Online Appendix

This document contains additional material referenced in the text. Appendix A describes the paper's datasets and variables in detail. Appendix B contains additional robustness exercises referenced in Section 6. Appendix C provides methodological details on the hedonic adjustment used to evaluate the robustness of the results in Section 8.

A Data

This appendix describes the raw collection and subsequent cleaning of the datasets referenced in Section 2 of the text. These datasets are: Trepp's T-ALLR (A.1) and T-Loan datasets (A.2); the Real Capital Analytics transactions dataset (A.3); and the Census' AHS dataset (A.4). Section A.5 describes additional datasets used in the paper. Section A.6 describes how the county-level variables used in the paper's main tables are constructed.

A.1 T-ALLR Dataset

The paper's first core dataset is Trepp's Anonymized Loan Level Repository (T-ALLR) dataset. The T-ALLR dataset contains information on bank portfolio loans secured by apartment properties. Trepp collects the raw data from clients of its Bank Solutions consulting service. The raw data cover 10% of U.S. counties, or 52% of counties on a population-weighted basis.

A.1.1 Timespan

The T-ALLR dataset is structured as a quarterly loan-level panel over 2013-19. I observe the loan's year of origination, which allows me to compute the aggregate time series shown in Figure A1b. To calculate the value of bank portfolio loan balances in a county in 2010 (i.e., $\textit{Bank Portfolio Balances}_c$), I first retain all loans originated in 2010 or earlier. Then, I amortize each loan's balance from the first year it is observed in the sample back to 2010 according to the reported amortization schedule. For amortizing loans, I apply a reverse straight-line amortization based on the loan's term. After amortizing each loan's balance back to 2010, I calculate the sum of balances in the county.

A.1.2 Lender-Level Information

I do not observe the bank's identity, but, according to Trepp, the T-ALLR dataset includes a majority of banks subject to CCAR stress tests and a quarter of those subject to DFAST tests. Moreover, again according to Trepp, no bank accounts for more than 16% of total loan balances. Thus, although the T-ALLR dataset only covers Trepp's clients, it is not skewed toward any one particular bank.

A.1.3 Property-Level Information

There is a unique identifier for each loan, but I do not observe identifying information about the encumbered property. This latter feature is intended to protect the lender's privacy. To further protect the lender's privacy, all dollar variables are scaled by a random factor between 95% and 105%. I observe whether the loan's purpose is construction, the terms of the loan (e.g., interest rate), and the property's occupancy. I do not observe whether the loan finances an improvement, the history of renovations on the property, the property's rent, the number of units in the property, or any other physical characteristics about the property apart from the zip code and county in which it is located. Reporting geographic information is optional, and for 15% of loans the bank chooses not to do so.

As stated in the note to Figure A1, I use two proxy measures for whether a loan in the T-ALLR dataset finances an improvement. First, I use an indicator for whether the loan's purpose is not construction. Second, I impute whether the loan finances a renovation using observable loan characteristics applied to Trepp's T-Loan dataset. Specifically, using the T-Loan dataset, I regress an indicator for whether the loan finances a renovation on the following characteristics of the loan: interest rate, loan-to-value ratio, occupancy, and a fixed effect for the property's county. Then, I use the estimated coefficients to predict the probability a loan in the T-ALLR dataset finances a renovation. I classify a loan as financing a renovation if this probability exceeds the empirical probability in the T-Loan dataset (8.6%). This procedure correctly classifies 85% of renovation loans in the T-Loan dataset.

A.2 T-Loan Dataset

The paper's second core dataset is a random sample of Trepp's merged Property, Loan, and Loan2 datasets, which I simply refer to as "T-Loan" in the text. The T-Loan dataset contains information on loans secured by apartment properties that have been securitized as commercial mortgage backed securities (CMBS). The raw data come from CMBS servicing records for loans that were securitized by the fourth quarter of 2017. Trepp utilizes all resources available to construct these data, including Annex A's, Servicer Set-Up files, CREFC Loan and Property Periodic Files, and various third party resources. The raw data cover 47% of U.S. counties, or 90% of counties on a population-weighted basis.

A.2.1 Timespan

The T-Loan dataset is structured as a monthly loan-level panel over 2010-16. Unlike the T-ALLR data, the T-Loan dataset has an identifier for both the loan and the encumbered property, and so I collapse the T-Loan dataset to an annual property-level panel. Since the T-Loan dataset begins in 2010, I can directly calculate the value of securitized loan balances in a county (i.e., $\textit{All Securitized Balances}_c$, $\textit{Bank Securitized Balances}_c$).

As mentioned below, I observe the history of renovations on a property dating back to 2000. This allows me to backfill the time series in Figure 1a as follows. For the numerator (i.e., number of renovated units), I compute the sum of in-sample units that were renovated in t, conditional on the property's loan being securitized by t so that the property would have been included in a pre-2010 version of the sample. For the denominator, I regress the log number of apartments in the sample over 2010-16 on the log aggregate stock of U.S. rental units from the Census' Housing and Vacancy Survey, which is available beginning in 2000. Then, I backfill the number of units that would have been in a pre-2010 version of the sample. Taking the ratio of numerator and denominator gives the pre-2010 time series in Figure 1a. Renovations undertaken in the latter part of the 2010-16 period may not appear in the sample because of securitization lags. Therefore, Figure 1a weights observations by the inverse probability of appearing in the sample (Solon, Haider and Wooldridge 2015), here defined as the empirical probability of being securitized by the fourth quarter of 2017.

A.2.2 Lender-Level Information

I observe the name of the loan's originator for 92% of the T-Loan sample, where, as mentioned in the text, I use the terms "originator" and "lender" synonymously for simplicity. I observe the name of the borrower for 14% of the sample. I address cases where the name's spelling changes using Stata's string grouping algorithm *strgroup*, developed by Julian Reif, to aggregate different spellings under a single identifier. I manually review the matches to check accuracy. For the small minority of cases in which a property has multiple loans from different lenders, I assign the lender with the largest balance to the property.

Banks are defined as having a record in the FDIC's Institution Directory. I do not classify independent nonbank subsidiaries as depository institutions. Based on this classification, 39% of lenders in my data are depository institutions. There are some non-depository institutions, like Prudential, that are classified as Designated Financial Companies and, thus, required to compute risk-based capital requirements as if they were a bank holding company. Since my focus is on the effects of capital requirements, I classify such lenders as banks. Apart from these special cases, "bank" is synonymous with "depository institution". In Section 6.8, I normalize originations to have unit variance within lender-purposes to account for different business models.

