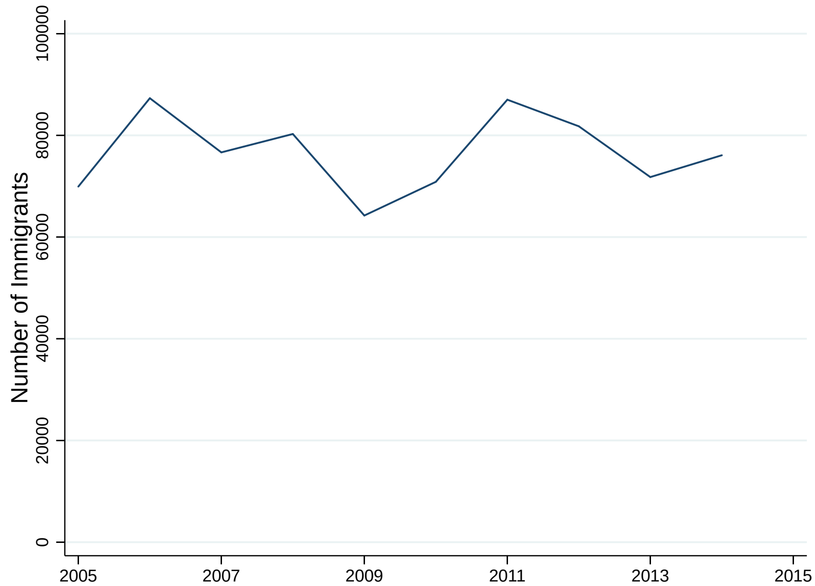
Figure A.9. House Purchases by Ethnic Chinese in the Los Angeles Region

(a) 2010–11 **(b)** 2011–12 **(c)** 2012–13



Note: This figure illustrates housing purchases by foreign Chinese in the Los Angeles region from 2010 to 2013. The blue shades in the background divides the region based on ZIP codes, where the darker shades represent ZIP codes with a higher share of ethnic Chinese population in 2000, based on the Census data. Panel (a) illustrates housing purchases by foreign Chinese in 2010 and 2011, where the white "X"s denote purchases in 2010 and the red triangles denote purchases in 2011. Panel (b) illustrates housing purchases by foreign Chinese in 2011 and 2012, where the red triangles denote purchases in 2011 and the white stars denote purchases in 2012. Panel (c) illustrates housing purchases by foreign Chinese in 2012 and 2013, where the white stars denote purchases in 2012 and the red circles denote purchases in 2013.

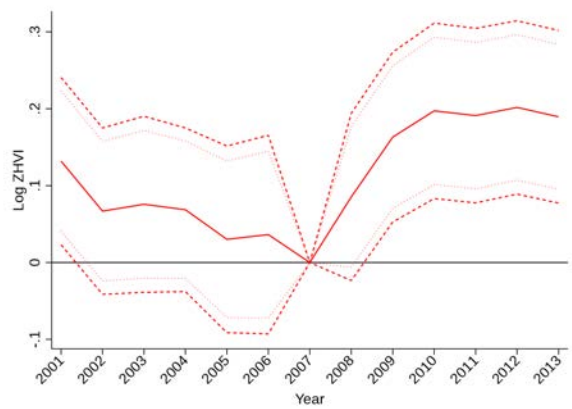
Figure A.10. New Chinese Immigrants in the United States



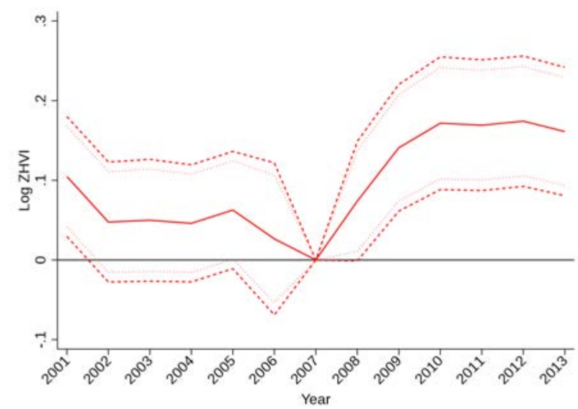
Note: This figure illustrates the number of Chinese obtaining Lawful Permanent Resident Status in the United States from 2005 to 2014, based on the 2014 Yearbook of Immigration Statistics from the U.S. Department of Homeland Security.

