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U.S. Housing as a Global Safe Asset: Evidence from China Shocks

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October 27, 2021

Abstract

This paper demonstrates that the measured stock of China's holding of U.S. assets could be much higher than indicated by the U.S. net international investment position data due to unrecorded historical Chinese inflows into an increasingly popular global safe haven asset: U.S. residential real estate. We first use aggregate capital flows data to show that the increase in unrecorded capital inflows in the U.S. balance of payment accounts over the past decade is mainly linked to inflows from China into U.S. housing markets. Then, using a unique web traffic dataset that provides a direct measure of Chinese demand for U.S. housing at the zip code level, we estimate via a difference-in-difference matching framework that house prices in major U.S. cities that are highly exposed to demand from China have on average grown 7 percentage points faster than similar neighborhoods with low exposure over the period 2010-2016. These average excess price growth gaps co-move closely with macro-level measures of U.S. capital inflows from China, and tend to widen following periods of economic stress in China, suggesting that Chinese households view U.S. housing as a safe haven asset.

Keywords: China, housing and real estate, capital flows, safe assets
JEL classification: F3, F6, R3

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1 Introduction

This paper uses a combination of macro and micro datasets to examine the impact of international capital flows on one of the least understood global safe haven assets: U.S. residential real estate. Flows of foreign capital into the U.S. housing market are not measured in the U.S. balance of payments data, but rather relegated to the inconspicuous "statistical discrepancy" line in official statistics.[1] Historically, the unmeasured net capital inflows subsumed into the statistical discrepancy have tended to rise during times of global financial stress, such as during the Asian Financial Crisis and the Global Financial Crisis (Flatness et al., 2009). However, in the past ten years unmeasured capital inflows have particularly surged during periods of economic distress in China, for example rising to 1.5 percent of U.S. GDP in 2015, a period when the scale of capital outflows from China dwarfed that of other countries. As we will show, these unmeasured capital inflows are most likely foreign purchases of U.S. housing.

The unknown scale of capital inflows into the residential real estate market in the U.S. and indeed most advanced economies has posed significant challenges not only for researchers but also for policymakers. An increasing number of national and local authorities in countries such as Canada, New Zealand, Australia, and Hong Kong have imposed restrictions on foreign buyers, basing their policy action on anecdotal reports of substantial purchases by foreign Chinese buyers. Some countries, such as Canada, have left it to individual municipal governments to adopt policies vis-à-vis foreign buyers as they see fit. Other countries, such as New Zealand, have implemented policies at the national level.

This paper tackles these measurement problems by first closely examining relevant macroeconomic data from China and the U.S. and second by using a novel micro-level dataset that allows us to directly measure cross-sectional variation in Chinese demand for U.S. residential real estate. In particular, we highlight the unusually close comovement between the unmeasured capital inflows captured by flows in the U.S. statistical discrepancy and inflows of money and deposits from China recorded by the U.S. Treasury International Capital (TIC) System. Then we use a unique

[1] While the most recent IMF Balance of Payments Manual (BPM6) specifies that "real estate investment, including investment properties and vacation homes" should be included in foreign direct investment (FDI), the U.S. and indeed most countries do not measure such flows. As a result, these flows are captured only in the residual line of the balance of payments. Some countries, notably China, refer to this line in the balance of payments as "errors and omissions." For this reason, we will use the term "statistical discrepancy" when referring to U.S. official statistics and "errors and omissions" when referring to Chinese data.

micro dataset to measure variation in Chinese demand for residential real estate across U.S. cities and estimate the causal impact of Chinese households' purchases of housing in cities all over the United States. Our micro data come from a rich web traffic dataset obtained from a popular Chinese website that specializes in listing foreign residential properties, broadly similar to Zillow but tailored for Chinese users. The dataset provides us with counts of Chinese users' views of U.S. properties in over 9,000 individual U.S. ZIP codes, thus giving us a direct measure of variation in Chinese residents' demand for local U.S. residential housing across the country. We then adopt a difference-in-difference matching framework to compare house price growth in areas heavily exposed to Chinese foreign buyers with price changes in areas that have low exposure to Chinese capital inflows, but which are otherwise similar. With this empirical framework, we disentangle the impact of the foreign demand shock from that of national and local factors, such as changes in mortgage rates or local economic activity, as well as unobserved local factors.

We find evidence of an impact of foreign capital inflows on the evolution of house prices in major U.S. cities. The magnitude of the premium in price growth in China-exposed over non-exposed areas averages about 2 percent in the two years following each of the two episodes of China shocks in the last decade. Then, using local projections, we find that Chinese capital inflows to the United States explain the majority of the widening in price growth differentials after Chinese stress episodes. Overall, the evidence we present is consistent with U.S. residential real estate serving as a safe haven asset for foreign Chinese households.

We conduct various checks to confirm that the patterns we uncover reflect the effect of capital inflows from China on the U.S. housing market rather than variation in local, national, or global economic conditions. We perform a placebo matching exercise in which we identify as the treatment group areas with high house price growth and show that the price gap between these hot markets and matched controls evolves completely differently than the gap for the areas we identified as China-exposed. This provides further confirmation that the treatment effect we uncover is not merely a result of Chinese households buying into hot markets. When relating the price growth gap we uncover to macro-level variables, we show that the gap is not explained by the state of the U.S. business cycle or the level of mortgage rates. We also verify that the price growth gap is unrelated to deposit inflows from countries other than China. Thus the data are not consistent with alternative stories relating the price growth gap to local, national, or global financial conditions.

Finally, informed by the conclusions drawn from both the macro and micro data, we estimate that the value of Chinese holding of U.S. residential housing stock ranges from \$170 to \$344 billion. Because these holdings are not recorded in the U.S. balance of payment accounts, we conclude that the measured net U.S. liability position with China could be understated by that much.

This paper contributes to three areas of literature. First, we add to the literature on how international capital flows affect housing prices by offering a fresh interpretation of existing macro data and a novel measure of foreign demand on U.S. housing at the national level. Recent work has documented that real estate purchases by foreign residents affect house prices in individual cities in the U.S. (Li et al., 2019), the United Kingdom (Badarinza and Ramadorai, 2018), and Germany (Bednarek et al., 2019). Due to a lack of data on foreign ownership of housing, these studies have proxied for foreign demand through indirect inferences. For example, Li et al. (2019) proxy for Chinese purchases of residential real estate in three cities in California by using the share of ethnic Chinese residents. Badarinza and Ramadorai (2018) also derives the foreign demand shock by linking the ethnicity of neighborhoods in London to related-country shocks. Our paper differs from both studies, not only in that that our analysis is national in scope, but also in our measure of foreign demand, page views data from a popular real estate listing site catered to users in China, which gives a more direct measure of demand from foreign buyers physically located in China. In addition, we control for other factors affecting prices by matching exposed and unexposed U.S. ZIP codes on relevant observable characteristics.

Other work has used VAR analysis to show that capital inflows put upward pressure on housing prices by loosening financial conditions in the recipient economy (Sa et al., 2014; Cesa-Bianchi et al., 2015), or employed regression analysis proxying foreign inflows with the recipient country's current account (Aizenman and Jinjarak, 2014); we provide evidence that flows going directly to the purchase of residential real estate also contribute to price increases.

Second, we contribute to the literature on out-of-town buyers. Previous work has shown that out of town buyers have significantly increased housing prices in specific U.S. cities (Chinco and Mayer, 2016; Favilukis and Van Nieuwerburgh, 2018). However, previous research has not separately identified the effect of foreign buyers on prices.

Third and finally, we add to the literature on the measurement of external assets and liabilities of countries, in particular the bilateral investment position between the United States and China.

Coppola et al. (2021) finds that U.S. national accounts understate the U.S. creditor position vis-à-vis China by $600 billion once U.S. holdings of equity issuances in offshore tax havens by subsidiaries of Chinese firms are reclassified as issuances by China. Our study finds that the U.S. balance of payments also understates U.S. liabilities to China due to unrecorded Chinese holdings of U.S. residential real estate. Taking those missing liabilities into account would offset the understatement in the *net* creditor position with China as found in Coppola et al. (2021) by a third to a half.

Indeed, Lane and Milesi-Ferretti (2007) has found that the under-reporting of U.S. assets held by foreign countries is responsible for half of the global balance of payments statistical discrepancy. This phenomenon occurs because unmeasured capital inflows to the United States tend to rise during times of global stress events (Flatness et al., 2009), consistent with U.S. assets being perceived by foreigners as a global safe haven. Curcuru et al. (2009) had attempted to estimate the historical stock of foreign holdings of U.S. real estate in 2007 and found that the inclusion of residential real estate would increase the measured net U.S. international investment liability position by $565 billion; using a similar method and source as that study, we find that the gross value of foreign holdings of U.S. real estate has increased significantly to $1.95 trillion in 2018, or 6% of U.S. housing stock. Our study highlights that U.S. residential real estate has become an increasingly popular global safe asset class in the decade since these studies were conducted.

This paper proceeds as follows. In the next section, we carefully examine data on capital flows between China and the U.S. and find patterns consistent with purchases of U.S. residential real estate by residents in China. In Section 3, we describe the data we use to identify cross-sectional variation in demand for U.S. housing from China and outline our matching methodology, then present our micro-level results. In Section 4, we assess how our micro-level estimates relate to macro-level measures of capital inflows. Section 5 concludes.

2 Motivating Facts

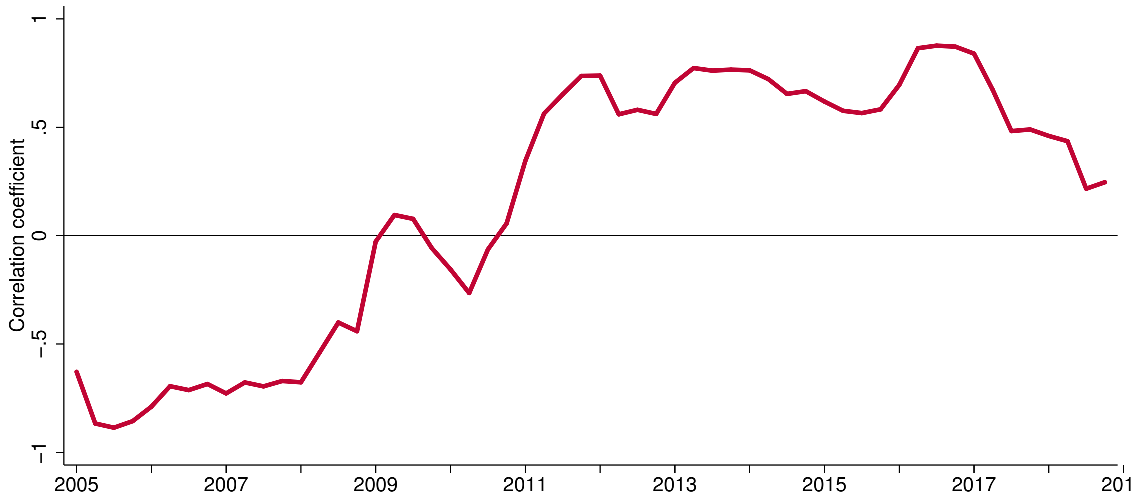
A variety of circumstantial evidence points to substantial capital flows originating in China to the U.S. residential real estate market, particularly during episodes of deteriorating macroeconomic conditions in China over the past decade. In this section, we describe this evidence in detail.

A commonly referenced source for data on foreign purchases of residential U.S. real estate is the U.S. National Association of Realtors (NAR), which publishes an annual estimate of foreign purchases of U.S. residential real estate based on a voluntary survey of realtors[2]. The NAR estimates that purchases by Chinese nationals increased from $2 billion in 2009 (5 percent of all foreign purchases) to $30 billion in 2018 (25 percent). A drawback to this data is that the voluntary survey typically has a low response rate (3 percent in 2016), and the survey does not guarantee that respondents use a uniform definition of what constitutes a foreign buyer or a uniform methodology for assessing what country he or she is from (e.g. country of residence versus nationality). Thus, while the NAR data are consistent with media coverage in indicating a substantial increase in purchases of residential real estate by Chinese buyers, they are at best an imprecise measure—albeit the only available measure, hence their popular use.

Aggregate capital flows data from balance of payments (BOP) accounts offer additional clues to the size of foreign purchases of U.S. residential real estate. While the most recent IMF Balance of Payments Manual (BPM6) specifies that foreign purchases of residential real estate should be included in foreign direct investment, the U.S. and indeed many countries do not measure such flows. As a result, these flows are captured only in the residual statistical discrepancy line of the balance of payments, or as the difference between the U.S. measured current account deficit and the measured financial inflows from abroad that finance that deficit. When the measured current account deficit exceeds the recorded net financial inflows, a positive statistical discrepancy arises. In the U.S. case, the statistical discrepancy primarily reflect two missing assets: financial derivatives, and the object of interest for our study—foreign purchases of U.S. residential real estate assets. Since 2008, the U.S. BOP statistical discrepancy experienced several episodes of turning positive, meaning that some U.S. capital inflows are not being captured in official statistics. In particular, since 2010 we note a striking increase in the comovement of private capital outflows from China and missing net capital inflows to the United States as captured by the statistical discrepancy line in the U.S. BOP. Figure 1 shows that the 12-quarter rolling correlation between the two variables went from being zero or negative to above 0.8 and remained elevated from 2012 to 2017. We next explore bilateral capital flows data between the U.S. and China at a more granular level.

[2]Copyright ©2021 "International Transactions in U.S. Residential Real Estate" *NATIONAL ASSOCIATION OF REALTORS®*. All rights reserved. Reprinted with permission. July 26, 2021, https://www.nar.realtor/research-and-statistics/research-reports/international-transactions-in-u-s-residential-real-estate.

Figure 1: Rolling Correlation: Net private capital outflows from China and the U.S. statistical discrepancy



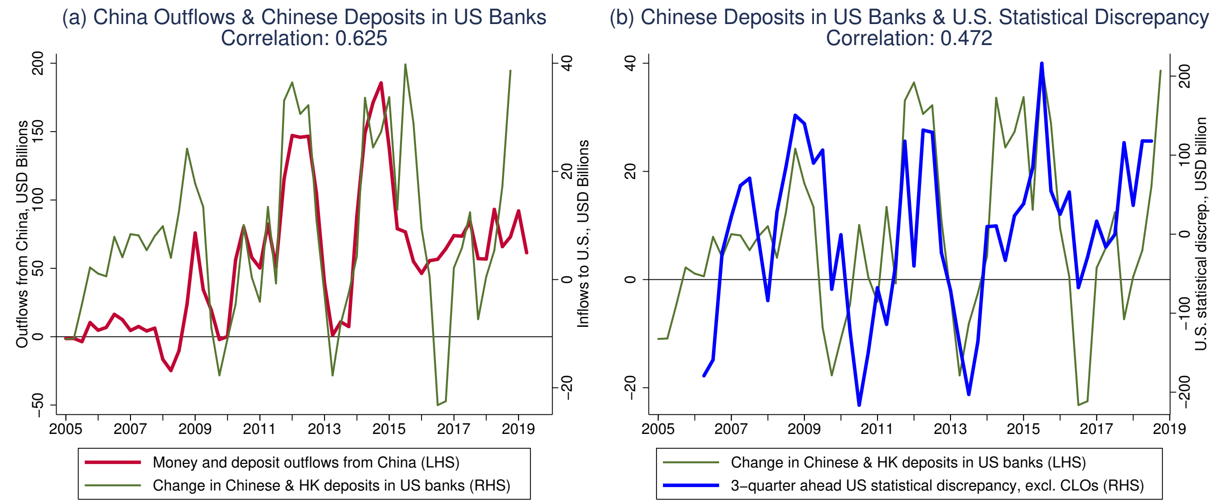
Source: Haver, authors' calculations. Graph plots correlation between 4−quarters rolling sum of net private outflows from China and US statistical discrepancy.