A.2.3 Property-Level Information

The T-Loan dataset has substantially more property-level information than the T-ALLR dataset. In particular, I observe: the latitude and longitude of the encumbered property; the number of units, occupancy, and revenue of the property, which I use to calculate rent as described in Section A.6 below; the terms on the property's loan (e.g., interest rate); the property's physical condition based on professional property inspection ratings; the year the property was built; whether the loan's purpose is construction; and the history of renovations dating back to 2000. Renovations are defined as improvements that require the inhabitant to vacate the housing unit for some period of time. They differ from new construction in that the building's foundation remains unchanged.

I classify a loan as financing a renovation if it is originated within 1 year of a renovation.

I classify a loan as financing construction if its stated purpose is construction or if it was originated within 3 years of the property being built. The latter restriction accounts for the fact that most loans for construction have a construction-to-permanent financing structure, where the lender provides a short-term variable rate note that converts to a long-term note once the project has stabilized. Such loans are more difficult to securitize prior to conversion (Black, Krainer and Nichols 2017).

A.3 RCA Dataset

In Section 6.1, I evaluate robustness to data provider by replicating the baseline analysis using a dataset on apartment transactions from Real Capital Analytics (RCA). The raw data come from transaction records for apartment properties and cover 40% of U.S. counties, or 88% of counties on a population-weighted basis.

A.3.1 Timespan

The RCA dataset spans 2009-16 and includes one observation per transaction. I calculate the value of loan balances in a county in 2010 using the value of loans originated in 2010.

A.3.2 Lender-Level Information

I observe the name of the lender who originates the loan associated with the transaction. Importantly, the RCA dataset includes both portfolio and securitized loans. I classify the lender as a bank if its name contains the terms "Bank", "Bk", "Bnk", "B&T", "Banc", "BANK", "bank", "FSB", "Savings", "Credit Union", or "CU", since savings banks and credit unions are present in the RCA dataset and are also subject to HVCRE regulation. I manually review the resulting classification for lenders with over 0.1% of origination volume over 2009-16 and adjust the classification based on whether the lender has a record in the FDIC's Institution Directory, accessed through the FFIEC's Institution Lookup Tool.

A.3.3 Property-Level Information

I observe the county of the transacting property and the year when the property was renovated. I do not observe the property's rent, occupancy, physical characteristics, or information about the loan associated with the transaction, apart from the loan's size in dollars.

A.4 AHS Dataset

I use the Census' American Housing Survey (AHS) dataset to produce Figure 1b and to perform the hedonic quality adjustment in Section 8.1. The raw data come from a survey administered by the U.S. Census Bureau in odd numbered years. I observe very little geographic information, but, in principle, the AHS dataset is representative of the universe of U.S. counties.

A.4.1 Timespan

The AHS was introduced in 1973 but has undergone several sample redesigns since then. In particular, the dataset is structured as a biennial panel of housing units, but the panel broke in 1995 and again in 2015 due to sample redesigns. Consequently, I can only track the same housing unit over time from 1997-2013.

A.4.2 Information about Housing Units

I observe the housing unit's rent, demographic information about the occupant, and relatively granular information about the housing unit's physical features (e.g., presence of a dishwasher), based on the AHS's Equipment and Appliances module. I clean the raw data as follows: I winsorize rent by 5% on both sides prior to aggregating rent in equation (C3); I restrict attention to housing units whose tenure did not change over the sample period, thus filtering out "condo conversions"; I define improvements as the installation of new features, as described in Section 8.1 of the text. Since the AHS panel broke in 1995 and 2015, I only observe such improvements over the 1997-2013 period. Table A6 provides summary statistics of improvements in the AHS dataset.

The public-use AHS dataset does not contain information about the housing unit's county. The only geographic observation I observe is the housing unit's MSA for a subset of 166 MSAs out of 384, or 43%. I use this limited geographic information to sort renters into quintiles by their log real income relative to the MSA-year mean, as described in the note to Figure 1b. Prior to sorting, I restrict renters to those living in apartments (i.e., multifamily properties) and bottom-code income at $12,000 in 2017 dollars. Income is calculated using the AHS's family income variable.

A.5 Additional Datasets

A.5.1 Call Reports

Data on bank balance sheets used in Table A5 come from Schedule FR Y-9C (i.e., the Call Reports). To merge Call Report data with the baseline Trepp dataset, I create a manual crosswalk file by cross-referencing each bank's name from the Trepp data with its closest match in the FDIC's Institution Directory, accessed through the FFIEC's Institution Lookup Tool. For cases where a bank's name in Trepp does not unambiguously map to a single name in the FDIC's Institution Directory, I match the Trepp name to the name of the largest bank within the set of candidates in the FDIC's Institution Directory, by assets. For example, if the bank is called "First Bank" in the Trepp data, and the closest matches in the FDIC's Institution Directory are the names "First Savings Bank" and "First Bank, N.A.", I match First Bank with the larger of First Savings Bank and First Bank, N.A., by assets.

A.5.2 Income

Data on county-level real income per capita come from the Bureau of Economic Analysis and are at the MSA-year level. I merge them to the Trepp county-level dataset using the MSA associated with each county. Zip code level income data come from the Internal Revenue Service (IRS) SOI Tax Stats. Average income is defined as total adjusted gross income divided by number of tax returns. Data were not available for 2016 at the time of this paper's writing, and so I forward fill the 2016 data using an average of 2014 and 2015 values.

A.5.3 Inflation

Data on inflation come from the Bureau of Labor Statistics (BLS) and the Federal Housing Finance Agency (FHFA). I deflate nominal rent using CPI excluding shelter, from the BLS. I deflate aggregate investment in residential improvements using the FHFA all-transactions price index, as shown in Figure A1a.

A.5.4 Rent Control

Data on states with rent control or stabilization policies come from Landlord.com and are as of 2011.

A.6 Description of Variables

(a) *Portfolio Bank Share*$_c$: This variable is defined as the ratio of bank portfolio loan balances in county c in 2010 to the sum of bank portfolio loan, bank securitized loan, and nonbank securitized loan balances in county c in 2010. Data on bank portfolio loan balances are from the T-ALLR dataset. Since the T-ALLR dataset begins in 2013, I amortize portfolio loan balances back to 2010 using the amortization method described in Section A.1. I impute a value of zero for portfolio loan balances in counties observed in the T-Loan dataset but not in T-ALLR. Data on securitized loan balances are from the T-Loan dataset.