Figure A.11. Dynamic Effects of Foreign Chinese Housing Demand on House Prices

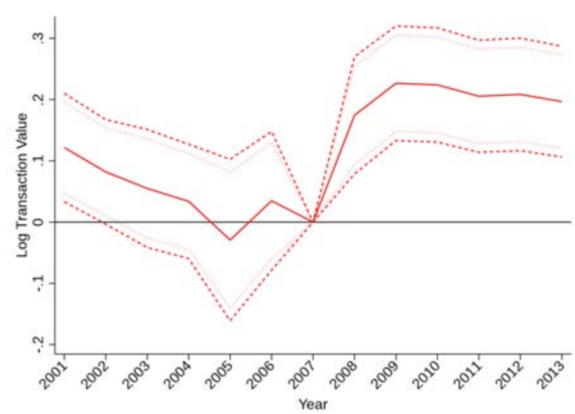
(a) House Prices–Zillow (CHTV)



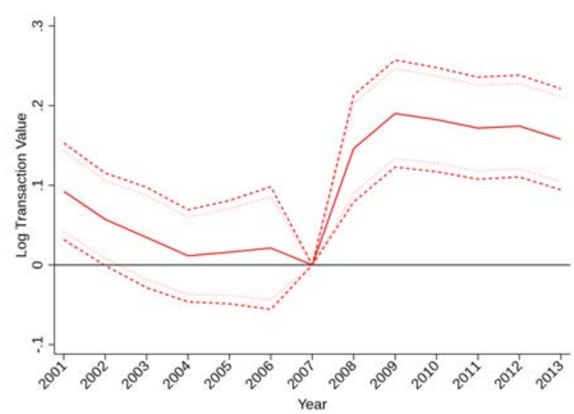
(b) House Prices–Zillow (CHTC)



(c) House Prices–Transactions (CHTV)