Large cross-border transactions, particularly for real estate purchases, oftentimes involve transactions between a foreign bank and a U.S. bank. So naturally, one might ask: how do recorded banking outflows from China comove with U.S. data on flows into U.S. banks from China? Panel (a) of Figure 2 plots gross outflows via money and deposits as reported in Chinese balance of payment statistics, along with recorded flows into deposits at U.S. financial institutions from China and Hong Kong, obtained from the U.S. Treasury International Capital (TIC) System.[3] We include flows from Hong Kong because of the widely documented practice of Chinese households using banks in Hong Kong as a conduit when moving funds abroad.

Panel (a) of Figure 2 shows a striking degree of comovement between total Chinese deposit outflows and the pattern of Chinese deposit inflows to the United States. Most notably, total bank outflows from China and bilateral bank inflows to the United States from China both spiked during the two recent periods of deteriorating economic conditions in the Chinese economy, first in 2011-2013 and again in 2014-2016. This comovement suggests that residents in China shifting money abroad place a substantial share into the U.S. banking system. At the peak of the first episode, in the fourth quarter of 2011, inflows to the United States accounted for 29 percent of total Chinese money and deposit outflows. And at the height of the second episode, when China

[3]Like many countries, China does not publish bilateral capital flows data. But the U.S. does, via the TIC System.

Figure 2: Outflows from China and U.S. inflows



Source: Haver, TIC System, and authors' calculations. Series are 4−quarter sums.

unexpectedly devalued its currency in the third quarter of 2015, flows from China and Hong Kong into U.S. deposits accounted for 48 percent of total Chinese money and deposit outflows.

To verify that the comovement observed in panel (a) of Figure 2 is not simply a reflection of a high degree of banking integration between the U.S. and China, we examined the correlation between foreign banking outflows from other countries and bilateral banking inflows to the U.S. from those same countries. The results of this exercise, which can be found in the Appendix (Figure A2-1 and also Table A21) confirm that the comovement we observe for Chinese flows is not the norm. Rather, from 2010 onward, we observe an unusually close relationship between bank flows out of China to the rest of the world and bank flows from China into the U.S.

We next examine the relationship between banking inflows to the U.S. from China and the U.S. statistical discrepancy, and find further evidence indicating that inflows from China are being used to purchase residential real estate in the U.S. As discussed previously, foreign purchases of residential real estate are one factor known to contribute to the statistical discrepancy. Another factor known to have systematically contributed to the U.S. statistical discrepancy over the past fifteen years is the purchase of U.S. loans by offshore entities set up to issue collateralized loan obligations (CLOs).[4] Using methodology detailed in Liu and Schmidt-Eisenlohr (2019), we construct estimates of the contribution of CLOs to the statistical discrepancy and subtract them out. The resulting adjusted

[4]For more details on this see BEA (2019), Guse et al. (2019), and Liu and Schmidt-Eisenlohr (2019).

series is shown by the blue line in panel (b) of Figure 2, and makes clear that CLOs were not the major driver of the large positive values of the statistical discrepancy observed in recent years. The size of the statistical discrepancy remaining after stripping out the effects of offshore issuance of CLOs suggests that the NAR estimates for the size of foreign purchases of U.S. residential real estate are likely on the low side.[5]

In normal times, the U.S. statistical discrepancy is small in size and has an average value of zero.[6] But the discrepancy has historically registered sizeable positive values during bouts of international financial turmoil such as the Asian Financial Crisis and (as seen in panel (b) of Figure 2) the Global Financial Crisis, due to unrecorded safe haven flows into the United States (Flatness et al., 2009). It is therefore notable that not only do banking inflows from China (the green line in Figure 2) peak during the 2011-13 and 2014-16 periods of heightened concern about a hard landing in China, but the U.S. statistical discrepancy became large and positive as well, despite those not being periods of *global* financial stress.

Panel (b) of Figure 2 shows inflows from China to the U.S. banking system along with the three-quarter-ahead value of the U.S. statistical discrepancy. Figure 2 makes clear that the U.S. statistical discrepancy peaked three quarters after bank inflows from China and Hong Kong during the two episodes of economic distress in China during the period we are studying. Conversely, the statistical discrepancy dropped to zero three quarters after banking inflows from China and Hong Kong dropped to their lowest level ever, in the third quarter of 2016. In Appendix Figure A2-2, we show that the correlation between the two series demonstrate a strong positive value starting at a lag of two quarters, peaking at a lag of three quarters.

What is the significance of the three quarter lag in the strong relationship between banking inflows from China and the U.S. statistical discrepancy? In fact, it is further suggestive of substantial inflows of Chinese capital to the U.S. residential real estate market. This is because bank

[5]The statistical discrepancy measures residual net capital inflows, not gross flows, so it cannot be directly interpreted as foreign purchases of U.S. real estate. However, Curcuru et al. (2009) estimates that U.S. has consistently experienced net capital inflows in residential real estate over the period 1989-2007, with inflows in this asset class much larger and rising much more rapidly than outflows. As a result, the variation in net real estate flows is almost entirely driven by changes in the gross real estate inflows. As of 2007, U.S. liabilities in residential real estate was $798 billion, compared with the $198 billion in U.S. claims on residential real estate abroad. If the remainder net statistical discrepancy after exclusion of CLOs does purely reflect net residential real estate flows, then the size of gross inflows, or gross foreign purchases of U.S. residential real estate purchases, would be larger than the net statistical discrepancy ex-CLOs shown in panel (b) of Figure 2.

[6]Although these flows do imply a large net position, as demonstrated by Curcuru et al. (2009)

transactions involving foreigners are measured in the U.S. balance of payments while real estate transactions are not. Consider an example in which a resident based in China moves money into a U.S. bank to purchase a house in the United States: When the Chinese resident deposits money in a U.S. bank, the bank reports an increase in its liabilities to China, which shows up as capital inflow from China. Six to nine months later, when the same foreign resident takes the money out to purchase a house, the bank reports a drop in its liabilities to China, generating a capital outflow to China in official statistics. The earlier capital inflow from China and subsequent outflow to China exactly nets out to zero, a neutral impact on the U.S. net investment position vis-à-vis China. Even though the foreigner has purchased a claim on a U.S. asset (the house), which is technically an inflow of direct investment from abroad, in practice it is not recorded in the balance of payments. This unrecorded FDI inflow adds to the U.S. statistical discrepancy, pushing it upwards. The three quarter lag in the relationship is consistent with foreign residents depositing funds in U.S. banks and then taking between six and nine months to find a house to buy and settle the resulting real estate transaction, a very plausible time frame. A larger implication of this idiosyncrasy in the U.S. balance of payments is that over time, the missing real estate inflows would lead to an understatement of the gross U.S. liabilities to China in the U.S. net international investment position accounts.

To more formally establish the connection between U.S. missing inflows and Chinese capital outflows, we regress the four quarter moving average of U.S. statistical discrepancy and three China-specific variables that proxy for shocks: Chinese FX reserve sales, net Chinese money and deposits outflows, and changes in the Chinese macro conditions, measured by the coincident macro climate index published by the Chinese National Bureau of Statistics (NBS). Taking into account the lagged relationship evident in Figures 1 and 2, we lag these explanatory variables by three quarters.

Because Figure 1 indicates that the relationship between Chinese flows and U.S. inflows changed dramatically in 2010, in the regressions we allow the coefficient on the Chinese variables to vary over time. Specifically, we create dummy variables for pre- and post- 2010Q2 periods and interact them with each China variable. Additionally, in the post-2010Q2 period, we allow the coefficient on the China variables to vary depending on whether it represents a positive or negative signal regarding the outlook for the Chinese economy. Net foreign exchange reserve sales, for example, would be a negative signal, indicating that the authorities are intervening against currency depreciation pressure emanating from private market participants. Conversely, net foreign exchange reserve purchases would suggest intervention to dampen appreciation due to net capital inflows to China. Finally, we include the year-on-year log change in the VIX to control for global financial conditions more generally.[7]

Table 1: Relationship Between U.S. Statistical Discrepancy and Economic Conditions in China

	US_stat_discrep		
	(1)	(2)	(3)
China FX Rsv sales x post-2010Q2(-)	0.264		
	(0.134)		
China FX Rsv sales x post-2010Q2(+)	-0.212**		
	(0.0725)		
China FX Rsv sales x pre-2010Q2	-0.0524		
	(0.0851)		
China deps outflows x post-2010Q2(-)		0.554**	
		(0.205)	
China deps outflows x post-2010Q2(+)		-2.474*	
		(0.961)	
China deps outflows x pre-2010Q2		0.358	
		(0.808)	
China macro chg x post-2010Q2(-)			6.852**
			(2.006)
China macro chg x post-2010Q2(+)			-4.143*
			(1.592)
China macro chg x pre-2010Q2			1.818
			(1.302)
dlnVIX	-8.020	-0.165	-5.246
	(8.128)	(9.806)	(7.733)
Observations	66	66	65
R^2	0.274	0.222	0.288

Standard errors in parentheses
Note: Positive coefficients correspond to net positive inflows in U.S. statistical discrepancy. All flows variables are four-quarter rolling sums. Macroeconomic conditions index is measured as the year-on-year percent change. VIX is measured as the year-on-year change in the log. All Chinese variables are lagged three quarters.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results, shown in Table 1, further confirm that negative (positive) shocks from China are associated with an increase (decrease) in U.S. statistical discrepancy net inflows since 2010Q2, with a three quarter lag. The pre-2010 China shocks are not important in explaining the safe haven flows, as none of these Chinese variables are significant when interacted with the pre-2010Q2

[7]The VIX measures implied volatility on options to buy the S&P500 U.S. equity index and is widely viewed as an indicator of global risk sentiment.

dummy. The VIX, our measure of global financial conditions, is insignificant across all specifications, suggesting that unrecorded capital inflows to the U.S. are better explained by Chinese factors than by global financial conditions more generally. Strikingly, the regressions using Chinese capital outflows variables have substantial explanatory power: the R-square is 0.42 for the net foreign reserves sales regressions, and 0.28 for the regressions with Chinese money and deposit outflows.

A back of the envelope calculation based on these results suggests that each $1 billion in net reserves sales by the Chinese authorities since 2010Q2 is associated with a $0.3 billion increase in unrecorded capital inflows to the United States; for each $1 billion in net money and deposit outflows from China, there is a $0.7 billion increase.

In this section, we have presented a variety of indirect evidence that since 2010, Chinese residents have shifted money into the United States in order to purchase residential real estate. We have shown that capital outflows from China have made their way into the U.S. banking system and also—with a lag—contributed to the large and positive unrecorded inflows seen over the period. The time structure of the relationships we have uncovered is consistent with capital inflows being used to purchase real estate. In the next section, we lay out empirical methodology for rigorously testing the impact of these flows on the U.S. residential real estate market at the micro level.

3 The Effect of Chinese Demand on U.S. House Prices

Our goal is to estimate the impact of Chinese inflows on the house price growth in the U.S. residential real estate market. The identification challenge is to be able to disentangle the impact of a foreign demand shock from other factors affecting house prices, such as U.S. domestic economic conditions like mortgage rates, as well as unobserved local factors. To overcome these challenges, we adopt a difference-in-difference matching framework. The general strategy is to compare house price growth in areas heavily exposed to foreign Chinese buyers to that in geographically proximate areas that have low exposure to Chinese demand, but which are otherwise similar across other attributes that matter for house price growth. In the language of the matching literature, our outcome variable is house price growth, the areas exposed to Chinese capital inflows are the treatment group, and areas not of interest to Chinese buyers make up the control group.

Three assumptions are central to identification in the matching methodology we adopt: the conditional independence assumption, the overlap assumption, and the independent and identically distributed assumption (Caliendo and Kopeinig, 2008). By using house price *growth* as the outcome variable, we difference out the time-invariant unobservable factors that affect the *level* of house prices of the neighborhoods we study. And by both conditioning the matches on observables that explain Chinese demand and restricting the geographic proximity of the control areas, we minimize selection bias, including bias generated by time-variant unobserved common local factors, which could jointly affect the treatment and outcome variables. The resulting difference in the house price growth between the treated and the matched control neighborhoods, we argue, produces an unbiased estimate of the effect of Chinese demand on local house prices in the U.S.

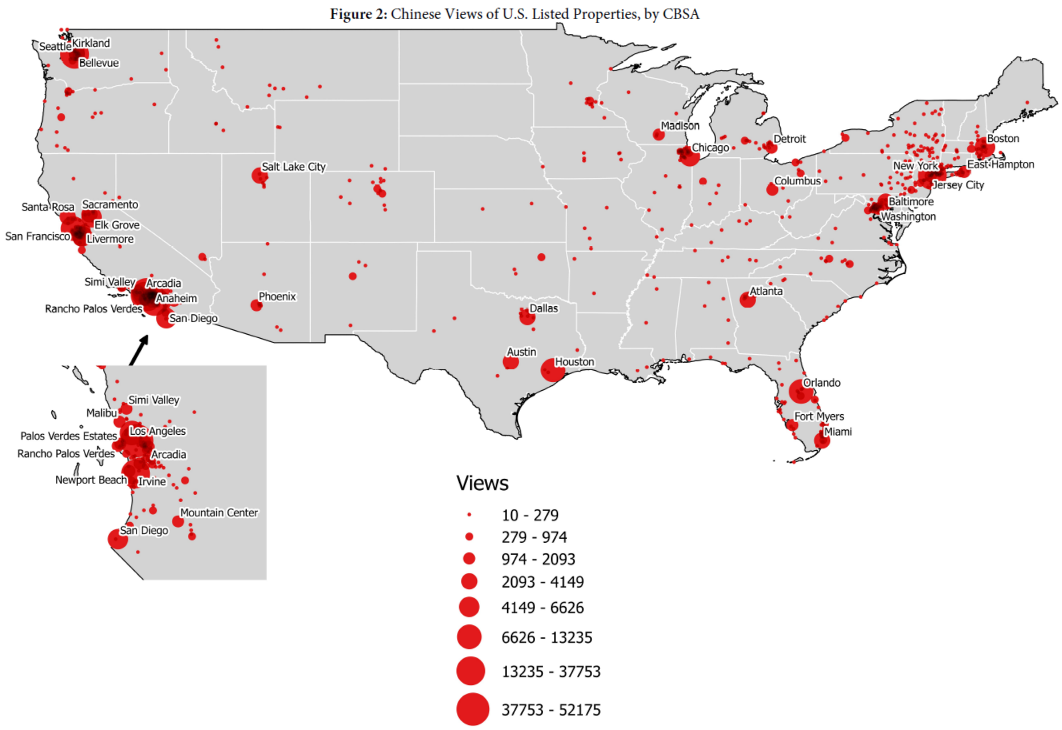
This section first describes in detail the dataset we use to measure exposure to Chinese demand. After outlining our matching design, we compute the gap in house price growth between the treated and control ZIP codes.

