Negative Capital Shock, Overseas Buyers, and Housing Market

Qian Wang*

Purdue University

This draft: December 29, 2024

Abstract

While local policies regarding foreign capital inflows into residential housing markets typically oscillate between promoting wealth effects and ensuring housing affordability, the majority of current literature focuses on the positive demand shocks to examine the necessity of implementing restrictions on foreign capital. In this paper, I explore the implications of a negative capital shock from China on local housing markets. By leveraging China's implementation of stricter foreign exchange purchase quota management for its citizens as an exogenous negative demand shock on foreign Chinese buyers in the US single-family homes market, my analysis reveals substantial effects on local housing assets. Not only did the volume of house transactions by foreign Chinese buyers significantly decline compared to other foreign ethnicities (Indian and Russian), but house prices also significantly dropped in neighborhoods that are popular among Chinese buyers. However, the magnitude of price drop is smaller than expected, especially when compared to positive demand shocks of similar magnitude reported in the literature. Additionally, the elasticity of housing supply, as implied by such a negative demand shock, is higher than that reported in existing literature. My findings provide an important rationale for why some cross-border bans or restrictions, aimed at curbing capital inflows and thus local house prices, have had limited effects.

Keywords: housing, foreign capital shock, local asset prices, elasticity

*wang4578@purdue.edu, Mitchell E. Daniels, Jr. School of Business, Purdue University. I thank Sergiy Chernenko, Micheal Eriksen, Ha Diep Nguyen, Lindsay Relihan, and all other discussants at Krannert Finance Brown Bag Conference for helpful comments and suggestions. All errors are mine.

1 Introduction

As is the case elsewhere, international capital is a double-edged sword in residential housing markets. On one hand, it fuels local economic growth (Borensztein, Gregorio, and Lee, 1998; Alfaro et al., 2004, 2010), boosts consumption (Bostic, Gabriel, and Painter, 2009; Mian, Rao, and Sufi, 2013), and generates wealth effects through appreciating house prices (Li, Shen, and Zhang, 2020; Stroebel and Vavra, 2019). On the other hand, it exacerbates housing affordability issues and distorts wealth distribution (Favilukis and Van Nieuwerburgh, 2021). With globalization, international capital flows started to impact on local assets such as housing (Bardhan and Kroll, 2007). Local policies regarding foreign capital inflows in residential housing markets often oscillate between prioritizing wealth effects and addressing housing affordability concerns. While foreign purchase bans or restrictions may be necessary to prevent foreign buyers from outbidding and displacing local buyers and improve city welfare (Favilukis and Van Nieuwerburgh, 2021), foreign capital is welcomed when there is a need to stimulate the housing market and improve prices. For instance, Hong Kong imposed taxes on foreign property buyers in 2012 to prevent overheating in housing markets but removed all restrictions and taxes on foreign buyers by the end of February 2024 amid declining housing prices.

However, the current literature on how international capital influences local economies overwhelmingly focuses on studying positive demand shocks (Li, Shen, and Zhang, 2020; Gorback and Keys, 2021; Badarinza and Ramadorai, 2018; Cvijanović and Spaenjers, 2021) as well as examining the necessity of restrictions on such capital inflows to local housing markets (Favilukis and Van Nieuwerburgh, 2021). I propose that a negative demand shock is worth discussing. This is because there could exist asymmetric effects on price reactions to positive and negative demand shocks as indicated in Glaeser and Gyourko (2005). A negative capital shock to local housing markets could provide clues about what happens when capital sources, such as large institutional buy-to-rent investors, exit the housing market. Therefore, in this paper, I utilize China's foreign exchange purchase quota management in 2017 as an exogenous negative demand shock to local residential housing assets to investigate foreign Chinese purchases and the implications for related housing prices.

I believe studying a negative capital shock from China has important implications. First, China is the largest foreign buyer of both commercial and residential properties in the US, and thus any negative demand shock from China is especially noteworthy and can have a profound influence on local housing assets. Prior research has highlighted how the lack of good investment opportunities in China (Li, 2021) led to a Chinese surge in purchases in the

US residential housing market (Li, Shen, and Zhang, 2020) following the housing purchase restrictions in China in 2007. With the implementation of more stringent foreign exchange control policies in 2017, I expect this trend to reverse since then.

Second, some states have proposed bans on cross-border capital from entering their local real estate markets. For example, Florida passed Senate Bill No.264 (SB264) in 2023, prohibiting foreign buyers from "countries of concern", especially China, from purchasing real estate properties in the state. While Florida was not the first state to propose such a ban, the passage of Florida's SB264 had a significant ripple effect on other states, and more state legislators subsequently introduced similar bills in dozens of states. As I study the changes in the home-buying behavior of foreign Chinese individual buyers and its impact on U.S. local real estate markets under China's capital controls on its own citizens, my study provides a reference for such (potential) cross-border capital control policies.

To fully understand the magnitude and impact of foreign Chinese purchasers' behavior in the U.S. residential housing market before and after China's foreign exchange quota management policy, it is essential to contextualize this impact through valid comparisons. There are two main challenges in establishing appropriate comparisons. First, it is impossible to identify the precise number of transactions by all foreigners. While foreign buyers are more likely to be cash buyers, not all cash buyers are foreign buyers. The number of cash transactions by local residents might be endogenous to various economic conditions, thus making cash transactions an unreliable proxy for foreign transactions. Second, a valid comparator country to China must meet two criteria: it should share parallel transaction trends with Chinese cash buyers in the U.S. prior to 2017, and it should have no major policy changes restricting foreign exchange use before the sample period ends in 2021. To ensure valid comparisons in my analysis, I have selected Indian and Russian purchasers as the primary placebo groups. These two countries serve as suitable comparators to China, as names from these countries often possess recognizable cultural traits that aid in their identification alongside Chinese names. Additionally, the parallel trend holds prior to 2017, with no significant foreign exchange policy changes from these countries before the end of 2021.

I obtained county deed records and transaction records in the United States from 2014 to 2021 from Infutor, focusing specifically on single-family house transactions. To identify Chinese, Indian, and Russian buyers from these transaction records, I developed an ethnic identification algorithm for each country based on their unique name culture characteristics.

Even though the practice of inferring ethnicity or country origin based on names is wellestablished in academic literature (Fernández and Fogli, 2009; Liu, 2016), my algorithm may not capture all buyers of a specific ethnicity. Although the number of Indian and Russian surnames used in this paper is much larger than that of Chinese surnames, my methodology is more likely to capture the majority of Chinese buyers, but a relatively smaller proportion of Indian and Russian buyers, due to the higher concentration of Chinese surnames compared to Indian and Russian surnames. According to the Ministry of Public Security in China, the Chinese surnames used in this paper cover over 85% of the entire Chinese population. Therefore, the effects of Chinese buyers, compared to Indian and Russian buyers, on the U.S. single-family housing market, as found in this paper, can be interpreted as a lower bound of the actual effects in terms of magnitude.

As transaction records do not explicitly indicate the nationality of a buyer and foreign buyers typically have limited access to the US mortgage markets, I use cash transactions as a proxy for foreign purchases. According to survey reports by NAR, foreign buyers are twice more likely to use cash transactions than resident buyers due to limited mortgage financing sources. If we further distinguish foreign buyers into non-resident and resident foreign buyers, as defined by NAR, then non-resident foreign buyers generally have an even higher probability of using all-cash transactions. In this paper, I interchangeably use the terms "cash", "foreign", and "overseas" transactions/purchases to refer to house transactions made by non-immigrant visa holders from certain specific countries in the US. Additionally, I use "Chinese/Indian/Russian" transactions to refer to all house transactions by individuals of these ethnicities in the US, without distinguishing whether the transactions are made by non-immigrant visa holders or not.

Using foreign Indian transactions and foreign Russian transactions as the placebo group respectively, I observe a significant decrease in the number of Chinese cash transactions compared to both Indian and Russian cash transactions post-2017. On average, foreign Chinese transactions decline by 0.013/0.014 units more than foreign Indian/Russian transactions at the neighborhood level (i.e., census tract). Given that the average number of cash transactions in a quarter in a census tract prior to 2017 from Chinese, Indian, and Russians respectively is only approximately 0.053, 0.012, and 0.009, a decrease of 0.013/0.014 units implies that the difference between Chinese cash transactions and Indian/Russian cash transactions narrows by over 30%. The decrease in Chinese cash transactions is most significant in states with a relatively large number of such transactions prior to 2017. These states, popular among foreign Chinese purchasers according to the data, are consistent with the NAR series reports titled *"Profile of International Activity in US Residential Real Estate"*.

The decrease in residential single-family house transactions by foreign Chinese has real effects on local economies. On average, a one percentage point increase in Chinese cash transactions over total transactions in a ZIP code in 2013 is associated with a 0.4% to 0.5% slower increase in the house price index at the ZIP code level post 2017, after controlling for metropolitan×quarter or county×quarter fixed effects. For an average house priced at $315,000 in a neighborhood, this means the house price on average drop 1,260 to 1,575 dollars for a one percentage point more in Chinese cash transactions in these neighborhoods post 2017. In the top 10 states with the highest numbers of Chinese cash transactions prior to 2017, the coefficients vary from -0.001 to -0.02. This means that a one percentage point increase in Chinese cash transactions over total transactions in a ZIP code in 2013 in those states is associated with a 0.1% to 2% slower increase in house price index at the ZIP code level.

In addition, I am able to estimate the elasticity of housing supply under this negative capital shock framework, since foreign Chinese buyers do not enter local labor markets like immigrants, and therefore, changes in demand from these buyers do not affect factors that shift the supply curve.

As a transitional step of estimating the housing supply elasticity, I use the same framework as in the house price index analysis but switch the dependent variable from house price indices to quantities. On average, a one percentage point increase in Chinese cash transactions relative to total transactions in a ZIP code in 2013 is associated with a 1.6% to 1.9% drop in quarterly house transactions at the ZIP code level post-2017, depending on whether I control for metropolitan×quarter or county×quarter fixed effects. Surprisingly, the number of house transactions correspond to this exogenous demand shock drops much more extensively than expected, assuming the existing literature correctly estimates the housing supply elasticity. The literature typically estimates the average housing supply elasticity in the US to be less than 2, with some estimates even below 0.5. Such low housing supply elasticity suggests that the magnitude of the drop in transactions should be less than 1%, given that the price drop is only about 0.4% to 0.5% in response to the same negative demand shock. Furthermore, low elasticity also implies that a 1.6% drop in house transactions should correspond to at least a 0.8% decrease of house prices on average. In other words, although the economic impact on local house prices from the reduced demand of overseas Chinese buyers is significant, it is smaller than expected based on the housing supply elasticity estimates commonly found in the literature.

The housing supply elasticity estimated in this paper ranges from 3.2 to 8.25, depending on whether the elasticity is calculated at the metropolitan or county level and whether short-term supplies or new home supplies are measured. This is significantly higher than the estimates found in the existing literature, which primarily focuses on positive demand shocks. The difference could be because potential home sellers, including home builders, are sensitive to changes in house prices and are flexible in determining whether and when to put their homes on the market. The opportunity costs of either halting new construction or holding properties until a later date may be relatively low for them.

The relatively high housing supply elasticity discussed in this paper carries significant policy implications. It provides a rationale for why measures like the 2012 tax imposition in Hong Kong, aimed at curbing capital inflows, were ineffective. Given this high elasticity, builders can quickly adjust their supply strategies in response to market changes. Specifically, they could deliberately reduce housing supply to sustain elevated price levels and preserve profit margins. This adaptive behavior among builders underscores a critical challenge for policymakers: designing interventions that not only target demand but also anticipate and mitigate potential adjustments in supply to ensure the desired economic outcomes are achieved. It also suggests that proposals like Florida's SB264, which prohibit purchases from certain foreign buyers, may have limited effects on improving housing affordability. Another example involves the exit of large-scale buy-to-rent institutional investors in the single-family home market, which emerged after the financial crisis. The findings in this paper suggest that housing supply could be more elastic than previously indicated in the literature, and the withdrawal of capital from large institutional home investors may have only limited impacts on local housing prices if their exit occurs gradually.

This paper contributes to several strands of literature and bears important policy implications. First, it adds to the growing body of literature exploring how international capital flows influence local housing assets. Existing research has highlighted that non-local home buyers, including foreign buyers, often pay premiums for identical houses compared to local home buyers (Siebert and Seiler, 2022; Cvijanović and Spaenjers, 2021), leading to increased local house prices and the displacement of low-income buyers (Favilukis et al., 2012; Sa, 2016; West and Botsch, 2020; Favilukis and Van Nieuwerburgh, 2021). However, much of the current literature focuses on the positive demand shock generated by foreign buyers in local communities. Badarinza and Ramadorai (2018) highlight the persistent gravitational pull of international capital flows towards preferred counter-parties from one's own or proximate countries, underscoring the agglomeration effect of foreign capital in specific areas. Gorback and Keys (2021) document the significant impacts of foreign buyer taxes imposed in certain foreign markets, such as Singapore and Hong Kong, on the US housing market. My study extends this perspective by examining the potential negative effects of capital controls implemented by major foreign countries on the US residential real estate market. While West and Botsch (2020) mentioned the impact of China's capital controls on its citizens in 2017 on the housing market in Vancouver, their analysis primarily focused on the period preceding the formal execution of the policy to demonstrate the phenomenon of foreign Chinese buyers "rushing to buy." Unlike West and Botsch (2020), I investigate the mid-to-long term impact of China's foreign exchange purchase quota management policy on US residential properties, providing valuable insights into how capital control measures from a major foreign country can influence both transaction volumes and prices in local housing markets in the US residential housing markets over time.