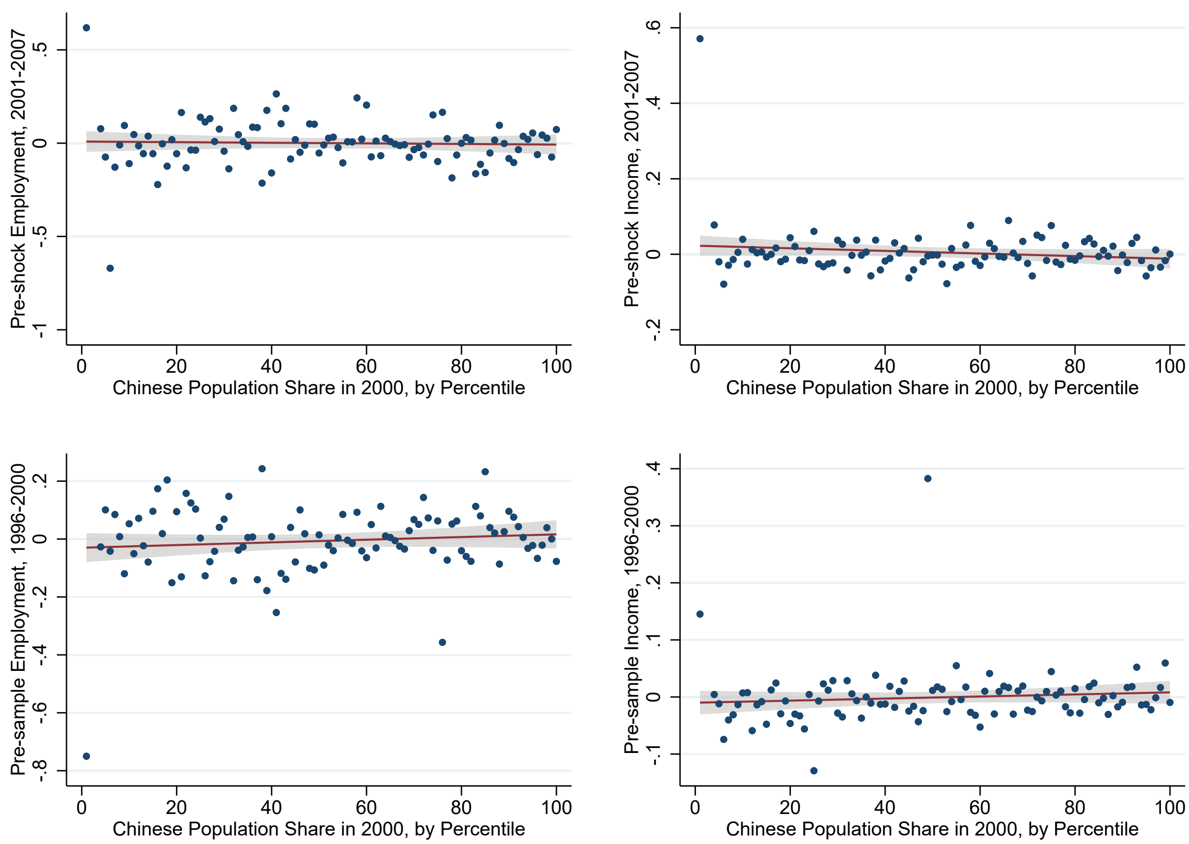


(d) House Prices–Transactions (CHTC)



Note: This figure plots the coefficients on the interaction terms between foreign Chinese housing transaction value ($CHTV$) or foreign Chinese housing transaction count ($CHTC$) and a series of year dummies from regressions equations (9a) and (9b). The regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), and pre-trends of income (1998–2001) and the outcome variable (1996–2000) and county-year fixed effects, with 2007 used as the reference period. Plots on the left panel show the effects on house prices (based on the Zillow Home Price Index and transaction values) and the number of tax returns using $CHTV$ as the key measure, and those on the right panel show the effects using $CHTC$ as the key measure. The 95 percent and 90 percent (in lighter color) confidence intervals are drawn based on standard errors clustered at the ZIP code level.

Figure A.12. Scatter Plots of Pre-shock Outcomes and Historical Ethnic Chinese Population



Note: This figure displays scatter plots of residualized employment and income (with the control variables and county fixed effects shown in regression equations (10a) and (10b) partialled out) in two pre-shock periods, 2001–07 and 1996–2000, against the historical ethnic Chinese population distribution by percentile based on the 2000 Census Bureau Survey, along with fitted lines. Grey areas around fitted lines are 95% confidence intervals.

TABLE A.1. First-stage Results

Panel A: Total Employment

	ln(CHTV) (1)	ln(CHTC) (2)	ln(CHTV) (3)	ln(CHTC) (4)	ln(CHTV)*Post (5)	ln(CHTC)*Post (6)
$\text{CHShare}_{z,0}$*CHTTV	0.470^{***}		0.349^{***}		0.015	
	(0.034)		(0.041)		(0.013)	
$\text{CHShare}_{z,0}$*CHTTV*Post			0.181^{***}		0.545^{***}	
			(0.038)		(0.038)	
$\text{CHShare}_{z,0}$*CHTTC		0.413^{***}		0.377^{***}		0.115^{***}
		(0.032)		(0.039)		(0.018)
$\text{CHShare}_{z,0}$*CHTTC*Post				0.053		0.300^{***}
				(0.038)		(0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4272	4336	4272	4336	4272	4336

Panel B: Home Prices (Zillow)

	ln(CHTV) (1)	ln(CHTC) (2)	ln(CHTV) (3)	ln(CHTC) (4)	ln(CHTV)*Post (5)	ln(CHTC)*Post (6)
$\text{CHShare}_{z,0}$*CHTTV	0.464^{***}		0.343^{***}		0.002	
	(0.037)		(0.043)		(0.016)	
$\text{CHShare}_{z,0}$*CHTTV *Post			0.179^{***}		0.550^{***}	
			(0.039)		(0.039)	
$\text{CHShare}_{z,0}$*CHTTC		0.394^{***}		0.354^{***}		0.101^{***}
		(0.034)		(0.041)		(0.022)
$\text{CHShare}_{z,0}$*CHTTC* Post				0.058		0.301^{***}
				(0.038)		(0.041)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3995	4053	3995	4053	3995	4053