3.1 Data

To measure the exposure of an area's residential real estate market to Chinese capital inflows, we make use of a unique dataset that allows us to directly measure Chinese demand for residential real estate at the micro level. We obtained web traffic data from a real estate listing website called Juwai, which is based in China and caters to individual residents in China who are looking to purchase residential property abroad (the name of the company translates to "living abroad"). The Juwai dataset provides us with the number of views of properties in each U.S. ZIP code, each month, from each Chinese city. In other words, Juwai provides us with data at the city-pair month level. We have three months of property views data from November 2016 to January 2017. Over these three months, there were 670,000 total views originating from China of U.S. real estate properties across more than 7000 ZIP codes, or 917 core-based statistical areas (CBSAs).[8] The geographic dispersion of these views can be seen in Figure 3, with 70 percent of the views concentrated in just 20 U.S. cities, of which about a third are in California and almost 20 percent in the Greater Los Angeles area. The top 20 U.S. cities in terms of real estate property views from China are listed in Appendix Table A31 .

[8]A CBSA is defined by the U.S. Office of Management and Budget as a geographic area that consists of one or more counties containing an urban center of at least 10,000 people and adjacent countries that are socioeconomically tied to the urban center via commuting. In the rest of the paper, we will use the terms CBSA and city interchangeably.

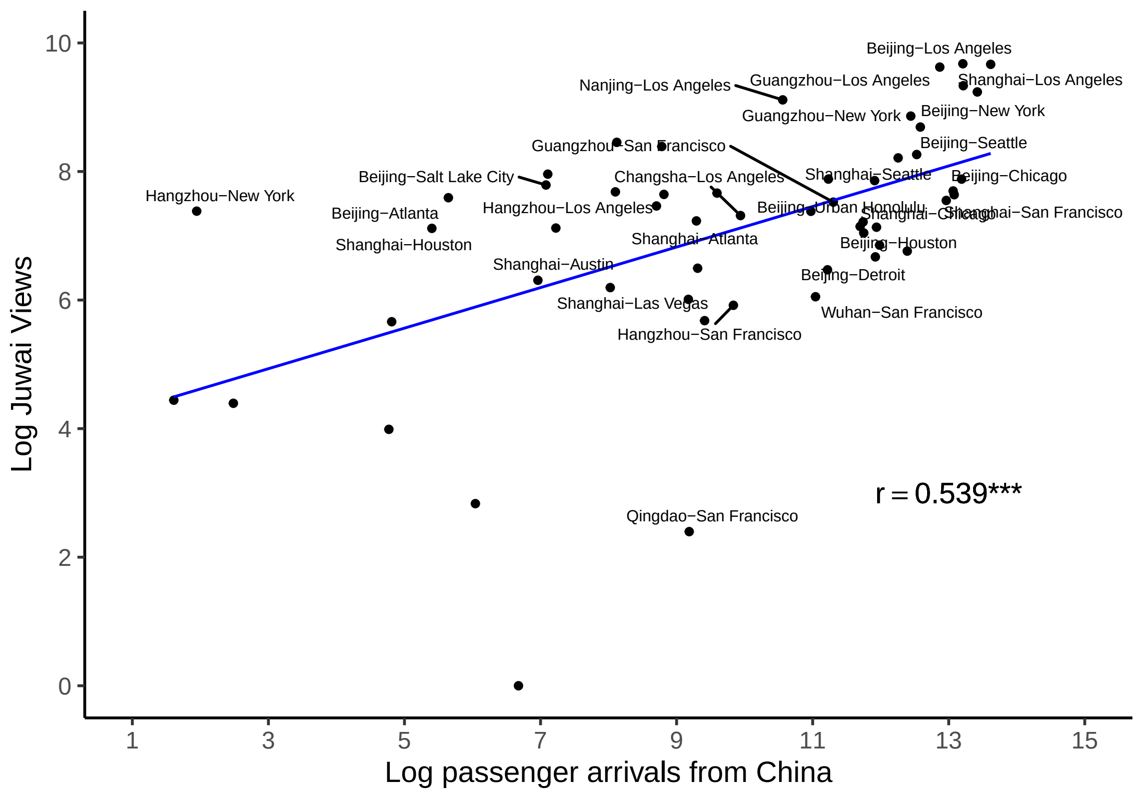
Figure 3: Web Traffic Hits from China of U.S. Listed Properties, by CBSA



To our knowledge, no other researcher has compiled a comparable dataset which *directly* measures Chinese demand at the local level for the entire United States. Nonetheless, we validate our data by checking the relationship between Juwai property views and two variables that, ex ante, we expect to correlate with Chinese purchases of residential real estate: airport passenger arrivals from China and the share of real estate transactions done in cash. While it is certainly possible to purchase a property from abroad without ever visiting it in person, discussions with representatives of Juwai indicated that potential buyers often make one visit to the city in which their property of interest is located and make a purchase within six months. In addition to providing information about an overseas real estate property on their website, Juwai also offers consulting services for the potential buyer and helps refer the potential buyer to a real estate brokerage firm abroad. We validate the Juwai data by pairing the passenger arrival data from a Chinese city to a U.S. city. Figure 4 shows that the city-pair arrival data has a 0.54 correlation with the Chinese city-U.S. city pair Juwai data.

To further confirm that the Juwai views data do meaningfully capture Chinese demand for residential real estate in individual cities and ZIP codes, we also check the relationship between

Figure 4: Juwai views vs. airline passenger arrivals



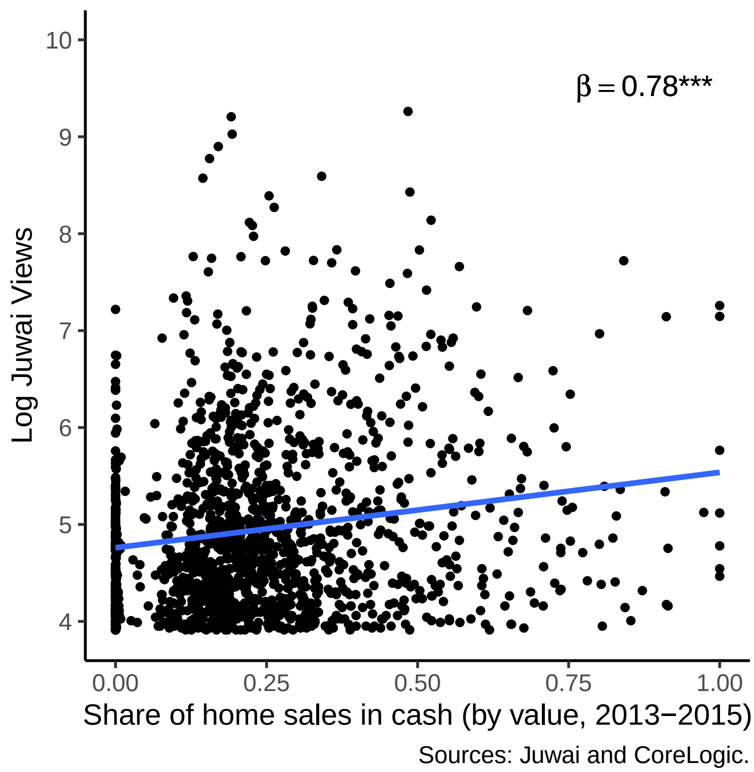
Source: Juwai, Centers for Medicare & Medicaid Services/Jean Roth, U.S. Department of Transportation, and U.S. Federal Communications Commission.

number of Juwai views in each ZIP code and the share of residential real estate transactions done in cash for the same ZIP code. Given that foreign buyers often prefer the more expedient option of settling real estate transactions with cash, we would expect that areas where Chinese residents purchase more properties would also have a higher share of sales in cash. And indeed, the correlation between views and the share (in value terms) of purchases done in cash is 0.157 (statistically significant at the one percent level). Figure 5 plots the significant and positive relationship between views and the cash purchases share. In Appendix Figure A3-1, we show this relationship holds even more strongly for major U.S. cities, including Seattle (correlation 0.34), Washington DC (0.34), Los Angeles (correlation 0.32), and New York (0.24).

3.2 Matching Design and the Drivers of Chinese Demand

A necessary condition for unbiased estimates of matching is that the potential outcome variable be conditionally mean independent of the treatment. Put differently, unbiasedness requires that

Figure 5: Juwai views vs. cash sales share



we control for factors that affect both house price growth and foreign buyer demand. The most likely confounding factor in this context is past price growth. Given that many Chinese buyers are purchasing houses in the U.S. as an investment, it seems reasonable to expect that they would self-select into local housing markets that tend to experience greater house price appreciation. Such a selection effect would upwardly bias any estimate of the price effect of foreign Chinese buyers. In fact, we will show in this section that once we use fixed effects to control for unobserved factors at the city level, house prices in the zip codes that attract the attention of Chinese buyers do not tend to historically appreciate faster than those that do not.

To gauge the severity of the selection bias, we ask the question: do foreign Chinese buyers tend to systematically buy from places that have experienced more rapid price appreciation? To answer the question, we estimate a cross-sectional regression model of determinants of foreign Chinese buyer demand, both at the CBSA and ZIP code level. The dependent variable is the log number of Juwai views in the geographic area. Our choice of explanatory variables is guided by a survey of potential Chinese buyers carried out by Juwai, the company from which we obtained our property views data. Users cited the following motivations for overseas property purchases: 46 percent said lifestyle, 42 percent investment, 64 percent emigration, and 83 percent education. Accordingly, we included explanatory variables that reflect these objectives, and added variables that capture the accessibility of the location to a foreigner arriving from China. The following is the specification for the cross section regression at the CBSA level, where i denotes a CBSA:

$$\begin{aligned}\Delta ln\_views_i = \alpha &+ \beta_1 chinese\_share\_init_i + \beta_2 dist\_to\_china_i + \beta_3 univ_i \\ &+ \beta_4 ln\_pop\_init_i + \beta_5 ln\_med\_price\_init_i \\ &+ \gamma_1 temp_i + \gamma_2 unemp_i + \gamma_3 commute\_time_i + \delta hist\_apprec_i + u_i \end{aligned} \tag{1}$$

The initial population size ($ln\_pop\_init_i$) is included because foreign buyers tend to be drawn to larger cities, with the wealth of amenities that a large city can offer. The initial median house price ($ln\_med\_price\_init_i$) is included because various studies hypothesized that Chinese buyers are more drawn to the luxury segment of the local housing market. We measure the accessibility of an area to Chinese buyers with two variables: the initial share of Chinese in local population ($chinese\_Share\_init_i$), and the (log) distance from the nearest airport with top passengers arrivals from China ($dist\_to\_china_i$). We include a variable that captures the average historical annual house price appreciation to reflect the investment motive of foreign buyers (the average price appreciation between 2001 to 2006, a period when Chinese or foreign capital inflows play little role in the U.S. housing boom; we also separately try the average appreciation for 2001 to 2010. We also include a variable that captures access to universities (number of universities or distance to the closest university), to reflect the commonly cited reason of purchasing houses close to the university attended by their offspring. Not only might obtaining housing for offspring studying at a U.S. university motivate Chinese parents to purchase property, but having a child studying in the U.S. university makes Chinese households eligible for a much greater annual quota of U.S. dollar purchases than is otherwise the case. In addition, we include other variables that commonly motivate local buyers to purchase a house, such as mean commute time, temperature, and unemployment rate (only available at the CBSA level).

We also regress Chinese property views on our set of determinants at the ZIP code level. For comparison with our CBSA-level regressions, we first include the three variables which are only available at the CBSA level (temperature, unemployment rate, and commute time):

$$\begin{aligned}\Delta ln\_views_z = \alpha &+ \beta_1 chinese\_share\_init_z + \beta_2 dist\_to\_china_z + \beta_3 univ_z \\ &+ \beta_4 ln\_pop\_init_z + \beta_5 ln\_med\_price\_init_z \\ &+ \gamma_1 temp_i + \gamma_2 unemp_i + \gamma_3 commute\_time_i + \delta hist\_apprec_i + u_i\end{aligned} \tag{2}$$

However, we then run a specification which drops variables available only at the CBSA label (temperature, unemployment) and instead include CBSA fixed effects (θ_i).

$$\begin{aligned}\Delta ln\_views_z = \alpha &+ \beta_1 chinese\_share\_init_z + \beta_2 dist\_to\_china_z + \beta_3 univ_z \\ &+ \beta_4 ln\_pop\_init_z + \beta_5 ln\_med\_price\_init_z \\ &+ \delta hist\_apprec_s + \theta_i + u_i\end{aligned} \tag{3}$$

The CBSA-specific fixed effects should control for other determinants of house prices found in the literature, such as changes in construction or wage costs or supply elasticities (Saiz, 2010), both of which have been measured at the CBSA-level in existing literature. We separately estimate the regression for up to 624 CBSAs (in all 50 states and the District of Columbia) where data were available, as well as for a trimmed sample of 224 CBSAs which had at least 50 views (located in 40 states).

Table 2 displays the results for the CBSA-level regressions. The variables included explain the pattern of Chinese housing search pattern well, with an adjusted R-squared of 0.7 to 0.8, and confirm a number of existing hypotheses about the motivation of foreign Chinese buyers. Large U.S. cities, cities with high existing share of ethnic Chinese population, and markets with higher median housing prices tend to draw foreign Chinese buyers. These findings are consistent with those in existing literature (e.g. Badarinza and Ramadorai, 2018, IMF GFSR, 2019). We also find that places with more universities and those that are located closer to airports with direct flights to China also have more Juwai hits, though these relationships are not consistently significant. Factors important to domestic buyers—commute time, unemployment—are not important in motivating potential Chinese buyers.

Table 2: Determinants of Demand from Foreign Chinese Buyers – CBSA-Level Regressions

	Full Sample				CBSAs with > 50 views			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial Chinese share	0.293***	0.305***	0.291***	0.258***	0.229***	0.225***	0.244***	0.213***
	(0.0599)	(0.0601)	(0.0620)	(0.0623)	(0.0592)	(0.0605)	(0.0625)	(0.0627)
Distance to China	-0.00604	0.0209	-0.0193	-0.00689	-0.119	-0.130*	-0.146*	-0.120
	(0.0493)	(0.0524)	(0.0527)	(0.0538)	(0.0615)	(0.0654)	(0.0648)	(0.0656)
Number of colleges	0.00804	0.00433	0.00101	-0.000144	0.0145*	0.0146*	0.00792	0.00749
	(0.00633)	(0.00642)	(0.00633)	(0.00642)	(0.00642)	(0.00682)	(0.00681)	(0.00701)
Population	1.023***	1.050***	1.107***	1.109***	0.711***	0.727***	0.846***	0.840***
	(0.0350)	(0.0366)	(0.0378)	(0.0385)	(0.0604)	(0.0664)	(0.0699)	(0.0728)
Initital median home price	0.807***	0.762***	0.469***	0.710***	0.430***	0.452***	0.208	0.431**
	(0.0908)	(0.0930)	(0.118)	(0.102)	(0.125)	(0.130)	(0.157)	(0.138)
Average temperature		-0.0132**	-0.0174***	-0.0148**		-0.00299	-0.0114	-0.00584
		(0.00462)	(0.00478)	(0.00479)		(0.00666)	(0.00685)	(0.00668)
Initial unemployment rate		0.00300	-0.0214	0.00201		0.0112	-0.0213	0.0197
		(0.0138)	(0.0159)	(0.0154)		(0.0272)	(0.0296)	(0.0274)
Initial average commute		0.0149	0.0155	0.0177		-0.0117	-0.00925	-0.00112
		(0.0102)	(0.0106)	(0.0108)		(0.0181)	(0.0186)	(0.0187)
Ave. Δ home price, pre-crisis			0.0404***				0.0452**	
			(0.00958)				(0.0154)	
Ave. Δ home price, pre-2010				0.0271				0.0276
				(0.0164)				(0.0292)
Observations	624	624	556	556	231	231	224	224
R^2	0.803	0.806	0.824	0.819	0.711	0.712	0.735	0.725
Adjusted R^2	0.802	0.804	0.821	0.816	0.705	0.701	0.724	0.714

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Most notably, average house appreciation during the 2001-2006 housing boom period is consistently positive and significant (columns 3 and 7). That the coefficient on this variable is positive and significant confirms that omitted variable bias and reverse causality are potential concerns: Even when we control for other relevant covariates, house prices in the places that foreign Chinese buyers desire tend to historically appreciate faster than those that do not, at least at the city level. At the same time, when we include as a regressor average house price appreciation from 2001 to 2010, the variable is not significant. For this reason, in what follows we control only for pre-crisis price changes, rather than price changes up to the start of the period when Chinese capital flows to the U.S. picked up.

