Negative Capital Shock, Overseas Buyers, and Housing Market

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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, we 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, our 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. Furthermore, the elasticity of house supply implied by such a negative demand shock is higher than that found in existing literature, which primarily utilizes positive demand shocks to estimate the elasticity.

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

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1 Introduction

As is the case elsewhere, international capital is a double-edged sword in residential housing market. On one hand, it fuels local economic growth (Borensztein et al. (1998), Alfaro et al. (2004), and Alfaro et al. (2010)), boosts consumption (Bostic et al. (2009) and Mian et al. (2013)), and generates wealth effects through appreciating house prices (Li et al. (2020) and 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 (e.g., Li et al. (2020), Gorback and Keys (2021), Badarinza and Ramadorai (2018), and Cvijanović and Spaenjers (2021)) as well as examining the necessity of restrictions on such capital inflows to local housing markets (e.g., Favilukis and Van Nieuwerburgh (2021)). We 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, we 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.

We believe studying a negative capital shock from China has important implications, because China is the largest 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 China surge in purchases in the

US residential housing market (Li et al. (2020)) following the housing purchase restrictions in China in 2007. With the implementation of more stringent foreign exchange control policies in 2017, we expect this trend to reverse.

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, following Florida's lead. As we study the changes in the home-buying behavior of foreign Chinese and its impact on local real estate markets under China's capital controls on its own citizens, our study provides a reference for such (potential) cross-border capital control policies.

While foreign Chinese buyers currently constitute the largest group of foreign buyers in the US residential property market, comparing them solely with all other foreign buyers in the US is insufficient to fully understand the nuances of their behavior and impact. To ensure valid comparisons in our analysis, we have selected Indian and Russian purchasers as the primary placebo groups in this paper, since China, India, and Russia are all Asian countries with shared economic and cultural characteristics.

We obtained county deeds 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, we 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 well-established in academic literature (see, e.g., Fernández and Fogli (2009) and Liu (2016)), our algorithm may not capture all buyers of a specific ethnicity since we have taken a conservative approach in constructing our algorithm. As a result, the buyers identified through our methodology should be considered a lower bound for each of the three ethnic groups. Therefore, our analysis provides lower bounds for the effects of Chinese buyers compared to Indian and Russian buyers in the US single-family housing market as well.

Although we acknowledge that it is not a perfect measurement, as transaction records do not explicitly indicate whether a transaction is made by a foreign buyer and foreign buyers typically have limited access to the US mortgage markets, we 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. In this paper, we 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, we 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, we 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 0.051, 0.012, and 0.008, 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, such as California, Florida, Texas, Washington, Georgia, and New York. These states, popular among foreign Chinese purchasers, 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. In states that are popular destinations for foreign Chinese purchases, including, but not limited to, California, Texas, Florida, Washington, New York, New Jersey, and North Carolina, 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, we are able to estimate the elasticity of house 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 the factors that shift the supply curve. The house price elasticity of supply estimated in our paper is higher than that found in the existing literature, which focuses mainly 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 for them to either stop building new homes or simply hold their properties until a later date could be low.

Our 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 (see, Siebert and Seiler (2020) and Cvijanović and Spaenjers (2021)), leading to increased local house prices and the displacement of low-income buyers (e.g., Favilukis et al. (2012), Sa (2016), West and Botsch (2020), and 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. Our 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), we 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 et al. (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 (see, e.g., Mills et al. (2019), Allen et al. (2018), D'Lima and Schultz (2022), and Ganduri et al. (2023)), understanding the market dynamics during of the ebb of this capital tide is equally important. Our 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 et al. (2020) identify as a "China shock" in California. Contrary to the "China shock", our study demonstrates that the decline in foreign Chinese investment in local real estate markets can also have significant economic impacts.

Lastly, our 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 (e.g., Reher and Valkanov (2020) and 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 our 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 spillover 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

Our housing dataset comprises county deeds records and transaction records obtained from Infutor, encompassing all purchase records and relevant house characteristics sourced from county register of deeds and assessor offices in the United States spanning from 2014 to 2021. However, we exclude Vermont from our sample because most records in Vermont do not contain the transaction dates and therefore cannot be used in our analysis. In this study, we concentrate on single-family houses, which we 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. We 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 our 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, we 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] However, for analyzing whether a specific ethnic group pays more for houses than others, we focus solely on resale and new construction transactions. Refinance and various nominal transfers of ownership are disregarded as they do not represent "real" transactions that can provide reliable market house prices.

