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

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Federal Reserve Board

AEA/CSWEP Session on
“Monetary Policy, Capital Flows, and Globalization”
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Motivation

- Foreign purchases of U.S. residential real estate is a "missing" asset class in U.S. balance of payment statistics.
- Most countries do not collect data on foreign purchases of residential real estate.
- But lots of anecdotes of capital flows from China going to housing markets of global cities, with policy-makers in several countries restricting or taxing foreign purchases.
Research Questions

1. Is there evidence of substantial purchases of U.S. residential real estate by foreign Chinese buyers in cross-border capital flows data?
2. What are the drivers of those capital inflows?
3. What, if any, is the price impact on U.S. housing market?
Related Literature

1. Capital flows and House Prices
   ▶ Micro evidence from London (Badarinza & Ramadorai JFE 2018), Germany (Bednarek et al 2019), and California (Li, Shen, and Zhang 2019)
   ▶ Macro evidence: Aizenman & Jinjark (JIMF 2014); Cesa-Bianchi, Cespedes, and Rebucci (JMCB 2015); Sa, Towbin, & Wieladek (JEEA 2014).

2. Out-of-Town Buyers
   ▶ Chinco & Mayer (2016); Favilukis & Van Nieuwerburgh (2018)

3. Foreign Assets and Liabilities
   ▶ Lane & Milesi-Ferretti (2007); Curcuru, Thomas, and Warnock (2008)
Methodology

1. Macro evidence
   - Use balance of payment (BOP) data and Treasury International Capital (TIC) system data to demonstrate that foreign Chinese purchases of U.S. residential real estate likely explain the "missing" capital inflows in U.S. BOP.

2. Micro evidence
   - Identify zip codes across 20-33 major U.S. cities that are relatively heavily exposed to Chinese demand for residential real estate by using a unique dataset of web traffic counts from China of U.S. residential properties listed on a popular Chinese-language real estate website
   - Match China-exposed areas ("treatment group") with otherwise similar non-exposed areas ("control group").
   - Calculate the average difference in house price growth between treatment and control group (ATET)

3. Linking Micro to Macro
   - Show that capital inflows from China explain the time variation in the ATET
Summary of the Findings

1. Aggregate capital flows data are consistent with inflows to U.S. residential real estate market from China.
   ▶ These flows follow periods of economic stress in China, suggesting they are safe haven flows.

2. Price growth is significantly faster in “treated” China-exposed ZIP codes than in matched controls
   ▶ Price growth gap widens by a cumulative 7-14% over 2010-2016, or 1-2% annually

3. Time variation of the price gaps calculated from the matching of micro data significantly explained by aggregate capital inflows from China. The timing of the peak effect (8 months) is consistent with the timing of real estate transactions.
Contributions

1. We offer a fresh interpretation of aggregate capital flows data that reveal the substantial size of the unrecorded asset class of cross-border residential real estate transactions, and demonstrate that they are linked to safe haven flows from China in the past decade.

2. We use a novel dataset that provide a more direct measure of Chinese households’ demand for residential real estate in the U.S. and show that Chinese demand for residential real estate has affected house prices several major U.S. cities.

3. We link micro-level evidence on the effect of Chinese demand on house prices with macroeconomic data on cross-border capital flows and show that they are significantly related.
Plan for the talk

Introduction

Macro Evidence: Aggregate Cross-Border Flows Data

Micro Evidence: The Effects of Foreign Chinese Buyers on U.S. House Prices
   Data
   Matching
   Results: The Average Treatment Effect on the Treated

Linking Micro to Macro

Robustness

Conclusions
Substantial share of Chinese capital outflows placed in U.S. banking system

Correlation: 0.625

Money and deposit outflows from China (LHS)
Change in Chinese & HK deposits in US banks (RHS)
Striking comovement of Chinese capital outflows with unrecorded or ”missing” U.S. inflows since 2010

Source: Haver, authors' calculations. Graph plots correlation between 4–quarters rolling sum of net private outflows from China and US statistical discrepancy.
Unrecorded inflows peaked three quarters after bank inflows from China

Correlation: 0.472

Change in Chinese & HK deposits in US banks (LHS)
3-quarter ahead US statistical discrepancy, excl. CLOs (RHS)
Micro Evidence: Measuring Chinese Demand for U.S. Residential Real Estate

We obtained page views data from Juwai.com (“living abroad”), which lists U.S. properties (and other countries’) on a website catered to potential buyers located in China

▶ Cross sectional snapshot: Nov 2016-Jan 2017
▶ 67,000 views of properties in 7,000 U.S. ZIP codes, located in 917 cities (“Core-based Statistical Areas’,’ CBSAs)

⇒ We use the Juwai views data to measure the demand for U.S. residential real estate originating from China at the ZIP code level

Validate the data by comparing it with

▶ Airline passenger arrivals from China
▶ Share of home sales done in cash in each ZIP
## Share of Juwai Views by City

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

Log passenger arrivals from China vs. Log Juwai Views

Source: Juwai and FAA.