The results of our ZIP code-level regressions suggest that the unobserved factors that drive house price appreciation are mostly at the broader city level. As Table 3 shows, the signs on the coefficients of the same variables that explain the city level regressions well are similar. The coefficient on the historical house price appreciation in the period 2001-2006 is also positive and significant. However, the significance disappears once we included CBSA-specific fixed effects.

Another key observation from the ZIP code level regressions is that there is much greater randomization of foreign Chinese demand *within* a CBSA, which is favorable for satisfying the overlapping assumption critical for a well-designed matching framework. The adjusted R-squared for the same group of explanatory variables in the CBSA regressions decreased substantially to 0.2-0.3 in the ZIP code level regressions. The lower R-square allows for a larger pool of untreated ZIP codes that share overlapping characteristics with the treated ZIP codes.

Taken altogether, the city-level and ZIP code-level regressions appear to suggest that foreign Chinese buyers tend to select into a city where they would buy a house based on city-specific factors that could be drive up house prices. But once the city of their desire is chosen, they tend to randomize selection into a ZIP code. City-level unobserved effects likely present a positive selection bias on the treatment.

For these reasons, we propose two solutions to alleviate the potential bias. First, we conduct the matching at the ZIP code level. Second, the matching should be conducted *within* the same CBSA, such that the treatment effect on the treated would difference out the unobserved city-level factor. In the next section, we describe in detail the implementation of our matching framework.

Table 3: Determinants of Demand from Foreign Chinese Buyers – ZIP-Level Regressions

	Dependent Variable: Log Juwai views			
	(1)	(2)	(3)	(4)
Initial Chinese share	0.0884***	0.0903***	0.0655***	0.0698***
	(0.0211)	(0.0214)	(0.0149)	(0.0161)
Distance to China	-0.0856*	-0.0792*	-2.832***	-3.039***
	(0.0359)	(0.0381)	(0.188)	(0.248)
Distance to nearest college	-0.227***	-0.215***	-0.279***	-0.268***
	(0.0336)	(0.0308)	(0.0292)	(0.0278)
Population	0.353***	0.427***	0.380***	0.425***
	(0.0262)	(0.0292)	(0.0229)	(0.0261)
Inital Median HH Income	0.531***	0.400**	0.194*	0.221*
	(0.106)	(0.128)	(0.0915)	(0.0916)
Average temperature	0.00835	0.000181		
	(0.00441)	(0.00453)		
Initial unemployment rate	0.0260*	0.00985		
	(0.0112)	(0.0121)		
Initial average commute	-0.00350	-0.0124		
	(0.00558)	(0.00637)		
Ave. Δ home price, pre-crisis		0.0433***		0.0146
		(0.00695)		(0.0144)
Observations	8139	6571	8142	6572
R^2	0.224	0.232	0.383	0.378
Adjusted R^2	0.223	0.231	0.327	0.323
CBSA FE	No	No	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.3 Match Results

We now formally describe our matching design. We conduct the matching in two ways. In the first, informed by the discussion in the previous section, we match a treatment ZIP code with a control ZIP code within the same CBSA. The treatment group (henceforth referred to as “treatment indicator 1”) consists of those ZIP codes which are in the top decile for Juwai views within their respective CBSAs, and the controls are drawn from the ZIP codes below the 50th percentile for Juwai views within the same CBSA. But a problem with this definition is that some CBSAs contain only a limited number of ZIP codes (i.e. Santa Rosa in California), and therefore have limited overlapping support and are unable to produce any matches, even if we restrict the matches to cities that contain more than 30 ZIP codes. Furthermore, in small cities, the untreated would presumably be more likely to experience spillovers effects from the treated ZIPs, thus biasing our estimate of the outcome variable to the downside.

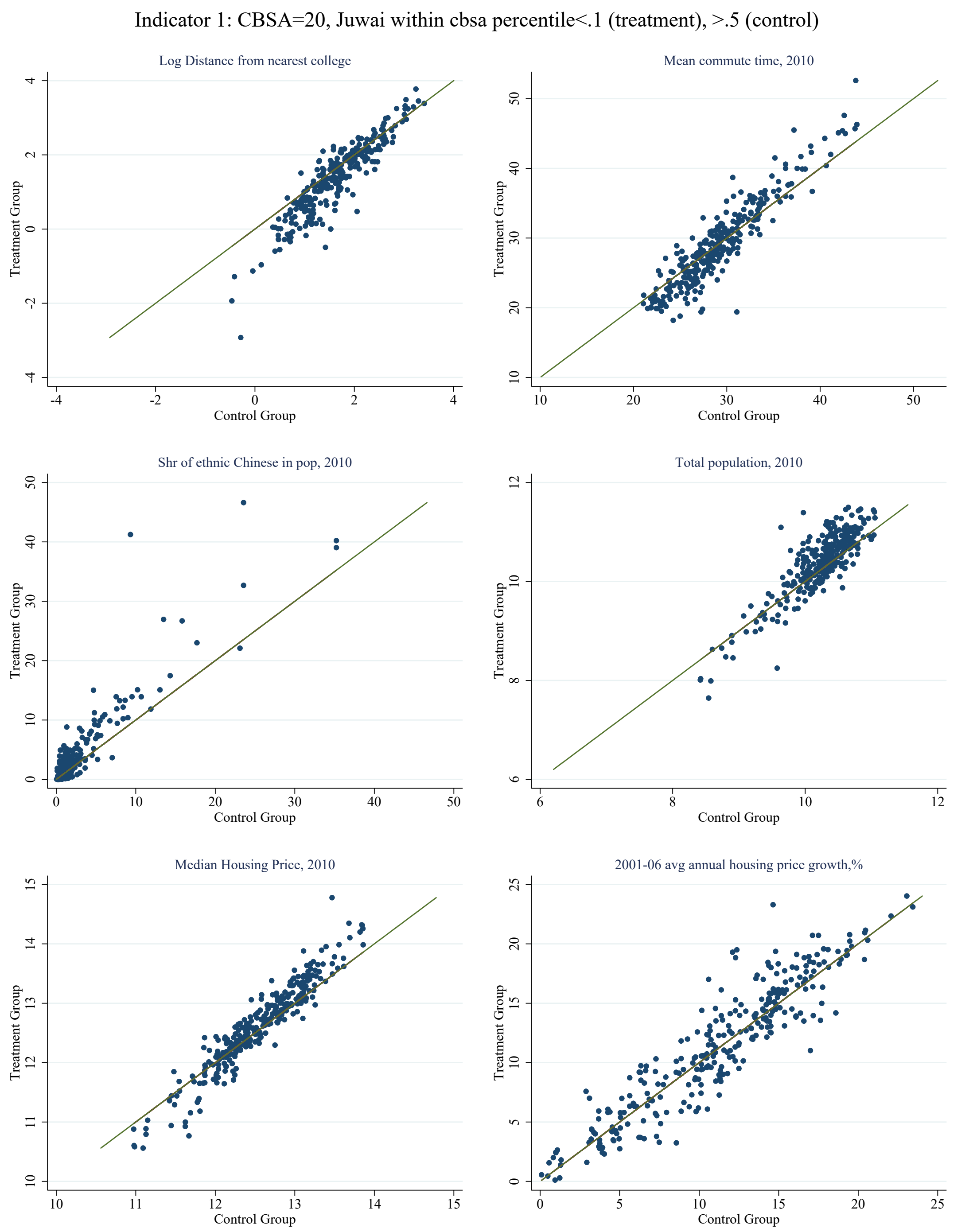
We thus devise an alternative treatment group ("treatment indicator 2") that somewhat relaxes the constraints of the match. This second treatment group is defined as the top 5 percent of Juwai views nationally, and the control group defined as those in the bottom 30 percent nationally. Instead of restricting the matches to be within the same CBSAs, we allow the treated ZIPs to be matched with those that are located outside of the treated ZIP codes city, but with the restriction that the city must be of similar attractiveness to foreign Chinese buyers – in practice, these are cities whose aggregate Juwai views percentile are similarly ranked as those CBSAs in which the treated ZIP codes are located. This last detail is important because we are not allowing a match with just any ZIP codes in the country, but only relaxing the match criteria to cities that draw a similar level of interest from foreign Chinese buyers. In this way, we expand the population of potential matched control areas while still minimizing the city-specific unobserved heterogeneity that could bias our estimates of the treatment effect.[9]

Both definitions of treatment yielded about 370 treatment ZIP codes, across 20 CBSAs in the first definition and 33 CBSAs in the second definition. The first group of cities accounts for 43 percent of total U.S. employment and similarly by as much in terms of population, and the second group of cities accounts for 52 percent of total U.S. employment and of U.S. population. The average median home price, as of December 2016, is $550,000 for the first treatment group, and $680,000 for the second. In comparison, the National Association of Realtors (NAR) reported an average purchase price of $940,000 by foreign Chinese buyer in 2016. Our much lower median purchase price of Chinese buyers may suggest that the survey based collection method employed by NAR may have over-sampled the top-end buyers, which is not surprisingly given that those purchases are more high-profiled and garner more attention from realtors.

The covariates on which the treated ZIP codes are matched to untreated ZIP codes within the same CBSA are: (1) population size in 2010, (2) percent of ethnic Chinese population in 2010, (3) log median house price in 2010, (4) distance from the nearest college, (5) average commute time in 2010, and (6) historical average house price appreciation over the period 2001-2006. For treatment indicator 2, the additional covariate is the percentile of Juwai views of the CBSA to which a ZIP code belongs to.

[9] With the second treatment definition, about 30 percent of the matched control ZIP codes belong to the same city as the treatment ZIP code.

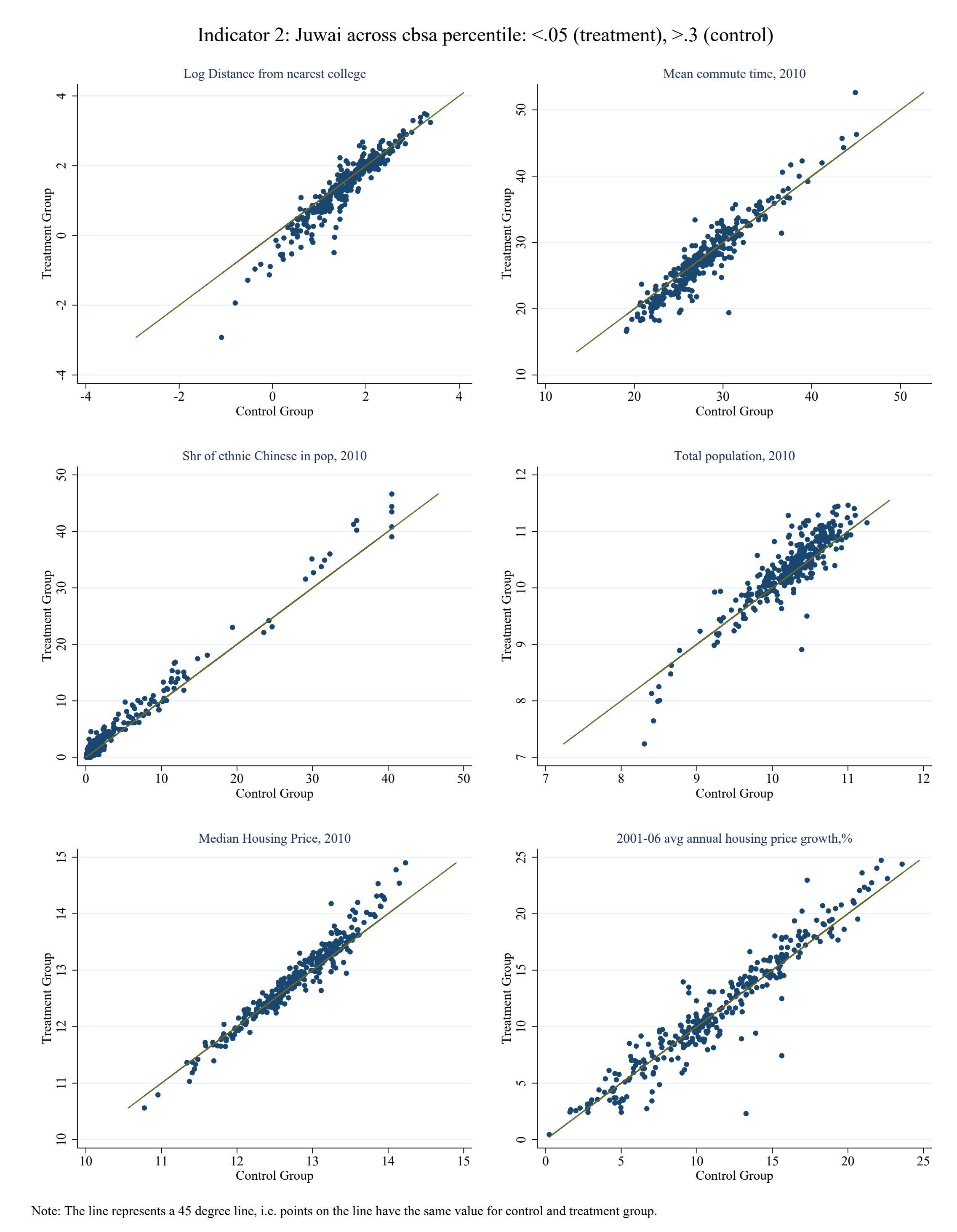
Figure 6: Matched Co-variates for Treatment vs. Average Control Group



Note: The line represents a 45 degree line, i.e. points on the line have the same value for control and treatment group.

Source: Zillow, Inc., Zillow Real Estate Data, `http://www.zillow.com/`.

Figure 7: Matched Co-variates vs. Average Control Group



Source: Zillow, Inc., Zillow Real Estate Data, `http://www.zillow.com/`.