Note: Panel A shows the first-stage regression results from the instrumental variables regression on log total employment based on equations (A.7a) and (A.7b) (columns 1–2) and equations (8a) and (8b) (columns 3–6). Panel B shows the first-stage regression results from the instrumental variables regression on log Zillow Housing Price Index based on equations (A.7a) and (A.7b) (columns 1–2) and equations (8a) and (8b) (columns 3–6). The regressors are $CHTV$ in column 1 and 3, $CHTC$ in columns 2 and 4, $CHTV \times Post$ in column 5, $CHTC \times Post$ in columns 6, where $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction values (count) and $Post$ is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. $CHTTV$ ($CHTTV$) denotes the aggregate foreign Chinese housing transaction value (count) in California, and $CHShare_{z,0}$ denotes the share of ethnic Chinese population across ZIP codes from the pre-sample period. All regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, pre-trends of income (1998–2001) and of the outcome variable (1996–2000), and county-year fixed effects. Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1, p < 0.05,$ and $p < 0.01$.

TABLE A.2. List of Non-tradable Industries

NAICS	Industry Name
4411	Automobile dealers
4412	Other motor vehicle dealers
4413	Automotive parts accessories and tire stores
4421	Furniture stores
4422	Home furnishings stores
4431	Electronics and appliance stores
4451	Grocery stores
4452	Specialty food stores
4453	Beer wine and liquor stores
4461	Health and personal care stores
4471	Gasoline stations
4481	Clothing stores
4482	Shoe stores
4483	Jewelry luggage and leather goods stores
4511	Sporting goods hobby and musical instrument stores
4512	Book periodical and music stores
4521	Department stores
4529	Other general merchandise stores
4531	Florists
4532	Office supplies stationery and gift stores
4533	Used merchandise stores
4539	Other miscellaneous store retailers
7221	Full-service restaurants
7222	Limited-service eating places
7223	Special food services
7224	Drinking places (alcoholic beverages)
1133	Logging
2361	Residential building construction
2362	Nonresidential building construction
2371	Utility system construction
2372	Land subdivision
2373	Highway street and bridge construction
2381	Foundation structure and building exterior contractors
2382	Building equipment contractors
2383	Building finishing contractors
2389	Other specialty trade contractors
3211	Sawmills and wood preservation
3212	Veneer plywood and engineered wood product manufacturing
3219	Other wood product manufacturing
3273	Cement and concrete product manufacturing
3323	Architectural and structural metals manufacturing
3371	Household and institutional furniture and kitchen cabinet manufacturing
4233	Lumber and other construction materials merchant wholesalers
4441	Building material and supplies dealers
4442	Lawn and garden equipment and supplies stores
5311	Lessors of real estate
5312	Offices of real estate agents and brokers
5313	Activities related to real estate
5413	Architectural engineering and related services

Note: This table lists non-tradable industries along with their 4-digit NAICS code, classified based on the methodology in Mian et al. (2013).

TABLE A.3. Controlling for Financial Crisis Confounding Factors (Pre-sample Period Controls)

Panel A: Total Employment

	(1)	(2)	(3)	(4)	(5)	(6)
ln(CHTV)*Post	0.165**		0.143**		0.144**	
	(0.067)		(0.067)		(0.066)	
ln(CHTV)	-0.024		0.017		0.013	
	(0.106)		(0.104)		(0.104)	
ln(CHTC)*Post		0.267***		0.241**		0.237**
		(0.099)		(0.095)		(0.094)
ln(CHTC)		-0.074		-0.026		-0.027
		(0.121)		(0.113)		(0.113)
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Foreclosure	Foreclosure	All-cash Transactions	All-cash Transactions	Financial Sector	Financial Sector
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat.	41	22	42	28	41	28
Obs.	3449	3509	4253	4318	4269	4333

Panel B: Home Prices (Zillow)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(CHTV)*Post	0.098***		0.109***		0.111***	
	(0.021)		(0.022)		(0.022)	
ln(CHTV)	-0.015		-0.030		-0.033	
	(0.028)		(0.028)		(0.029)	
ln(CHTC)*Post		0.181***		0.192***		0.195***
		(0.040)		(0.041)		(0.041)
ln(CHTC)		-0.062		-0.081**		-0.083**
		(0.040)		(0.039)		(0.040)
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Foreclosure	Foreclosure	All-cash Transactions	All-cash Transactions	Financial Sector	Financial Sector
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat.	45	20	43	24	42	23
Obs.	3254	3310	3979	4038	3995	4053