Furthermore, this paper contributes to the literature on estimating elasticity of house supply in the US. The elasticity of house supply estimated in this paper is higher than that found in the existing literature, such as Saiz (2010), Aastveit and Anundsen (2022), Aastveit, Albuquerque, and Anundsen (2023), and Gorback and Keys (2021). Since the existing literature predominantly utilizes positive demand shocks, the higher elasticity of house supply estimated using this negative capital shock implies a greater sensitivity of potential home sellers to changes in house prices. It also offers insights into what occurs when capital sources, such as large institutional buy-to-rent investors, exit the single-family housing markets. While current literature focuses on how these institutional investors boost local house prices (Mills, Molloy, and Zarutskie, 2019; Allen et al., 2018; D'Lima and Schultz, 2022; Ganduri, Xiao, and Xiao, 2023), understanding the market dynamics during of the ebb of this capital tide is equally important. My findings suggest that house supply could be more elastic than previously documented, and that the withdrawal of capital from large institutional home investors may only have limited impacts on housing prices if they exit gradually.

This paper adds to the body of literature focusing on Chinese buyers in international real estate markets as well. Foreign Chinese buyers have emerged as the largest group of foreign buyers in residential housing markets in certain regions as noted by West and Botsch (2020) and Pavlov and Somerville (2020). Notably, they have significantly increased their real estate purchases in the US, leading to what Li, Shen, and Zhang (2020) identify as a "China shock" in California. Contrary to the "China shock", my study demonstrates that the decline in foreign Chinese investment in local real estate markets can also have significant economic impacts.

Lastly, my study helps understand the role of cash purchases in residential real estate markets. It has recently been observed that cash buyers pay a discount when purchasing houses compared to buyers using mortgage financing (Reher and Valkanov, 2020; Han and Hong, 2024). Such discounts are too large to be explained by market efficiency alone, even when the risk of financing failure of mortgage buyers is taken into consideration (Reher and Valkanov, 2020). Although my study does not directly examine the cash discount issue, it demonstrates that a decrease in cash purchases from even one specific group can have real effects in local neighborhood-level house prices.

The remainder of this paper is structured as follows: Section 2 describes the data and the ethnic identification algorithm based on names, and provides some background information about the capital control policy in China. Section 3 presents the models and corresponding results regarding foreign Chinese buyers in the US residential single-family house market, in comparison with foreign Indian and foreign Russian buyers, after China's implementation of its capital management policy. It also examines the local house price impacts in neighborhoods with a relatively large number of foreign Chinese buyers. Section 4 estimates the elasticity of house supply as indicated in this exogenous negative capital shock framework and discusses its economic implications. Section 5 concludes the paper.

2 Data and Identification

2.1 House Characteristics and Transactions

My housing dataset comprises county deeds records and transaction records obtained from Infutor, encompassing all purchase records and relevant house characteristics sourced annually from county register of deeds and assessor offices in the United States spanning from 2014 to 2021. In this study, I concentrate on single-family houses, which I identify by filtering property land use as "single-family residence" and ensuring that property primary building code and primary improvement type are not related to non-residential or residential apartment codes. I exclude records with missing key information, such as house number and county code, as well as mobile homes and single-family residence land parcel purchases from my sample.

Regarding transactions, Infutor captures all types of transactions recorded in county deeds records. When examining the number of transactions by different ethnicities (Chinese, Indian, and Russian) in each county or census tract, I consider all types of transactions, prioritizing the distribution of the number of houses held by different ethnic groups over the validity of prices associated with those transactions.[1] In Vermont, accurate transaction

[1] Restricting the transaction types to resale and new construction will not substantially alter all the analysis.

dates are almost never available in the Infutor data. To overcome this issue, I use accurate transaction dates when they are available from Infutor, and use record dates instead when they are not. [2] I define cash transactions as those that have a missing mortgage amount or a mortgage amount of zero.

Due to inconsistencies in deeds records across different counties and the presence of missing or inaccurate information for certain key house characteristics, I have made certain assumptions during the data cleaning process to minimize the loss of observations due to missing data. Firstly, I assign any house with missing information on the number of stories a default value of 1, as single-story homes are the most common in single-family residences. In cases where the recorded number of stories is given as a decimal, such as 1.21 or 2.8, I round the value to the nearest 0.5, ensuring that the number of stories remains within a reasonable range, with a minimum of 1 story and a maximum of 4 stories or more. This adjustment is based on the understanding that buyers typically assess whether a house has a full or partial second floor rather than scrutinizing precise story numbers.

Secondly, some raw data entries for house characteristics obtained from Infutor may contain obvious errors due to misparsing county records or other factors. However, certain input errors can be rectified using additional related information provided by Infutor. Specifically, Infutor records lot sizes in both square feet and acres, and it also records bathroom numbers using various formats, including transformed numerical values, raw county inputs, and sometimes even counts of bath fixtures. These diverse data points enable me to cross-validate the information and correct any inaccuracies or missing inputs as needed. For example, I exercise caution when dealing with unusually large lots, and if the lot size in acres is disproportionately larger or smaller than the corresponding square footage, I prioritize the more reliable measurement based on square feet or acres accordingly.

To mitigate the influence of outliers on my results, I winsorize key house characteristics, including lot size, living space, number of baths and bedrooms, at the top and bottom 1% at the county level. Additionally, I trim the purchase price values at the top and bottom 1% at county level. [3]

[2] Record dates are the dates when transactions are recorded in the county, and they are typically only a few days behind the actual transaction dates.

[3] Winsorizing key house characteristics at the top and bottom 5% and trimming the price values at the top and bottom 5% at the county level, will not change the trend of house characteristics by ethnicity in Table 3 as shown in Internet Appendix Table IA2.

2.2 Ethnic Identification Algorithm

To quantify and analyze the impact of foreign purchases by different ethnic groups on the housing market, I rely on measures that allow me to identify these groups based on unique features in their names, particularly surnames. While it is not feasible to ascertain all ethnicities solely from names, certain groups, such as Chinese, exhibit distinctive name characteristics that facilitate their identification. Consequently, I can examine how overseas Chinese buyers adjust their behavior in response to capital controls.

Although my primary focus is on overseas Chinese buyers due to the negative capital shock from China's foreign exchange quota management policy, it is essential to contextualize this impact through valid comparisons. There are two main challenges in establishing appropriate comparisons. First, it is impossible to identify the precise number of transactions by all foreigners. While foreign buyers are more likely to be cash buyers, not all cash buyers are foreign buyers, and the number of cash transactions by local residents might be endogenous to various economic conditions. Second, a valid comparator country to China must meet two criteria: it should share parallel transaction trends with Chinese cash buyers in the U.S. prior to 2017, and it should have no major policy changes restricting foreign exchange use before the sample period ends in 2021.

To ensure valid comparisons in my analysis, I have selected Indian and Russian purchasers as the primary placebo groups. These countries serve as suitable comparators to China: First, names from these countries often possess recognizable cultural traits, which aids in their identification alongside Chinese names. Second, Indian and Russian both share some cultural and/or economic similarities to China. For China and India, there are both cultural and economic ties that make them comparable. The Buddhist culture believed by the Chinese originated in India and has the same origin as the Hinduism prevalent in India. Additionally, both China and India are emerging economies with substantial populations and rapid GDP growth rates. Both countries also contribute significantly to immigration flows to the US. As for China and Russia, they not only share certain political ideologies but also share some similar cultures due to sharing a relatively long border. Finally, and most importantly, there are no major foreign exchange policy changes in either India or Russia during the sample period, and the parallel trend of transactions relative to Chinese cash transaction in the US housing market holds well as shown in Figure 1.

To identify individuals of Chinese, Indian, and Russian ethnicity, I initially reference the top 100 surnames provided by Kerr (2008) for each ethnic group. However, I refine this algorithm to suit my specific research context. Specifically, I exclude surnames common in independent former Soviet republics from the Russian ethnic group, as my focus is solely on current Russian purchasers. Similarly, while Kerr (2008) encompasses Chinese individuals from Mainland China, Hong Kong, Macao, Taiwan, and Singapore, I omit surnames that are not representative of Mainland China.

Secondly, I update the list of most commonly used surnames based on recent trends in each of these countries. For Chinese surnames, the initial surname lists covers the 114 surnames with more than 2 million people based on the results of 2010 population census.[4] To capture the latest changes in China's most commonly used surnames, I supplemented the existing list of 114 surnames with data from the National Names Report for 2018–2020, published annually by the Ministry of Public Security since 2019. Additionally, "Ouyang", the most commonly used compound surname, is also included in the data. There are 119 surnames in the final list,[5] which account for over 85% of the entire Chinese population.

India and Russia have a broader range of surnames compared to China, so I first expand my list to include the top 1,000 most common surnames in each country, as sourced from Forebears.[6] Additionally, I search for surnames with Indian or Russian origins on Wikipedia and incorporate any new findings not included in the Forebears list.[7] In the case of India, where the tradition of using the father's given name as a surname is prevalent in certain regions, I also include the top 1000 most commonly used given names sourced from Forebears for Indian identification. Unlike Chinese and Russian identification, an individual is classified as Indian only when both their given name and surname appear on the list. There are 2,828 unique Indian names (including both surnames and forenames) and 2,502 unique Russian surnames,[8] used in this paper. The detailed list of all Chinese surnames used in this paper can be found in the Internet Appendix Table IA1. As the detailed lists of all Indian surnames and forenames and Russian surnames used in this paper are too long, they are not reported

[4] Data source: Wu Jie and Yang Jianchun, Who Is Most Common - Zhang, Wang, Li, or Zhao? An Analysis of Surname Structures and Distribution Characteristics from the 2010 Population Census, China Statistics, Issue No. 6, 2014.

[5] Due to different Chinese surnames being spelled the same way in English, there are fewer unique surname spellings in English than there are distinct surnames represented by Chinese characters.

[6] For Indian surnames, please refer to `https://forebears.io/india/surnames`. For Russian surnames, please refer to `https://forebears.io/russia/surnames`.

[7] For Indian surnames, please refer to `https://en.wikipedia.org/w/index.php?title=Category:Surnames_of_Indian_origin&from=A`. The names on this page may be updated over time; please refer to the Internet Appendix for the exact list of Indian surnames used in this paper. For Russian surnames, please refer to `https://simple.wikipedia.org/wiki/List_of_surnames_in_Russia`.

[8] It is common for names in both Indian and Russian cultures to have multiple variations.

but are available upon request.

Since passports issued in Mainland China follow specific spelling rules that do not allow for hyphens or middle names, I incorporate these rules into my algorithm to differentiate mainland Chinese from individuals in Hong Kong, Macao, and Taiwan.

Additionally, I recognize that the following surnames – "Bi", "Ji", "Ma", "Mo", "Rao", and"Sha" – are shared by Chinese and Indians when transliterated into English. To address this, I manually verify these names to ensure accurate identification. A name is classified as Chinese if it is spelled in the manner typical of Chinese names, and otherwise as Indian. A small number of observations are classified as both Indian and Chinese if a property is owned by two individuals, one with a name indicating Chinese origin and the other, Indian.

I acknowledge that my algorithm may not capture all transactions made by individuals from each of these three ethnic groups. According to Forebears, there are 3,955,695 unique surnames in India, with an average of 327 people per name. In Russia, Forebears identifies 1,424,981 unique surnames, with an average of 101 people per name. For China, there are 137,913 unique surnames, with an average of 9,892 people per name. Additionally, the Chinese surnames used in this paper are confirmed to cover at least 85% of the entire Chinese population, based on data from the Ministry of Public Security in China. Although the number of Indian and Russian surnames used in this paper is much larger than the number of Chinese surnames, my methodology is more likely to capture a higher proportion of Chinese buyers. This is due to the higher concentration of Chinese surnames compared to the more diverse Indian and Russian surnames, which may result in a relatively lower coverage of Indian and Russian buyers. In other words, the analysis presented in this paper provides lower bounds for the effects of Chinese buyers compared to Indian and Russian buyers in the single-family housing market as stated in 3.1 due to the limitations of the name ethnic identification algorithm.

On average, my algorithm identifies approximately 37,100 Chinese transactions, 19,144 Indian transactions, and 9,710 Russian transactions per year from 2014 to 2021 in the US. Among these, about 19%, 14% and 20% of transactions for each respective ethnicity are cash transactions. Table 1 displays the number of all types of transactions and cash transactions identified using my name ethnic algorithm for Chinese, Indian, and Russian buyers from 2014 to 2021. As depicted in Table 1, Chinese cash transactions on average represent only about 1% of total cash transactions and only approximately 0.3% of total transactions in the States.

The summary statistics of house prices and house characteristics for all transactions, cash transactions, transactions involving Chinese, Indian, or Russian buyers, and cash transactions involving these buyers, are reported in Table 2. As shown in the data, cash buyers from China, India, and Russia typically purchase smaller and less expensive houses compared with non-cash buyers. Furthermore, I test the differences in house characteristics for Chinese, Indian, and Russian cash transactions before and after 2017 in Table 3. The house characteristics for all three ethnic groups change in the same direction, indicating that my results below are not influenced by the fundamental changes in the houses available in the markets or by shifts in the preferences of foreign Chinese buyers.

2.3 House Price Index

I obtain ZIP code level house price index data from Zillow Research. Specifically, I use the Zillow Home Value Index (ZHVI) single-family homes time series, as this paper focuses on single-family homes. The ZHVI data reflect typical value for homes in the 33th to 67th percentile range and are smoothed and seasonally adjusted. Since the Zillow house price index is presented as monthly data, I use the data for March, June, September, and December as the quarterly indices, and the data for each December as the annual index in my analysis.