$r = 0.539^{***}$
Validation (2): Share of Cash Sales

Sources: Juwai and CoreLogic.

By City
Determinants of Demand from Foreign Chinese Buyers

City (CBSA) level:

\[ \Delta \ln \text{views}_i = \alpha + \beta_1 \text{chinese\_share\_init}_i + \beta_2 \text{dist\_to\_china}_i + \beta_3 \text{univ}_i \\
+ \beta_4 \ln \text{pop\_init}_i + \beta_5 \ln \text{med\_price\_init}_i \\
+ \gamma_1 \text{temp}_i + \gamma_2 \text{unemp}_i + \gamma_3 \text{commute\_time}_i \\
+ \delta \text{hist\_apprec}_i + \theta_i + u_i \]

ZIP level, with CBSA fixed effect:

\[ \Delta \ln \text{views}_i = \alpha + \beta_1 \text{chinese\_share\_init}_z + \beta_2 \text{dist\_to\_china}_z + \beta_3 \text{univ}_z \\
+ \beta_4 \ln \text{pop\_init}_z + \beta_5 \ln \text{med\_price\_init}_z \\
+ \delta \text{hist\_apprec}_s + \theta_i + u_i \]
## Determinants of Demand from Foreign Chinese Buyers

<table>
<thead>
<tr>
<th></th>
<th>CBSA-level</th>
<th>ZIP-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Chinese share</td>
<td>0.291***</td>
<td>0.258***</td>
</tr>
<tr>
<td></td>
<td>(0.0620)</td>
<td>(0.0623)</td>
</tr>
<tr>
<td>Distance to China</td>
<td>-0.0193</td>
<td>-0.00689</td>
</tr>
<tr>
<td></td>
<td>(0.0527)</td>
<td>(0.0538)</td>
</tr>
<tr>
<td>No.of/Distance to Univ</td>
<td>0.00101</td>
<td>-0.000144</td>
</tr>
<tr>
<td></td>
<td>(0.00633)</td>
<td>(0.00642)</td>
</tr>
<tr>
<td>Population</td>
<td>1.107***</td>
<td>1.109***</td>
</tr>
<tr>
<td></td>
<td>(0.0378)</td>
<td>(0.0385)</td>
</tr>
<tr>
<td>Initial median home price</td>
<td>0.469***</td>
<td>0.710***</td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>Average temperature</td>
<td>-0.0174***</td>
<td>-0.0148**</td>
</tr>
<tr>
<td></td>
<td>(0.00478)</td>
<td>(0.00479)</td>
</tr>
<tr>
<td>Initial unemployment rate</td>
<td>-0.0214</td>
<td>0.00201</td>
</tr>
<tr>
<td></td>
<td>(0.0159)</td>
<td>(0.0154)</td>
</tr>
<tr>
<td>Initial average commute</td>
<td>0.0155</td>
<td>0.0177</td>
</tr>
<tr>
<td></td>
<td>(0.0106)</td>
<td>(0.0108)</td>
</tr>
<tr>
<td>Ave. Δ home price, pre-crisis</td>
<td>0.0404***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00958)</td>
<td></td>
</tr>
<tr>
<td>Ave. Δ home price, pre-2010</td>
<td>0.0271</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0164)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>556</td>
<td>556</td>
</tr>
<tr>
<td></td>
<td>7271</td>
<td>6564</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.824</td>
<td>0.819</td>
</tr>
<tr>
<td></td>
<td>0.383</td>
<td>0.378</td>
</tr>
<tr>
<td>CBSA FE</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

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U.S. Housing as a Global Safe Asset
Matching: Defining Treatment and Control Groups

1. To control for unobserved local effects: match within same CBSA:
   - Treatment: Top 10% of ZIPs in terms of views within the city
   - Control: Bottom 50% in terms of views in same city
   “Apples-to-apples” but limits us to CBSAs with many ZIPs

2. For robustness (shown in paper), match nationally:
   - Treatment: Top 5% of ZIPs in terms of views nationally
   - Control: Bottom 30% in terms of views nationally
   But add additional matching variable: CBSA’s rank in terms of Chinese views
Matching Procedure

Nearest neighbor matching methodology based on Abadie and Imbens (2006)

Match on

- Population size in 2010
- Percent of ethnic Chinese population in 2010
- Log median house price in 2010
- Distance from the nearest college
- Average commute time in 2010
- Average house price appreciation, 2001-2006

For each treated ZIP, select the 5 control ZIPs which have smallest sum of squared differences from the treated ZIP in terms of these six variables
Calculating the Treatment on the Treated Effect

Calculate average treatment effect on the treated

$$\text{ATET} = \sum_{z=1}^{N^{\text{treated}}} \omega_z \left( \Delta \text{price}_z - \Delta \text{price}_z^{\text{control}} \right)$$

Where

$$\Delta \text{price}_z^{\text{untreated}} = \text{average of price growth in the five matched control areas.}$$
Matching Results