Taking the unweighted sum of balances observed in T-ALLR and T-Loan leads to measurement error because neither dataset is fully representative of each U.S. county. I attenuate this measurement error by reweighting securitized loan balances by a factor such that the share of loan balances held on banks' portfolios within each MSA matches the aggregate share as reported in the 2010 Financial Accounts of the United States. I apply this reweighting whenever I take the sum of quantities observed in the T-ALLR and T-Loan datasets.

(b) *Securitized Bank Share*$_c$: This variable is defined in the same way as in (a), except that the numerator is replaced by bank securitized loan balances in county c in 2010.

(c) *Total Bank Share*$_c$: This variable is defined in the same way as in (a), except that the numerator is replaced by the sum of bank portfolio and bank securitized loan balances in county c in 2010. In Table 3, I calculate this variable using the RCA dataset and define it as the ratio of bank portfolio loan origination volume in county c in 2010 to total loan origination volume in county c in 2010, since I do not observe outstanding balances in the RCA dataset.

(d) $\log(\textit{Bank Loans}_{c,t})$: This variable is defined as the log of one plus the number of bank portfolio loans originated in county c and year t for purposes other than construction. Data are from the T-ALLR dataset.

(e) $\log\left(\textit{Renovated Properties}_{c,t}\right)$: This variable is defined as the log of one plus the number of properties experiencing a renovation in county c and year t. Data are from the T-Loan dataset. In Table 3, I calculate this variable using the RCA dataset and define it in the same way as when using the T-Loan dataset. With both datasets, I exclude renovations occurring before the first year the property appears in the sample, and I include renovations that do not coincide with a new loan.

(f) $\log\left(\textit{Renovated Apartments}_{c,t}\right)$: This variable is defined as the log of one plus the product of the number of properties experiencing a renovation in county c and year t times the number of units in each of those properties. Data are from the T-Loan dataset. I exclude renovations occurring before the first year the property appears in the sample, and I include renovations that do not coincide with a new loan.

(g) $\log(\textit{Renovation Value}_{c,t})$: This variable is defined as the log of one plus the sum of revenue across properties experiencing a renovation in county c and year t. Data are from the T-Loan dataset. I exclude renovations occurring before the first year the property appears in the sample, and I include renovations that do not coincide with a new loan.

(h) $\log\left(\textit{Newly-Built Properties}_{c,t}\right)$: This variable is defined as the log of one plus the sum of construction projects observed in the T-ALLR and T-Loan datasets in county c and year t. If there are no construction projects observed in the combined Trepp dataset, then I replace this variable with the log of one plus the number of apartment construction permits issued, based on data from the Census' Building Permits Survey.

(i) $\Delta\log\left(\textit{Top-Quality Properties}_{c,t}\right)$: This variable is defined as the one-year change in the log of one plus the product of the number of properties in county c and year t times share of apartments ranked in the top quality segment by professional property inspectors. Property inspection ratings are based on the Mortgage Bankers Association and Commercial Real Estate Finance Council's (MBA/CREFC) property inspection rating. This rating is regularly collected as part of the standard apartment loan servicing protocol. Its purpose is to minimize agency frictions that might incentivize the borrower to not maintain the property's competitiveness. This rating has a discrete scale from 1 to 5, where lower values indicate greater quality relative to a unit that reflects "the highest current market standards". There is a checklist of features to help inspectors assign properties the appropriate score. Data are from the T-Loan dataset.

(j) $\Delta \log \left(\textit{Average Rent}_{c,t} \right)$: This variable is defined as the one-year change in the log of the weighted average rent across properties in county c and year t, weighting by the number of units in each property. A property's rent is calculated as revenue per occupied unit. I replace this variable with an empty value when it exceeds 25 log points. Data are from the T-Loan dataset.

(k) $\Delta \textit{Cost-Burdened Share}_{c,t}$: This variable is defined as the one-year change in the weighted share of properties in county c and year t whose rent exceeds 30% of the average income for its corresponding zip code in year t, weighting by the number of units in each property. A property's rent is calculated as revenue per occupied unit. Data on rent are from the T-Loan dataset. Average zip code-level income is defined as total adjusted gross income divided by the number of tax returns, based on data from the IRS SOI Tax Stats.

(l) $\Delta \log \left(\textit{Top-Quintile Rent}_{c,t} \right)$: This variable is defined as the one-year change in the log of the weighted average rent across properties in county c and year t whose rent is above the 80^{th} percentile within c and t, weighting by the number of units in each property. A property's rent is calculated as revenue per occupied unit. I replace this variable with an empty value when $\Delta \log \left(\textit{Average Rent}_{c,t} \right)$ exceeds 25 log points. Data are from the T-Loan dataset.

(m) $\textit{GSE Share}_{c,t}$: This variable is defined as the share of securitized loan balances in county c and year t that are backed by the Government Sponsored Enterprises (GSEs). Data are from the T-Loan dataset. I identify loans backed by the GSEs as those whose CMBS deal begins with the strings "fn" or "fh".

B Additional Robustness

This appendix describes additional robustness tests referenced in Section 6.

B.1 Time-Varying Local Demand

I reperform the baseline analysis after allowing for nonparametric time trends by county characteristics related to household demand and physical supply. This exercise allows me to test whether the treatment variable, $\textit{Total Bank Share}_c \times \textit{Post}_t$, spuriously captures time-varying, non-financial shocks to improvement activity. The estimated effect in Table A8 is stable across specifications, making it unlikely that such unobserved shocks bias the results.

B.2 Measuring Exposure with the Office Sector

In Table A9, I measure exposure to HVCRE regulation using loans secured by office buildings, based on a version of the T-Loan dataset that covers the office sector. The corresponding results are similar to those from Table 2, supporting their validity.

B.3 Sensitivity to Functional Form

I estimate a cross-sectional version of equation (1) and plot the results in Figure A3. There is no clear nonlinearity in the treatment effect, which suggests that the linear functional form in equation (1) is a best-approximation.

B.4 Geographic Distribution of Exposure

In Figure A4, I plot the distribution of banks' share of apartment loan balances in 2010 across states to assess geographic clustering. If the effect of any such clustering on improvement activity is slow-moving, then it would be subsumed by the county fixed effect in equation (1). On the other hand, if such clustering predisposes a county to changes in improvement activity that coincide with the introduction of HVCRE regulation, then the baseline results could be biased. However, Figure A4 shows how the distribution is fairly uniform across states, suggesting that the scope for bias due to geographic clustering is small.