Due to inconsistencies in deeds records across different counties and the presence of missing or inaccurate information for certain key house characteristics, we have made certain assumptions during the data cleaning process to minimize the loss of observations due to missing data. Firstly, we 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, we 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

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

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. For instance, 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 us to cross-validate the information and correct any inaccuracies or missing inputs as needed. For example, we 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, we prioritize the more reliable measurement based on square feet or acres accordingly.

To mitigate the influence of outliers on our results, we conduct a thorough examination of extreme values for key house characteristics such as lot size, living space, number of baths and bedrooms, and house age. Observations with raw inputs that are likely to be input errors are removed from our analysis. For instance, we exclude observations where the house age exceeds 100 years, where the number of full baths exceeds 30, and where the living space is less than 5000 square feet but the number of full baths exceeds 10. Additionally, we winsorize and trim the values for purchase price at top and bottom 1%.

2.2 Ethnic Identification Algorithm

To quantify and analyze the impact of foreign purchases by different ethnic groups on the housing market, we rely on measures that allow us 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, we can examine how overseas Chinese buyers adjust their behavior in response to capital controls. Although our primary focus is on overseas Chinese buyers due to the negative capital shock resulting from China's imposition of foreign exchange quota management, it's essential to contextualize this impact through valid comparisons. India and Russia serve as suitable comparators to China, as they share cultural and economic similarities. Moreover, names from these countries often possess recognizable cultural traits, aiding in their identification alongside Chinese names.

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.

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

Secondly, we update the list of most commonly used surnames based on recent trends in each of these countries. For Chinese surnames, we consult annual statistics covering the years 2013 to 2020 and include any surname appearing in the top 100 most frequently used surnames during this period. India and Russia have a broader range of surnames compared to China, so we expand our list to include the top 1000 most common surnames in each country, as sourced from Forebears. Additionally, we search for surnames with Indian or Russian origins on Wikipedia and incorporate any new findings not included in the Forebears list. In the case of India, where the tradition of using the father's given name as a surname is prevalent in certain regions, we 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.

Our name ethnic algorithm enables us to differentiate mainland Chinese from individuals in Hong Kong, Macao, and Taiwan. For instance, passports issued in Mainland China follow specific spelling rules that do not allow for hyphens or middle names, and we incorporate these rules into our algorithm.

Additionally, we recognize that Chinese and Indians may share several surnames when transliterated into English. To address this, we manually verify these names and make any necessary corrections to ensure accurate identification.

We acknowledge that our algorithm may not capture all transactions made by individuals from each of these three ethnic groups. However, our conservative approach in constructing the ethnic identification algorithm ensures that the buyers identified using the algorithm represent a lower bound for each of the three ethnics. Furthermore, due to the higher concentration of Chinese surnames compared to Indian and Russian surnames, our methodology is more likely to cover most Chinese buyers but may capture a relatively lower proportion 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 due to the limitations of the name ethnic identification algorithm.

On average, our algorithm identified approximately 36,782 Chinese transactions, 18,899 Indian transactions, and 9,538 Russian transactions each year from 2014 to 2021 in the 49 states and Washington DC. Table 1 displays the number of all types of transactions and cash transactions identified using our 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.

2.3 House Price Index

We obtain ZIP code level house price index data from Zillow Research. Specifically, we 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, we use the data for March, June, September, and December as the quarterly indices, and the data for each December as the annual index in our analysis.

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.[2] 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

[2] 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 $\$10,000$.

$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. 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, we 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. We 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. Moreover, we hypothesize that this reduction in Chinese cash purchases may also have a spillover effect on the prices paid by Chinese cash buyers in the US residential market.

3 Models and Results

In this section, we 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 of capital from a major foreign country affects the transactions and prices of local real estate properties in the US.

