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Lee Seltzer

FEDERAL RESERVE BANK *of* NEW YORK

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Abstract

This paper studies whether financing constraints adversely affect renters by reducing maintenance. Consistent with a sensitivity of maintenance to financial resources, housing code violations increased after a change in the law that effectively decreased cash flows available to maintain some rent stabilized buildings in New York City. The effect is most severe when financing constraints are present. Moreover, results of panel regressions using a dataset of 45 cities obtained with Freedom of Information Act (FOIA) requests are consistent with a hypothesis that buildings with higher LTV ratio mortgages have more code violations. Together, the results provide evidence that financing constraints reduce maintenance, an outcome that exacerbates the unintended consequences of rent control.

Key words: corporate finance, commercial real estate, housing code violations

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1. Introduction

A recent survey shows that 43% of renters worry that maintenance in their homes is poor enough to cause adverse health effects (Will, 2022). Renters rely on investments by the building owner to mitigate maintenance problems, investments that require either internal cash flows or access to external financing. In the presence of financing frictions, insufficient financial resources (i.e., cash or borrowing capacity) could prevent building owners from making crucial maintenance investments.

This paper asks whether a building's maintenance is sensitive to how the building is financed. Specifically, excessive debt or insufficient access to cash can lead to reductions in investment (Myers, 1977; Fazzari et al., 1988), especially in cases where the investment primarily benefits non-financial stakeholders (Titman, 1984; Maksimovic and Titman, 1991). Therefore, buildings may be less well maintained when their owners have less access to financial resources.

Testing such a hypothesis is challenging, though, for two reasons. First, it is difficult to observe both building maintenance investments and financial resources available to maintain a building. I address this challenge with a novel dataset containing information on housing code violations to identify instances of poor building maintenance, and building loan-to-value (LTV) ratios at origination to observe whether the building's owner faces financing constraints.

Second, financial resources are not randomly assigned to buildings. For instance, the previous literature shows that firms may choose lower debt levels to maintain financial slack when they anticipate future growth opportunities (Myers, 1977; Titman and Wessels, 1988; Parsons and Titman, 2009). Similarly, building owners might choose to borrow less for buildings with greater growth prospects in order to maintain financial flexibility to invest in capital expenditures. I address these endogeneity concerns with a natural experiment in the setting of the rent-stabilized building stock in New York City. Owners of rent-stabilized apartments in New York are allowed to pass on a portion of the cost of improvements to their tenants through a rent increase. I exploit a 2011 revision to rent-stabilization laws that decreases the amount by which monthly rents can be increased to recoup improvement costs from one-fortieth of the costs to one-sixtieth. By decreasing building rental income, the 2011 Rent Act effectively decreases the financial resources available to maintain the building.

Importantly, the change in the law only applies to buildings with over 35 apartment units. I therefore use rent-stabilized buildings with 35 or fewer units as controls to filter out the effects of any time-varying factors affecting the aggregate rent-stabilized building stock in New York City. Specifically, I estimate generalized difference-in-differences regressions with matched samples to compare changes in violations after the law passed in 2011 for rent-stabilized buildings with over 35 units to a group of observationally similar rent-stabilized buildings with 35 or fewer units. The estimates show that violations per building increase by over three-quarters of a standard deviation for buildings with over 35 units relative to controls.

The Rent Act likely decreased building quality both by leading to fewer capital expenditure investments and by decreasing access to financial resources to spend on maintenance. If insufficient financial resources exacerbated the decline in maintenance, the increase in code violations should be largest in cases where the buildings' owner faced financing constraints when the law went into effect. Consistent with this hypothesis, I show that the change in violations is strongest for buildings in the top tercile of LTV ratios and absent for those in the bottom tercile, based on their LTV ratios before the passage of the law.

I conduct several tests to examine alternative explanations for the change in code violations. For instance, I conduct a version of the difference-in-differences analysis matching each treated building to a control building within the same real estate company's portfolio. Even when I compare treated buildings to controls owned by the same real estate company, code violations increase for treated buildings after the Rent Act. This implies that the change in code violations is unlikely driven by real estate company characteristics such as a company's management style.