Note: The dependent variables are log total employment size in Panel A and log Zillow Single-Family Home Value Index in Panel B. $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction value (count) instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. $Post$ is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. Columns (1)-(2) show the results for the post-global financial crisis period of 2012–13. Columns (3)–(4) additionally control for the share of foreclosed homes in each zip code from the pre-sample period. Columns (5)–(6) additionally control for the share of all-cash house transactions in each zip code from the pre-sample period. Columns (7)–(8) additionally control for the size of the financial sector, measured as the share of finance sector employment in each zip code, from the pre-sample period. Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1$, $p < 0.05$, and $p < 0.01$.

Appendix E Additional Robustness Analyses

In this section, we conduct a series of analyses to further check the robustness of our results. First, we study the employment and house price effects of foreign Chinese housing purchases using two alternative specifications. Second, we assess the robustness of the baseline results to the imputation algorithm based on which the foreign Chinese housing transactions measures are constructed.

Difference-in-differences. First, we apply a standard difference-in-differences empirical design to give a simple estimate of the differential effects between ZIP codes that received more and less capital inflows. We compare house prices and employment of ZIP codes with more historical ethnic Chinese population—ZIP code in the top two deciles of the pre-sample period ethnic Chinese population share (the treated group)—to those with less (the control group), before and after 2008, the year of the China shock. The definition of the treatment status is motivated by the fact that foreign Chinese house transaction value and count are substantially higher in ZIP codes in the top two deciles of the historical ethnic Chinese population than those in the remaining eight deciles, as shown in Figure 3. The results are qualitatively similar when we use an alternative treatment status definition—ZIP codes above or below the median historical ethnic Chinese population share.

Specifically, we estimate the following regression models:

$$\ln(Y_{zt}) = \alpha + \beta(\text{Top Chn Region})_{z,0} \times \mathbb{I}\{t \geq 2008\} + \theta_1(\text{Top Chn Region})_z + \theta_2\mathbb{I}\{t \geq 2008\} + \gamma X_{z,0} + \varepsilon_{zt} \tag{A.5}$$

$$\ln(Y_{zt}) = \alpha + \beta(\text{Top Chn Region})_{z,0} \times \mathbb{I}\{t \geq 2008\} + \lambda_z + \eta_t + \varepsilon_{zt} \tag{A.6}$$

where Y_{zt} denotes home prices or employment in ZIP code z at t; $(\text{Top Chn Region})_z$ is an indicator variable that takes the value of one if ZIP code z belongs to the top two deciles of the pre-sample period ethnic Chinese population share and zero otherwise; $\mathbb{I}\{t \geq 2008\}$ is an indicator variable that takes the value one if the year is 2008 or after and zero otherwise; X_z denotes a vector of ZIP code-level socioeconomic characteristics from the pre-sample period of 2000, including population, education (measured as the share of population with bachelor degree), and median household income; and λ_z and η_t denote ZIP code and year fixed effects, respectively.

Appendix Table A.4 reports the results. Columns (1)–(3) of Appendix Table A.4 show the estimated differences in employment between the treated and control ZIP codes. We find that after the China shock in 2008, total employment in treated ZIP codes is 3.4 percent higher than the control ZIP codes, controlling for ZIP code and time fixed effects (column 6). This finding echoes our baseline result that the Chinese-capital-inflow-induced increase in house prices had real economic effects.

Columns (4)–(6) show the estimated differences in house prices between the treated and control ZIP codes, using (log) Zillow Single-Family Home Value Index as the dependent variable. We find that after the China shock in 2008, house prices in treated ZIP codes are 19 percent higher than the control ZIP codes, controlling for ZIP code-level population, education, and median household income (column 2) or ZIP code and time fixed effects (column 3). This finding is consistent with the result in Gorback and Keys (2020), who use a similar empirical design.