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

Although not explicitly shown here, our 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 779, 735, 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 our sample. However, these transactions accounted for only approximately 18.7%, 7.0%, and 6.1% of the total number of cash transactions, and for about 2.8%, 1.2%, and 1.3% of all transactions in those respective counties. In contrast, over 70% of counties virtually have no foreign Chinese buyers, and over 60% of counties virtually have no Chinese buyers in 2016 in the US.

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. Furthermore, we 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 our 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.

3.1 Transaction Quantity

Our first step aims to illustrate the significant decrease in Chinese cash transactions following China's implementation of stricter foreign currency quota management. Figure 1 illustrates the 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.

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, we 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. We 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. We 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 our 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 0.039 and 0.042 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 is only about 0.051, 0.012, and 0.008, 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 et al. (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.

In addition, we conduct similar tests (but drop state fixed effects) for each state in the US. While the results are not presented here, our subsample tests indicate that the significant drop in Chinese cash transactions we 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 our 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"*.

Overall, Table 4 and the unreported 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, we investigate how the drop in purchases from overseas Chinese buyers since 2017 affect neighborhood house prices. We 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.

We 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 our sample period starts in 2014, our 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, we run the following model for each state:

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

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, we 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 we control for metropolitan $\times$ quarter or county $\times$ quarter fixed effects.

In our unreported subsample tests by state, the results 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. In states including, but not limited to, California, Texas, Florida, Washington, New York, New Jersey, Nevada, and North Carolina, the coefficients for the interaction term vary from -0.001 to -0.02, meaning a one percentage point increase in 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 at the ZIP code level. While the magnitude of the effects varies, the negative coefficients on the interaction of Chinese treatment intensity variable and $Post$ indicator for the majority of states underscore the significance of such international capital flows on local house prices.

In summary, Table 5 and our state-by-state subsample tests by state 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.

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, we further examine the implied house price elasticity of supply under our framework.

Similar to Equation 2, we run regressions using the logarithm of the number of house transactions and the number of new 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, we use quarterly data for the number of house transactions and annual data for the number of newly constructed houses. We 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 1.8% to 2% drop in quarterly house transactions at the ZIP code level post-2017, depending on whether we control for metropolitan-quarter or county-quarter fixed effects.

The δs in Equation 2 and 3 together give us the average house price elasticity of supply. They indicate that the average price elasticity of supply in the US housing markets is about 5 when controlling for metropolitan-quarter fixed effects, and about 3.6 when controlling for county-quarter fixed effects. Although our 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, we find that the price elasticity of house supply we estimated is larger than that reported in their study, and also larger than the estimates found in other literature, such as Saiz (2010) and Baum-Snow and Han (2024). 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.

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, we rerun Equation 2 using the corresponding annual data to make easier comparisons, and the results are reported in Panel B. Similar to short-term supply, the implied price elasticity of new home supply is large, indicating the new home supply is quite elastic. Although changes in demand from foreign Chinese buyers do not alter the factors that shift the supply curve, there is a concern that our 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, we limit our sample to the end of 2019 and rerun the regressions. While the tables are not presented, the results are very similar to the reported results in Table 7, demonstrating that our findings are robust and are not influenced by the pandemic.

At first glance, the high elasticity of house supply indicated in our 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, our 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, we focus on the segment of the house supply curve that is quite flat. Consistent with this flat house supply curve, our 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 we focus on a negative demand shock, our estimation of house 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 et al. (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 constract, home builders can immediately halt new construction. That is to say, the supply curve may respond differently to positive and negative demand shocks when we focus on the relatively flat part of the supply curve, suggesting asymmetry in house 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.

The asymmetric house supply elasticity for positive and negative demand shocks has important implications. One implication is in explaining why purchase bans on foreign capital may have limited effects on controlling house prices. Potential home sellers might simply hold their assets and wait for a more opportune window to sell. 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 (see, e.g., Mills et al. (2019), Allen et al. (2018), D'Lima and Schultz (2022), and Ganduri et al. (2023)); however, what is equally important to the market but not examined by the literature is what happens when the capital tide recedes. Our 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. We use China as a specific illustration to explore this phenomenon.