Furthermore, the estimates are similar when conducting a test limiting the sample to narrow size bins around the 35-unit cutoff, indicating that exogenous variation from the cutoff drives the results rather than differences in building size. Additionally, results are similar in a test where treated buildings are matched to controls according to their rents right before the law passed, indicating that the results are unlikely driven by differences in rental rates.[1] The conclusions are also similar in a test matching treated buildings to controls according to whether a building permit for a major project was obtained in the years leading up to the law, implying that results are unlikely driven by the need to make major property improvements. Placebo test results also show that no change in code violations is present for market-rate buildings with over 35 units, indicating that the results are unlikely due to unrelated conditions in the New York rental market.

The difference-in-differences results show that building owners reduce maintenance spending after the Rent Act, especially in the presence of financing constraints. To test the hypothesis of whether buildings with less financing capacity tend to have worse maintenance in a more general setting, I implement panel regressions of housing code violations on building LTV ratios in a sample of 45 US cities collected with Freedom of Information Act (FOIA) requests. The analysis reveals that after controlling for zip-code-by-year and mortgage-issue-year fixed effects, as well as building, loan, real estate company, and lender characteristics, buildings with higher LTV ratio mortgages tend to have more code violations. While this test is not causal, these results provide evidence suggesting that the insights from the natural experiment are generalizable to a broader sample.

To summarize, the findings in this paper show an increase in code violations of over three-quarters of a standard deviation for treated buildings relative to controls after the Rent Act. The effect is concentrated in buildings financed with mortgages that had high LTV ratios before the law passed, suggesting that the increase in violations is exacerbated when owners lack financial resources. Moreover, regression results using data from 45 cities provide

[1]Similarly, long-term tenants may be more concerned with building maintenance. However, this is unlikely to confound the results because BLS data show that 91% of leases are no longer than one year.

evidence consistent with buildings with less financing capacity having more code violations. The results provide evidence that building maintenance is sensitive to the building's financing structure, which can exacerbate the unintended consequences of rent control.

This paper is closely related to the literature on rent regulation. Previous work has shown that rent regulation leads to reduced property values (Autor et al., 2014; Ahern and Giacoletti, 2022), misallocation of housing (Glaeser and Luttmer, 2003; Munch and Svarer, 2002; Favilukis et al., 2023), reduced housing supply (Diamond et al., 2019), and reduced housing quality (Downs, 1988; Moon and Stotsky, 1993; Sims, 2007; Arnott and Shevyakhova, 2014).

I contribute to this literature by showing that reductions in housing quality from rent regulation are more severe in the presence of financing constraints. In doing so, this paper provides the first evidence that frictions associated with a building's financing structure can exacerbate the unintended consequences from rent regulation. This evidence on the heterogeneous effects of rent regulation is important for policymakers, given the recently announced White House plan to implement rent control at the federal level for multifamily buildings.[2]

This paper also contributes to the literature on financing frictions in real estate markets and, in doing so, complements work showing that financing constraints can reduce investments in owner-occupied homes (Haughwout et al., 2013; Li, 2016; Harding et al., 2022), work showing that mortgage financing affects commercial real estate rent and earnings (Hughes, 2022; Liebersohn et al., 2022), as well as work by Melzer (2017), who shows homeowners tend to underinvest as a result of debt overhang.[3]

My work is closest to Melzer (2017) in that we both study maintenance spending. However, I expand on the analysis in Melzer (2017) in at least two important ways. First, while his focus is on owner-occupied homes, my focus is on the multifamily rental market,

[2]The White House Plan would make multifamily tax breaks conditional on capping rent increases at 5% for buildings with over 50 units. See White House Fact Sheet for details.

[3]Also relevant are several studies showing that financing can affect homeowners' labor market incentives (Bernstein, 2021; Bernstein et al., 2021; Donaldson et al., 2019; Jensen et al., 2022).

which differs from the owner-occupied home setting. For instance, since the building owner does not typically live in the building, costs from insufficient maintenance may be borne by renters in the form of an externality. Similarly, homeowners may be forced to move after a default, incurring nonpecuniary costs, while multifamily building owners are shielded from such costs. Additionally, in contrast to Melzer (2017), whose findings could potentially be driven by both debt overhang and a wealth effect, I exploit a change in multifamily rental cash flows that is exogenous to the real estate company's wealth. This arguably allows me to better identify the effect of a building's financing structure on its maintenance.

Lastly, since renters are the customers of real estate firms, this paper is related to the literature on how financing can affect a firm's customers. It is well known that financing frictions can reduce investment,[4] with negative consequences for firms' stakeholders such as customers.[5] In particular, financing frictions have been shown to adversely affect the quality of customer service in a variety of settings (Matsa, 2011; Phillips and Sertsios, 2013; Adelino et al., 2022; Kini et al., 2016; Bernini et al., 2015; Malshe and Agarwal, 2015). This paper uses insights into how financing affects customers to better understand how frictions related to how a building is financed affect rental markets.