Each treated ZIP code is matched to five untreated ZIP codes, with replacement and using the nearest-neighbor algorithm, which minimizes the weighted sum across the differences of each of the matching covariates. Figure 6 and Figure 7 compare each of the matched covariates of the treated ZIP code to the average of their matched control for treatment indicators 1 and 2, respectively. It shows that the values are similar between the treated and control groups across each of these matched characteristics. The slopes of these scatter plots are mostly not statistically different from one (except for share of ethnic Chinese and median home prices for both indicators, and the average 2001-2006 house price growth rate for indicator 1). From these plots, one can also see that there is a substantial overlapping support for the matches between the treated and the control, satisfying a crucial condition for the matching design. We also illustrate our matching process by providing the example of Seattle (see Figure A3-2 in Appendix A).

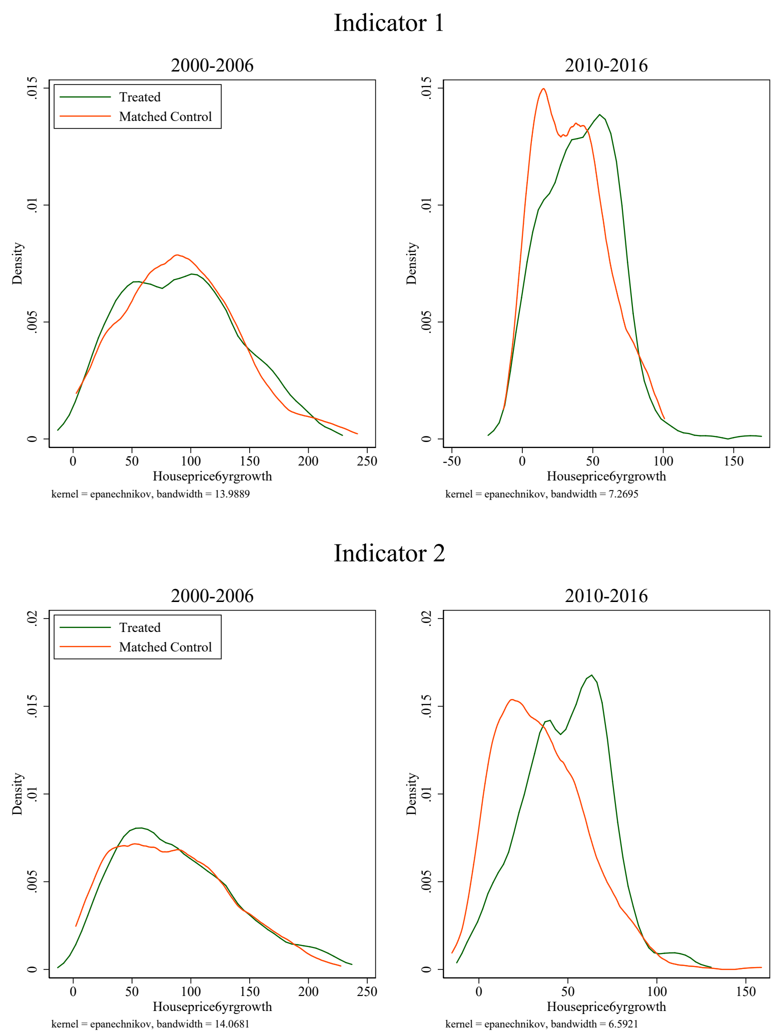
3.4 Cumulative Impact: Average Treatment Effect on the Treated

The outcome variable, or our object of interest, is the difference in house price growth between treated and untreated areas. Figure 8 shows the fitted kernel distribution of 6-year cumulative house price growth in the 2010-2016 period of the treated ZIPs and the matched control ZIPs. For comparison purpose, we also show the distributions of the house price growth for the 2000-2006 period, when the United States experienced a broad housing market boom. By design, the distribution of house price growth of the treated over this earlier period was to be similar to the matched ZIPs, confirmed by these plots. Indeed, for both definitions of treatment, a two-sample Kolmogoros-Smirnov test for equality of distribution found that they are statistically indistinguishable in this period. However, the distribution of house price growth in the period 2010-2016, when the China shock was present, had shifted right of the control ZIP codes. The rightward shift of the treated ZIPs in this later period is even more apparent using the second treatment definition. A test for equality of distribution confirms with high significance that the housing price appreciation of the treated group is larger than for the control group for both definitions of treatment.

The difference in the mean growth rates of the two distributions provides the average treatment effect on the treated (ATET) of exposure to foreign Chinese capital over the 6-year window. For treatment definition 1, the mean house prices over this period for the treatment grew 7 percent faster than for the control group, or 1.1 percent faster per year. For treatment definition 2, mean house price growth for the treatment group was 14 percent faster over the 6 year period, or 2.2 percent per year, compared to that of the control.

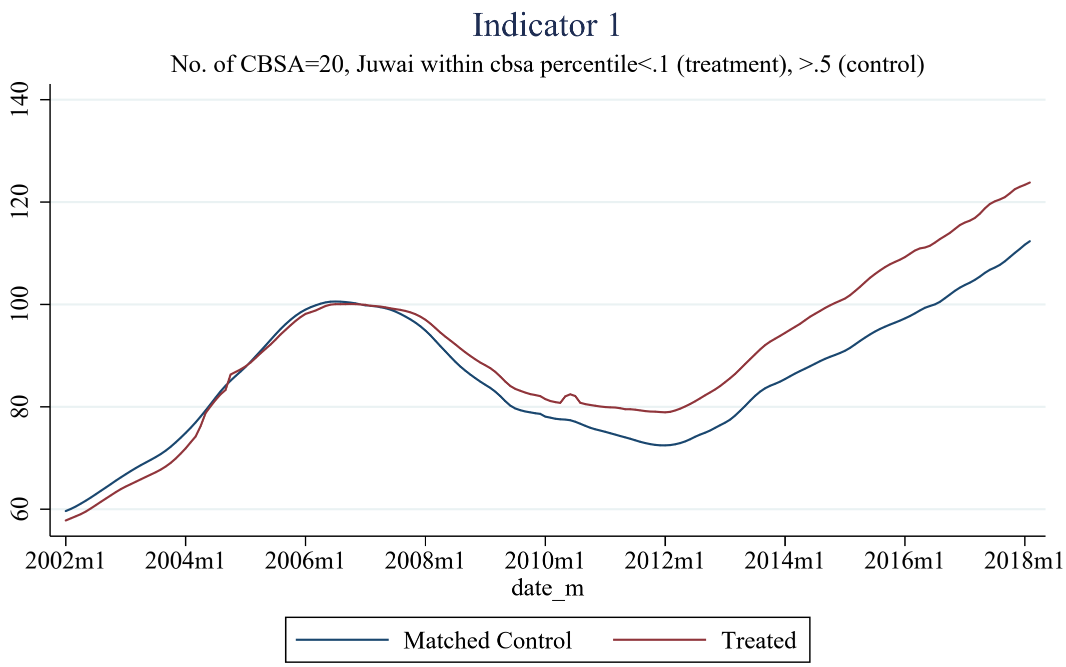
Another way to visualize the cumulative impact is to look at the evolution of the house price index of the treatment and control group (Figure 9). Because of their differential growth rates, the house price level of the treatment group has diverged significantly from the control group in recent years. For the 20 cities included in the treatment definition 1, the divergence picked up after 2008, and for the 34 cities in the treatment group 2, the divergence picked up since 2010.

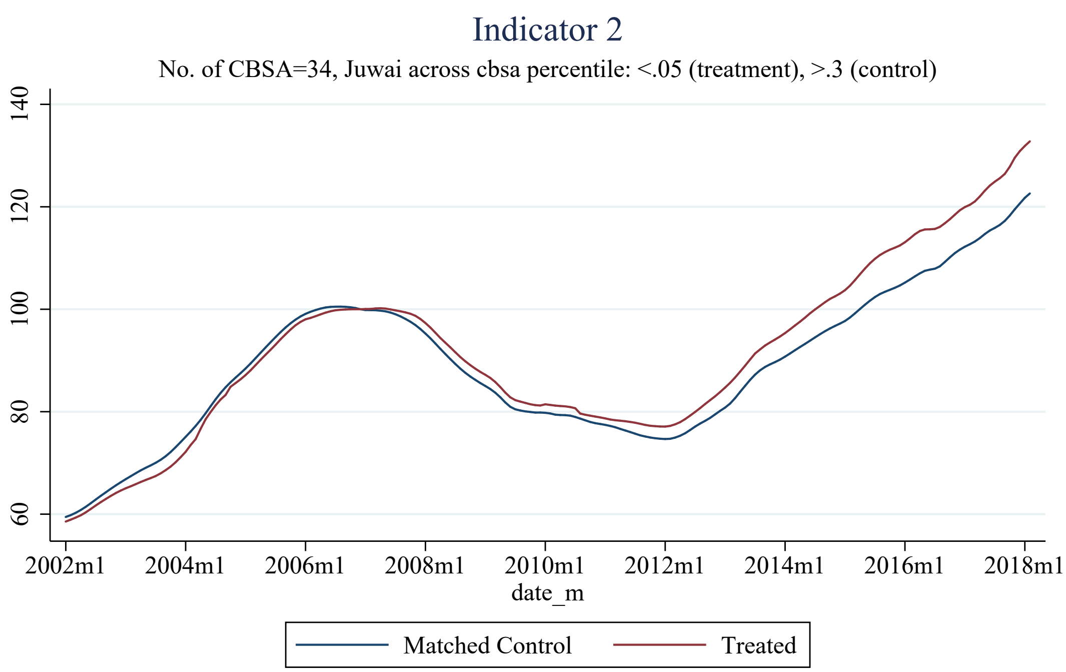
Figure 8: Distribution of 6-yr House Price Growth



Source: Zillow, Inc., Zillow Real Estate Data, `http://www.zillow.com/`.

Figure 9: House Price Level (Weighted Avg, Index 2006m12=100)



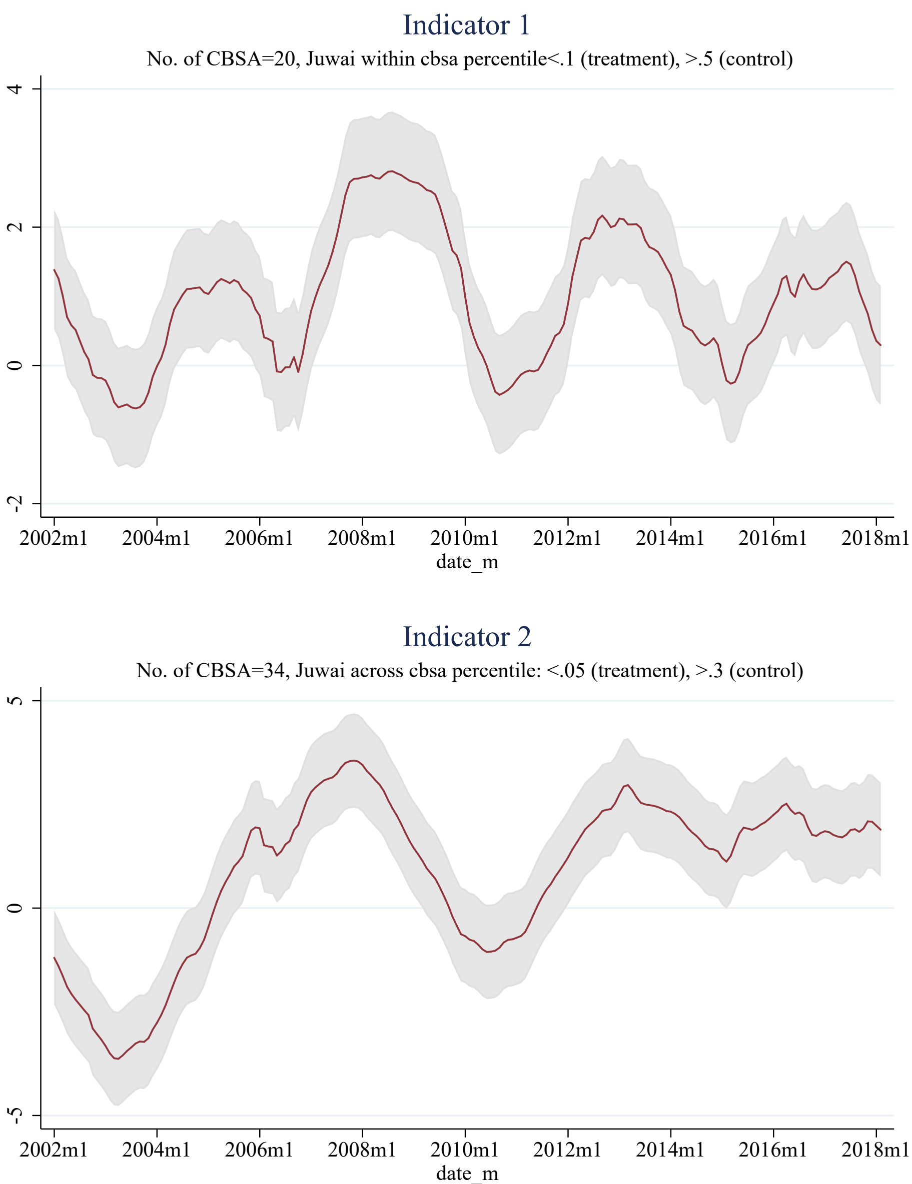


Source: Zillow, Inc., Zillow Real Estate Data, `http://www.zillow.com/`.

3.5 Evolution of the Average Treatment Effect on the Treated Over Time

Because there are multiple periods of China shocks since the Global Financial Crisis, we now explore the time evolution of the average treatment effect on the treated. We calculate the ATET as the weighted average of the difference in the 2-year house price growth between the treatment and control group. We calculate this on a rolling monthly basis. Figure 10 shows the time evolution of this variable for both treatment indicator 1 and 2, with a 95 percent confidence interval around using the standard errors estimated by the nearest-neighbor matching procedure. Both treatment definitions produce three local peaks in the premium of house price growth of the treated over the control ZIPs: in January 2009, December 2012, and January 2016. For treatment indicator 1, the two-year house growth premium of the treated was 3 percent at its 2009 peak, 2 percent at its 2013 peak, and close to 2 percent at its 2016 peak. For indicator 2, the premium on house price growth was 4 percent in 2009, 3 percent in 2013, and also around 3 percent in 2016.

Figure 10: Average Treatment Effect on the Treated



Source: Zillow, Inc., Zillow Real Estate Data, `http://www.zillow.com/`.

3.6 Robustness Tests: Placebo Matching

Despite our matching exercise, the possibility remains that the observables on which we have matched China-exposed ZIP codes to unexposed control ZIP codes do not fully capture pre-existing differences in price growth. If that is the case, then the price growth divergence we have found would merely reflect the self-selection of Chinese demand in real estate markets with rapid price growth, rather than any causal effect of Chinese housing purchases. To further allay this concern, we now conduct a placebo exercise.

Rather than analyzing the gap between China-exposed areas in the U.S. and matched control areas, we instead select as a placebo treatment group the ZIP codes that scored in the top 5 percentile of house price growth in the period 2010-2016 but are not defined as treatment group in our earlier exercise. We match them with similar ZIPs using the same procedure described in Section 5.1. The results are shown in Figure 11 .