C Quality-Adjusted Rent

This appendix provides additional methodological details and results related to the hedonic adjustment referenced in Section 8 of the text. As mentioned in the text, the purpose of this exercise is to assess the plausibility of the large estimated aggregate effect of HVCRE regulation shown in Table 9.

Hedonic adjustments have a long tradition in the housing literature, as summarized by Sheppard (1999). The pricing kernel shown in equation (11) of the text combines elements of repeat-"sale" (i.e., repeat-rent) and hedonic indices, which has several well-known advantages (e.g., Meese and Wallace 1997). Reproducing that equation below, I estimate

$$\Delta \log \left(Rent_{i,t}\right) = \beta^{\Theta} \Delta\Theta_{i,t} + \alpha_i + \alpha_t + u_{i,t}, \tag{C1}$$

where the notation is the same as in Section 8.1 of the text. All changes are over 2 years because the AHS is administered biennially. I estimate equation (C1) over 1997-2013 to utilize additional variation, but I only perform the adjustment over 2007-13. Finally, the housing unit and year fixed effects α_i and α_t account for the possibility that improvements only occur in some locations or in certain years.

The features in $\Theta_{i,t}$ are: a dishwasher, trash compactor, garbage disposal, washing machine, dryer, air conditioning (A/C), central A/C conditional on installing A/C, and log square feet. For the case of square feet, $\Delta\theta_{i,t}$ is the increase in log square feet and not an indicator for the installment of the feature. I choose these features because they are available for 85% of units in the sample. The estimated loadings on each feature are shown in Appendix Table A7.

I next compute a housing unit's quality-adjusted rent as shown in equation (12), reproduced below as

$$Rent^{H}_{i,t} = Rent_{i,t_0} \times \exp\left[\sum_{\tau=t_0+2}^{t} \left(\Delta \log\left(Rent_{i,\tau}\right) - \beta^{\Theta}\Delta\Theta_{i,\tau}\right)\right] \tag{C2}$$

where the notation is again the same as in Section 8.1. Then, I define the hedonic index π^H_t as the normalized average of $Rent^H_{i,t}$ across housing units i,

$$\pi^H_t = \frac{\sum_i Rent^H_{i,t}}{\sum_i Rent_{i,t_0}}. \tag{C3}$$

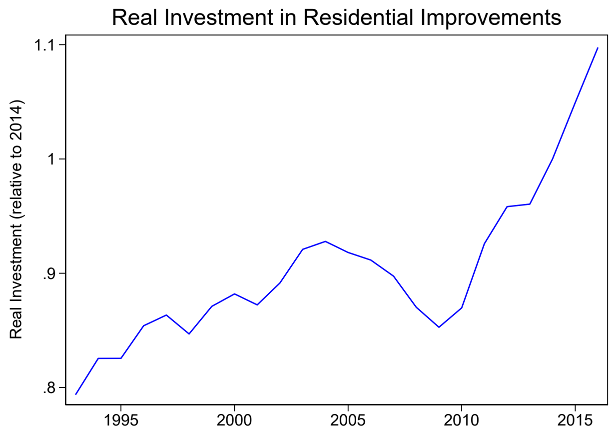
As described in Appendix A, I drop units that experienced a change in tenure (e.g., "condo conversions") from my analysis. The aggregation in equation (C3) has the same basic form as that used by the Bureau of Labor Statistics (BLS) after accounting for the fact that I work at a biennial frequency (Gallin and Verbrugge 2007).

Figure A5a summarizes 2007-13 annual growth in π^H_t and other related indices. The baseline hedonic index, shown in the center of the figure, saw 0.5% real growth, as in Figure 5. Moving to the left, I perform an age adjustment similar to that used by the BLS. This gives a real growth rate of 1.8%, slightly higher than the 1.7% growth in unadjusted average rent. The overall level of rent growth is close to what one would expect given growth in the CPI's rent of primary residence over the period, since rent growth based on the AHS is on average 0.8 pps higher than CPI-based rent growth (McCarthy, Peach and Ploenzke 2015). The indices to the right of the baseline in Figure A5a perform two robustness checks. First, I reestimate equation (C1) after allowing the price vector β^{Θ} to vary by year. This results in a similar growth rate of 0.7%. Second, I control for the change in the renter's income in the pricing equation (C1). While non-standard, this additional control absorbs the effect of time-varying characteristics of the housing unit that correlate with both improvements and the renter's income growth. The resulting growth rate is almost unchanged at 0.5%. Finally, Figure A5b recalculates the hedonic index over various subperiods. The results suggest that the large contribution of improvements to rent growth is largely a post-Recession phenomenon, as there is little difference between unadjusted and quality-adjusted rent growth over 1997-2007 or 2001-05.

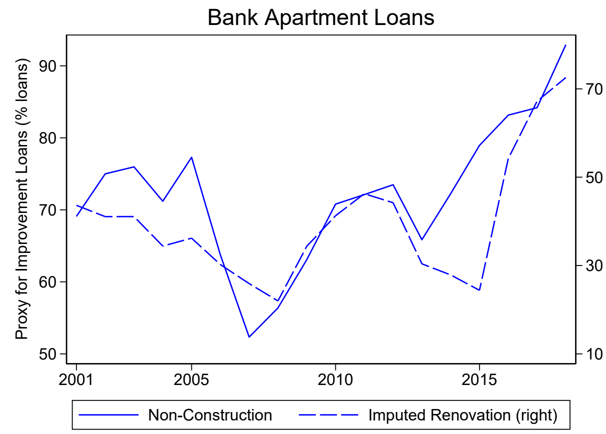
Collectively, the results of this hedonic adjustment imply that quality improvements explain a significant share (e.g., 70%) of observed real rent growth over 2007-13. This finding lends plausibility to the large effect of HVCRE regulation on rent growth over 2015-16 shown in Table 9.