The paper proceeds as follows. The next section motivates the hypotheses tested in the paper. Section 3 describes the data used in the analysis. Section 4 presents the results from the Rent Act natural experiment. Section 5 presents regression results of code violations on LTV ratios in a panel of 45 cities. Section 6 concludes and provides final remarks.

[4]See, for example, Myers (1977), Whited (1992), Lamont (1997), Fazzari et al. (1988), Kaplan and Zingales (1997), Kaplan and Zingales (2000), Rauh (2006), Alti (2003), Almeida et al. (2004), Opler and Titman (1994), Wittry (2021), Aiello (2022), and Giroud et al. (2012).

[5]See, for example Titman (1984), Maksimovic and Titman (1991), Cohn and Wardlaw (2016), Bae et al. (2011), Benmelech et al. (2021) and Xu and Kim (2022).

2. Theoretical Motivation

2.1. Decision-Making by Owners of Multifamily Real Estate

In this section, I first provide a framework for how multifamily real estate firms are organized and how they make property-level decisions, and afterward I discuss the theoretical literature motivating the empirical hypotheses. Multifamily real estate assets in the United States are often financed using non-recourse mortgages, where lenders are not able to claim possession of the borrower's assets aside from the pledged collateral (Glancy et al., 2023). As a result, multifamily real estate firms effectively treat each of the properties in their portfolios as independent subsidiaries. Therefore, I consider multifamily real estate firms as effectively making decisions about each of their individual properties in isolation, without regard to their other properties.

The limited liability nature of real estate assets allows researchers to study them as if each multifamily property is an individual firm. These are extremely simple firms, with exactly one asset and external debt collateralized by that asset. The simple nature of these firms provides a unique laboratory for studying issues from the corporate finance literature.

Throughout this paper, I refer to several different entities and assets in the corporate real estate structure. A "building" is the apartment building itself (i.e., the real estate asset). The "owner" or "building owner" is the legal entity that holds the apartment building, which in some cases may be a limited liability company (LLC). Lastly, the "real estate company" is the ultimate parent company that holds the entity. For example, in the case of a real estate investment trust (REIT), the REIT is the "real estate company," and the apartments owned by the REIT are its "buildings." The REIT often organizes itself by allocating each building to an individual LLC, where the LLCs are the "building owners."

2.2. Hypothesis Development

Frictions related to excessive debt or insufficient access to liquidity can reduce investment (Myers, 1977; Fazzari et al., 1988). In particular, bankruptcy costs can disrupt the ability to make relationship-specific investments that are important to stakeholders, such as customers (Titman, 1984). At the same time, the most important investments for customers tend to generate long-run cash flows, but require incurring costs in the short run. Since equityholders lose out on these long-run cash flows in the case of default, financing frictions can disincentivize investments that are important to customers, even if there is no imminent risk of bankruptcy (Maksimovic and Titman, 1991).

The rental real estate market presents clear analogies to the types of investments described in Maksimovic and Titman (1991). For instance, any intermittent maintenance investments during a lease term are, by their nature, relationship-specific investments. At the same time, maintenance investments are often costly in the short run, but yield long-run cash flows in the form of tenant retention. Lastly, building owners do not benefit from tenant retention in the case of default, so we may expect financing frictions to disincentivize investment in maintenance. Moreover, since commercial real estate mortgages are typically non-recourse, real estate companies are unlikely to subsidize unprofitable buildings with outside cash holdings. For this reason, buildings should be less well maintained when their owners have less access to financial resources:

Hypothesis 1. *Buildings should be less well maintained when their owners have less access to financial resources.*

To test this hypothesis, I examine if reductions in cash flows lead to increases in housing code violations, where the source of this reduction in cash flows is a change in rent regulation laws. I also use panel regressions to examine whether buildings financed with larger mortgages (i.e., facing greater financing constraints) have more code violations.

Moreover, the corporate finance literature has shown that financing constraints increase sensitivity to cash flows (Almeida et al., 2004). Therefore, I predict that building maintenance should be more sensitive to cash flows when financing constraints are present:

Hypothesis 2. *Building maintenance should decrease more after reductions in cash flows when financing constraints are present.*

In the context of this paper, housing code violations should increase more for buildings with larger mortgages relative to others after the change in rent regulation laws.