The time evolution of the house price growth of this placebo treatment group is drastically different that the pattern evinced in the actual treatment group. By design, this group of ZIP codes experienced strong price appreciation over the period 2010-2016, hence Figure 11 does show an increase in house price growth rate over this period. However, unlike the results with the actual treatment group, the price growth gap only turned positive once in 2015, and the price growth gap was significantly negative for an extended period. It appears that the placebo ZIP codes suffered sharper housing price declines during the global financial crisis and saw a sharper rebound since 2012. Broadly speaking, the drivers of the price growth in the placebo ZIPs that we select based on their having hot housing markets appear to be different than the drivers of price growth in the actual treatment group. And more importantly, the trajectory of the gap between the placebo group and their matched controls bears no obvious relationship to the measures of capital inflows from China that we analyzed in Section 2.

Figure 11: Placebo Difference in House Price Growth and Level

Source: Zillow, Inc., Zillow Real Estate Data, `http://www.zillow.com/`.

4 Connecting the Macro and the Micro: Capital Inflows from China and U.S. House Prices

In this section, we link the macroeconomic variables we examined in Section 2 with the micro-level effects that we identified in the previous section. We show that the price growth gap between China-exposed and non-exposed areas is significantly related to deposit inflows to the United States from China, and that this relationship is strongest after three quarters, consistent with capital flows from China entering the U.S. housing market. We then rule out alternative explanations for this comovement. First, we control for U.S. economic conditions in order to rule out the possibility that the dynamics of the price gap and capital inflows simply reflect the state of the U.S. economy. Second, we show that deposit inflows from other countries are unrelated to the price gap, demonstrating that the China inflow-price gap comovement is not generated by global economic conditions, but rather from China-specific shocks. Thus the analysis in this section provides further evidence that Chinese households have moved money into the U.S. via the banking system, money then used to purchase residential property. This then generates excess price growth in China-exposed areas as well as increase the size of the U.S. statistical discrepancy when the funds leave the banking system. Having established that much of the statistical discrepancy in the past decade is attributable to China-specific shocks, we estimate the U.S. investment position vis-à-vis China for the missing asset class of residential real estate.

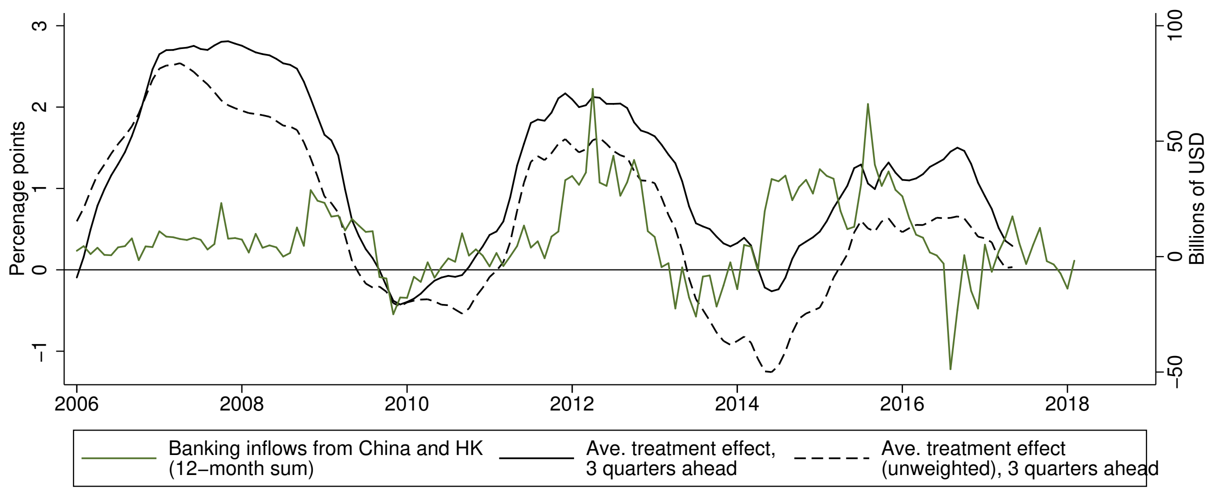
4.1 Relationship Between Excess Price Gaps and Capital Inflows from China

Figure 12 plots the relationship between deposit inflows from China and Hong Kong along with the evolution of the gap in house price growth between China-exposed ZIP codes and the matched controls.[10] Recall that in Section 2 we presented evidence that funds brought to the U.S. via the banking system were being used for house purchases with a lag. The relationship between inflows and the estimated treatment effect also exhibits this behavior: the contemporaneous correlation is only 0.06, but rises to 0.36 with a three-quarter lag. This is why Figure 12 plots the treatment effect three quarters ahead. The degree of comovement between the two series is striking, and we

[10] To conserve space, in this section we work exclusively with estimates constructed using Treatment Definition 1 described in the previous section.

see that peaks in capital inflows from China and Hong Kong coincide with peaks in the treatment effect three quarters ahead. It is also notable that there was essentially no relationship between the two series prior to 2010, the year in which China liberalized some controls on capital outflows.

Figure 12: Average Treatment Effect on the Treated and Capital Inflows from China



Treatment effect is the difference in 2−year house price growth between China−exposed ZIP codes and matched controls, calculated using Treatment Definition 1.
Sources: TIC system, authors' calculations.

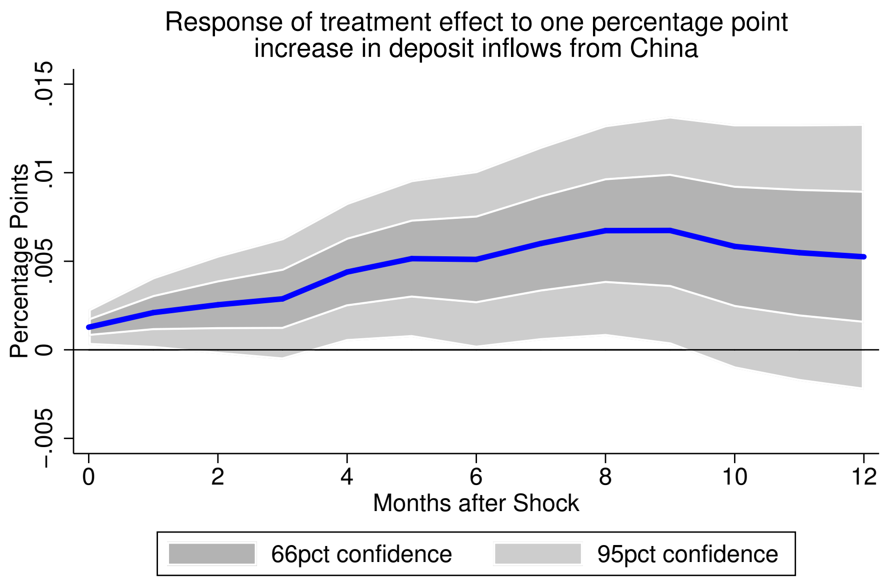
In the remainder of this section, we will examine the relationship between the divergence in price growth and Chinese inflows to the U.S. more formally. In particular, we estimate the cumulative response of the gap between China-exposed and non-China-exposed U.S. ZIP codes to capital inflows by estimating the following local projection, following Jordá (2005):

$$ATET_{t+h} = \alpha^h + \beta^h \text{China\_Deposit\_Inflows}_t + \gamma_1^h \Delta NFP_t + \gamma_2^h r_t^{mort} + \sum_{j=1}^{9} X_{t-j}\Lambda_{\text{j}}^h + \varepsilon_t$$

Where $ATET_{t+h}$ is the treatment effect plotted in Figure 10: the difference in two-year house price growth between China-exposed ZIP codes and matched non-exposed ZIP codes. We measure capital inflows from China ($\text{China\_Deposits\_Inflows}_t$) using the one-month change in deposits held by residents of China and Hong Kong in U.S. financial institutions, measured as a percentage of the level of Chinese and Hong Kong deposits at the end of the previous period. As we discussed in Section 2, deposit inflows are the type of capital flow appearing in official statistics most likely to reflect households moving money into the U.S. to purchase residential properties. Again, we include flows from Hong Kong based on media reports and mainland Chinese policies that suggest that Hong Kong acts as a major conduit for capital outflows from the Chinese household sector. To control for the state of the U.S. economy as it relates to the housing market, we include as controls the month-on-month growth in seasonally adjusted U.S. non-farm payrolls (ΔNFP_t) as well as the average 30-year mortgage rate in the U.S. (r_t^{mort}). The matrix X_{t-j} contains lagged values of the dependent variable, the shock, and the controls, with our specification containing nine lags. We experiment with alternative lag structures and differencing (e.g.year-on-year rather than month-on-month changes); the results are qualitatively similar to those presented below.

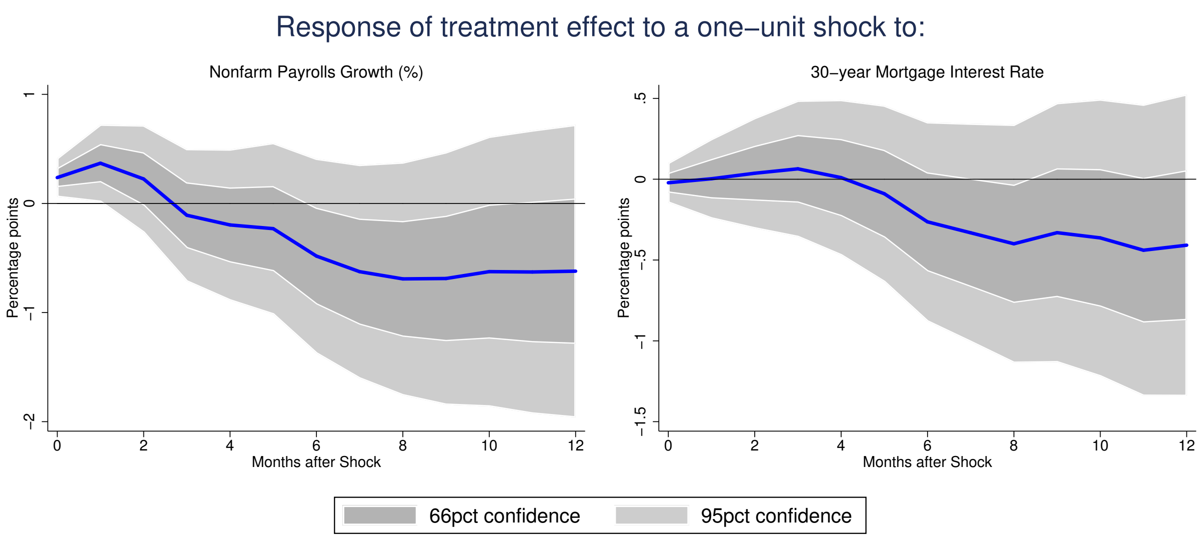
The results of the estimation are presented in Figure 13. We find a significant and positive relationship between deposit flows from China to the U.S. and the gap in house price growth between exposed and non-exposed ZIP codes. The effect peaks at around eight months. Recall that in Section 2 we showed that deposit outflows from China showed a strong correlation with the U.S. statistical discrepancy with a lag of three quarters and noted that this pattern is consistent with Chinese residents moving money into U.S. banks and using it to purchase real estate on average three quarters later. It is therefore striking that the impulse response in Figure 13 is also consistent with such timing. As the China deposit inflows variable enters our specification in logs, the estimates in Figure 13 imply that a one percentage point increase in flows generates an 0.008 percentage point widening in the gap in price growth between China-exposed and non-exposed areas in the U.S. This effect may seem small at first glance, but recall from Figure 12 above that inflows reached roughly \$70 billion during periods of concern about a China hard landing in 2012 and 2015. Taking a concrete example, banking inflows from China were \$10.1 billion in July of 2015 and \$32.2 in August of that year. Our estimates imply this increase explains 90 percent of the widening gap in house price growth between China-exposed areas and those not exposed.

Figure 13: Treatment Effect and Deposit Inflows from China



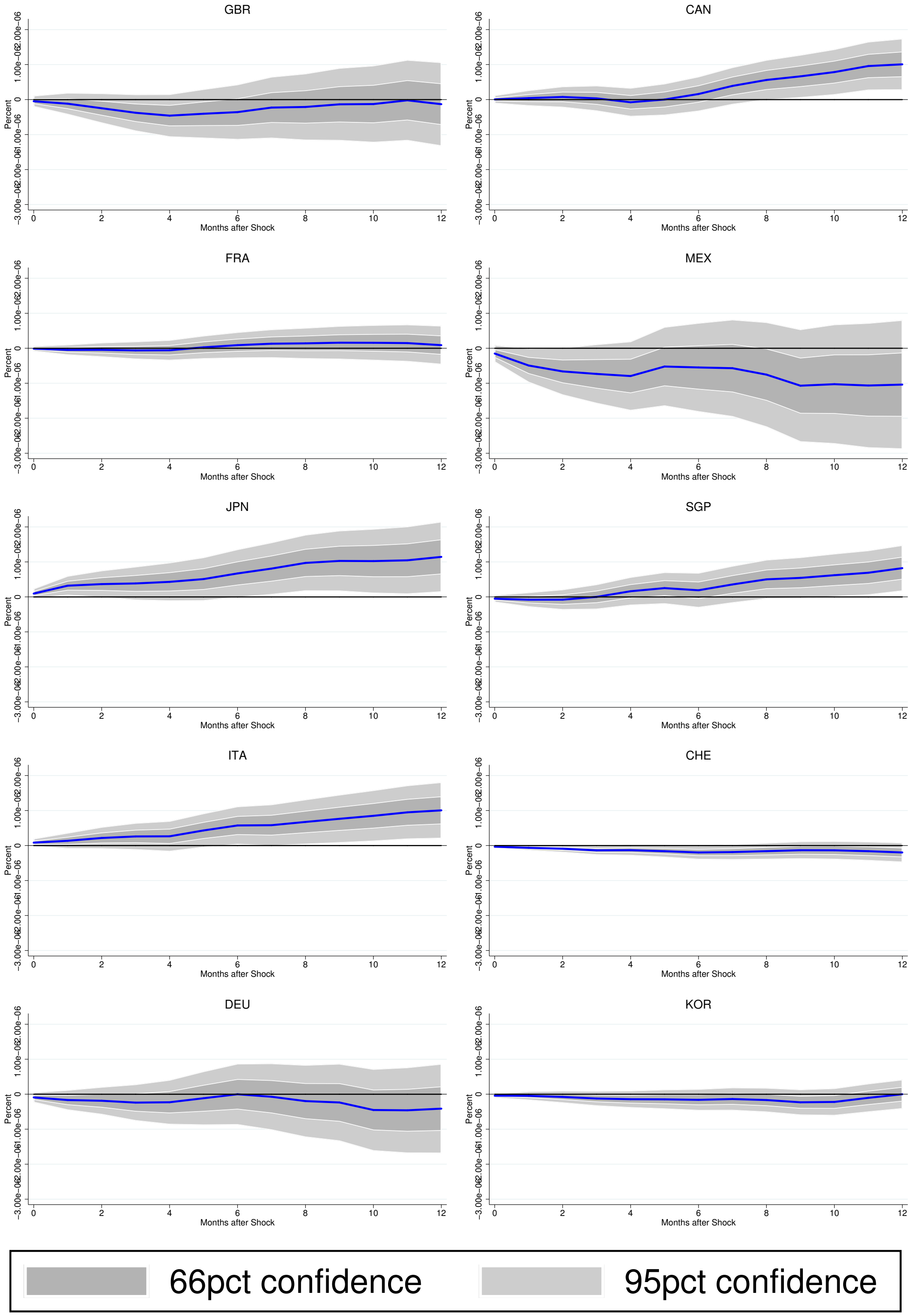
All regressions include 9 lags of the treatment effect, as well as contemporaneous values and 9 lags of China_Deposit_Inflows and the domestic control variables (nonfarm payrolls and 30−year mortgage rates.