By analyzing single-family home transaction and deed records across the United States, we 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.

Our analysis also reveals a spillover 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.

We also estimated the elasticity of house supply using this exogenous negative demand shock. Our 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 house 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. Our 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., Albuquerque, B., and Anundsen, A. K. (2023). Changing Supply Elasticities and Regional Housing Booms. *Journal of Money, Credit and Banking*, 55(7):1749–1783. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jmcb.13009.

Aastveit, K. A. and Anundsen, A. K. (2022). Asymmetric Effects of Monetary Policy in Regional Housing Markets. *American Economic Journal: Macroeconomics*, 14(4):499–529.

Alfaro, L., Chanda, A., Kalemli-Ozcan, S., and Sayek, S. (2004). FDI and economic growth: the role of local financial markets. *Journal of International Economics*, 64(1):89–112.

Alfaro, L., Chanda, A., Kalemli-Ozcan, S., and Sayek, S. (2010). Does foreign direct investment promote growth? Exploring the role of financial markets on linkages. *Journal of development economics*, 91(2):242–256.

Allen, M. T., Rutherford, J., Rutherford, R., and Yavas, A. (2018). Impact of Investors in Distressed Housing Markets. *The journal of real estate finance and economics*, 56(4):622–652.

Badarinza, C. and Ramadorai, T. (2018). Home away from home? Foreign demand and London house prices. *Journal of Financial Economics*, 130(3):532–555.

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

Baum-Snow, N. and Han, L. (2024). The Microgeography of Housing Supply. *Journal of Political Economy*, 132(6):1793–2178.

Borensztein, E., Gregorio, J. D., and Lee, J.-W. (1998). How does foreign direct investment affect economic growth? *Journal of International Economics*, 45(1998):115–135.

Bostic, R., Gabriel, S., and Painter, G. (2009). Housing wealth, financial wealth, and consumption: New evidence from micro data. *Regional Science and Urban Economics*, 39(1):79–89.

Cohen, L., Gurun, U. G., and Malloy, C. (2017). Resident Networks and Corporate Connections: Evidence from World War II Internment Camps. *The Journal of finance (New York)*, 72(1):207–248.

Cvijanović, D. and Spaenjers, C. (2021). “We’ll Always Have Paris”: Out-of-Country Buyers in the Housing Market. *Management Science*, 67(7):4120–4138.

D’Lima, W. and Schultz, P. (2022). Buy-to-Rent Investors and the Market for Single Family Homes. *The journal of real estate finance and economics*, 64(1):116–152.

Favilukis, J., Kohn, D., Ludvigson, S. C., and Van Nieuwerburgh, S. (2012). International Capital Flows and House Prices: Theory and Evidence. Working Paper 17751, National Bureau of Economic Research.

Favilukis, J. and Van Nieuwerburgh, S. (2021). Out-of-Town Home Buyers and City Welfare. *The Journal of finance (New York)*, 76(5):2577–2638.

Fernández, R. and Fogli, A. (2009). Culture: An Empirical Investigation of Beliefs, Work, and Fertility. *American Economic Journal: Macroeconomics*, 1(1):146–77.

Ganduri, R., Xiao, S. C., and Xiao, S. W. (2023). Tracing the source of liquidity for distressed housing markets. *Real estate economics*, 51(2):408–440.

Glaeser, E. L. and Gyourko, J. (2005). Urban Decline and Durable Housing. *The Journal of political economy*, 113(2):345–375.

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

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

Kerr, W. (2008). The Ethnic Composition of US Inventors. Working Paper ID 1010142.

Li, G. (2021). Chinese Overseas Buyers in U.S. Housing Markets. Working Paper.

Li, Z., Shen, L. S., and Zhang, C. (2020). Capital Flows, Asset Prices, and the Real Economy: A ”China Shock” in the U.S. Real Estate Market. *Working Paper*.

Liu, X. (2016). Corruption culture and corporate misconduct. *Journal of financial economics*, 122(2):307–327.

Mian, A., Rao, K., and Sufi, A. (2013). Household Balance Sheets, Consumption, and the Economic Slump. *The Quarterly Journal of Economics*, 128(4):1687–1726.