3. Data

3.1. Code Violations Data

I identify poor maintenance of multifamily buildings using municipal code violations. In the United States, tenants can typically complain to the city government if they feel that the building's owner is not providing them with minimum standards of living. If the city finds that the complaint is valid, the building's owner will be served with a code violation.

Building owners are typically fined when they incur violations, and in some cases, penalties for violations can be severe. For instance, when building owners fail to make repairs sufficiently quickly in New York City, the government may make the repair itself and bill the building's owner afterward.[6] The billed repair carries the same weight as a tax lien, sometimes leading to foreclosure.[7]

Since violations capture instances where building maintenance is poor enough that it violates local laws, this study best speaks to extreme instances of poor building maintenance. As few continuous data sources on investments in maintaining commercial real estate exist, and many of those are not well-populated, the data on violations provide a unique opportunity to examine building maintenance. It is also important to note that building owners sometimes respond to reported violations with punitive action such as eviction, which could

[6] https://www.nyc.gov/site/hpd/services-and-information/emergency-repair-program-erp.page
[7] https://www.nyc.gov/site/finance/property/property-in-rem-forclosure.page

lead to under-reporting of code violations (Desmond, 2016). For this reason, I expect that data on code violations underestimate the true extent of poor building quality.

Note that the data on code violations also do not include variation in building maintenance in cases where code violations are not reported. This could introduce a bias to the results if the relationship between financing and building maintenance is different for buildings where tenants report housing code violations and other buildings. While it is impossible to test this claim with certainty, it is not clear why the relationship between financing and maintenance should differ in these two groups of buildings. At the same time, this feature of the data allows me to focus on reductions in building maintenance that are severe enough to result in code violations, which are the most economically important cases.

I collect data on housing code violations for various cities throughout the United States.[8] The data are gathered via municipal open data portals if they are available. Otherwise, I submit a FOIA request to the relevant city department. The process yields data on code violations for 45 cities. Data are aggregated at the building-by-year level.

Information on the geographic distribution of data is shown in Figure IA.1 and Table IA.1. The aggregate time-series of code violations are shown in Figure IA.2. The availability of data on code violations varies by city and extends from 2002 to 2018. Note that more code violations are observed as time goes on. There are two main reasons for this. One is that different cities provide data for different windows of time. The other is that the data from New York City only include violations open as of October 1, 2012, leading to a sharp increase in violations observed in New York City in 2012. Some cities also have more data available than others. I conduct several robustness checks to ensure that the variation in the availability of code violations data over time and between cities does not drive the results.

Some cities provide text descriptions of the violations. Examples of the violations include:

"Repair the roof so that it will not leak above the ceiling..." – New York, NY

[8] Cities are selected based on their representation in the Real Capital Analytics mortgage data, which are described in subsection 3.2.

> "Neighbor is running a barber shop out of hisgarage. garage has a waiting room with table chairs, barber chair. Customersall the time of day and night (sic)." – Tucson, AZ

The examples show that it is not always clear that the violation is due to a failure to maintain the building. To account for these cases, I parse the text of the violations and identify violations indicating the need for the building's owner to make repairs. Due to the vagueness of the text, I likely underestimate the number of violations requiring repairs, making these estimates a lower bound. I exclude violations indicating the need to make large-scale investments to focus on basic maintenance, although results are similar when including large-scale investments. I detail how violations are classified in Internet Appendix IA.A.

I exploit three outcome variables in the code violations data. Specifically, I examine the number of violations per building, the number of violations scaled by the number of units (in hundreds), and an indicator variable equal to one if a building has at least one violation. The variables are calculated for both all violations and only those requiring a repair.

3.2. Mortgage Data

I obtain apartment mortgage and transactions data from Real Capital Analytics (RCA). RCA collects data on transactions of commercial buildings throughout the United States from property deeds. RCA contains information on mortgages used to finance apartment buildings for transactions associated with both building sales and mortgage refinancing activity that are at least $2.5 million. Data from RCA include building LTV ratios at the time of loan origination, transaction prices, loan origination dates, loan interest rates, loan maturity dates, building locations, the number of units in a building, building ages, the buyer of the building, and firm types.[9] The data also include lender and originator characteristics. I drop buildings labeled as co-ops, condos, military-owned or subsidized, as well as observations

[9] I assume that the buyer of the building is the real estate company for the building.

where the number of units, zip code, or address is missing. Finally, I drop observations where the loan has a cross-default provision, that is, when a default in a mortgage triggers defaults in other debt on the borrower's books.