TABLE A.4. Foreign Chinese Housing Demand, Employment, and House Prices: Standard Difference-in-Differences Estimates

	Total Employment			Home Prices (Zillow)		
	(1)	(2)	(3)	(4)	(5)	(6)
Top Chn Region*Post	0.049***	0.032**	0.034***	0.192***	0.188***	0.190***
	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Controls	No	Yes	No	No	Yes	No
ZIP code FE	No	No	Yes	No	No	Yes
Time FE	No	No	Yes	No	No	Yes
Obs.	12,848	12,848	12,848	12,848	12,848	12,848

Note: This table reports regression results from equations (A.5) and (A.6). The dependent variables are log employment levels (columns 1–3) and log house prices based on the Zillow Single-Family Home Value Index (columns 4–6). *Top Chinese Region* denotes ZIP codes belonging to top two deciles of the ethnic Chinese population shares in the pre-sample period. *Post* is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. Controls include the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, and median household income. Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1$, $p < 0.05$, and $p < 0.01$.

A limitation of the difference-in-differences specifications is that they rely on a binary definition of the treatment status and do not use information about the intensity of the treatment, which prevents an estimation of the elasticity of employment or house prices with respect to foreign Chinese real estate capital flows. Thus, our main analysis uses a regression framework with continuous treatment to fully account for the cross-sectional variation in foreign Chinese housing transactions.

Alternative IV regression. Second, we run a version of equations (8a) and (8b) without the post-China shock period interaction. The specific estimation equations are as follows:

$$\ln(Y_{zt}) = \alpha + \beta \ln(CHTV_{zt}) + \gamma X_{z,0} + \eta_{ct} + \varepsilon_{zt}; \quad \text{(A.7a)}$$

$$\ln(Y_{zt}) = \tilde{\alpha} + \tilde{\beta} \ln(CHTC_{zt}) + \tilde{\gamma} X_{z,0} + \tilde{\eta}_{ct} + \tilde{\varepsilon}_{zt}.. \quad \text{(A.7b)}$$

The definition of the variables are the same as the ones described in the text above for equations (8a) and (8b). We also instrument foreign Chinese housing transaction value ($CHTV$) and foreign Chinese housing transaction count ($CHTC$) by the aggregate foreign Chinese housing transaction value and count in California, respectively, weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period: $CHShare_{z,0} \times CHTTV_t$ and $CHShare_{z,0} \times CHTTC_t$.

The results, shown in Appendix Table A.5, are consistent with our baseline results. Foreign Chinese home purchases have a positive and significant effect on local housing and labor market. A one percent increase in housing demand by foreign Chinese, as measured by transaction value, increases local employment and home prices by 0.139 and 0.061 percent, respectively,

TABLE A.5. Foreign Chinese Housing Demand, Employment, and House Prices: Alternative IV Regression

	Total Employment		Home Prices (Zillow)	
	(1)	(2)	(3)	(4)
ln(CHTV)	0.140^{**}		0.059^{***}	
	(0.065)		(0.018)	
ln(CHTC)		0.167^{**}		0.071^{***}
		(0.074)		(0.022)
Controls	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
First-stage F-stat.	194	171	177	149
Obs.	4272	4336	3995	4053

Note: This table reports regression results from equations (A.7a) and (A.7b). The dependent variables are log total employment (column 1–2) and log Zillow Housing Price Index (column 3–4). $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction value (count) instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. All regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, pre-trends of income (1998–2001) and of the outcome variable (1996–2000), and county-year fixed effects. Standard errors are clustered at the ZIP code level. *, **, and *** denote $p < 0.1$, $p < 0.05$, and $p < 0.01$.

on average. As expected, the economic magnitudes are smaller relative to the baseline results in 2 and Tables 3, as results in Appendix Table A.5 show the average effects of foreign Chinese housing purchases for the entire sample period, including the pre-China shock period.