Although the ZHVI has been available for a relatively short period compared to other house price indices such as Federal Housing Finance Agency (FHFA) House Price Index (HPI), I choose to use ZHVI for the following reasons: First, ZHVI provides a house price index at ZIP code level, which is the smallest geographic unit covered among commonly used indices. As foreign capital is likely to flow into areas where same ethnic foreign born people enclave (Cohen, Gurun, and Malloy, 2017; Badarinza and Ramadorai, 2018), such fine granularity helps capture the variations of overseas buyers at neighborhood level. Second, ZHVI encompasses a vast array of homes nationwide, whereas FHFA HPI only covers repeated sales involving conventional or conforming mortgages. Since overseas buyers predominantly make cash purchases, FHFA HPI may not fully represent the broader market, particularly in areas where cash purchases are common. Third, ZHVI is increasingly used in academia. For instance, Hanson (2022), Favilukis and Van Nieuwerburgh (2021), Li, Shen, and Zhang (2020) and Greenstone, Mas, and Nguyen (2020) have employed ZHVI as the primary house price index in their research. Additionally, Gorback and Keys (2021) have verified that the results obtained using their quarterly house price index estimated from a hedonic model through transactions are similar to those derived from ZHVI.

2.4 Foreign Exchange Purchase Quota Management in China

Foreign exchange management is a common practice in many developing countries, including China, India, and Russia. Before 2022, China's foreign exchange management measures were the most stringent among the three countries.[9] Individual residents in China were subject to the lowest limit for free exchange, set at US $50,000 per person per year, which was approximately one-fifth of the limit in India.

Before 2017, although Chinese residents were theoretically allowed to exchange up to $50,000 in US currency freely, enforcement of this limit was lax, and individuals often exchanged currency as desired without facing severe consequences in many cases. However, starting from January 1st, 2017, the Chinese government implemented stricter management of personal foreign exchange declarations. They refined the content of these declarations and mandated that banks verify the authenticity of the information provided by individuals starting from June, 2017. Under the new regulations, every individual resident must complete a form indicating the purpose of the foreign currency exchange. Additionally, certain investments using this facilitated foreign exchange quota, such as those in foreign securities markets, real estate markets, and certain insurance products, are prohibited. Any requests exceeding the facilitated quota must be validated with relevant supporting documents. Furthermore, the penalties for violating these rules were significantly increased.

The strengthening of foreign exchange purchase quota management by China in 2017 effectively restricted the most convenient method for individual Chinese citizens to make investments in foreign countries. Consequently, I utilize this event as an exogenous shock that specifically affects the behavior of Chinese cash purchasers, while leaving the behavior of other foreign purchasers in the US unchanged. This provides us with an opportunity to conduct a detailed analysis using a difference-in-differences framework. I expect that following the implementation of these measures in 2017, the number of Chinese cash purchases in the US residential housing market will experience a significant decrease.

3 Models and Results

In this section, I employ the difference-in-differences framework and use China's foreign exchange purchase quota management policy as a case study to examine how the withdrawal

[9] Russia has implemented several economic policies since the invasion of Ukraine in February 2022, including restrictions on the amount of foreign currency Russian citizens can withdraw, capped at $10,000.

of capital from a major foreign country affects the transactions and prices of local real estate properties in the US.

I compile datasets at both the county, ZIP code and census tract levels, leveraging the geographic identification information provided by Infutor. I define a census tract as a neighborhood, and include a census tract in my dataset for a given year if there is at least one transaction recorded in that tract. When census tract level information is not available, I use ZIP code as the smallest neighborhood geography instead.

Although not explicitly shown here, my data reveal that even in counties where Chinese cash buyers are most concentrated, their purchases represent only a small fraction of the total transactions. For example, in 2016, there were 778, 736, and 525 Chinese cash transactions in King County-Washington, Los Angeles County-California, and Clark County-Nevada, respectively. These counties had the highest volume of Chinese cash transactions among all counties in my sample. However, these transactions accounted for only approximately 18.3%, 6.5%, and 5.8% of the total number of cash transactions, and for about 2.7%, 1.2%, and 1.2% of all transactions in those respective counties. In contrast, over 70% of counties have no foreign Chinese buyers, and over 60% of counties have no Chinese buyers in 2016 in the US.

3.1 Transaction Quantity

My first step aims to illustrate the significant decrease in Chinese cash transactions following China's implementation of stricter foreign currency quota management. Notably, China's implementation of stricter personal foreign exchange management in 2017 coincided with the third round of domestic real estate purchase restrictions. Studies, such as Li, Shen, and Zhang (2020) and Gorback and Keys (2021), have focused on the growth in overseas property demand from Chinese buyers based on the first or second rounds of real estate purchase restrictions in China. If the 2017 foreign exchange management measures had no substantial effect, the third round of restrictions might have triggered a new wave of property purchases from overseas Chinese buyers in the US housing market. However, Figure 1 shows that the implementation of stricter personal foreign currency quota management significantly depressed the demand from overseas Chinese buyers in the US housing market.

Figure 1 illustrates the quarterly total number of cash transactions for Chinese, Indians, and Russians in the US. While Indian and Russian cash transactions remain relatively stable, Chinese cash transactions exhibit a sharp decline after 2017. In the Internet Appendix

Figure IA1, the reported sub-figures are for the top 10 states with the highest number of Chinese cash transactions in the US. The top 10 states are California, Texas, Florida, Washington, New York, Georgia, Nevada, New Jersey, North Carolina, and Pennsylvania. As shown in Figure IA1, Chinese cash transactions exhibit a sharper decline in each of these states, while Indian and Russian cash transactions remain relatively stable over the period.

Figure 2 further reports the non-cash transactions and cash transactions of Chinese, Indian, and Russian buyers from 2014 to 2021. Although the transaction volumes fluctuate quarterly, only the cash transactions made by Chinese buyers significantly dropped after 2017, while the non-cash transactions from all three ethnicities remained relatively stable before COVID. As only the number of Chinese cash buyers significantly dropped, this further indicates that the results in this paper are driven by an investment channel that was curtailed through China's implementation of a stricter foreign exchange purchase quota management policy in 2017.

To quantify the extent to which the strengthened capital control policy in China influences foreign Chinese purchases in the US residential market compared with Indian and Russian transactions, I run the following model:

$$Y_{i,r,c,s,t} = \alpha_{i,r,c,s,t} + \beta CN_i + \gamma Post_t + \delta CN_i \times Post_t + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{i,r,c,s,t}, \quad (1)$$

where Y is the quantity of cash transactions, or percentage of cash transactions over all transactions by ethnic i (Chinese, Indian, or Russian) in census tract r of county c in state s at time of quarter t. CN is a dummy variable indicates whether the quantity/percentage is of Chinese cash purchases or not, and $Post$ is a dummy variable which equals 1 if the year is greater than or equal to 2017. I expect significant negative coefficients on the interaction of Chinese and post for cash transactions and percentage of cash transactions over all transactions relative to Indian and Russian transactions. I control for state fixed effects, quarter fixed effects, county fixed effects, and county $\times$ quarter fixed effects in all models, and additionally control for neighborhood fixed effects in some models.

The results presented in Table 4 align with my expectations. In Panel A and Panel B of the table, transactions by Indians and Russians are utilized as the control groups, respectively. The inclusion of neighborhood fixed effects, in addition to county, quarter, and county $\times$ quarter fixed effects, does not notably alter the results. Due to how $Post$ indicator is constructed, the coefficients for this indicator are partialled out in the fixed effects models. On average, Chinese buyers make more purchases compared to Indians and Russians at the neighborhood level. However, Chinese cash transactions have significantly decreased following the tightening of foreign currency management in China.

The first two columns of Table 4 indicate that, on average, Chinese buyers make approximately 0.041 and 0.045 more cash transactions than Indians and Russians, respectively, at the neighborhood level. As anticipated, the coefficients of the interaction terms between Chinese and *Post* indicator are negative and statistically significant. Post-2017, Chinese cash transactions drop by approximately 0.013 and 0.014 more than Indian and Russian cash transactions, respectively, at the neighborhood level. Considering that the average number of quarterly cash transactions by Chinese, Indians, and Russians from 2014 to 2016 is only about 0.053, 0.012, and 0.009, respectively, at the neighborhood level, a decrease of 0.013 or 0.014 units implies that the difference between Chinese cash transactions and Indian/Russian cash transactions narrows by over 30% post-China's policy.

The last two columns of Table 4 employ the percentage of cash transactions over all transactions for each ethnic group (Chinese, Indian, and Russian) at the census tract level as the main dependent variable. The sample size becomes smaller due to the concentration of cash purchases by each ethnic group in certain census tracts, possibly due to ethnic enclaves, as demonstrated in Badarinza and Ramadorai (2018) and Cohen, Gurun, and Malloy (2017). The results indicate that the percentage of cash transactions by Chinese is approximately 20 and 17 percentage points higher than that by Indians and Russians, respectively. However, it decreases by over 7 percentage points compared to the rates by Indians and Russians post-2017, resulting in a net difference of about 10 to 12 percentage points. Again, since the name ethnic identification algorithm is capable of covering most Chinese buyers but only a relatively smaller portion of Indian and Russian buyers, the results presented here should be interpreted as lower bounds of the actual effects.

Next, I plot the coefficients of CN indicator on the quantity of cash transactions by Chinese and Indians or by Chinese and Russians over time in Figure 3, controlling for all fixed effects in Equation 1. In Figure 3, the blue dots represent the placebo using Indian cash transactions, while the red dots represent the placebo using Russian cash transactions. As the coefficients of Chinese indicator remain stable from 2014 to 2016, it is evident that the parallel trends assumption holds before the negative shock happened in 2017.

In addition, I conduct similar tests (but drop state fixed effects) for each state in the US. The subsample tests reveal that the significant drop in Chinese cash transactions I observed is not driven by a single state but is consistent across the majority of states, especially those with a relatively large number of Chinese cash transactions prior to 2017, such as California, Texas, Florida, Washington, New York, New Jersey, Nevada, Georgia, and North

Carolina. Most of these popular states, which are popular among foreign Chinese buyers according to the data, correspond with the popular destinations for international Chinese buyers highlighted in the NAR series reports titled *"Profile of International Activity in US Residential Real Estate"*. Detailed results for these states are available in the Internet Appendix Table IA3.

Overall, Table 4 and the subsample tests by state illustrate that purchases by foreign Chinese buyers have markedly decreased following the enforcement of more stringent foreign exchange purchase quota management in China, compared to purchases by both foreign Indian and foreign Russian buyers.

3.2 Economic Impacts on Neighborhoods

Next, I investigate how the drop in purchases from overseas Chinese buyers since 2017 affect neighborhood house prices. I use ZIP codes rather than census tracts as the basis for neighborhoods, since ZIP codes are the smallest standard geography unit for which the house price index is available for single-family homes from Zillow Research.

I construct treatment intensity variables at the ZIP code level using the proportion of overseas Chinese buyers relative to all transactions in a ZIP code in the year 2013 for each state. The underlying assumption of the treatment intensity variable is that overseas Chinese buyers share common preferences for certain types of houses, such that neighborhoods attracted more overseas Chinese buyers in 2013 are also likely to attract more overseas Chinese buyers in the following years. Furthermore, since the sample period starts in 2014, the treatment intensity variable - the neighborhood-level ratio of overseas Chinese buyers to all buyers in 2013 - is unlikely to be correlated with the error terms. Specifically, I run the following model:

$$\begin{aligned} lnHPI_{r,c,s,t} = \alpha_{r,c,s,t} + \beta CNratio_{r,c,s} + \gamma Post_t + \delta CNratio_{r,c,s} \times Post_t \\ + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{r,c,t}. \end{aligned} \tag{2}$$

where $lnHPI$ represents the log of house price index in ZIP code r of county or metropolitan area c in state s at quarter t, and $CNratio$ is the percentage ratio of Chinese cash buyers to all buyers in 2013. $Post$ is defined the same as in the previous model. State fixed effects, quarter fixed effects, and ZIP code fixed effect are controlled in all models. County and county $\times$ quarter or metropolitan and metropolitan $\times$ quarter fixed effects are controlled as well depending on the specific model. In the reported table, I do not report the coefficients for $CNratio$ and $Post$ indicator because $CNratio$ is constructed at the ZIP code level and do not have variations over time, $Post$ indicator is constructed by time, and thus these variables are partialled out in fixed effects models.

Table 5 reports the results for the above model. On average, a one percentage point increase in Chinese cash transactions over total transactions in a ZIP code in 2013 results in a 0.4% to 0.5% slower increase in the quarterly house price index at the ZIP code level post 2017, depending on whether I control for metropolitan $\times$ quarter or county $\times$ quarter fixed effects. For an average house priced at \$315,000 in a neighborhood, this means the house price on average drop 1,260 to 1,575 dollars for a one percentage point more in Chinese cash transactions in these neighborhoods post 2017.

To check the robustness of the above results, I conduct similar tests for each state but omit state fixed effects. The subsample tests show that in most states, which are popular destinations for overseas Chinese buyers, there are significant negative effects on quarterly house prices at ZIP code level post-2017. However, there are two states – Georgia and Pennsylvania, among the top 10 states with the highest numbers of overseas Chinese buyers – where the coefficients for the interaction term between Chinese and $Post$ are significant positive. In contrast, the coefficients for the majority states are negative as expected. The other eight states in the top 10 states with the highest numbers of overseas Chinese buyers, the coefficients for the interaction term vary from -0.001 to -0.02. This means that a one percentage point increase in the share of Chinese cash transactions over total transactions in a ZIP code in 2013 is correlated with a 0.1% to 2% slower increase in the quarterly house price index in that ZIP code. While the magnitude of the effects varies, the negative coefficients on the interaction of Chinese treatment intensity variable and $Post$ indicator for most of states underscore the significance of such international capital flows on local house prices. Detailed results for the top 10 states are available in the Internet Appendix Table IA5.