The transaction-level dataset is reformatted into a building-by-year level panel dataset. Information on a given mortgage and property is used from the most recent transaction observed for a building at a given time. Therefore, when the LTV ratio at origination or the transaction price is used, this is the LTV ratio at origination for the most recent mortgage originated, and the price of the most recent property sale. Data on code violations are then merged with this building-by-year level dataset according to the building address, zip code and the year the violation took place.[10]

The building LTV ratio at origination, defined as the size of the loan used to finance the building at origination scaled by the building's appraisal value, is used to proxy for whether a building faces financing constraints. This is a useful indicator of financing frictions, since a higher LTV ratio at origination shows that the building's owner needs to make higher mortgage payments, reducing the cash available to meet other needs. Results with alternative proxies are included in the appendix.

3.3. Other Data Sources

Panel data on rental rates and occupancy rates for rent-stabilized apartment buildings in New York City are collected from the CoStar Group, which provides operating information on multifamily buildings. I merge these data with the code violations and mortgage data by zip code, address, and year. I identify the 2011 rent-stabilized building stock using data obtained in a Freedom of Information Law (FOIL) request and then posted publicly.[11] Zip code house price indices from Zillow, a list of all apartments under jurisdiction of the New York Department of Housing Preservation and Development, and New York building permits data are also used in analyses in the appendix.

[10] If no violations are observed in the code violations data, the variable is set equal to zero.
[11] https://github.com/clhenrick/dhcr-rent-stabilized-data

3.4. Summary Statistics

Table 1 displays summary statistics. The average number of violations per building in each year is 1.029; the average number of violations per 100 units is 2.82; and 0.14 of all buildings have a violation in a given year. The average LTV ratio at origination is 0.65.[12]

4. The 2011 NYC Rent Law

4.1. Determinants of a Building's Financial Structure

How an owner chooses to finance their building is endogenous, which can make it difficult to test Hypothesis 1. To illustrate this point, panel (a) of Figure 1 displays maps of New York City showing average LTV ratios by zip code. Panel (b) displays apartment capitalization rates (i.e., building rates of return) by zip code within New York City. Comparing the two figures reveals an overlap between zip codes with high capitalization rates and those with high LTV ratios. Indeed, buildings in these zip codes may be financed with larger mortgages because owners of buildings with lower returns to investment may be less concerned with ensuring those buildings have ample financial resources.[13]

Due to the aforementioned endogeneity problem, it is not possible to causally examine the effect of financing frictions on investment in maintenance without random variation in financial resources. To obtain such variation, I exploit a natural experiment involving a change to rent-stabilization laws in New York City.

4.2. New York Rent Act of 2011

Approximately 1 million apartment units in New York City are rent-stabilized. Owners of rent-stabilized buildings must follow the guidance of the New York City Rent Guidelines

[12]Results in the appendix also consider the combined LTV ratio, an estimated amortized LTV ratio, and the debt service coverage ratio (DSCR) as alternative indicators of the existence of financing constraints.

[13]Internet Appendix IA.B provides a detailed analysis of the determinants of building LTV ratios.

Board's in setting their rent; these guidelines are updated annually based on rental market conditions. One key provision of New York rent-stabilization is that if either the unit is vacant or the existing tenant agrees, building owners can make additional increases to rent for qualifying apartment unit improvements, or Individual Apartment Improvements (IAIs). Examples of IAIs include replacing equipment such as a stove, renovating the bathroom, or replacing the carpeting. Importantly, an investment can only qualify as an IAI if it plausibly increases the value of the apartment unit. This prohibits classifying basic repairs as IAIs.

Up until 2011, building owners were allowed to increase monthly rents by one-fortieth of the value of an IAI. However, New York State updated its rent laws with the passage of the New York Rent Act of 2011 on June 24, 2011. While the law largely maintained the previous rent regulation law, one concession to tenant advocates was an attempt to address excessive rent increases following IAIs. For buildings with over 35 units, rent could only be increased by one-sixtieth of the cost of the improvement, thereby decreasing building owners' ability to recover costs incurred when making IAIs.[14,15] These changes to how rent could be increased following IAIs were first recommended in a March 13, 2011, press release by the New York Assembly Speaker of the House[16] and a March 15, 2011, letter to Governor Cuomo by Democratic state lawmakers.[17]

Since cash is fungible, increased rent obtained from making IAIs could be used to invest in housing maintenance, especially if building owners view maintenance spending as an operating expense, and therefore fund it out of current income. In this sense, the Rent Act could increase code violations through the channel of reducing cash available for maintenance.[18]

An example using a hypothetical $5,000 bathroom renovation displays how the Rent Act

[14]This provision was effective on September 24, 2011.