Mills, J., Molloy, R., and Zarutskie, R. (2019). Large-Scale Buy-to-Rent Investors in the Single-Family Housing Market: The Emergence of a New Asset Class. *Real estate economics*, 47(2):399–430.

Pavlov, A. and Somerville, T. (2020). Immigration, Capital Flows and Housing Prices. *Real Estate Economics*, 48(3):915–949.

Reher, M. and Valkanov, R. (2020). The Mortgage-Cash Premium Puzzle. *Working Paper*.

Sa, F. (2016). The Effect of Foreign Investors on Local Housing Markets: Evidence from the UK. Technical Report 1639, Centre for Macroeconomics (CFM).

Saiz, A. (2010). The Geographic Determinants of Housing Supply *. *Quarterly Journal of Economics*, 125(3):1253–1296.

Siebert, R. and Seiler, M. J. (2020). Why Do Buyers Pay Different Prices for Comparable Products? Evidence from the Housing Market. Working Paper.

Stroebel, J. and Vavra, J. (2019). House Prices, Local Demand, and Retail Prices. *Journal of Political Economy*, 127(3):1391–1436.

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

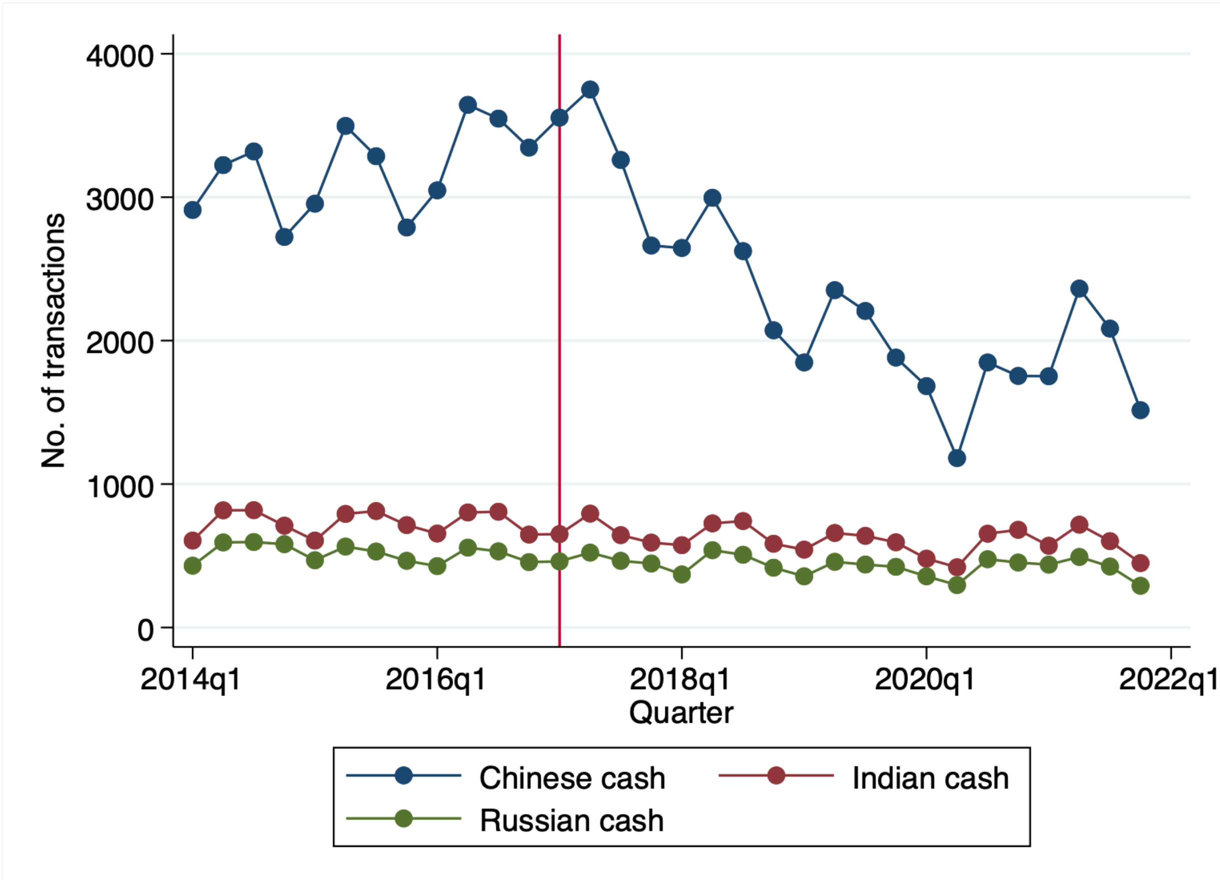

Figure 1. Number of Cash Transactions by Ethnicity in the US
This figure compares the quarterly total number of cash transactions by Chinese, Indians and Russians in the United States (49 States and Washington DC) from 2014 to 2021.

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 (including 49 states and DC) 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	3412911	914603	34 150	12 178	18 452	2951	9665	2201
2015	3573871	894132	35 533	12 528	18 893	2924	9746	2028
2016	3585923	860855	38 260	13 586	19 460	2912	9616	1972
2017	3635150	888691	42 714	13 229	19 043	2681	9373	1894
2018	3647471	901941	38 085	10 338	19 207	2626	9384	1833