Figure 14: Treatment Effect and U.S. Variables



Regressions include 9 lags of the dependent variable and shock variable China_Deposit_Inflows as well as contemporaneous domestic control variables plotted here.

Figure 15: Flows from other countries and U.S. real estate prices



All regressions include 9 lags of the treatment effect as well as contemporaneous values and 9 lags of deposit inflows from China and the two U.S. controls (nonfarm payrolls and the 30−yr mortgage rate.

In contrast to the significant effect evident in Figure 13, the relationship between the treatment effect and the domestic U.S. variables relevant to the housing market that we include in our specification is either negative or not statistically significant, as shown in Figure 14. This increases our confidence that the price effect we uncover and its relationship with inflows from China are not merely an effect of the areas we classify as China-exposed being more sensitive to national or global shocks which also happen to attract inflows from China.

To demonstrate that our results reflect a causal relationship between capital flows from China and the price of U.S. real estate, we conduct another placebo test. The primary concern with our analysis relating inflows to the U.S. from China to U.S. house prices is omitted variable bias—perhaps these two variables are both driven by some third factor, such as the state of the global economy. To verify that this is not the case, we test whether there is a relationship between inflows from other countries and gap in house price appreciation between the China-exposed and non-exposed areas we are studying.

In Figure 15 we repeat the original exercise of estimating the relationship between deposit inflows to the U.S. and the average treatment effect estimated above, but instead of using inflows from China and Hong Kong as the shock variable we use capital flows from several other countries. In particular, we analyze the relationship for the ten countries other than China that are the top sources of foreign deposits in U.S. financial institutions and which are not global financial centers.[11] Figure 15 makes clear that inflows from these countries generally have no significant relationship with the relative growth of house prices in the China-exposed ZIP codes we study. While flows from some of these countries do have a significant relationship with US real estate prices, the timing of the relationship as well as the magnitude are quite different. Importantly, China is not consistently the largest source of deposit inflows to the U.S. nor is the variance of flows from China systematically higher than flows from the other countries we focus on in this placebo exercise. Thus the lack of significance for these other countries is not simply due to flows from China being larger or more variable. In addition, the point estimates of the effects for these countries are orders of magnitude smaller than what we find for China. Overall, this exercise confirms that our results on the relationship between capital inflows from China and the trajectory of house prices in China-

[11] We exclude from this exercise financial centers including the Cayman Islands, the Bahamas, and the British Virgin Islands.

exposed areas is not the result of both variables moving in response to general global financial conditions.

4.2 U.S. Investment Position vis-à-vis China in Residential Real Estate

Unrecorded Chinese purchases of U.S. residential real estate have an important implication for the U.S. net investment position: it means that the true size of U.S. liabilities to China is larger than the measured position. Curcuru et al. (2009) is the first study to quantify the size of this missing asset class, and the authors find that the aggregate U.S. international investment position in U.S. housing was a net liability position of $565 billion as of 2007, the last year of their dataset.[12] Using a similar method as Curcuru et al. (2009), we construct the stock series for Chinese holdings of U.S. residential real estate with price appreciation and transaction estimates reported by NAR.[13] Our calculation indicates that U.S. gross liabilities to China in U.S. housing is valued at $226 billion at the end of 2018, as shown in Column 2 of Table 4.

However, as NAR data suffers from certain methodological shortcomings (see section 2), it behooves us to seek alternative estimates of Chinese purchases of U.S. housing. Our analysis in the previous sections suggests that the U.S. BOP statistical discrepancy contains valuable information about this missing asset class. First, we had established that the variation in the U.S. BOP statistical discrepancy over the period 2009-2018 can be significantly explained by Chinese capital inflows; then, we had shown that Chinese capital inflows, rather than inflows from other countries, primarily explain the excess house price premiums in cities with high foreign house demand in the United States. Informed by these findings, we allocate the entirety of the U.S. BOP statistical discrepancy during 2009-2018 to Chinese transactions, and construct the stock series by adding the statistical

[12]The net liability position of $565 billion consists of gross liabilities of $798 billion and gross assets of $233 billion. We update the gross liability position in housing using the latest NAR data and the same valuation methodology as Curcuru et al. (2009) and find that it has increased to $1.95 trillion by the end of 2018, which is 6% percent of the U.S. housing stock.

[13]NAR began to provide estimates of the dollar transaction value of Chinese purchases of U.S. housing in their annual profile of international home buying activity report published in 2010, and prior to that, only the percent of Chinese buyers in total foreign purchases. The starting liability position of $13 billion in 2008 in Table 4 was constructed in the following way: we first obtain a time series of Chinese buyers transactions in the U.S. housing market for the period 2001-2007 by multiplying the estimated value of total foreign inflows into U.S. residential real estate market in Appendix table B.2 in Curcuru et al. (2009) by 5%, which is the share of Chinese buyers in total foreign purchases in 2007, the earliest data published by NAR. This assumes that Chinese inflows into U.S. housing was negligible before China's accession to WTO in 2001 and was maintained at 5% of total foreign inflows thereafter until 2007. We then derive the value of holdings at the end of each year by adding the flow to the holding position from the year prior adjusted for house price appreciation.

Table 4: Estimated Chinese Holdings of U.S. Residential Real Estate

	Mean U.S. sales price	Annual % Chg	Gross Inflows ($B)	Gross Holdings ($B)	Net Inflows ($B)	Net Holdings ($B)	Net Inflows ($B)	Net Holdings ($B)
			(1)	(2)	(3)	(4)	(5)	(6)
Data:	NAR	NAR	NAR		U.S. BOP Statistical Discrepancy		0.47*U.S. BOP Statistical Discrepancy	
2008	242,700	-8.8%	-	13	-	13	-	13
2009	216,900	-10.6%	2	14	146	158	69	81
2010	220,000	1.4%	11	25	-7	153	-4	78
2011	214,000	-2.7%	7	32	-62	87	-29	47
2012	225,400	5.3%	12	46	-31	61	-14	35
2013	245,500	8.9%	13	62	-54	12	-25	13
2014	255,300	4.0%	22	87	79	92	37	51
2015	266,400	4.3%	28	119	84	180	39	92
2016	276,000	3.6%	27	150	41	227	19	115
2017	289,200	4.8%	32	189	5	242	2	122
2018	298,200	3.1%	30	226	94	344	44	170

Source: NAR, BEA, and Authors' calculations.

discrepancy to the previous year's holdings adjusted for annual house price appreciation.[14] As shown in column 4 of table 4, the estimated net investment position with China amounts to a net liability position of $344 billion in 2018. While this estimate is not directly comparable to the $226 billion estimated from NAR data —because the U.S. BOP statistical discrepancy is measured on a *net* basis, as opposed to the *gross* basis of the NAR estimate—it is all the more remarkable that the net position, which has already deducted the value of gross assets, is substantially larger than the estimated gross liability position using NAR data. This suggests that the gross liability position implied by the U.S. BOP statistical discrepancy approach most likely is even larger than $344 billion.

[14]Note that because the statistical discrepancy is the residual of all other measured items in the balance of payment accounts, it is interpreted as unmeasured *net* capital inflows. The more precise way to construct the bilateral net liability position should have been applying U.S. house price appreciation on Chinese holding of U.S. housing minus U.S. holding of Chinese real estate adjusted for China's house price appreciation. We make the simplifying assumption that U.S. gross asset position in China's housing stock is negligible for the following reasons: first, China has stringent rules that rendered it extremely difficult for foreigners to own domestic real estate, for example, requiring foreigners to have lived in China for at least a year, and in the more highly valued first-tier cities like Beijing, foreigners are required to have paid taxes and social security for five years before meeting eligibility to buy a property; second, in the period 2009-2018 (the period of concern to this paper), China experienced a total net capital outflows of $705 billion; third, a proxy for American demand for Chinese housing—the number of American visits to China—was roughly flat during the period of concern in this paper, in contrast to the sharp increase in Chinese visits to the United States. For these reasons, it is not far-fetched to assume that U.S. holdings of Chinese housing is negligible.

One might argue that allocating the entire statistical discrepancy to Chinese transactions might overestimate the portion attributable to China, given that there are other well-known foreign transaction activities, such as purchases by Canadians. To proxy for the percent of Chinese purchases, we use the correlation between the change in Chinese deposits in U.S. banks and the U.S. BOP statistical discrepancy (0.47), previously shown in figure 2. Multiplying the U.S. BOP statistical discrepancy by 0.47 yields the transaction estimates shown in column 5 of table 4. This adjustment reduces the U.S. net liability position with China in U.S. housing to $170 billion in 2018 (column 6), compared with $344 billion without the adjustment.

Overall, these estimates suggest that U.S. liability position with China could be understated by $170-$344 billion due to unrecorded Chinese holdings of U.S. housing. Our results also stand in contrast to those of Coppola et al. (2021), which find that the U.S. credit position vis-à-vis China is understated by $600 billion due to U.S. holdings of equity issuances in offshore tax havens. Taking our results together with theirs, the impact on the *net* U.S. creditor position vis-à-vis China would only be a third to a half of the magnitude cited in their study.

5 Conclusion

In this paper we have presented a broad range of evidence suggesting substantial purchases of U.S. residential real estate as safe haven inflows from China following periods of economic stress in China since 2010. We have shown that this novel type of safe haven capital flow has generated multiple China shocks in the U.S. housing market, with house prices in China-exposed areas having risen significantly faster than those in areas not exposed to Chinese demand.

At the macro-level, we have shown that measures of macroeconomic and financial stress in China, as well as inflows of deposits from China and Hong Kong into the United States, strongly comove with the unrecorded capital inflows captured by the U.S. statistical discrepancy, with a lag of three quarters. And we have discussed in detail why this relationship is consistent with Chinese households moving money into U.S. and subsequently using the funds to purchase residential real estate. Due to the way U.S. balance of payments statistics are collected, over time, these purchases lead to an understatement of U.S. gross liabilities to China.

Our micro-level analysis makes use of a novel dataset to directly measure variation in Chinese demand for residential real estate across U.S. ZIP codes, showing that house prices have increased on average faster in China-exposed areas than in otherwise similar areas which have not attracted interest from potential Chinese buyers. After exploring in detail the drivers of the foreign interest at the city and ZIP code level, we match ZIP codes in our dataset that attract a relatively high level of Chinese interest with control ZIP codes receiving relatively low interest, but which are otherwise similar along several dimensions. The resulting estimate of the average treatment effect on the treated ZIP codes indicates that exposure to Chinese demand accelerated price growth by on average one or two percent per year after 2010. Looking at the dynamics of this treatment effect over time, we find that the price growth gap widened markedly following periods of economic stress in China, an indication that Chinese households have purchased U.S. residential real estate as a safe haven asset.

Finally, we link the time-varying average treatment effect that we estimated using micro data with the aggregate measures of capital inflows from China that we initially analyzed. In local projections we find that the two series are significantly related, with the timing of the peak response consistent with the findings of our macro-level analysis.

Throughout the paper, we have conducted robustness tests to rule out alternative explanations for our findings. A placebo exercise defining hot housing markets as the treated group generates an estimated treatment effect that is qualitatively different from ours. Our estimated treatment effect is not significantly related to domestic U.S. variables. And deposit inflows from countries other than China which are important sources of capital flows to the U.S. behave differently and are not significantly related to the treatment effect we estimated.

Overall, our findings suggest that housing markets in major U.S. cities have been subject to global safe haven flows from China following periods of economic stress in China. The fact that authorities in most countries do not collect data on foreign purchases of residential real estate makes clear the novelty of this type of capital flow. The Chinese government's purchases of U.S. Treasury debt has previously attracted attention, as have Chinese firms' direct investment in the United States. Our findings show that another very different, albeit less accurately measured, type of capital inflow has significant economic effects in the United States, both at the local and the macroeconomic levels. Accounting for these inflows suggests that U.S. liabilities to China are potentially \$170 to \$344 billion larger than indicated in the measured U.S. balance of payments accounts.

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Appendix 1: Data Documentation

A1.1 Juwai views data

Data on Chinese residents' views of U.S. property listings were obtained from directly from the management of Juwai.com in August 2017. The original dataset is a 3-way Chinese city-U.S. ZIP Code-month panel dataset. For this paper the data were collapsed to a cross sectional dataset consisting of total Chinese views of listed properties in each U.S. ZIP code during the period covered by the dataset.

A1.2 Zillow home price data

We use the Zillow Home Value Index data from Zillow to measure house prices. This smoothed, seasonally adjusted data is published by Zillow at the monthly frequency at several levels of geographical aggregation, including zip code and metro area, and for several classes of home, including for tiers defined by price percentiles and by types of home. The data is available from 1996 to present. More details are available on Zillow's website[15]

A1.3 Drivers of Chinese Demand

This section documents the data sources for the variables used in the cross sectional determinants of demand regressions.

A1.3.1 CBSA-level regression

- Chinese share of population - Annual data pulled from ACS 5-year estimates table DP05 for 2011-2016, decennial census for 2010. Mean of values from ZCTAs within CBSA.
- Distance to airport with top Chinese arrivals - Airport coordinate data was obtained from Department of Transportation.[16] Data on passenger arrivals data are from the U.S. Department of Transportation Bureau of Transit Statistics "Air Carrier Statistics (Form 41 Traffic)" Database.[17] Distance from CBSA centroid to nearest airport with top Chinese arrivals was calculated using QGIS software.

[15] https://www.zillow.com/research/data/

[16] https://data-usdot.opendata.arcgis.com/datasets/airports

[17] https://www.transtats.bts.gov/

- Number of universities - College point data from Oak Ridge National Laboratory Colleges and Universities dataset.[18] Colleges were limited to not-for-profit institutions offering at least 2 or 4 year degrees with at least 1,000 total enrollment. Then, using QGIS, we count the number of institutions within each CBSA.

- Total population - Annual data pulled from ACS 5-year estimates table DP05 for 2011-2016, decennial census for 2010. Sum of values from ZCTAs within the CBSA.

- Median home price - Monthly Zillow Home Value Index value for middle tier homes pulled from Zillow's website for April 1996 - ?. After collapsing to CBSA level by taking the mean across ZCTA values, we lag the series by 12 months and take the natural log.

- Average temperature - Annual 30-year normal average temperature pulled from National Oceanic and Atmospheric Administration, available from 1981-2010.[19] Data for each ZCTA taken from weather station closest to ZCTA centroid. Median value of ZCTAs within the CBSA.

- Unemployment rate - Annual data pulled from ACS 5-year estimates table S2301 for 2011-2016. Median value of ZCTAs within the CBSA.

- Mean commute time in minutes - Annual data pulled from ACS 5-year estimates table DP03 for 2011-2016. Median value of ZCTAs within the CBSA.

- 10-year housing price change - 10 year change between December 2001 and December 2010 in Zillow Home Value Index for all homes. Monthly ZHVI pulled from Zillow. Mean of ZCTA values within CBSA taken before percent change is calculated.