[15]The law also limited the number of times per year that building owners could legally increase rent upon vacancy, and changed the circumstances under which building owners can deregulate previously rent-stabilized buildings based on either the rent charged or the income of tenants. For reference, see the full text of the law here: https://rentguidelinesboard.cityofnewyork.us/wp-content/uploads/2019/10/rentact2011.pdf.

[16]Sheldon Silver, March 13, 2011, press release

[17]Letter to Governor Cuomo on Rent Regulation Law

[18]The reduction in capital expenditures could also lead to reduced building quality, which could increase the likelihood of code violations. The empirical design will control for building quality in order to prevent this effect from contaminating the results.

affected building cash flows (Figure 2). Prior to the change in the law, monthly rent could be increased by $125 for all buildings. Afterward, monthly rent could only be increased by $83.33 for buildings with over 35 units. This change in the law, therefore, decreased a building's future cash flows conditional on investing in IAIs for buildings with over 35 units, but not those with 35 or fewer.

The Rent Act could also affect building quality through the channel of disincentivizing IAIs. IAIs are best characterized as significant capital expenditure investments, which are associated with increases in building values and rental rates (Reher, 2021). Disincentives to invest in IAIs could be associated with a decrease in building quality, although I cannot directly test this due to a lack of data on IAI spending.

4.3. Empirical Design: Difference-in-Differences

Hypothesis 1 predicts that reductions in available cash should lead to decreases in building maintenance. To test this causally, I compare changes in code violations for rent-stabilized buildings with more than 35 units in New York City, which were the buildings affected by the Rent Act, to those for buildings with 35 or fewer units, before and after 2011 with a difference-in-differences regression. This econometric design allows me to exploit both the cross-sectional variation from the size cutoff and the time-series variation from the timing of the passage of the law. The control group is composed of rent-stabilized buildings that were not affected by the Rent Act.[19]

To control for differences between rent-stabilized buildings with over 35 units and those with 35 or fewer units, I conduct a one-to-one nearest neighbor matching procedure with replacement. This approach matches each treated building to the most similar control building based on observable characteristics (Mahalanobis, 1936).[20] Matching covariates include building LTV ratios, transaction prices, building ages, whether a building was owned by an

[19] In general, rent-stabilized buildings in New York City have six or more units and were built in 1974 or prior, or they take advantage of certain affordable housing tax abatements. For more detail on rent-stabilized buildings, see https://rentguidelinesboard.cityofnewyork.us/resources/rent-stabilized-building-lists/.

[20] Results without matching are also included in the appendix.

institutional investor, and zip-code-level occupancy rates.[21]

This sample is then used to estimate the following difference-in-differences regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it}. \quad (1)$$

In Equation 1, $Violations_{it}$ are either the number of violations per building, the number of violations per 100 units, or an indicator variable equal to one if a building has a violation in year t. $Treat_i$ is one if building i has more than 35 units, and $After_t$ is one if t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Standard errors are clustered at the building level. β_1 can be interpreted as the difference in the change in code violations after 2011 for rent-stabilized buildings with over 35 units in New York City relative to other very similar rent-stabilized buildings in New York City. $\beta_1 > 0$ would be consistent with Hypothesis 1. The difference-in-differences sample window is 2007-2015, and I restrict the sample to buildings I can observe for the full sample period.

Table IA.2 displays summary statistics for the treated and control groups as of 2010 in the unmatched sample, and the two groups appear very different. Table IA.3 displays summary statistics for the treated and control groups in the matched sample. Differences between the treated and control groups appear to be reduced by the matching. I will also later show that there are no observable differences in pre-trends for the treated and control groups.

While I cannot observe whether building cash balances changed after the law passed, I conduct suggestive tests of whether building values changed after the Rent Act. Figure IA.3 shows that, on average, capitalization rates increased for treated buildings after the law passed, but not for controls. Similarly, Table IA.4 shows that appraisal values increased for treated buildings relative to controls from 2010 to 2012.