Even though the negative capital shock from China post-2017 has real effects on local housing prices, the magnitude of the decrease in house prices is quite surprising when compared with findings in the literature. Specifically, when I examine cash transactions in California, as analyzed by Li, Shen, and Zhang (2020), I find that a one percentage point increase in Chinese cash transactions as a share of total transactions in a ZIP code in 2013 results in a 1.1% to 1.2% slower increase in the quarterly house price index. Given that that Li, Shen, and Zhang (2020) focus exclusively on cash transactions, I switch to a similar metric in my analysis: the ratio of Chinese cash transactions to all cash transactions. Table IA4 indicates that a one percentage point increase in Chinese cash transactions over all cash transactions in a ZIP code in 2013 results in only about a 0.3% slower increase in the quarterly house price index. In contrast, Li, Shen, and Zhang (2020) report that "a one standard deviation increase in exposure to real estate capital inflows from China...raises the home price in an average ZIP code by 15%." This comparison suggests that positive and negative demand shocks of similar magnitude have significantly asymmetric effects on local house prices.

In summary, Table 5 and the state-by-state subsample tests demonstrate that the decline in residential single-family house transactions by foreign Chinese has tangible effects on local economies by directly influencing the local house prices. However, the magnitude of the decrease in house prices under this negative capital shock is small compared to the impact of a positive capital shock of similar magnitude.

4 Elasticity of House Supply and Implications

Since foreign Chinese buyers do not participate in local labor markets like immigrants, the demand changes from these buyers do not alter the factors that shift the supply curve. Therefore, in this section, I further examine the implied house price elasticity of supply under this framework.

Similar to Equation 2, I run regressions using the logarithm of the number of house transactions and the number of newly constructed houses as the dependent variables, respectively:

$$\begin{aligned} lnQ_{r,c,s,t} = \alpha_{r,c,s,t} + \beta CNratio_{r,c,s} + \gamma Post_t + \delta CNratio_{r,c,s} \times Post_t \\ + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{r,c,t}. \end{aligned} \tag{3}$$

where lnQ represents the logarithm of the number of house transactions or the number of newly constructed houses in ZIP code r of county or metropolitan area c in state s at quarter t or in year t. Specifically, I use quarterly data for the number of house transactions and annual data for the number of newly constructed houses. I opt for annual data instead of quarterly data for newly constructed houses because these figures are calculated based on the year a property was built, according to data from Infutor. All other variables are defined in the same manner as for Equation 2. Similarly, $CNratio$ and $Post$ indicator are partialled out in fixed effects models and thus are not reported in the tables.

Table 6 reports the results for the above model using the logarithm of the number of house transactions as the dependent variable. This can be interpreted as representing the short-term house supply in the market, assuming that all intended house sales were completed.

On average, a one percentage point increase in Chinese cash transactions relative to total transactions in a ZIP code in 2013 is associated with a 1.6% to 1.9% drop in quarterly house transactions at the ZIP code level post-2017, depending on whether I control for metropolitan×quarter or county×quarter fixed effects.

As the existing literature typically estimates the average housing supply elasticity in the US to be less than 2, with some estimates even below 0.5, the magnitude of the drop in transactions is quite surprising, considering that the price drop is only about 0.4% to 0.5% in response to the same negative demand shock. If the average housing supply elasticity in the US is about 0.5, then a 0.4% to 0.5% drop in price should correspond to only a 0.2% to 0.25% decrease in housing transactions. Even if the average housing supply elasticity in the US is about 2, then a 0.4% to 0.5% drop in price should correspond to 0.8% to 1% decrease in transactions. Therefore, next, I figure out the implied house elasticity of supply under this setting.

As in Equation 2, δ is:

$$\delta_p = \frac{\partial \ln(HPI)}{\partial(CNratio \times Post)}, \tag{4}$$

whereas in Equation 3, δ is:

$$\delta_q = \frac{\partial \ln(Q)}{\partial(CNratio \times Post)}, \tag{5}$$

thus the δs in Equation 2 and 3 together give us the average house price elasticity of supply:

$$E = \frac{\delta_q}{\delta_p} = \frac{\frac{\partial \ln(Q)}{\partial(CNratio \times Post)}}{\frac{\partial \ln(HPI)}{\partial(CNratio \times Post)}} = \frac{\partial \ln(Q)}{\partial \ln(HPI)}. \tag{6}$$

That is, the results in Table 5 and Table 6 together indicate that the average price elasticity of supply in the US housing markets is about 4.75 when controlling for metropolitan×quarter fixed effects, and about 3.2 when controlling for county×quarter fixed effects.

Although my method for estimating the house price elasticity of supply is very similar to that of Gorback and Keys (2021), by focusing on an exogenous negative demand shock from foreign Chinese buyers, I find that the price elasticity of house supply I estimated is much larger than the average supply elasticity of 0.26 reported in their study. It is also larger than estimates found in other literature, such as Saiz (2010) (approximately 1.75 for the average metropolitan area with a population-weighted elasticity) and Baum-Snow and Han (2024) (about 0.5 for housing unit elasticity). This result suggests that potential home sellers are sensitive to house price changes and are flexible in deciding whether and when to put their homes on the market.

To ensure the finding above is robust to other supply measures, next I examine the supply indicated by new homes. Panel A of Table 7 reports the result of Equation 3 using the logarithm of the number of new homes constructed annually as the dependent variable. Since only annual data are available for new constructions, I rerun Equation 2 using the corresponding annual data to make easier comparisons, and the results are reported in Panel B. The implied price elasticity of new home supply is even larger, approximately 8.25 at the metropolitan level and 5 at the county level, indicating that new home supply is highly elastic.

Although changes in demand from foreign Chinese buyers do not alter the factors that shift the supply curve, there is a concern that my results might be influenced by the COVID-19 pandemic starting from 2020, during which new home constructions were extensively affected by logistics and supply chain disruptions. To address this issue, I limit my sample to the end of 2019 and rerun the regressions. As shown in Internet Appendix Table IA6, the results are very similar to the results in Table 7, demonstrating that my findings are robust and are not influenced by the pandemic.

At first glance, the high elasticity of house supply indicated in my analysis is surprising, since Glaeser and Gyourko (2005) state that a negative demand shock should have much larger impacts on prices than on quantities. However, the negative demand shock discussed in this paper differs from what is primarily discussed in Glaeser and Gyourko (2005). In their study, they focus on the inelastic part of the house supply curve, where a large demand shock causes house prices to fall below construction costs. In contrast, my framework focuses on a relatively small demand shock from the overseas investors from China. If the market is not operating exactly on the equilibrium point – where new house prices equal construction costs – but at a point where demand is above the equilibrium, then a small demand shock from overseas investors is unlikely to move the demand curve below the equilibrium. In other words, I focus on the segment of the house supply curve that is quite flat. Consistent with this flat house supply curve, my results show that home builders and other potential home sellers are sensitive to price changes, making it easy for them to either hold their properties or cease building new homes.

As I focus on a negative demand shock, my estimation of housing supply elasticity differs from that found in the existing literature, which mainly focuses on positive demand shocks, such as those studied by Aastveit and Anundsen (2022), Aastveit, Albuquerque, and Anundsen (2023) and Gorback and Keys (2021). This difference arises because, although home builders can construct homes relatively quickly, the building process still requires time. In contrast, home builders can immediately halt new constructions. That is to say, the supply curve may respond differently to positive and negative demand shocks when I focus on the relatively flat part of the supply curve, suggesting asymmetry in housing supply elasticity for positive and negative demand shocks. Similarly, for potential second-hand home sellers, many may delay selling their houses due to factors such as having renters or the sale price being lower than expected. However, the decision to "not sell" could be much more straightforward to execute if they are not urgently needing funds from selling the houses.

To further illustrate the points above, I build on the supply curve in Glaeser and Gyourko (2005) by adding another kink above the construction costs and assuming that home builders require a profit margin m in operation as in Figure 4. Panel (a) illustrates that there would not be asymmetric effects on local house prices if the demand curve shifts above the construction costs, that is, moving along the red highlighted part of the supply curve. Asymmetric effects on house prices only occur when there is a significant demand drop, which shifts the demand curve to below the construction costs, as seen at $D1$. Panel (b) demonstrates how adding another kink in the supply curve above the construction costs and assuming a profit margin of m can explain the asymmetric effects on house prices found in this paper compared with the literature. Assuming home builders aim to maintain their profitability at the level of $1 + m$ of construction costs, then, facing a negative demand shock, they can relatively quickly halt or delay their constructions to maintain prices at a desired level. The supply curve is relatively flat in this scenario, suggesting that a small price decrease results in a significant quantity drop. However, facing a positive demand shock, it always takes time for builders to construct new houses. In this case, the supply curve is relatively steep, and a relatively large price increase will only result in a relatively small quantity increase.

The asymmetric housing supply elasticity for positive and negative demand shocks has important implications. It offers a rationale for why measures such as the 2012 tax imposition in Hong Kong, aimed at curbing capital inflows, were ineffective. Given this high elasticity, builders have the capability to quickly adjust their supply strategies in response to market changes. Specifically, they could reduce their housing supplies deliberately to sustain elevated price levels and preserve profit margins. Another example involves the large-scale buy-to-rent institutional investors in the single-family home markets, which emerged after the financial crisis. Current literature focuses on how these institutional investors enhance local house prices (Mills, Molloy, and Zarutskie, 2019; Allen et al., 2018; D'Lima and Schultz, 2022; Ganduri, Xiao, and Xiao, 2023); however, what is equally important to the market but not examined by the literature is what happens when the capital tide recedes. My findings in this paper indicate that house supply could be more elastic than previously found in the literature, and the withdrawal of capital from large institutional home investors may only have limited impacts on local housing prices if they exit gradually.

5 Conclusion

This study leverages China's reinforcement of foreign exchange purchase quotas as an exogenous shock to examine how capital retrieval from major foreign countries affects the behavior of foreign buyers in the US single-family housing market. I use China as a specific illustration to explore this phenomenon.

By analyzing single-family home transaction and deed records across the United States, I find that the number of transactions by overseas Chinese buyers significantly dropped post-2017, compared to other foreign buyers. In contrast, transaction volumes for other minority groups, primarily identified as Indian and Russian based on owner names in transaction records, remained relatively stable throughout the sample period (2014-2021). The gaps between Chinese and Indian transaction volumes, as well as Chinese and Russian transaction volumes, narrowed by over 30% on average at the neighborhood level.

My analysis also reveals a direct effect from transaction volume of foreign Chinese buyers to local house price indices. Neighborhoods with a high concentration of overseas Chinese buyers experience slower growth in house prices post-2017. On average, a one percentage point increase in Chinese cash transactions relative to total transactions in a ZIP code in 2013 resulted in a 0.4% to 0.5% slower increase in the house price index at the ZIP code level. This shows that the decrease in residential single-family house transactions by foreign Chinese buyers has real effects on local economies by directly influencing the local house prices. However, the magnitude of such effects on depressing prices is relatively small, considering that housing supply, measured either by short-term transactions or newly constructed homes, dropped by 1.6% to 1.9% and 2.5% to 3.3%, respectively.

I also estimated the elasticity of house supply using this exogenous negative demand shock. My estimation of elasticity is higher than that in existing literature, which primarily uses positive demand shocks. This suggests that the supply curve may respond differently to positive and negative demand shocks, especially when focusing on the relatively flat part of the curve, thereby indicating an asymmetry in housing supply elasticity for positive and negative demand shocks. The high elasticity of house supply observed in this framework implies that potential home sellers, including home builders, are sensitive to price changes and are likely to halt construction or hold their properties in response to even a minor decrease in demand. My findings of high elasticity of house supply in response to a small negative demand shock not only explain why the ban on cross-border capital may have limited effects on controlling house prices, but also suggest that the withdrawal of capital from large institutional home investors may only have limited impacts on housing prices if they exit gradually.

References

Aastveit, K. A., B. Albuquerque, and A. K. Anundsen. 2023. Changing Supply Elasticities and Regional Housing Booms. *Journal of Money, Credit and Banking* 55:1749–83. doi:10.1111/jmcb.13009.

Aastveit, K. A., and A. K. Anundsen. 2022. Asymmetric Effects of Monetary Policy in Regional Housing Markets. *American Economic Journal: Macroeconomics* 14:499–529. doi:10.1257/mac.20190011.

Alfaro, L., A. Chanda, S. Kalemli-Ozcan, and S. Sayek. 2004. FDI and economic growth: the role of local financial markets. *Journal of International Economics* 64:89–112. doi:10.1016/S0022-1996(03)00081-3.

———. 2010. Does foreign direct investment promote growth? Exploring the role of financial markets on linkages. *Journal of Development Economics* 91:242–56. doi:10.1016/j.jdeveco.2009.09.004.

Allen, M. T., J. Rutherford, R. Rutherford, and A. Yavas. 2018. Impact of Investors in Distressed Housing Markets. *The Journal of Real Estate Finance and Economics* 56:622–52. doi:10.1007/s11146-017-9609-0.