2019	3705824	847881	34 097	8289	18 754	2435	9353	1677
2020	3636249	758140	30 530	6466	18 375	2234	9726	1582
2021	3185037	770455	40 887	7714	19 005	2339	9440	1646

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 (including 49 states and DC). 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)	276.38	226.48	499.59	420.61	426.77	282.31	373.32	284.10
	(235.50)	(252.88)	(420.21)	(426.69)	(334.49)	(293.61)	(310.35)	(304.59)
Living (sqft)	1974.29	1798.62	2290.97	2181.88	2491.72	2054.89	2141.77	1941.57
	(922.08)	(928.81)	(1039.54)	(1132.12)	(1164.78)	(1173.99)	(996.14)	(1020.02)
Lot (acres)	0.71	1.11	0.35	0.42	0.41	0.62	0.54	0.81
	(5.33)	(8.25)	(3.99)	(5.47)	(3.51)	(3.43)	(3.15)	(4.53)
Story	1.62	1.49	1.74	1.68	1.82	1.66	1.68	1.55
	(0.93)	(0.85)	(0.87)	(0.84)	(0.94)	(0.93)	(0.91)	(0.86)
House age	31.71	38.26	29.06	31.94	23.75	35.33	30.42	35.79
	(26.11)	(27.19)	(25.34)	(26.21)	(24.59)	(28.02)	(25.65)	(26.79)
Bedrooms	3.20	2.99	3.55	3.45	3.60	3.22	3.33	3.10
	(0.85)	(0.88)	(0.90)	(0.98)	(0.92)	(0.95)	(0.87)	(0.91)
Full baths	1.98	1.79	2.32	2.23	2.39	2.00	2.13	1.93
	(0.81)	(0.83)	(0.89)	(0.99)	(0.95)	(0.96)	(0.85)	(0.89)
Half baths	0.31	0.25	0.40	0.37	0.42	0.31	0.36	0.29
	(0.49)	(0.46)	(0.52)	(0.51)	(0.53)	(0.50)	(0.51)	(0.48)
Has pool	0.10	0.09	0.11	0.11	0.10	0.09	0.12	0.12
	(0.29)	(0.28)	(0.31)	(0.31)	(0.29)	(0.29)	(0.32)	(0.32)
Has fireplace	0.45	0.36	0.55	0.48	0.52	0.39	0.51	0.40
	(0.50)	(0.48)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.49)
Has garage	0.72	0.64	0.79	0.74	0.78	0.66	0.74	0.67
	(0.45)	(0.48)	(0.41)	(0.44)	(0.42)	(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 (including 49 states and DC). Sample period is from 2014 to 2021. *, **, and *** indicate statistical significance at 5%, 1%, and 0.1%.