[21]Values of the covariates as of 2010 are used. LTV ratios at origination and transaction prices are based on the most recent transaction observed as of 2010. Matching is conducted using a caliper of 0.5. I use the adjustment from Abadie and Imbens (2006) to address bias from calculating the Mahalanobis distance with two or more continuous variables.

4.4. *Difference-in-Differences Results*

Table 2 displays difference-in-differences results, which show a decrease in building maintenance following the Rent Act. Panel A shows results using all code violations. Column (1) shows that the number of violations per building increases by 3.76 for treated buildings relative to controls after the Rent Act, an increase of over three-quarters of a standard deviation. Similarly, column (2) reveals that violations per 100 units increase by 7.71 for treated buildings relative to controls after the Rent Act. Column (3) includes results using the violation indicator, where the probability of a violation increases by 7.4 percentage points for treated buildings relative to controls after the Rent Act. Overall, code violations tend to increase for affected buildings after the Rent Act.

Panel B uses only violations requiring a repair. Column (1) shows the number of violations requiring a repair per building increases by 2.54 for treated buildings relative to controls following the Rent Act. According to column (2), violations requiring a repair per 100 units increase by 5.60 relative to controls following the Rent Act. Finally, column (3) shows the probability of a violation increases by 9.3 percentage points. The findings in panel B are consistent with the Rent Act leading to a reduction in repairs, resulting in code violations.

As a whole, the results in Table 2 are consistent with affected buildings having more code violations following the Rent Act. Similar effects are observed in violations requiring repairs, indicating that the change in violations corresponded with decreases in maintenance.

Next, I dynamically examine the effect of the Rent Act on treated buildings by plotting the coefficients and 95% confidence intervals estimated from the following regression:

$$Outcome = \Sigma_{j=2007,j\neq 2010}^{2015}\beta_{1j}[Treat_i \times \mathbb{1}(j=t)] + \gamma_i + \kappa_{pt} + \epsilon_{it}. \tag{2}$$

Each β_{1j} can be interpreted as the difference in changes to the outcome variable in year j for New York City rent-stabilized buildings with over 35 units relative to those with 35 or fewer units. The coefficient for 2010 is excluded from the regression, so 2010 is the base year. β_{1j} near zero for $j < 2011$ would be consistent with the parallel trends assumption.

The results are displayed in Figure 3. Figures 3(a), (b), and (c) contain results where the outcome variables are the number of violations, the number of violations per 100 units, and the violation indicator, respectively. Consistent with parallel trends, the coefficients tend to be statistically indistinguishable from zero prior to 2011. However, the estimates increase after 2011. In particular, treated buildings have about 2.5 more violations immediately after the change in the law relative to controls, and the effect is persistent.[22]

As a whole, the findings in this section show that code violations increase for buildings larger than 35 units relative to other buildings starting in 2011. This is consistent with the Rent Act leading to increases in violations.

4.5. Sensitivity to a Building's LTV Ratio

Difference-in-differences regressions show that code violations increased for treated buildings after the Rent Act, which could be due to either declining building quality from fewer IAIs or reduced financial resources to spend on maintenance. If the increase in violations is related to a reduction in financial resources, the effect should be stronger in buildings with mortgages with higher LTV ratios, since they face greater financing frictions. To evaluate this claim, I test whether violations increase more for treated buildings with mortgages that had high LTV ratios before the change in the law relative to other treated buildings. Specifically, I divide the sample into terciles based on the building's LTV ratio calculated prior to the Rent Act.[23] Afterward, I separately conduct the difference-in-differences analysis within each tercile.[24]

Results are displayed in Table 3. Panel A examines the change in violations for buildings in the bottom tercile of LTV ratios, which are not statistically significant except for the number of violations related to repairs indicator. Panel B has regression results for buildings

[22]Figure IA.4 shows results for violations requiring repairs, and the conclusions are similar.

[23]Since the terciles are determined based on the mortgage LTV ratio prior to the Rent Act, the groupings are not affected by changes in the LTV ratio that occurs as a result of the Rent Act.

[24]Note this serves as a test of Hypothesis 2.

in the second LTV ratio tercile. The estimates are all larger than those in Panel A, and aside from the violation indicator, they are all statistically significant.