Additional Figures and Tables

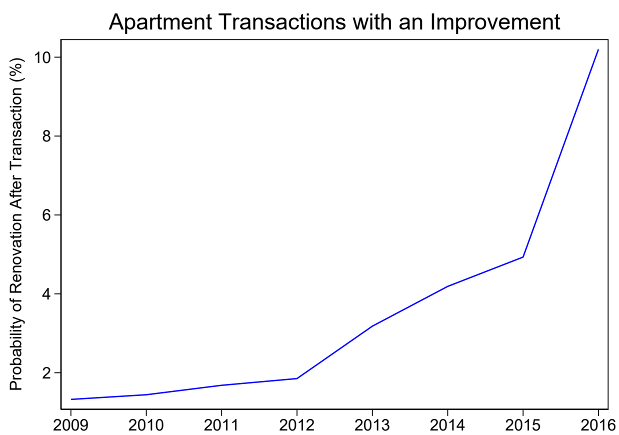
Figure A1: Robustness of Stylized Facts



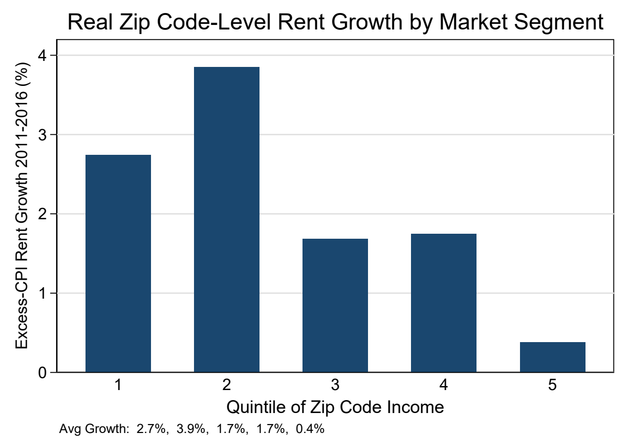
(a) Aggregate Improvement Spending



(b) Bank Apartment Improvement Loans



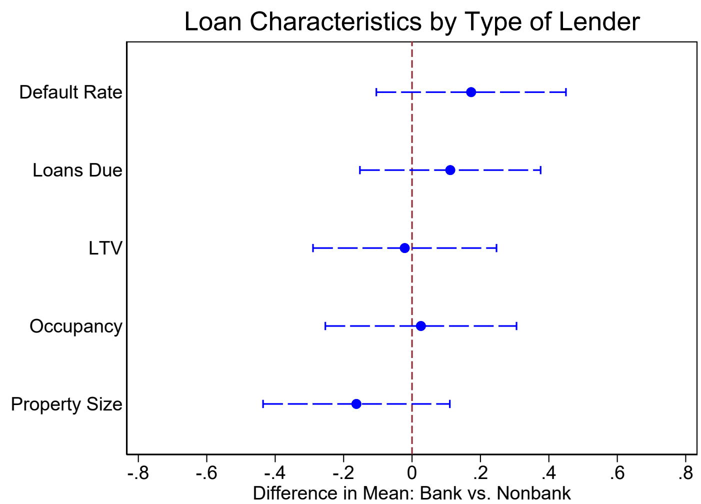
(c) Apartment Transactions with an Improvement



(d) Zillow-Based Real Rent Growth by Segment

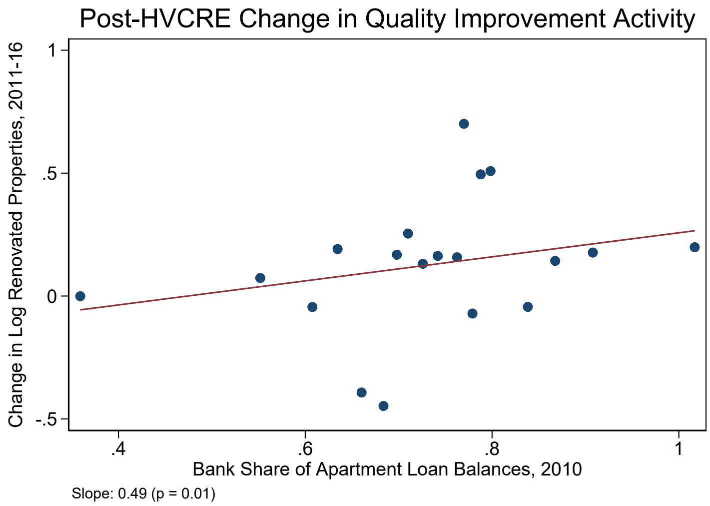
Note: This figure assesses the robustness of the stylized facts in Figure 1 to alternative datasets and measures of improvement activity. Panel (a) plots real aggregate investment in residential improvements, based on the U.S. Fixed Assets Accounts. Panel (b) plots the share of bank loans that are for apartment improvements, based on Trepp's T-ALLR dataset. The plot uses two proxy measures for whether the loan finances an improvement: whether the loan's purpose is not construction (Non-Construction); or whether the loan is imputed as financing a renovation using observable loan characteristics applied to Trepp's T-Loan dataset, as described in Appendix A.1.3 (Imputed Renovation). Panel (c) plots the share of property-years experiencing a renovation conditional on the property transacting in the year shown on the horizontal axis or in the year after it, based on the RCA dataset. Panel (d) plots real growth in average zip code level apartment rent by income quintile, based on Zillow's Zip Code Level Multifamily Rent Index. Zip codes are sorted into quintiles by log average real income in the zip code relative to the MSA-year mean, based on the IRS SOI Tax Stats.

Figure A2: Difference in Loan Specialization between Banks and Nonbanks



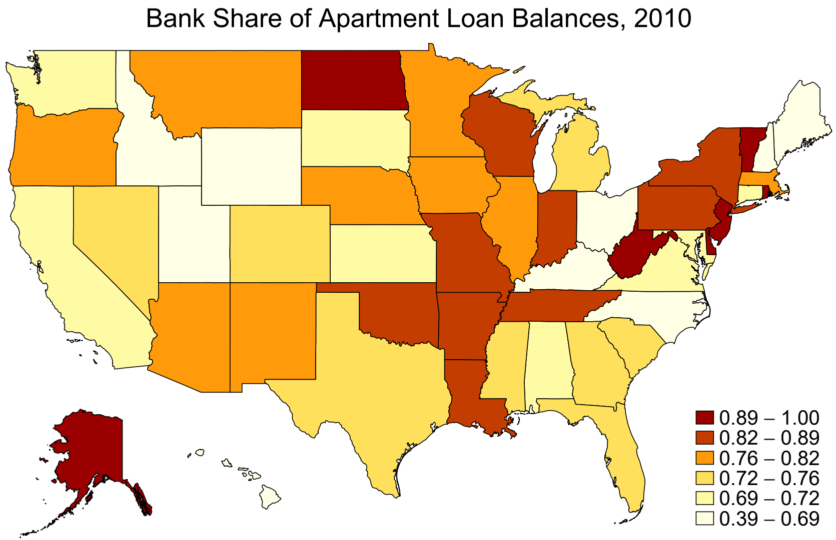
Note: This figure assesses the exclusion restriction associated with the first-stage results in Table 6 by plotting the average difference in the indicated variable between bank and nonbank lenders. Variables are normalized to have zero mean and unit variance and aggregated to the lender-level by averaging across loans over 2011-16, weighting by loan principal. Default Rate and Loans Due are, respectively, the share of loans 60+ days delinquent and the share of loans coming due in a given year. LTV is the current loan-to-value ratio. Occupancy is the property's occupancy rate. Property Size is in number of apartment units. Brackets are a 95% confidence interval with heteroskedasticity robust standard errors. Data are from Trepp's T-Loan dataset.