	(1)		(2)		(3)	
	Pre-2017		Post-2017		Difference	
	mean	*sd*	*mean*	*sd*	*b*	*t*
Panel A: Chinese Cash						
Living (sqft)	2155.06	1117.48	2229.65	1156.21	74.59***	(9.84)
Lot (acres)	0.40	5.28	0.47	5.80	0.07	(1.91)
Story	1.66	0.83	1.70	0.86	0.04***	(7.61)
House age	30.49	25.62	34.55	27.05	4.06***	(22.82)
Bedrooms	3.44	0.96	3.47	1.02	0.03***	(4.45)
Full baths	2.22	0.96	2.26	1.03	0.04***	(5.50)
Half baths	0.37	0.51	0.39	0.52	0.02***	(6.78)
Has pool	0.11	0.31	0.12	0.32	0.01***	(5.47)
Has fireplace	0.48	0.50	0.48	0.50	−0.01	(−1.58)
Has garage	0.74	0.44	0.72	0.45	−0.02***	(−7.01)
Panel B: Indian Cash						
Living (sqft)	2034.31	1144.70	2096.05	1229.50	61.74***	(4.12)
Lot (acres)	0.61	3.18	0.64	3.89	0.03	(0.63)
Story	1.63	0.91	1.71	0.97	0.08***	(6.66)
House age	33.32	27.64	39.43	28.35	6.11***	(16.74)
Bedrooms	3.21	0.94	3.25	0.98	0.05***	(3.57)
Full baths	1.99	0.93	2.04	1.03	0.05***	(4.15)
Half baths	0.31	0.49	0.33	0.51	0.02***	(3.65)
Has pool	0.09	0.28	0.10	0.29	0.01*	(2.15)
Has fireplace	0.39	0.49	0.38	0.49	−0.01	(−1.28)
Has garage	0.67	0.47	0.65	0.48	−0.02*	(−2.57)
Panel C: Russian Cash						
Living (sqft)	1917.60	1006.97	1991.22	1044.86	73.62***	(4.88)
Lot (acres)	0.82	4.71	0.78	4.13	−0.04	(−0.57)
Story	1.53	0.84	1.59	0.90	0.06***	(4.84)
House age	34.20	26.70	39.14	26.67	4.95***	(12.18)
Bedrooms	3.09	0.91	3.12	0.91	0.03	(1.82)
Full baths	1.91	0.88	1.98	0.91	0.07***	(5.44)
Half baths	0.28	0.47	0.30	0.49	0.03***	(3.86)
Has pool	0.11	0.32	0.12	0.33	0.01	(1.65)
Has fireplace	0.39	0.49	0.41	0.49	0.02**	(2.93)
Has garage	0.67	0.47	0.66	0.47	−0.01	(−1.71)

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	0.042***	0.039***	20.212***	19.608***
	(0.000)	(0.000)	(0.255)	(0.276)
Chinese × Post	−0.012***	−0.013***	−7.607***	−7.439***
	(0.001)	(0.000)	(0.319)	(0.342)
Neighborhood FE	No	Yes	No	Yes
R^2	0.062	0.181	0.189	0.342
N	3634894	3500772	264850	238315
Panel B: Chinese vs Russian				
Chinese	0.046***	0.042***	17.063***	17.155***
	(0.000)	(0.000)	(0.315)	(0.358)
Chinese × Post	−0.012***	−0.014***	−7.126***	−7.331***
	(0.001)	(0.000)	(0.395)	(0.445)
Neighborhood FE	No	Yes	No	Yes
R^2	0.063	0.172	0.183	0.343
N	3634894	3500772	225787	201023

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)
Post × Chinese	-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	508131	575845

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)
Post × Chinese	-0.020^{***}	-0.018^{***}
	(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	0.938	0.952
N	508131	575845

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		
Post × Chinese	-0.033^{***}	-0.027^{***}
	(0.006)	(0.006)
R^2	0.865	0.898
Panel B: House Price Index		
Post × Chinese	-0.004^{***}	-0.005^{***}
	(0.001)	(0.001)
R^2	0.996	0.997
Metro FE	Yes	No
Quarter-Metro FE	Yes	No
County FE	No	Yes
Quarter-County FE	No	Yes
Neighborhood FE	Yes	Yes
N	114807	129632