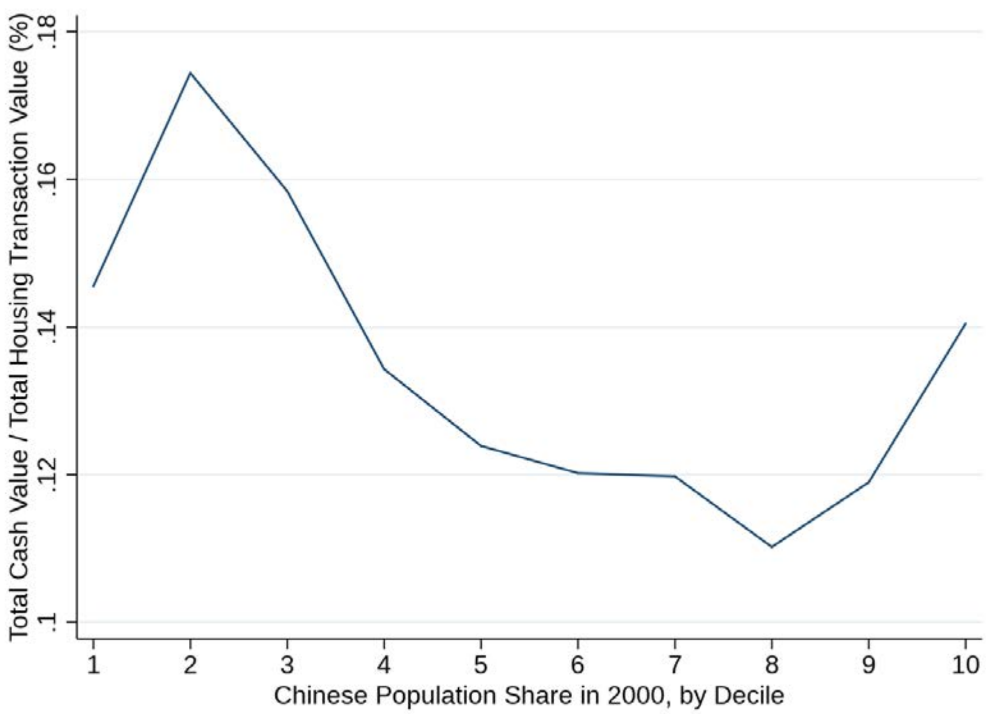
This set of specification estimates the average effect of foreign Chinese real estate capital inflows over the entire sample period, while our preferred estimation equations (8a) and (8b) allow us to exploit the timing of China's capital control and HPR policies and net out potential secular effects from the the pre-policy shock period. The latter strategy, which combines an event study framework and an IV approach, more considerably improves identification compared to traditional time-series analysis for estimating the effects of capital flows.

Robustness to imputation algorithm. Finally, we conduct three sets of analysis to address potential concerns related to measurement error in $CHTV$ and $CHTC$ and assess the robustness of the baseline results to the foreign housing purchases imputation algorithm. Firstly, our second step of constructing the foreign Chinese housing transactions measures—keeping only housing transactions by ethnic Chinese made entirely in cash—may understate the true magnitude of foreign Chinese housing purchases, as it excludes purchases made by non-resident foreign Chinese who managed to obtain mortgages from U.S. private lenders. To examine whether this filtering significantly biases our results, we conduct two robustness checks. First, we examine whether there is a specific pattern in the share of all-cash housing transactions across ZIP codes based on historical ethnic Chinese population shares—the key source of variation in our empirical methodology. As shown in Appendix Figure A.13, there is not an obvious relationship, which suggests the filtering should not strongly affect the baseline results.

Second, we assess whether our results are sensitive to the third step of constructing the foreign Chinese housing transactions measures—distinguishing resident vs. foreign Chinese homebuyer using the assumption that the propensity to make all-cash purchases of resident Chinese is similar to Anglo-Americans. To this end, we re-run our baseline regressions using a modified version of $CHTV$ and $CHTC$ that does not attempt at filtering out resident Chinese (i. e., excludes the third step of the procedure). As shown in Appendix Table A.6, the coefficients of interest on all key outcomes are similar to the baseline results, which suggests our results are not sensitive to the corresponding step of the imputation algorithm.