Figure A3: County-Level Improvements and HVCRE Regulation in the Cross-Section



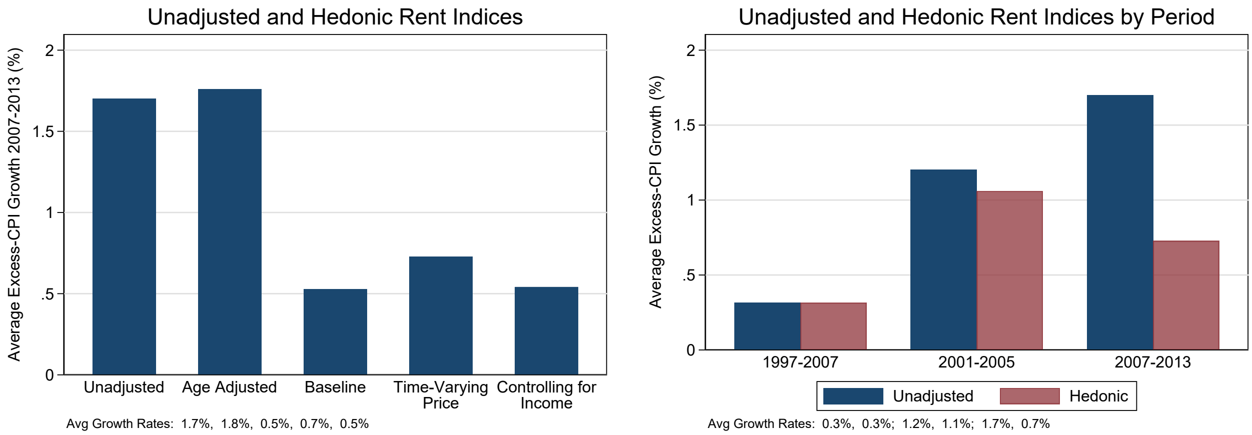
Note: This figure plots the results of a cross-sectional version of equation (1), which assesses robustness to functional form. The vertical axis shows the change in log renovated apartment properties from the 2011-14 period to the 2015-16 period. The horizontal axis shows banks' share of apartment loan balances in 2010, corresponding to the variable *Total Bank Share*$_c$. Variables are demeaned by state. The plot is binned so that each point corresponds to roughly 30 counties. Data for the variable on the vertical axis are from Trepp's T-Loan dataset. Data for the variable on the horizontal axis are from Trepp's T-ALLR and T-Loan datasets.

Figure A4: Geographic Distribution of Exposure Variable



Note: This figure plots banks' share of apartment loan balances in 2010 across states to assess whether exposure to HVCRE regulation exhibits geographic clustering. Data are from Trepp's T-ALLR and T-Loan datasets.

Figure A5: Robustness of the Hedonic Adjustment



Note: This figure plots additional results described in Appendix C that assess the robustness of the baseline hedonic adjustment in Section 8.1. Panel (a) plots average annual growth in real (i.e., excess-CPI) rent over 2007-13 for various rent indices. Unadjusted denotes average observed rent. Age Adjusted performs an age adjustment similar to that used by statistical agencies. Baseline denotes the hedonic index. Time-Varying Price denotes the baseline index after allowing the coefficients in equation (11) to vary by year. Controlling for Income denotes the baseline index after controlling for the change in the renter's income percentile. Panel (b) plots average annual real growth in unadjusted rent and the hedonic index for various periods, allowing the coefficients in equation (11) to vary by year. Data are from the Census' AHS dataset.

Table A1: Largest Originators over 2011-16

Rank	Originator	Type of Originator
1	CBRE Capital	Nonbank
2	Berkadia	Nonbank
3	Holliday Fenoglio Fowler	Nonbank
4	Walker & Dunlop	Nonbank
5	Berkeley Point Capital	Nonbank
6	Wells Fargo	Bank
7	NorthMarq Capital	Nonbank
8	KeyCorp	Bank
9	Capital One	Bank
10	Jones Lang LaSalle	Nonbank
11	Grandbridge Real Estate	Nonbank
12	JP Morgan	Bank
13	Beech Street Capital	Nonbank
14	PNC	Bank
15	Prudential	Bank

Note: This table shows the largest 15 originators of securitized apartment loans over 2011-16 based on Trepp's T-Loan dataset. Originators are ranked by volume of loans originated. Prudential is classified as a bank because it is a Designated Financial Company, as described in Appendix A.2.

Table A2: Robustness to Excluding Improvements by Large Borrowers or Reclassified Improvements

Outcome:	$\log\left(Renovated\ Properties_{c,t}\right)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Total\ Bank\ Share_c \times Post_t$	0.323	0.352	0.323	0.326	0.353	0.318
	(0.068)	(0.029)	(0.002)	(0.066)	(0.030)	(0.002)
Excluded Renovations	Large Borrowers	Large Borrowers	Large Borrowers	Potentially Reclassified	Potentially Reclassified	Potentially Reclassified
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	No	Yes	Yes	No	Yes	Yes
State-Year FE	No	No	Yes	No	No	Yes
R-squared	0.566	0.609	0.719	0.569	0.610	0.723
Number of Observations	3,128	3,128	3,128	3,128	3,128	3,128

Note: P-values are in parentheses. This table estimates equation (1), the paper's baseline equation. Columns 1-3 exclude renovations by borrowers (i.e., real estate investors) with more than one distinct source of credit in 2010 to assess whether oversampling of large, unconstrained borrowers biases the baseline estimates. Columns 4-6 exclude renovations that could potentially be classified as construction projects to assess whether reclassification incentives bias the baseline estimates. Subscripts c and t denote county and year. Potentially reclassified renovations are defined as occurring on properties built within the previous 3 years or built before 1940. Data for the outcome variable are from Trepp's T-Loan dataset. Data for the exposure variable are from Trepp's T-ALLR and T-Loan datasets. The remaining notes are the same as in Table 2.