Badarinza, C., and T. Ramadorai. 2018. Home away from home? Foreign demand and London house prices. *Journal of Financial Economics* 130:532–55. doi:10.1016/j.jfineco.2018.07.010.

Bardhan, A., and C. A. Kroll. 2007. Globalization and the Real Estate Industry: Issues, Implications, Opportunities. *Conference Report Paper* .

Baum-Snow, N., and L. Han. 2024. The Microgeography of Housing Supply. *Journal of Political Economy* 132:1793–2178. doi:10.1086/728110.

Borensztein, E., J. D. Gregorio, and J.-W. Lee. 1998. How does foreign direct investment affect economic growth? *Journal of International Economics* 45:115–35. doi:10.1016/S0022-1996(97)00033-0.

Bostic, R., S. Gabriel, and G. Painter. 2009. Housing wealth, financial wealth, and consumption: New evidence from micro data. *Regional Science and Urban Economics* 39:79–89. doi:10.1016/j.regsciurbeco.2008.06.002.

Cohen, L., U. G. Gurun, and C. Malloy. 2017. Resident Networks and Corporate Connections: Evidence from World War II Internment Camps. *The Journal of Finance* 72:207–48. doi:10.1111/jofi.12407.

Cvijanović, D., and C. Spaenjers. 2021. “We’ll Always Have Paris”: Out-of-Country Buyers in the Housing Market. *Management Science* 67:4120–38. doi:10.1287/mnsc.2020.3686.

D’Lima, W., and P. Schultz. 2022. Buy-to-Rent Investors and the Market for Single Family Homes. *The Journal of Real Estate Finance and Economics* 64:116–52. doi:10.1007/s11146-020-09790-5.

Favilukis, J., D. Kohn, S. C. Ludvigson, and S. Van Nieuwerburgh. 2012. International Capital Flows and House Prices: Theory and Evidence. *NBER Working Paper* doi:10.3386/w17751.

Favilukis, J., and S. Van Nieuwerburgh. 2021. Out-of-Town Home Buyers and City Welfare. *The Journal of Finance* 76:2577–638. doi:10.1111/jofi.13057.

Fernández, R., and A. Fogli. 2009. Culture: An Empirical Investigation of Beliefs, Work, and Fertility. *American Economic Journal: Macroeconomics* 1:146–77. doi:10.1257/mac.1.1.146.

Ganduri, R., S. C. Xiao, and S. W. Xiao. 2023. Tracing the source of liquidity for distressed housing markets. *Real Estate Economics* 51:408–40. doi:10.1111/1540-6229.12388.

Glaeser, E. L., and J. Gyourko. 2005. Urban Decline and Durable Housing. *Journal of Political Economy* 113:345–75. doi:10.1086/427465.

Gorback, C., and B. J. Keys. 2021. Global Capital and Local Assets: House Prices, Quantities, and Elasticities. *Working Paper* .

Greenstone, M., A. Mas, and H.-L. Nguyen. 2020. Do Credit Market Shocks Affect the Real Economy? Quasi-experimental Evidence from the Great Recession and “Normal” Economic Times. *American Economic Journal: Economic Policy* 12:200–25. doi:10.1257/pol.20160005.

Han, L., and S.-H. Hong. 2024. Cash is King? Understanding Financing Risk in Housing Markets. *Working Paper* .

Hanson, S. 2022. Institutional Investors In The Market For Single-Family Housing: Where Did They Come From, Where Did They Go? *Working Paper* doi:10.2139/ssrn.4268640.

Kerr, W. 2008. The Ethnic Composition of US Inventors. *Working Paper* doi:10.2139/ssrn.1010142.

Li, G. 2021. Chinese Overseas Buyers in U.S. Housing Markets. *Working Paper* doi:10.2139/ssrn.4445791.

Li, Z., L. S. Shen, and C. Zhang. 2020. Capital Flows, Asset Prices, and the Real Economy: A "China Shock" in the U.S. Real Estate Market. *International Finance Discussion Papers 1286* doi:10.17016/IFDP.2020.1286.

Liu, X. 2016. Corruption culture and corporate misconduct. *Journal of Financial Economics* 122:307–27. doi:10.1016/j.jfineco.2016.06.005.

Mian, A., K. Rao, and A. Sufi. 2013. Household Balance Sheets, Consumption, and the Economic Slump. *The Quarterly Journal of Economics* 128:1687–726.

Mills, J., R. Molloy, and R. Zarutskie. 2019. Large-Scale Buy-to-Rent Investors in the Single-Family Housing Market: The Emergence of a New Asset Class. *Real Estate Economics* 47:399–430. doi:10.1111/1540-6229.12189.

Pavlov, A., and T. Somerville. 2020. Immigration, Capital Flows and Housing Prices. *Real Estate Economics* 48:915–49. doi:10.1111/1540-6229.12267.

Reher, M., and R. Valkanov. 2020. The Mortgage-Cash Premium Puzzle. *Working Paper* doi:10.2139/ssrn.3751917.

Sa, F. 2016. The Effect of Foreign Investors on Local Housing Markets: Evidence from the UK. *CEPR Discussion Paper No. DP11658* .

Saiz, A. 2010. The Geographic Determinants of Housing Supply. *Quarterly Journal of Economics* 125:1253–96. doi:10.1162/qjec.2010.125.3.1253.

Siebert, R. B., and M. J. Seiler. 2022. Why Do Buyers Pay Different Prices for Comparable Products? A Structural Approach on the Housing Market. *The Journal of Real Estate Finance and Economics* 65:261–92. doi:10.1007/s11146-021-09841-5.

Stroebel, J., and J. Vavra. 2019. House Prices, Local Demand, and Retail Prices. *Journal of Political Economy* 127:1391–436. doi:10.1086/701422.

West, I., and M. J. Botsch. 2020. Are Foreign Buyers Making Housing Unaffordable? *Working Paper* .

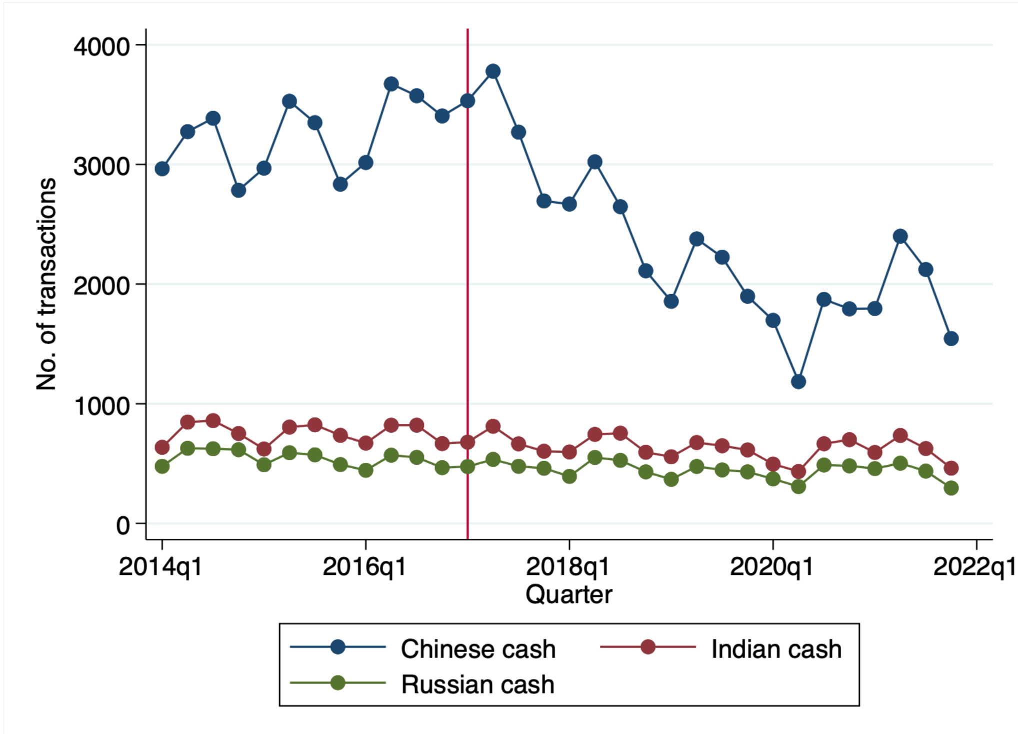
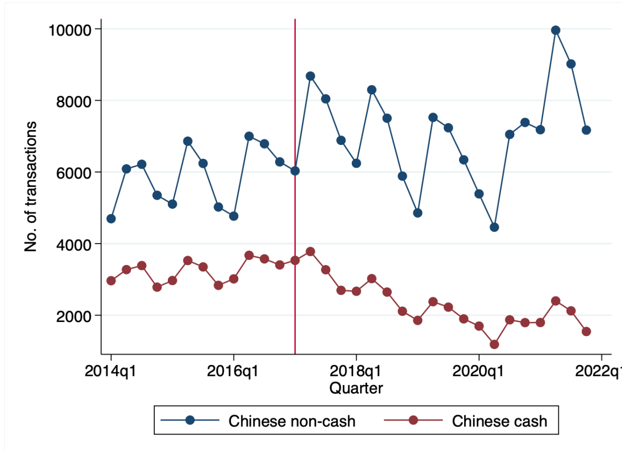
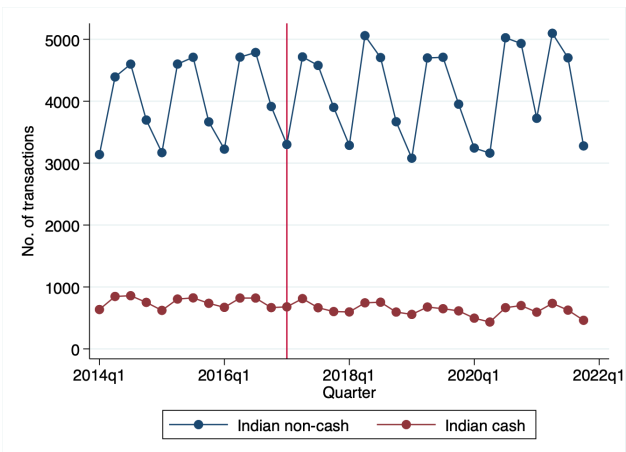


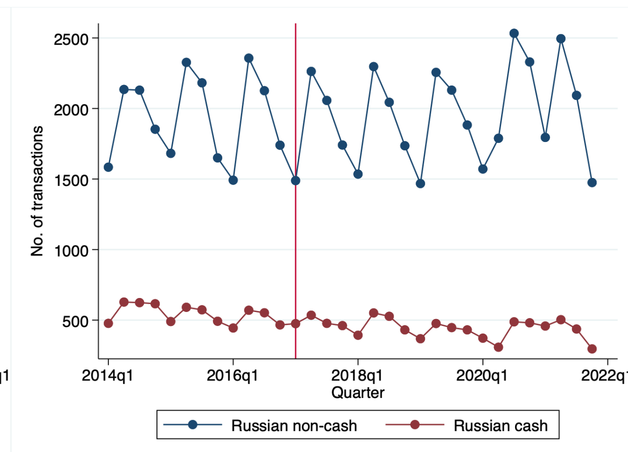
Figure 1. Number of Cash Transactions by Ethnicity in the US
This figure reports the quarterly total number of cash transactions by Chinese, Indians and Russians in the United States from 2014 to 2021.



(a) Chinese



(b) Indian



(c) Russian

Figure 2. Number of Non-cash and Cash Transactions by Ethnicity

This figure compares the quarterly number of non-cash transactions and cash transactions by Chinese, Indian, and Russians in the United States from 2014 to 2021.

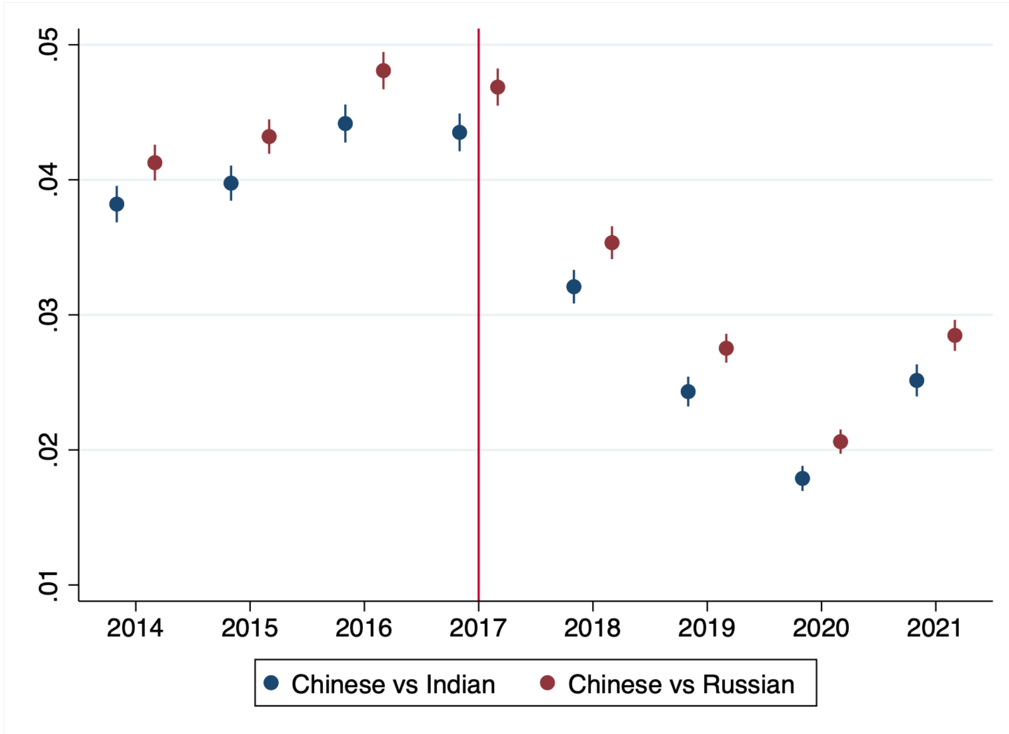
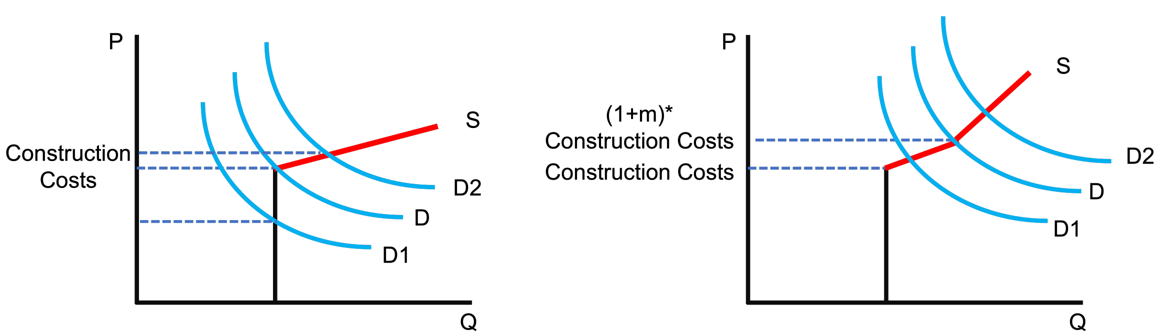


Figure 3. Coefficients of Chinese vs Indian/Russian Cash Transactions by Year
This figure reports the coefficients of Chinese indicator on the quantity of cash transactions by year. The blue dots represent the placebo using Indian cash transactions, while the red dots represent the placebo using Russian cash transactions.