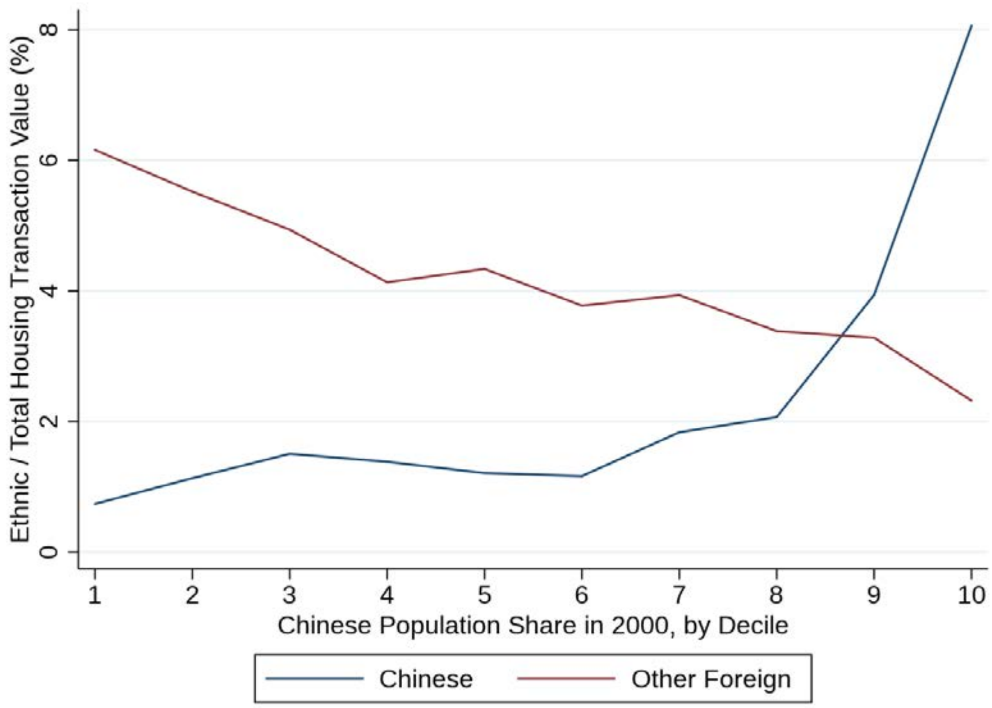
Third, one may wonder whether purchases by non-Chinese foreigners are driving the results. As shown in Appendix Figure A.14, we observe that other foreigners' purchases are not correlated with the concentration of historical ethnic Chinese settlements across ZIP codes. Purchases by foreign Chinese and other foreigners, in fact, seem to be slightly negatively correlated with the historical Chinese population share.

Figure A.13. All-Cash Housing Transactions versus Historical Ethnic Chinese Population



Note: This figure illustrates the share of all-cash house transaction made by ethnic Chinese (by dollar value) by deciles of historical ethnic Chinese population based on the 2000 Census Survey.

Figure A.14. Housing Transactions Share by Foreign Chinese and Other Ethnicities versus Historical Ethnic Chinese Population



Note: This figure illustrates the share of house transaction made by foreign Chinese and other ethnic groups by deciles of historical ethnic Chinese population based on the 2000 Census Survey.

TABLE A.6. Robust Results based on Alternative Imputation of Chinese Housing Purchases

	Employment		Home Prices		Number of Tax Returns	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(CHTV)*Post	0.142***		0.098***		-0.032***	
	(0.048)		(0.015)		(0.009)	
ln(CHTV)	-0.001		-0.019		0.016	
	(0.079)		(0.021)		(0.013)	
ln(CHTC)*Post		0.149***		0.098***		-0.028***
		(0.036)		(0.013)		(0.008)
ln(CHTC)		-0.014		-0.019		0.012
		(0.048)		(0.014)		(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat.	109	212	106	193	106	206
Obs.	4877	4877	4567	4567	4572	4572

Note: This table reports the main regression results from equations (8a) and (8b) using measures of $CHTV$ and $CHTC$ that do not distinguish between resident and non-resident Chinese in the imputation procedure (i. e., ignoring the third step). The dependent variables are log employment in columns (1)–(2), Zillow Single-Family Home Value Index in (3)–(4), and log number of tax filers in (5)–(6). $CHTV$ ($CHTC$) denotes the foreign Chinese housing transaction value (count) instrumented by the aggregate foreign Chinese housing transaction value (count) in California weighted by the share of ethnic Chinese population across ZIP codes from the pre-sample period. $Post$ is an indicator variable that takes the value 1 if the year is 2008 or after and 0 otherwise. All regressions control for the pre-sample period ZIP code-level population, population density, education (the population share with bachelor's degrees), an indicator variable for whether there is a college within a five-mile distance, and pre-trends of income (1998–2001) and of the outcome variable (1996–2000). *, **, and *** denote $p < 0.1, p < 0.05,$ and $p < 0.01$.