Table A3: Robustness of Constrained Demand as an Amplification Mechanism

Outcome:	$\log\left(\textit{Renovated Properties}_{c,t}\right)$ (1)	(2)	(3)
$\textit{Total Bank Share}_c \times \textit{Post}_t$	0.629	0.320	-0.115
	(0.003)	(0.002)	(0.186)
$\textit{Total Bank Share}_c \times \textit{Post}_t \times \textit{Interaction}_{c,t}$	-0.224	0.112	0.298
	(0.043)	(0.022)	(0.000)
Definition of Interaction	Borrower Credit Sources	Renter Income	No Rent Stabilization
Control for Interaction	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes
R-squared	0.705	0.712	0.705
Number of Observations	3,128	3,128	3,128

Note: P-values are in parentheses. This table estimates a variant of equation (1) that assesses whether the baseline effect is amplified when there are borrowing constraints and the unconstrained demand for improvement financing is higher. Subscripts c and t denote county and year. The regression equation is of the form

$$Y_{c,t} = \beta_0 \left(\textit{Total Bank Share}_c \times \textit{Post}_t\right) + \beta_1 \left(\textit{Total Bank Share}_c \times \textit{Post}_t \times \textit{Interaction}_{c,t}\right) + \alpha_c + \alpha_t + \gamma X_{c,t} + u_{c,t},$$

where $\textit{Interaction}_{c,t}$ is a characteristic of county c in year t; and the remaining notation is the same as in Table 2. All specifications control for $\textit{Interaction}_{c,t}$. The interaction variables are defined as follows: Borrower Credit Sources is the product between $\textit{Post}_t$ and the average borrower's (i.e., real estate investor's) number of distinct sources of credit in 2010, based on Trepp's T-Loan dataset; Renter Income is log average real income per capita in t, based on data from the Bureau of Economic Analysis; No Rent Stabilization is the product between $\textit{Post}_t$ and an indicator for whether the county is outside a state where rent control or stabilization policies are in place, based on data from Landlord.com. I only observe the borrower's identity for 14% of properties, and for the remaining 86% I impute the borrower's number of distinct sources of credit from a linear projection onto log property size, log loan balance, loan-to-value ratio, debt service coverage ratio, and indicators for whether the loan is adjustable-rate or 60+ days delinquent. Interaction variables are normalized to have zero mean and unit variance. The first interaction variable inversely proxies for borrowing constraints, and the second two interactions proxy for the unconstrained demand for improvement financing. Data for the outcome variable are from Trepp's T-Loan dataset. Data for the exposure variable are from Trepp's T-ALLR and T-Loan datasets. The remaining notes are the same as in Table 2.

Table A4: Summary Statistics for the T-Loan Property-Level and Lender-Level Datasets

	Observations	Mean	Standard Deviation
Property-Level Variables:			
$Bank_\ell$	30,733	0.473	0.499
$Probability\ of\ Renovation_{i,\ell,t}$	30,733	0.026	0.158
Lender-Level Variables:			
$Bank_\ell$	582	0.306	0.461
$\log(Renovations_{\ell,t})$	582	5.153	3.153
Baseline Number of Properties: 6,100			
Baseline Number of Lenders: 122			

Note: This table presents summary statistics of the key variables from the property-level and lender-level datasets used in Section 6. Subscripts i, ℓ, and t denote property, lender, and year. The upper panel summarizes property-level variables: $Bank_\ell$ indicates if the existing loan on the property is originated by a bank; and $Probability\ of\ Renovation_{i,\ell,t}$ indicates if the property is renovated in t. Observations are property-years. The lower panel summarizes lender-level variables: $Bank_\ell$ indicates if ℓ is a bank; and $Renovations_{\ell,t}$ is the number of renovated apartments financed by a new loan in t. Observations are lender-years weighted by market share. The sample period is 2011-16. Data are from Trepp's T-Loan dataset.

Table A5: Additional Robustness of the First-Stage Effect

Outcome:	$\log(Renovations_{\ell,t})$			$Interest\ Rate_{\ell,t}$	$ARM\ Margin_{\ell,t}$
	(1)	(2)	(3)	(4)	(5)
$Bank_\ell \times Post_t$	3.538	1.282	3.419	-0.140	-0.141
	(0.000)	(0.075)	(0.008)	(0.086)	(0.040)
$Bank_\ell \times Post_t \times Construction\text{-}to\text{-}Assets_\ell$	5.446				
	(0.000)				
$Bank_\ell \times Post_t \times Capital\ Ratio_\ell$			-3.574		
			(0.002)		
Sample	All	Non Big-4	All	All	All
Post × Construction-to-Assets	Yes	No	No	No	No
Post × Capital Ratio	No	No	Yes	No	No
Lender FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.661	0.654	0.656	0.834	0.674
Number of Observations	366	512	366	424	424

Note: P-values are in parentheses. This table estimates a variant of equation (8) that assesses the robustness of the first-stage effect documented in Table 6. Subscripts ℓ and t denote lender and year. $Construction\text{-}to\text{-}Assets_\ell$ and $Capital\ Ratio_\ell$ are the 2010 ratios of construction loans to total assets and total equity to total assets, respectively, based on data from the Call Reports. Both variables are normalized to have zero mean and unit variance, and nonbanks are assigned a value of zero. $Interest\ Rate_{\ell,t}$ and $ARM\ Margin_{\ell,t}$ are the principal-weighted average interest rate and adjustable-rate mortgage (ARM) margin on loans for renovations originated by ℓ as of t, respectively. Column 2 reestimates equation (8) after dropping the Big-4 banks: JP Morgan, Citi, Bank of America, and Wells Fargo. Data are from the Call Reports and Trepp's T-Loan dataset. The remaining notes are the same as in Table 6.

Table A6: Summary Statistics for the AHS Dataset

	Observations	Mean	Standard Deviation
$\Delta \log(Rent_{i,t})$	81,733	0.050	0.964
Installment of:			
$Dishwasher_{i,t}$	81,733	0.034	0.182
$Washing\ Machine_{i,t}$	81,733	0.068	0.252
$Trash\ Compactor_{i,t}$	81,733	0.010	0.100
$Disposal_{i,t}$	81,733	0.043	0.202
$Central\ A/C_{i,t}$	81,733	0.042	0.200
$A/C_{i,t}$	81,733	0.076	0.266
$Dryer_{i,t}$	81,733	0.063	0.244
$\log\left(Square\ Feet_{i,t}\right)$	81,733	0.006	0.082
Baseline Number of Housing Units: 13,186			

Note: This table presents summary statistics of the key variables from the Census' AHS dataset. Subscripts i and t denote housing unit and year. The variable $\Delta \log(Rent_{i,t})$ is the change in log rent. The remaining variables are indicators for the installment of the given feature, except for $\log\left(Square\ Feet_{i,t}\right)$ where, instead of an indicator, the variable is the increase in log square feet. A/C denotes air conditioning. Central A/C is conditional on having any air conditioning. All changes are over two-year intervals. Observations are rental housing unit-years. The sample period is 1997-2013.