(a) Glaeser and Gyourko (2005) **(b)** Two Kinks and Profit Margin

Figure 4. Double Kinked Supply Curve
This figure builds on the supply curve in Glaeser and Gyourko (2005) by adding another kink in the supply curve and assuming home builders require a profit margin.

Table 1

Annual Number of Transactions by Ethnicity

This table reports the annual number of transactions and cash transactions for all, Chinese, Indian, and Russian in the US from 2014 to 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	All	Cash	Chinese	Chinese cash	Indian	Indian cash	Russian	Russian cash
2014	3,798,497	1,076,084	34,757	12,408	18,919	3,093	10,047	2,345
2015	3,828,340	1,002,374	35,909	12,681	19,134	2,987	9,987	2,146
2016	3,692,103	916,623	38,506	13,668	19,620	2,980	9,747	2,032
2017	3,742,462	945,015	42,916	13,276	19,255	2,759	9,498	1,948
2018	3,757,466	958,237	38,378	10,449	19,410	2,690	9,514	1,902
2019	3,802,553	899,464	34,315	8,357	18,937	2,496	9,459	1,722
2020	3,733,170	800,866	30,830	6,547	18,659	2,296	9,872	1,649
2021	3,249,040	800,747	41,194	7,863	19,216	2,416	9,552	1,694

Table 2

Summary Statistics of House Prices and Characteristics

This table reports the summary statistics of house prices and characteristics for transactions and cash transactions of all, Chinese, Indian, and Russian in the US. Sample period is from 2014 to 2021. Mean values are reported as the main value, standard deviations are in parentheses.

	(1) All	(2) Cash	(3) Chinese	(4) Chinese cash	(5) Indian	(6) Indian cash	(7) Russian	(8) Russian cash
Price (in 1000s)	314.58	272.57	592.21	508.35	495.88	332.91	429.95	335.00
	(310.84)	(388.10)	(522.83)	(533.70)	(417.44)	(379.32)	(384.61)	(384.99)
Living (sqft)	1,959.43	1,802.96	2,265.07	2,213.74	2,468.30	2,094.84	2,116.09	1,940.34
	(881.08)	(865.56)	(982.06)	(1,024.82)	(1,096.37)	(1067.88)	(939.65)	(940.73)
Lot (acres)	0.69	0.88	0.32	0.35	0.38	0.51	0.52	0.71
	(7.33)	(9.62)	(3.80)	(1.63)	(1.39)	(2.24)	(1.99)	(3.21)
Story	1.35	1.28	1.52	1.49	1.55	1.41	1.43	1.34
	(0.50)	(0.48)	(0.54)	(0.54)	(0.54)	(0.53)	(0.53)	(0.51)
House age	39.37	46.16	33.86	34.46	29.18	40.86	37.27	43.17
	(31.05)	(32.79)	(28.57)	(29.74)	(28.63)	(32.78)	(29.76)	(32.09)
Bedrooms	3.90	3.60	6.23	6.91	5.06	5.34	4.08	4.25
	(71.36)	(64.18)	(145.86)	(164.50)	(100.02)	(110.02)	(74.26)	(94.19)
Full baths	2.69	2.40	5.01	5.71	3.87	4.14	2.89	3.09
	(71.53)	(64.37)	(146.08)	(164.85)	(100.29)	(110.45)	(74.40)	(94.41)
Half baths	0.30	0.24	0.39	0.37	0.42	0.31	0.35	0.28
	(0.48)	(0.45)	(0.51)	(0.50)	(0.52)	(0.49)	(0.50)	(0.47)
Has pool	0.09	0.08	0.12	0.10	0.10	0.08	0.12	0.10
	(0.29)	(0.27)	(0.32)	(0.30)	(0.30)	(0.28)	(0.32)	(0.31)
Has fireplace	0.44	0.37	0.55	0.51	0.51	0.41	0.50	0.41
	(0.50)	(0.48)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.49)
Has garage	0.71	0.64	0.79	0.76	0.78	0.68	0.73	0.67
	(0.46)	(0.48)	(0.41)	(0.43)	(0.41)	(0.47)	(0.44)	(0.47)

Table 3

Differences of House Characteristics for Foreign Buyer Transactions

This table reports the summary statistics of house characteristics with t-stat of differences for Chinese, Indian, and Russian cash transactions pre- and post-2017 across the US. Sample period is from 2014 to 2021. *, **, and *** indicate statistical significance at 5%, 1%, and 0.1%.

	(1) Pre-2017		(2) Post-2017		(3) Difference	
	mean	*sd*	*mean*	*sd*	*b*	*t*
Panel A: Chinese Cash						
Living (sqft)	2,220.43	1,040.01	2,208.15	1,011.93	−12.28	(−1.74)
Lot (acres)	0.33	1.79	0.36	1.49	0.04***	(3.36)
Story	1.48	0.53	1.49	0.54	0.01*	(2.53)
House age	33.65	28.86	35.13	30.44	1.48***	(7.25)
Bedrooms	6.85	162.46	6.96	166.18	0.11	(0.10)
Full baths	5.65	162.83	5.76	166.51	0.11	(0.10)
Half baths	0.36	0.50	0.37	0.50	0.01*	(2.30)
Has pool	0.10	0.30	0.10	0.31	0.00	(1.75)
Has fireplace	0.52	0.50	0.50	0.50	−0.01***	(−4.05)
Has garage	0.76	0.43	0.76	0.43	0.00	(0.84)
Panel B: Indian Cash						
Living (sqft)	2,062.72	1,052.61	2,117.81	1,078.12	55.09***	(3.74)
Lot (acres)	0.49	1.90	0.52	2.46	0.03	(0.97)
Story	1.39	0.52	1.42	0.53	0.03***	(4.57)
House age	40.27	32.05	41.28	33.29	1.01*	(2.23)
Bedrooms	6.36	138.86	4.63	84.50	−1.73	(−1.08)
Full baths	5.18	139.41	3.43	84.83	−1.75	(−1.09)
Half baths	0.29	0.47	0.33	0.50	0.04***	(5.61)
Has pool	0.08	0.27	0.09	0.29	0.01**	(2.83)
Has fireplace	0.39	0.49	0.41	0.49	0.02**	(3.15)
Has garage	0.67	0.47	0.69	0.46	0.02*	(2.37)
Panel C: Russian Cash						
Living (sqft)	1,903.08	914.62	1,967.62	958.53	64.54***	(4.20)
Lot (acres)	0.67	3.02	0.74	3.34	0.06	(1.22)
Story	1.33	0.50	1.35	0.51	0.02	(1.95)
House age	42.35	31.29	43.78	32.65	1.43**	(2.73)
Bedrooms	4.41	102.52	4.13	87.63	−0.28	(−0.18)
Full baths	3.25	102.78	2.98	87.81	−0.26	(−0.16)
Half baths	0.27	0.46	0.28	0.47	0.01	(1.62)
Has pool	0.10	0.30	0.11	0.31	0.01*	(2.30)
Has fireplace	0.41	0.49	0.42	0.49	0.01	(1.41)
Has garage	0.66	0.47	0.67	0.47	0.01	(0.93)

Table 4

Foreign Chinese Purchases Relative to Indian and Russian Purchases

This table reports the results of regressions of the number of cash transactions, or percentage of cash transactions over all transactions of Chinese relative to each of the two placebo ethnicities, Indian (Panel A) and Russian (Panel B), on the Chinese indicator and its interaction with the *Post* indicator for the period starting in 2017:

$$Y_{i,r,c,t} = \alpha_{i,r,c,t} + \beta CN_i + \gamma Post_t + \delta CN_i \times Post_t + \zeta_c + \eta_t + \theta_{c\times t} + \lambda_r + \epsilon_{i,r,c,t}.$$

If the number of cash transactions, or percentage of cash transactions over all transactions is by ethnicity i of Chinese at census tract r of county c in year t, then CN_i equals 1; otherwise, if ethnicity i refers to Indian, then CN_i equals 0. Coefficients for *Post* indicator partialled out due to adding quarter fixed effects. Sample period is from 2014 to 2021. State fixed effects, quarter fixed effects, county fixed effects, and county $\times$ quarter fixed effects are controlled in all columns. Neighborhood fixed effects are at census tract level. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1) Cash	(2) Cash	(3) Cash/All	(4) Cash/All
Panel A: Chinese vs Indian				
Chinese	0.041***	0.041***	20.327***	19.460***
	(0.000)	(0.000)	(0.248)	(0.260)
Chinese× Post	−0.012***	−0.013***	−7.869***	−7.742***
	(0.000)	(0.000)	(0.306)	(0.318)
Neighborhood FE	No	Yes	No	Yes
R^2	0.047	0.198	0.189	0.342
N	3,816,808	3,698,200	289,130	270,860
Panel B: Chinese vs Russian				
Chinese	0.044***	0.045***	16.796***	16.575***
	(0.000)	(0.000)	(0.308)	(0.336)
Chinese× Post	−0.012***	−0.014***	−7.146***	−7.160***
Neighborhood FE	No	Yes	No	Yes
R^2	0.045	0.187	0.182	0.343
N	3,816,808	3,698,200	245,820	228,629

Table 5
House Price Indices and Foreign Chinese Buyers in Neighborhoods

This table reports the results of regressions of log of the house prices index in a ZIP code on the percentage ratio of Chinese cash buyers relative to all buyers in 2013 and its interaction with the *Post* indicator for the period starting in 2017:

$$lnHPI_{r,c,s,t} = \alpha_{r,c,s,t} + \beta CNratio_{r,c,s} + \gamma Post_t + \delta CNratio_{r,c,s} \times Post_t + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{r,c,s,t}.$$

Coefficents for $CNratio$ and $Post$ indicator are partialled out due to ZIP code fixed effects and quarter fixed effects respectively. Sample period is from 2014 to 2021. State fixed effects and quarter fixed effects are controlled in all columns. Neighborhood fixed effects are at ZIP code level. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)
Chinese × Post	-0.004^{***}	-0.005^{***}
	(0.000)	(0.000)
Metro FE	Yes	No
Quarter×Metro FE	Yes	No
County FE	No	Yes
Quarter×County FE	No	Yes
Neighborhood FE	Yes	Yes
R^2	0.996	0.997
N	515,244	586,256

Table 6
House Transaction Volumes and Foreign Chinese Buyers in Neighborhoods

This table reports the results of regressions of log of the number of house transactions in a ZIP code on the percentage ratio of Chinese cash buyers relative to all buyers in 2013 and its interaction with the *Post* indicator for the period starting in 2017:

$$lnQ_{r,c,s,t} = \alpha_{r,c,s,t} + \beta CNratio_{r,c,s} + \gamma Post_t + \delta CNratio_{r,c,s} \times Post_t + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{r,c,s,t}.$$

Coefficents for $CNratio$ and $Post$ indicator are partialled out due to ZIP code fixed effects and quarter fixed effects respectively. Sample period is from 2014 to 2021. State fixed effects and quarter fixed effects are controlled in all columns. Neighborhood fixed effects are at ZIP code level. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)
Chinese × Post	-0.019^{***}	-0.016^{***}
	(0.002)	(0.002)
Metro FE	Yes	No
Quarter×Metro FE	Yes	No
County FE	No	Yes
Quarter×County FE	No	Yes
Neighborhood FE	Yes	Yes
R^2	0.940	0.954
N	515,244	586,256

Table 7
Price Elasticity of New Home Supply

Panel A of this table reports the results of regressions of log of the number of newly constructed houses in a year in a ZIP code on the percentage ratio of Chinese cash buyers over all buyers in 2013 and its interaction with the *Post* indicator for the period starting in 2017:

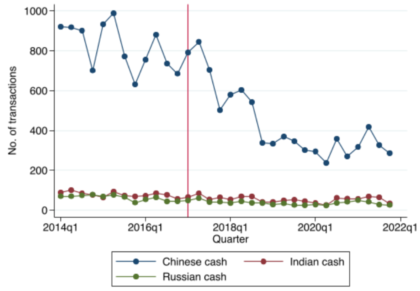
$$lnQ_{r,c,s,t} = \alpha_{r,c,s,t} + \beta CNratio_{r,c,s} + \gamma Post_t + \delta CNratio_{r,c,s} \times Post_t + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{r,c,s,t}.$$

Panel B of this table reports the results of regressions of log of the house price index at the end of a year in a ZIP code on the percentage ratio of Chinese cash buyers over all buyers in 2013 and its interaction with the *Post* indicator for the period starting in 2017:

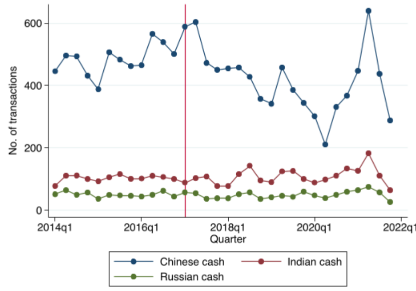
$$lnHPI_{r,c,s,t} = \alpha_{r,c,s,t} + \beta CNratio_{r,c,s} + \gamma Post_t + \delta CNratio_{r,c,s} \times Post_t + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{r,c,s,t}.$$

Coefficents for $CNratio$ and $Post$ indicator are partialled out due to ZIP code fixed effects and year fixed effects respectively. Sample period is from 2014 to 2021. State fixed effects and year fixed effects are controlled in all columns. Neighborhood fixed effects are at ZIP code level. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

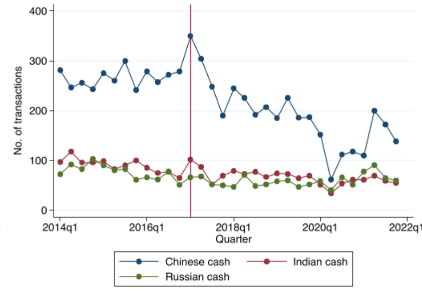
	(1)	(2)
Panel A: Number of New Home Constructed		
Chinese × Post	-0.033^{***}	-0.025^{***}
	(0.006)	(0.006)
R^2	0.865	0.898
Panel B: House Price Index		
Chinese × Post	-0.004^{***}	-0.005^{***}
	(0.001)	(0.001)
R^2	0.996	0.997
Metro FE	Yes	No
Year×Metro FE	Yes	No
County FE	No	Yes
Year×County FE	No	Yes
Neighborhood FE	Yes	Yes
N	116,405	131,869



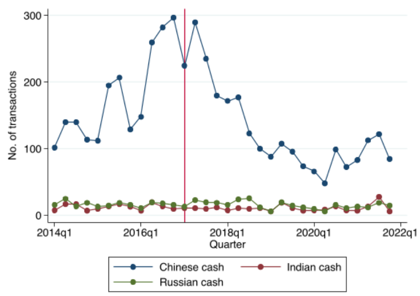
(a) California



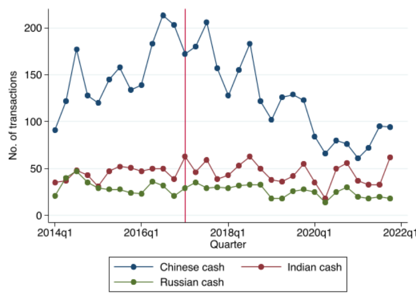
(b) Texas



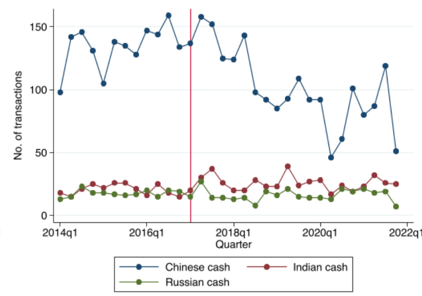
(c) Florida



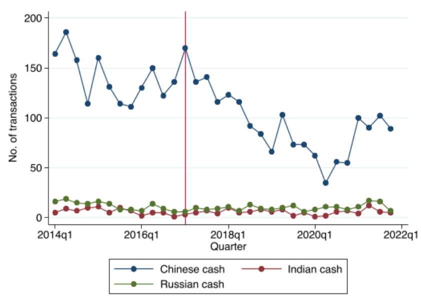
(d) Washington



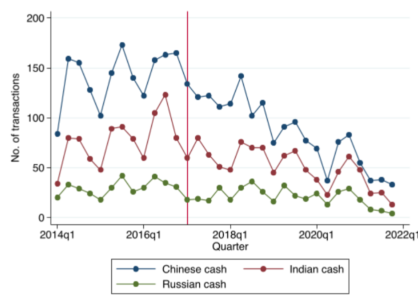
(e) New York



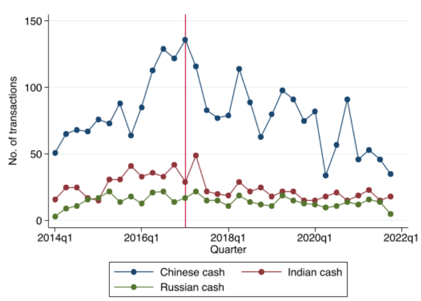
(f) Georgia



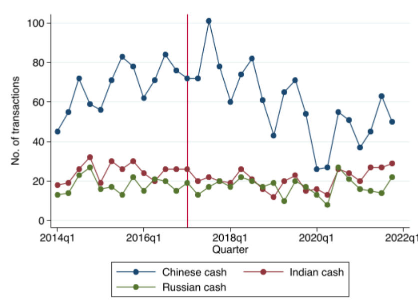
(g) Nevada



(h) New Jersey



(i) North Carolina



(j) Pennsylvania

Figure IA1. Number of Cash Transactions by Ethnicity in the 10 States
This figure compares the quarterly total number of cash transactions by Chinese, Indians and Russians in the top 10 states with the highest numbers of Chinese cash transactions from 2014 to 2021.

Table IA1
Chinese Surname List

This table reports the surnames used in this paper for identification of Chinese.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BAI	BAO	BI	CAI	CAO	CHANG	CHAO	CHEN
CAO	CHANG	CHAO	CHEN	CHENG	CHU	CUI	DAI
CHENG	CHU	CUI	DAI	DENG	DING	DONG	DOU
DENG	DING	DONG	DOU	DU	DUAN	FAN	FANG
DU	DUAN	FAN	FANG	FENG	FU	GAO	GONG
FENG	FU	GAO	GONG	GU	GUO	HAN	HAO
GU	GUO	HAN	HAO	HE	HONG	HOU	HU
HE	HONG	HOU	HU	HUANG	JI	JIA	JIANG
HUANG	JI	JIA	JIANG	JIAO	JIN	JU	KANG
JIAO	JIN	JU	KANG	KONG	LAI	LEI	LI
KONG	LAI	LEI	LI	LIANG	LIAO	LIN	LING
LIANG	LIAO	LIN	LING	LIU	LONG	LU	LUO
LIU	LONG	LU	LUO	LYU	MA	MAO	MENG
LYU	MA	MAO	MENG	MIAO	MO	NIE	NIU
MIAO	MO	NIE	NIU	OUYANG	PAN	PANG	PENG
OUYANG	PAN	PANG	PENG	QI	QIAN	QIAO	QIN
QI	QIAN	QIAO	QIN	QIU	QU	RAO	REN
QIU	QU	RAO	REN	SHA	SHAO	SHEN	SHI
SHA	SHAO	SHEN	SHI	SONG	SU	SUN	TAI
SONG	SU	SUN	TAI	TAN	TANG	TAO	TENG
TAN	TANG	TAO	TENG	TIAN	TONG	TU	WAN
TIAN	TONG	TU	WAN	WANG	WEI	WEN	WU
WANG	WEI	WEN	WU	XI	XIA	XIANG	XIAO
XI	XIA	XIANG	XIAO	XIE	XIONG	XU	XUE
XIE	XIONG	XU	XUE	YAN	YANG	YAO	YE
YAN	YANG	YAO	YE	YIN	YOU	YU	YUAN
YIN	YOU	YU	YUAN	ZENG	ZHAI	ZHANG	ZHAO
ZENG	ZHAI	ZHANG	ZHAO	ZHENG	ZHONG	ZHOU	ZHU
ZHENG	ZHONG	ZHOU	ZHU	ZHUANG	ZHUO	ZOU	
ZHUANG	ZHUO	ZOU					

Table IA2
Differences of House Characteristics for Foreign Buyer Transactions

This table replicates Table 3 but variables of living space, lot size, number of baths and bedrooms are winsorized at the top and bottom 5% at the county level. This table reports the summary statistics of house characteristics with t-stat of differences for Chinese, Indian, and Russian cash transactions pre- and post-2017 across the US. Sample period is from 2014 to 2021. *, **, and *** indicate statistical significance at 5%, 1%, and 0.1%.

	(1) Pre-2017		(2) Post-2017		(3) Difference	
	mean	*sd*	*mean*	*sd*	*b*	*t*
Panel A: Chinese Cash						
Living (sqft)	2,160.45	885.25	2,153.88	866.27	−6.57	(−1.09)
Lot (acres)	0.28	0.96	0.31	0.82	0.03***	(5.70)
Story	1.48	0.53	1.49	0.54	0.01*	(2.53)
House age	33.23	27.97	34.51	29.23	1.28***	(6.51)
Bedrooms	6.72	161.68	6.86	165.57	0.15	(0.13)
Full baths	5.58	162.81	5.71	166.51	0.13	(0.11)
Half baths	0.36	0.48	0.36	0.48	0.01*	(2.39)
Has pool	0.10	0.30	0.10	0.31	0.00	(1.75)
Has fireplace	0.52	0.50	0.50	0.50	−0.01***	(−4.05)
Has garage	0.76	0.43	0.76	0.43	0.00	(0.84)
Panel B: Indian Cash						
Living (sqft)	2,010.60	901.90	2,059.67	920.78	49.07***	(3.89)
Lot (acres)	0.40	1.00	0.42	1.84	0.03	(1.24)
Story	1.39	0.52	1.42	0.53	0.03***	(4.57)
House age	39.48	30.62	40.28	31.58	0.79	(1.85)
Bedrooms	5.20	126.21	3.97	74.23	−1.23	(−0.85)
Full baths	5.12	139.40	3.26	84.33	−1.85	(−1.15)
Half baths	0.28	0.45	0.32	0.47	0.04***	(5.57)
Has pool	0.08	0.27	0.09	0.29	0.01**	(2.83)
Has fireplace	0.39	0.49	0.41	0.49	0.02**	(3.15)
Has garage	0.67	0.47	0.69	0.46	0.02*	(2.37)
Panel C: Russian Cash						
Living (sqft)	1,874.94	802.50	1,928.42	827.31	53.48***	(4.00)
Lot (acres)	0.52	1.87	0.60	2.20	0.07*	(2.15)
Story	1.33	0.50	1.35	0.51	0.02	(1.95)
House age	41.55	29.96	42.67	30.84	1.12*	(2.25)
Bedrooms	4.38	102.52	4.12	87.63	−0.26	(−0.17)
Full baths	3.21	102.77	2.95	87.81	−0.25	(−0.16)
Half baths	0.26	0.44	0.28	0.45	0.01	(1.64)
Has pool	0.10	0.30	0.11	0.31	0.01*	(2.30)
Has fireplace	0.41	0.49	0.42	0.49	0.01	(1.41)
Has garage	0.66	0.47	0.67	0.47	0.01	(0.93)

Table IA3

Foreign Chinese Purchases Relative to Indian and Russian Purchases by State

This table replicates Table 4 but limits the sample to each of the top 10 states with the highest numbers of overseas Chinese buyers: California, Texas, Florida, Washington, New York, Georgia, Nevada, New Jersey, North Carolina, and Pennsylvania. Sample period is from 2014 to 2021. Quarter fixed effects, county fixed effects, and county × quarter fixed effects are controlled in all columns. Neighborhood fixed effects are at census tract level. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1) Cash	(2) Cash	(3) Cash/All	(4) Cash/All
Panel A: California				
Panel A1: Chinese vs Indian				
Chinese	0.104***	0.104***	18.732***	17.917***
	(0.002)	(0.002)	(0.457)	(0.472)
Chinese × Post	−0.048***	−0.050***	−10.446***	−10.332***
	(0.002)	(0.002)	(0.565)	(0.576)
Neighborhood FE	No	Yes	No	Yes
R^2	0.036	0.179	0.101	0.229
N	444,530	441,294	63,811	62,177
Panel A2: Chinese vs Russian				
Chinese	0.107***	0.106***	16.456***	15.627***
	(0.002)	(0.001)	(0.586)	(0.632)
Chinese × Post	−0.048***	−0.050***	−8.639***	−8.669***
	(0.002)	(0.002)	(0.731)	(0.771)
Neighborhood FE	No	Yes	No	Yes
R^2	0.037	0.179	0.089	0.224
N	444,530	441,294	56,938	55,506
Panel B: Texas				
Panel B1: Chinese vs Indian				
Chinese	0.077***	0.079***	23.633***	22.705***
	(0.002)	(0.002)	(0.704)	(0.713)
Chinese × Post	−0.012***	−0.016***	−7.719***	−7.645***
	(0.003)	(0.002)	(0.884)	(0.890)
Neighborhood FE	No	Yes	No	Yes
R^2	0.079	0.320	0.119	0.263
N	308,748	299,114	33,571	31,955