To convert our ZCTA data to the CBSA level, we use the official crosswalk published by the U.S. Census Bureau for 2010 ZCTAs to CBSAs to associate one CBSA with each ZCTA.[20] When a ZCTA falls into multiple CBSAs, we select the CBSA which contains the largest share of the ZCTA's population.

[18] `https://www.sciencebase.gov/catalog/item/4f4e4acee4b07f02db67fb39`

[19] `https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/climate-normals/1981-2010-normals-data`

[20] `https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.html`

A1.3.2 ZCTA-level regression

- Chinese share of population - Annual data pulled from ACS 5-year estimates table DP05 for 2011-2016, decennial census for 2010.

- Distance to nearest college - College point data from Oak Ridge National Laboratory Colleges and Universities dataset.[21] Colleges were limited to not-for-profit institutions offering at least 2 or 4 year degrees with at least 1,000 total enrollment. Then, using QGIS, we calculate the distance between the ZCTA centroid and the nearest college.

- Total population - Annual data pulled from ACS 5-year estimates table DP05 for 2011-2016, decennial census for 2010.

- Median home price - Monthly Zillow Home Value Index value for middle tier homes pulled from Zillow's website for April 1996 - ?.We lag the series by 12 months and take the natural log.

- Average temperature - Annual 30-year normal average temperature pulled from National Oceanic and Atmospheric Administration, available from 1981-2010. Data for each ZCTA taken from weather station closest to ZCTA centroid.

- Unemployment rate - Annual data pulled from ACS 5-year estimates table S2301 for 2011-2016.

- Mean commute time in minutes - Annual data pulled from ACS 5-year estimates table DP03 for 2011-2016.

- 10-year housing price change - 10 year change between December 2001 and December 2010 in Zillow Home Value Index for all homes. Monthly ZHVI pulled from Zillow.

A1.4 Matching

When matching ZCTAs to define our treatment and control groups, we match on the following covariates:

[21] https://www.sciencebase.gov/catalog/item/4f4e4acee4b07f02db67fb39

- Population size in 2010 - Annual data pulled from 2010 ACS 5-year estimates table DP05.
- Percent of ethnic Chinese population in 2010 - Annual data pulled from 2010 ACS 5-year estimates table DP05.
- Log median house price in 2010 - Zillow Home Value Index for middle tier homes converted to annual by taking maximum monthly value.
- Distance from nearest college - College point data also from Oak Ridge National Laboratory Colleges and Universities dataset. Colleges were limited to not-for-profit institutions offering at least 2 or 4 year degrees with at least 1,000 total enrollment. Then, using QGIS, we calculate the distance between the ZCTA centroid and the nearest college.
- Average commute time in 2010 - Annual data pulled from ACS 5-year estimates table DP03.
- Historical average house price appreciation over the period 2001-2006 - Change in Zillow Home Value Index for all homes between December 2001 and December 2006.

A1.5 CoreLogic Real Estate Data

We use CoreLogic real estate data to validate the Juwai views data. This data is collected by CoreLogic from local records for home sale & refinance transactions, tax information, real estate listings, and mortgages. The data is available for some areas back to the 1990s, with the most complete records for almost all counties in the U.S. in the last decade. The data is available through 2015. Before performing our calculations, we limit records to single family residency or townhouse sales (either new construction or resales), stripping out foreclosures or records that are missing a sales price. We explore if zip codes with more Juwai views have (i) higher shares of home purchases completed in cash, and (ii) higher shares of home purchases by absentee buyers that don't live at the property.

A1.5.1 Cash sales

We calculate the share of home purchases completed using exclusively cash by zip code. We identify a sale as a cash sale if the CASH_SALE_FLAG variable equals 'C', indicating cash, or if the MTG_CODE variable is null and the MTG_AMT variable is 0, indicating there is no mortgage associated with the purchase. We calculate the cash sale share by zip code and year on a quantity basis (i.e., number of cash sales / total number of sales) and a value basis (i.e., sum of sales prices for cash sales / sum of sales prices for all sales).

A1.5.2 Absentee buyers

We calculate the share of home purchases that are done by absentee buyers (i.e., by those that don't live at the property) by zip code. We classify a purchase as being done by an absentee buyer if the ABSENTEE_BUYER_FLAG equals 'T'. The data dictionary says 'T' indicates "PROPERTY ADDRESS TAKEN FROM SALES TRANSACTION - DETERMINED ABSENTEE OWNER." In the denominator of our share of home purchases calculation, we only include records that are not missing the ABSENTEE_BUYER_FLAG field.

Appendix 2: Supplemental Figures and Tables

Figure A2-1: Correlations: Foreign deposit outflows
vs U.S. foreign deposit inflows

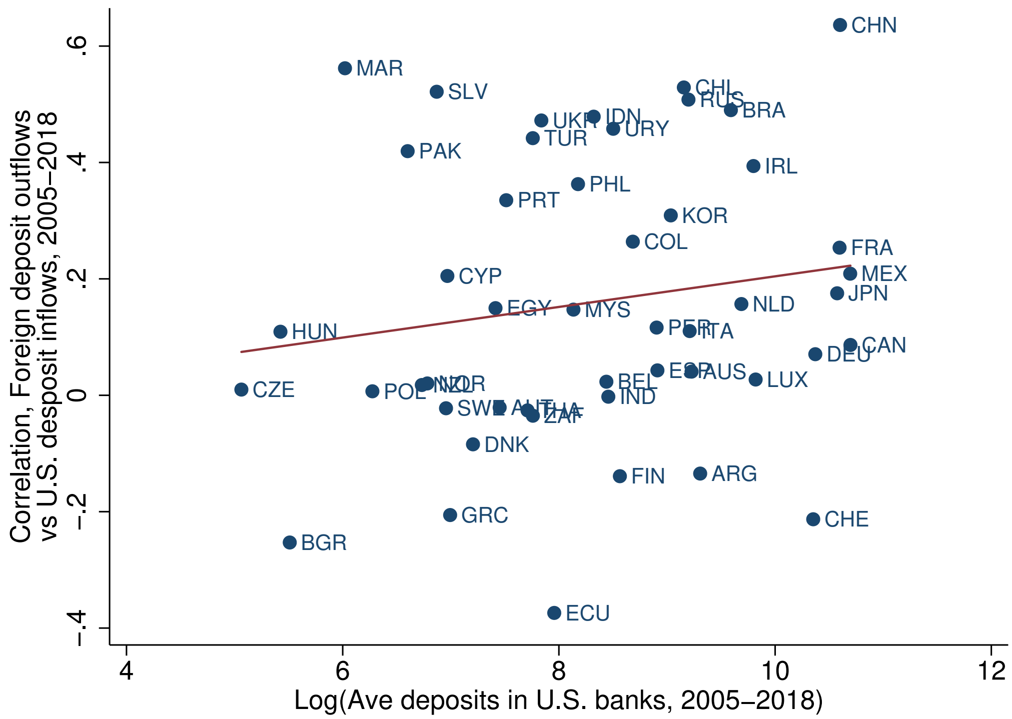
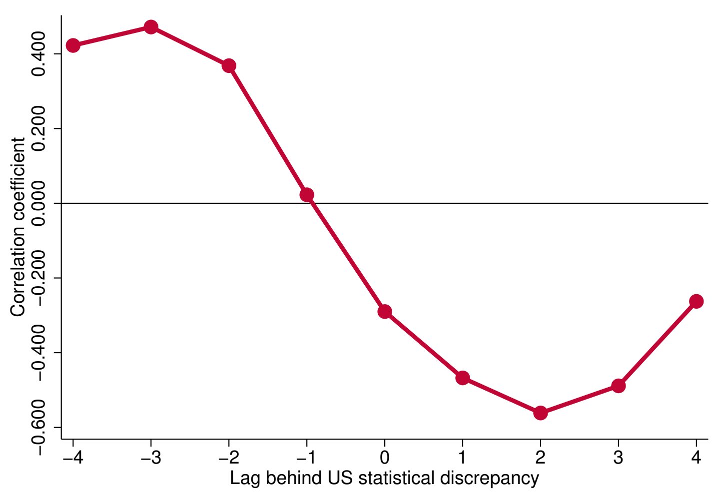


Table A21: Correlations: Foreign deposit outflows vs U.S. foreign deposit inflows

Country	Correlation between foreign deposit outflows & U.S.deposit Inflows	Ave. deposits in banks (USD Billions)
CAN	0.086	44220.02
MEX	0.209	44115.93
CHN	0.636	40169.52
FRA	0.254	39986.32
JPN	0.175	39096.38
DEU	0.071	31945.02
CHE	-0.213	31336.30
IRL	0.394	18025.86
NLD	0.157	16123.29
BRA	0.490	14628.95
ARG	-0.135	11012.84
AUS	0.041	10169.16
ITA	0.110	9993.05
RUS	0.508	9881.36
CHL	0.529	9468.34
KOR	0.309	8390.27
ESP	0.043	7414.02
PER	0.116	7360.84
COL	0.264	5906.38

Source: TIC data and IMF BoPS. Excludes financial centers.

Figure A2-2: Correlation Structure—Bank inflows to the U.S. from China and Hong Kong vs. the U.S. statistical discrepancy



Source: Haver, TIC System, authors' calculations.

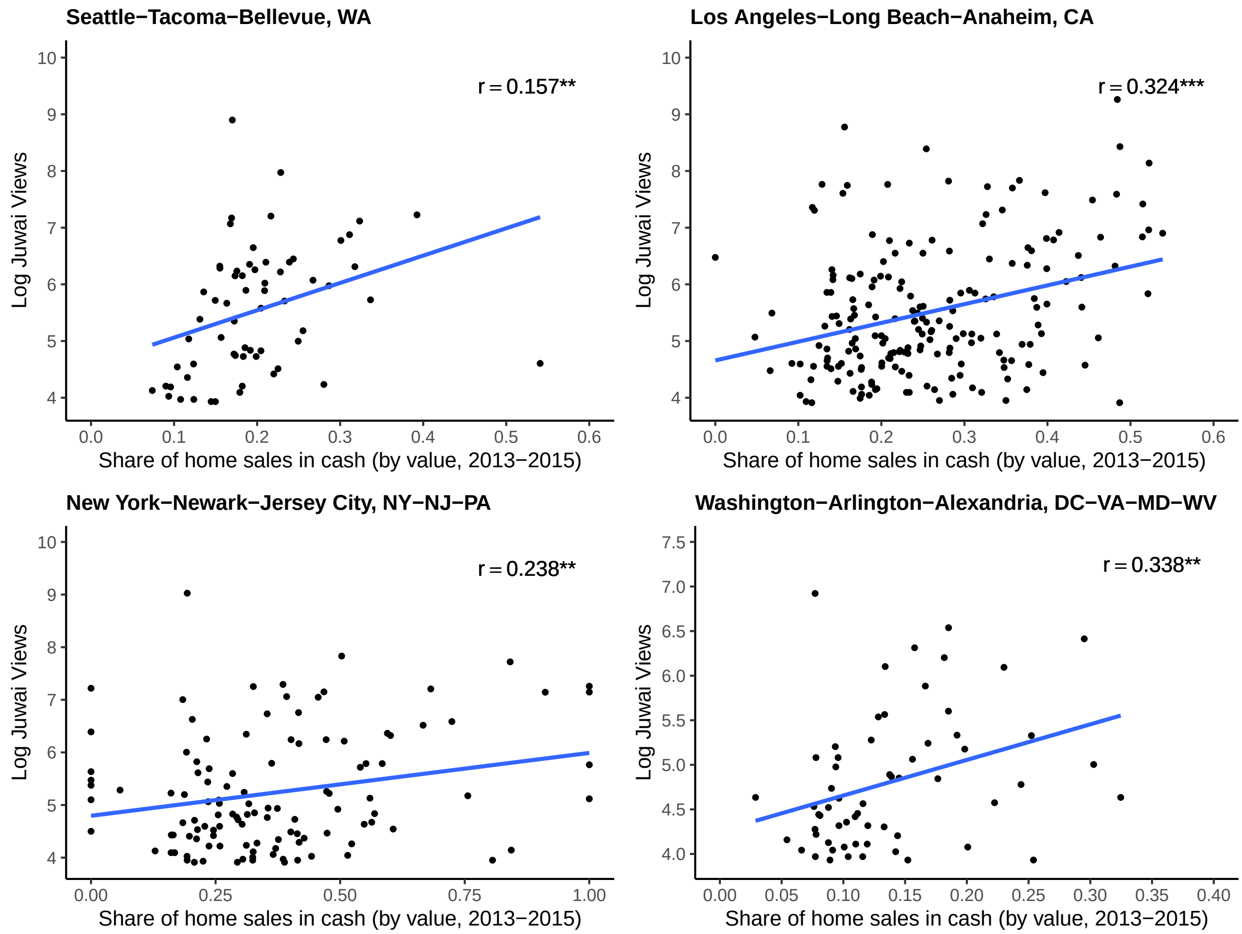
Appendix 3: Additional Analysis of Juwai View Data

In additional to providing information of an overseas real estate property on their website, Juwai also offers consulting services for the potential buyer and helps refer the potential buyer to a real estate brokerage firm abroad. As reported by the Juwai CEO, potential buyers would oftentimes make one visit to the city which their property of interest is located and make a purchase within 6 months. We validate the Juwai data by pairing the passenger arrival data from a Chinese city to a U.S. city. Figure 4 shows that the city-pair arrival data has a 0.54 correlation with the Chinese city-U.S. city pair Juwai data. We also cross-checked the cities which have high Juwai views with the percent of houses purchased wit

Table A31: Share of Juwai U.S. Listing Views, by CBSA

Rank	CBSA	State	Share of Juwai U.S. Views
1	Los Angeles-Long Beach-Anaheim	CA	18.9%
2	New York-Newark-Jersey City	NY-NJ-PA	12.3%
3	Seattle-Tacoma-Bellevue	WA	5.5%
4	Riverside-San Bernardino-Ontario	CA	4.3%
5	San Jose-Sunnyvale-Santa Clara	CA	3.0%
6	Houston-The Woodlands-Sugar Land	TX	2.8%
7	San Francisco-Oakland-Hayward	CA	2.8%
8	Orlando-Kissimmee-Sanford	FL	2.6%
9	Chicago-Naperville-Elgin	IL-IN-WI	2.2%
10	Miami-Fort Lauderdale-West Palm Beach	FL	2.2%
11	Boston-Cambridge-Newton	MA-NH	2.0%
12	San Diego-Carlsbad	CA	2.0%
13	Washington-Arlington-Alexandria	DC-VA-MD-WV	2.0%
14	Sacramento–Roseville–Arden-Arcade	CA	1.9%
15	Philadelphia-Camden-Wilmington	PA-NJ-DE-MD	1.4%
16	Urban Honolulu	HI	1.4%
17	Atlanta-Sandy Springs-Roswell	GA	1.4%
18	Oxnard-Thousand Oaks-Ventura	CA	1.2%
19	Dallas-Fort Worth-Arlington	TX	0.9%
20	Detroit-Warren-Dearborn	MI	0.9%

Figure A3-1: Juwai views vs. cash sales share, by city



Sources: Juwai and CoreLogic.

Figure A3-2: An Example of Matching (Indicator 1): Seattle