Table A7: Pricing Kernel for Hedonic Rent Index

Outcome:	$\Delta \log \left(Rent_{i,t}\right)$
Installment of:	
$Dishwasher_{i,t}$	0.118
	(0.000)
$Washing\ Machine_{i,t}$	0.097
	(0.000)
$Disposal_{i,t}$	0.031
	(0.117)
$Trash\ Compactor_{i,t}$	0.013
	(0.749)
$Central\ A/C_{i,t}$	0.023
	(0.259)
$A/C_{i,t}$	0.063
	(0.000)
$Dryer_{i,t}$	-0.007
	(0.811)
$\log\left(Square\ Feet_{i,t}\right)$	0.121
	(0.012)
Property FE	Yes
Year FE	Yes
R-squared	0.065
Number of Observations	76,148

Note: P-values are in parentheses. This table estimates equation (11), which is the pricing kernel used to construct the hedonic rent index in Section 8.1 that assesses the plausibility of the implied aggregate effect of HVCRE regulation. Subscripts i and t denote housing unit and year. The regression equation is

$$\Delta \log \left(Rent_{i,t}\right) = \beta^{\Theta} \Delta\Theta_{i,t} + \alpha_i + \alpha_t + u_{i,t},$$

where observations are rental housing unit-years; and $\Delta \log \left(Rent_{i,t}\right)$ is the change in log rent. The vector of regressors, $\Delta\Theta_{i,t}$, are indicators for the installment of the given feature, except for $\log\left(Square\ Feet_{i,t}\right)$ where, instead of an indicator, the variable is the increase in log square feet. A/C denotes air conditioning. Central A/C is conditional on having any air conditioning. All changes are over two-year intervals. There are 13,186 housing units. The sample period is 1997-2013. Data are from the Census' AHS dataset.

Table A8: Robustness to Including Heterogeneous Time Trends

Outcome:	$\log\left(Renovated\ Properties_{c,t}\right)$				
	(1)	(2)	(3)	(4)	(5)
$Total\ Bank\ Share_c \times Post_t$	0.345	0.304	0.319	0.306	0.326
	(0.002)	(0.003)	(0.002)	(0.003)	(0.009)
$Characteristic_c \times Year\text{-}2012_t$	0.064	-0.003	-0.063	-0.013	-0.102
	(0.099)	(0.870)	(0.082)	(0.510)	(0.083)
$Characteristic_c \times Year\text{-}2013_t$	0.101	0.029	-0.081	-0.003	-0.161
	(0.002)	(0.379)	(0.075)	(0.921)	(0.010)
$Characteristic_c \times Year\text{-}2014_t$	0.178	-0.017	-0.209	-0.015	-0.272
	(0.020)	(0.702)	(0.005)	(0.760)	(0.014)
$Characteristic_c \times Year\text{-}2015_t$	0 0.138	-0.014	-0.134	-0.037	-0.168
	(0.017)	(0.678)	(0.015)	(0.320)	(0.054)
$Characteristic_c \times Year\text{-}2016_t$	0.172	0.049	-0.206	-0.043	-0.229
	(0.044)	(0.169)	(0.016)	(0.547)	(0.081)
Characteristic	Income	Winter Storms	White Share	College Education	Supply Elasticity
Year FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.725	0.708	0.722	0.706	0.728
Number of Observations	3,128	3,128	3,128	3,128	2,620

Note: P-values are in parentheses. This table estimates a variant of equation (1) that assesses the robustness of the baseline results to heterogeneous time trends. Subscripts c and t denote county and year. The regression equation is of the form

$$Y_{c,t} = \beta\left(Total\ Bank\ Share_c \times Post_t\right) + \sum_{t=2012}^{2016} \delta_t\left(Characteristic_c \times Year_t\right) + \alpha_c + \alpha_t + \gamma X_{c,t} + u_{c,t},$$

where $Year_t$ is a year indicator; $Characteristic_c$ is a characteristic of county c; and the remaining notation is the same as in Table 2. The characteristics are defined as follows: Income is real income per capita for the surrounding MSA averaged over 2011-16, based on data from the Bureau of Economic Analysis; Winter Storms is the average number of winter storms per year over 2011-16, based on data from the National Oceanic and Atmospheric Association; White Share is the 2010 share of inhabitants over age 16 that are white, based on the 2010 Census; College Education is the 2010 share of inhabitants with at least a bachelor's degree, based on the 2010 Census; Supply Elasticity is the elasticity of housing supply as estimated by Saiz (2010). Characteristics are normalized to have zero mean and unit variance. Data for the outcome variable are from Trepp's T-Loan dataset. Data for the exposure variable are from Trepp's T-ALLR and T-Loan datasets. The remaining notes are the same as in Table 2.

Table A9: Robustness to Measuring Exposure with the Office Sector

Outcome:	$\log\left(Renovated\ Properties_{c,t}\right)$	
	(1)	(2)
$Bank\ Office\ Share_c \times Post_t$	0.171	0.462
	(0.078)	(0.049)
Base Period	2010	2001-09
Year FE	Yes	Yes
County FE	Yes	Yes
R-squared	0.565	0.586
Number of Observations	3,159	3,159

Note: P-values are in parentheses. This table estimates a variant of equation (1) that assesses the robustness of the baseline results to using loans secured by office buildings to measure exposure to HVCRE regulation. Subscripts c and t denote county and year. Each column uses a different measure of banks' share of office loan balances, denoted $Bank\ Office\ Share_c$. The measure in column 1 is bank securitized office loan balances in 2010 divided by the sum of bank and nonbank securitized office loan balances in 2010. The measure in column 2 is similarly defined using loan balances averaged over 2001-09. Data for the outcome variable are from Trepp's T-Loan dataset. Data for the exposure variable are from a version of the T-Loan dataset that covers the office sector. The remaining notes are the same as in Table 2.