(Continued)

Table IA3—*continued*

	(1) Cash	(2) Cash	(3) Cash/All	(4) Cash/All
Panel B2: Chinese vs Russian				
Chinese	0.088***	0.090***	19.012***	19.101***
	(0.002)	(0.002)	(0.983)	(1.022)
Chinese × Post	−0.011***	−0.015***	−6.975***	−7.770***
	(0.003)	(0.002)	(1.237)	(1.290)
Neighborhood FE	No	Yes	No	Yes
R^2	0.072	0.286	0.101	0.261
N	308,748	299,114	25,984	24,427
Panel C: Florida				
Panel C1: Chinese vs Indian				
Chinese	0.044***	0.044***	29.415***	29.564***
	(0.002)	(0.002)	(1.103)	(1.201)
Chinese × Post	−0.013***	−0.015***	−11.572***	−11.352***
	(0.003)	(0.002)	(1.392)	(1.515)
Neighborhood FE	No	Yes	No	Yes
R^2	0.028	0.225	0.163	0.344
N	252,964	249,494	17,830	16,679
Panel C2: Chinese vs Russian				
Chinese	0.048***	0.048***	24.269***	24.530***
	(0.002)	(0.002)	(1.291)	(1.429)
Chinese × Post	−0.014***	−0.017***	−8.124***	−7.642***
	(0.003)	(0.002)	(1.591)	(1.751)
Neighborhood FE	No	Yes	No	Yes
R^2	0.025	0.214	0.155	0.347
N	252,964	249,494	16,281	15,196
Panel D: Washington				
Panel D1: Chinese vs Indian				
Chinese	0.128***	0.130***	22.465***	21.514***
	(0.004)	(0.004)	(1.034)	(1.044)
Chinese × Post	−0.037***	−0.039***	−9.866***	−10.213***
	(0.005)	(0.005)	(1.196)	(1.207)

(Continued)

Table IA3—*continued*

	(1) Cash	(2) Cash	(3) Cash/All	(4) Cash/All
Neighborhood FE	No	Yes	No	Yes
R^2	0.071	0.201	0.122	0.222
N	81,828	79,894	13,825	13,476
Panel D2: Chinese vs Russian				
Chinese	0.125***	0.127***	20.649***	19.821***
	(0.004)	(0.004)	(1.190)	(1.236)
Chinese × Post	−0.037***	−0.039***	−12.066***	−11.030***
	(0.005)	(0.005)	(1.419)	(1.471)
Neighborhood FE	No	Yes	No	Yes
R^2	0.068	0.198	0.102	0.199
N	81,828	79,894	13,365	13,029
Panel E: New York				
Panel E1: Chinese vs Indian				
Chinese	0.032***	0.032***	17.239***	16.530***
	(0.001)	(0.001)	(1.148)	(1.296)
Chinese × Post	−0.009***	−0.009***	−8.134***	−7.139***
	(0.002)	(0.002)	(1.377)	(1.463)
Neighborhood FE	No	Yes	No	Yes
R^2	0.026	0.134	0.286	0.412
N	210,966	207,154	15,919	14,973
Panel E2: Chinese vs Russian				
Chinese	0.036***	0.037***	15.559***	14.625***
	(0.001)	(0.001)	(1.347)	(1.517)
Chinese × Post	−0.007***	−0.007***	−7.743***	−7.698***
	(0.002)	(0.002)	(1.687)	(1.852)
Neighborhood FE	No	Yes	No	Yes
R^2	0.028	0.136	0.297	0.419
N	210,966	207,154	13,139	12,155
Panel F: Georgia				
Panel F1: Chinese vs Indian				
Chinese	0.058***	0.061***	28.529***	26.841***

(Continued)

Table IA3—*continued*

	(1) Cash	(2) Cash	(3) Cash/All	(4) Cash/All
	(0.002)	(0.002)	(1.287)	(1.351)
Chinese × Post	−0.017***	−0.021***	−13.037***	−12.457***
	(0.003)	(0.003)	(1.635)	(1.714)
Neighborhood FE	No	Yes	No	Yes
R^2	0.060	0.150	0.216	0.341
N	121,086	113,970	10,072	9,385
Panel F2: Chinese vs Russian				
Chinese	0.060***	0.062***	21.690***	20.332***
	(0.002)	(0.002)	(1.735)	(1.839)
Chinese × Post	−0.013***	−0.017***	−9.496***	−10.323***
	(0.003)	(0.003)	(2.169)	(2.363)
Neighborhood FE	No	Yes	No	Yes
R^2	0.062	0.160	0.183	0.325
N	121,086	113,970	8,038	7,432
Panel G: Nevada				
Panel G1: Chinese vs Indian				
Chinese	0.206***	0.209***	33.972***	31.736***
	(0.007)	(0.007)	(2.140)	(2.309)
Chinese × Post	−0.069***	−0.082***	−12.738***	−12.226***
	(0.009)	(0.008)	(2.676)	(2.866)
Neighborhood FE	No	Yes	No	Yes
R^2	0.052	0.222	0.136	0.256
N	41,196	40,446	5,559	5,396
Panel G2: Chinese vs Russian				
Chinese	0.197***	0.200***	27.876***	27.551***
	(0.008)	(0.007)	(2.198)	(2.223)
Chinese × Post	−0.066***	−0.078***	−11.775***	−12.395***
	(0.009)	(0.008)	(2.736)	(2.812)
Neighborhood FE	No	Yes	No	Yes
R^2	0.049	0.223	0.110	0.235
N	41,196	40,446	5,762	5,612

(Continued)

Table IA3—*continued*

	(1) Cash	(2) Cash	(3) Cash/All	(4) Cash/All
Panel H: New Jersey				
Panel H1: Chinese vs Indian				
Chinese	0.033***	0.033***	17.305***	16.585***
	(0.003)	(0.003)	(1.093)	(1.119)
Chinese × Post	−0.014***	−0.013***	−3.768***	−3.759***
	(0.003)	(0.003)	(1.379)	(1.377)
Neighborhood FE	No	Yes	No	Yes
R^2	0.030	0.166	0.189	0.348
N	117,484	116,172	14,589	14,079
Panel H2: Chinese vs Russian				
Chinese	0.058***	0.058***	15.162***	15.321***
	(0.003)	(0.002)	(1.505)	(1.640)
Chinese × Post	−0.021***	−0.021***	−4.027**	−5.902***
	(0.003)	(0.003)	(1.900)	(2.038)
Neighborhood FE	No	Yes	No	Yes
R^2	0.029	0.134	0.177	0.355
N	117,484	116,172	10,185	9,746
Panel I: North Carolina				
Panel I1: Chinese vs Indian				
Chinese	0.025***	0.026***	21.970***	21.043***
	(0.002)	(0.002)	(1.604)	(1.747)
Chinese × Post	0.001	0.000	−4.200**	−3.260
	(0.002)	(0.002)	(1.940)	(2.104)
Neighborhood FE	No	Yes	No	Yes
R^2	0.045	0.160	0.214	0.354
N	134,672	128,968	8,215	7,350
Panel I2: Chinese vs Russian				
Chinese	0.032***	0.032***	16.293***	15.188***
	(0.002)	(0.002)	(2.127)	(2.394)
Chinese × Post	−0.001	−0.003	−0.998	1.214
	(0.002)	(0.002)	(2.520)	(2.860)

(Continued)

Table IA3—*continued*

	(1) Cash	(2) Cash	(3) Cash/All	(4) Cash/All
Neighborhood FE	No	Yes	No	Yes
R^2	0.041	0.138	0.205	0.353
N	134,672	128,968	6,664	5,918
Panel J: Pennsylvania				
Panel J1: Chinese vs Indian				
Chinese	0.018***	0.019***	17.665***	16.878***
	(0.001)	(0.001)	(1.606)	(1.693)
Chinese × Post	−0.002	−0.002	−4.841**	−5.860***
	(0.002)	(0.002)	(1.930)	(2.042)
Neighborhood FE	No	Yes	No	Yes
R^2	0.019	0.103	0.153	0.360
N	147,660	144,562	8,760	7,967
Panel J2: Chinese vs Russian				
Chinese	0.021***	0.022***	16.036***	15.547***
	(0.001)	(0.001)	(1.898)	(2.115)
Chinese × Post	−0.003*	−0.003**	−7.219***	−6.091**
	(0.002)	(0.002)	(2.307)	(2.516)
Neighborhood FE	No	Yes	No	Yes
R^2	0.022	0.106	0.144	0.381
N	147,660	144,562	7,299	6,546

Table IA4

House Prices, Foreign Chinese Buyers, and Cash Transactions in California

This table replicates Table 5 but replaces the denominator in $CNratio$ from total transactions to total cash transactions and limits the sample to be in California. Sample period is from 2014 to 2021. Quarter fixed effects are controlled in all columns. Neighborhood fixed effects are at ZIP code level. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)
Chinese × Post	-0.003^{***}	-0.003^{***}
	(0.000)	(0.000)
Metro FE	Yes	No
Quarter×Metro FE	Yes	No
County FE	No	Yes
Quarter×County FE	No	Yes
Neighborhood FE	Yes	Yes
R^2	0.996	0.996
N	40,819	43,053

Table IA5
House Price Indices and Foreign Chinese Buyers in Neighborhoods by State

This table replicates Table 5 but limits the sample to each of the top 10 states with the highest numbers of overseas Chinese buyers: California, Texas, Florida, Washington, New York, Georgia, Nevada, New Jersey, North Carolina, and Pennsylvania. Sample period is from 2014 to 2021. Quarter fixed effects are controlled in all columns. Neighborhood fixed effects are at census tract level. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)
Panel A: California		
Chinese × Post	-0.011^{***}	-0.012^{***}
	(0.001)	(0.001)
R^2	0.996	0.996
N	40,819	43,053
Panel B: Texas		
Chinese × Post	-0.018^{***}	-0.012^{***}
	(0.002)	(0.001)
R^2	0.990	0.992
N	33,015	37,535
Panel C: Florida		
Chinese × Post	-0.015^{***}	-0.013^{***}
	(0.002)	(0.002)
R^2	0.988	0.989
N	27,337	28,660
Panel D: Washington		
Chinese × Post	-0.004^{***}	-0.001
	(0.001)	(0.001)
R^2	0.995	0.997
N	11,329	12,462
Panel E: New York		
Chinese × Post	-0.002^{***}	-0.002^{***}
	(0.000)	(0.000)
R^2	0.998	0.998
N	37,368	43,170
Panel F: Georgia		
Chinese × Post	0.004^{**}	0.009^{***}
	(0.002)	(0.002)

(Continued)

Table IA5—*continued*

	(1)	(2)
R^2	0.990	0.993
N	14,655	17,121
Panel G: Nevada		
Chinese × Post	-0.010^{***}	-0.010^{***}
	(0.001)	(0.001)
R^2	0.990	0.991
N	3,627	3,839
Panel H: New Jersey		
Chinese × Post	-0.015^{***}	-0.022^{***}
	(0.002)	(0.001)
R^2	0.990	0.993
N	16,352	16,342
Panel I: North Carolina		
Chinese × Post	-0.010^{***}	-0.004^{**}
	(0.002)	(0.002)
R^2	0.995	0.996
N	17,726	20,387
Panel J: Pennsylvania		
Chinese × Post	0.022^{***}	0.006^{***}
	(0.001)	(0.001)
R^2	0.994	0.996
N	26,108	27,847
Metro FE	Yes	No
Quarter×Metro FE	Yes	No
County FE	No	Yes
Quarter×County FE	No	Yes
Neighborhood FE	Yes	Yes

Table IA6
Price Elasticity of New Home Supply Before COVID

This table replicates Table 7 but limits the sample period from 2014 to 2019. Panel A of this table reports the results of regressions of log of the number of newly constructed houses in a year in a ZIP code on the percentage ratio of Chinese cash buyers over all buyers in 2013 and its interaction with the *Post* indicator for the period starting in 2017:

$$lnQ_{r,c,s,t} = \alpha_{r,c,s,t} + \beta CNratio_{r,c,s} + \gamma Post_t + \delta CNratio_{r,c,s} \times Post_t + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{r,c,s,t}.$$

Panel B of this table reports the results of regressions of log of the house price index at the end of a year in a ZIP code on the percentage ratio of Chinese cash buyers over all buyers in 2013 and its interaction with the *Post* indicator for the period starting in 2017:

$$lnHPI_{r,c,s,t} = \alpha_{r,c,s,t} + \beta CNratio_{r,c,s} + \gamma Post_t + \delta CNratio_{r,c,s} \times Post_t + \kappa_s + \eta_t + \zeta_c + \theta_{c\times t} + \lambda_r + \epsilon_{r,c,s,t}.$$

Coefficents for $CNratio$ and $Post$ indicator are partialled out due to ZIP code fixed effects and year fixed effects respectively. State fixed effects and year fixed effects are controlled in all columns. Neighborhood fixed effects are at ZIP code level. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)
Panel A: Number of New Home Constructed		
Chinese × Post	-0.030^{***}	-0.023^{***}
	(0.006)	(0.006)
R^2	0.894	0.914
Panel B: House Price Index		
Chinese × Post	-0.002^{***}	-0.004^{***}
	(0.001)	(0.001)
R^2	0.997	0.998
Metro FE	Yes	No
Year×Metro FE	Yes	No
County FE	No	Yes
Year×County FE	No	Yes
Neighborhood FE	Yes	Yes
N	967,22	109,434