Treatment group: ~370 ZIP codes

- Located in 20 CBSAs
- Account for 43 percent of U.S. employment
- Median home price is $500,000 (as of Dec 2016)
Matching Results: Covariates in Treatment and Control

Indicator 1: CBSA=20, Juwai within cbsa percentile<.1 (treatment), >.5 (control)

Note: The line represents a 45 degree line, i.e. points on the line have the same value for control and treatment group.
Matching Results: House price growth 7% faster over the period 2010-2016

Density

6-year house price growth

kernel = epanechnikov, bandwidth = 13.9889

2000-2006

Treated

Matched Control

Density

6-year house price growth

kernel = epanechnikov, bandwidth = 7.2695

2010-2016

Treatment Definition 2
Indicator 1

No. of CBSA=20, Juwai within cbsa percentile<.1 (treatment), >.5 (control)

Treated Matched Control

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U.S. Housing as a Global Safe Asset
Time variation of the price growth gaps reveal local peaks around times of China economic distress after 2010.

**Indicator 1**

No. of CBSA=20, Juwai within cbsa percentile<.1 (treatment), >.5 (control)

![Graph showing time variation of price growth gaps.](#)
Linking Micro Results to Macro Data: time variation of price growth gaps consistent with aggregate 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.
Linking Micro Results to Macro Data

We estimate the following local projection

\[ \text{ATET}_{t+h} = \alpha^h + \beta^h \text{China}_\text{Deposit}_\text{Inflows}_t + \gamma^h_1 \Delta \text{NFP}_t + \gamma^h_2 r^\text{mort}_t \]

\[ + \sum_{j=1}^{9} X_{t-j} \Lambda_j^h + \varepsilon_t \]

Where

\[ \text{ATET}_{t+h} = \text{Average gap between price growth in China-exposed U.S. ZIP codes and matched non-exposed ZIP codes at time } t + h \]

\[ \text{China}_\text{Deposit}_\text{Inflows}_t = \text{Deposit inflows to the U.S. from China and HK at time } t, \% \text{ of Chinese and HK deposits at } t - 1 \]

\[ \Delta \text{NFP}_t = \text{Growth in U.S. nonfarm payrolls, seasonally adjusted, month-on-month} \]

\[ r^\text{mort}_t = 30\text{-year U.S. mortgage rate} \]

\[ X_{t-j} = \text{vector of lagged dependent variable and controls} \]
Results:
Chinese Inflows and the Price Growth Gap

Response of treatment effect to one percentage point increase in 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.)
Robustness Tests

1. Construct same matching estimator for placebo ZIP codes
   ▶ Identify as treated “hot” areas with a recent history of rapid house price appreciation.
   ▶ Resulting price growth gap (significant by construction) is unrelated to any China shocks.

2. Treatment effect is not significantly related to U.S. domestic variables in the local projections. ▶ Results

3. Test relationship between our estimated treatment effect and capital inflows from countries other than China
   ▶ Confirm that the relationship we uncover is not simply a reflection of a global financial or global housing cycle.
Conclusions

Aggregate capital flows data suggests inflows from China being used to purchase U.S. residential real estate following periods of economic stress in China since 2010. Suggests these are safe haven flows.

Areas of the U.S. exposed to Chinese demand see significantly higher house price appreciation than matched control areas that attract little of these safe haven flows.

Local projections show a significant relationship between aggregate deposit inflows to the U.S. from China and the average treatment on the treated effect using micro data, with the timing consistent with real estate transactions.
Appendix Slides
Share of Cash Sales, Major Cities

Seattle–Tacoma–Bellevue, WA

Los Angeles–Long Beach–Anaheim, CA

New York–Newark–Jersey City, NY–NJ–PA

Washington–Arlington–Alexandria, DC–VA–MD–WV


Log Juwai Views

Sources: Juwai and CoreLogic.
Distribution 6-year House Price Growth, Treatment Definition 2

2000-2006

6-year house price growth

Density 0.005 0.01 0.015 0.02

Treated
Matched Control

kernel = epanechnikov, bandwidth = 14.0681

2010-2016

6-year house price growth

Density 0.005 0.01 0.015

Treated
Matched Control

kernel = epanechnikov, bandwidth = 6.5921
House Price Levels, Treated vs. Control Areas

Indicator 2

No. of CBSA=33, Juwai across cbsa percentile: <.05 (treatment), >.3 (control)
Price Growth Gap, Treated vs. Control Areas

Indicator 2

No. of CBSA=33, Juwai across cbsa percentile: <.05 (treatment), >.3 (control)
Results:
Chinese Inflows and U.S. Domestic Variables

Response of treatment effect to a one-unit shock to:

- Nonfarm Payrolls Growth (%)
- 30-year Mortgage Interest Rate

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

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Placebo Tests:
Other Countries’ Inflows and the Price Growth Gap

![Graph showing the price growth gap over time.](image-url)