Panel C displays results for buildings in the top LTV ratio tercile. Column (1) shows the number of violations per building increases by 5.8 for treated buildings relative to controls after the Rent Act. Moreover, the number of violations per 100 units increases by 13.5 for treated buildings relative to controls. Column (3) shows that the probability of a violation increases by 11.9 percentage points for treated buildings financed with high LTV ratio mortgages relative to controls financed with high LTV ratio mortgages. In all three specifications, the results for the top tercile of LTV ratios are larger than those observed in Table 2 and those observed in the two other terciles. In fact, the effect for the number of violations is more than three times the size of that observed for the bottom tercile of LTV ratios. Columns (4) through (6) display results using violations requiring repairs. For all cases except the violation indicator, the effect is once again larger than that observed for both the middle tercile and the bottom tercile.[25]

These subsample results provide evidence that the Rent Act led to more significant increases in code violations in the presence of financing constraints. Since there is a heterogeneous treatment effect according to a building's financing capacity, these findings are consistent with the reduction in financial resources from the Rent Act exacerbating the increase in violations.

4.6. Examining Alternative Explanations

The subsample results provide evidence that financing constraints are an important driving force behind the change in code violations following the Rent Act. Next, I examine several alternative explanations for the change in violations following the Rent Act.[26]

[25] Figure IA.5 shows results of the dynamic difference-in-differences regression for the top LTV ratio tercile; these results are consistent with parallel trends and a change in code violations after passage of the law.

[26] Note: the results for a battery of additional robustness checks are described in Section IA.C.

4.6.1. Controlling for Real Estate Company Characteristics

Since RCA provides information on the ultimate parent company that owns each building, I can observe multiple buildings in the same real estate company's portfolio. I exploit this feature by implementing difference-in-differences regressions on a sample matched within real estate company. The matching specification is the same as that for the main tests except the institutional investor indicator is excluded, since matching is done within a real estate company. By comparing the change in code violations after the Rent Act for buildings with more than 35 units to control buildings with the same real estate company, this test controls for any systematic differences between real estate companies.

Results are displayed in Table 4 and are qualitatively similar to those in the main test. In particular, even when looking within a real estate company, violations increase by 3.8 for treated buildings relative to controls, and violations requiring repairs increase by 2.7 for treated buildings relative to controls. Based on these findings, the increase in violations surrounding the Rent Act is likely not driven by a real estate company's characteristics, such as its management style.

4.6.2. Controlling for Differences in Size

I next repeat the analysis on subsamples containing buildings within narrow size ranges around the 35-unit cutoff. The intuition of this test is similar to that of a regression discontinuity design: buildings sufficiently close to the cutoff are likely very similar, reducing concerns about omitted variable bias. I compare the change in code violations for buildings with a similar number of units at either side of the 35-unit cutoff. Results are presented in Table 5, where panel A includes buildings with 10 to 60 units, panel B includes buildings with 15 to 55 units, panel C includes buildings with 20 to 50 units, panel D includes buildings with 25 to 45 units, and panel E includes buildings with 30 to 40 units.

In every subsample, there is a positive and statistically significant increase in the probability of having a violation. Moreover, in all subsamples except panel D, there is a positive and statistically significant increase in the number of violations per building and the number of violations per 100 units. It is even true in the very restrictive 30- to 40-unit subsample, making it unlikely that the results are driven by outliers. These findings provide evidence that the change in violations after the Rent Act was driven by building size relative to the cutoff of 35 units, rather than differences between large and small buildings.[27]

4.6.3. Controlling for Differences in Rental Rates and Capital Expenditures

To control for differences in rental rates between treated and control buildings, I collect data on rent for rent-stabilized buildings from the CoStar Group. I then construct a sample where I match according to the building's rent in 2010 in addition to the covariates used in previous specifications.[28] In this analysis I limit the sample to buildings where rents grew by no more than 2% at the time the law was passed, which allows me to ensure they are complying with the rent-stabilization laws. I repeat the difference-in-differences analysis in Table 6 and find results qualitatively similar to those in the baseline specification. This provides evidence that the results are not driven by differences in the rental rates of the assets.

Similarly, the Rent Act decreased incentives to invest in capital expenditures, which could decrease building quality, making code violations more likely. To address this concern, I obtain data on New York City building permits, and match on whether the building had any permits for major projects that could affect use, occupancy, or egress in the four years before the Rent Act. Results, shown in Table 7, are qualitatively similar to those in the baseline specification. This indicates that the change in code violations is not primarily due to reduced building quality from forgone capital expenditures. Together, the results from these two tests imply that the change in code violations after the Rent Act was not primarily due to differences in incentives to maintain treated and control buildings.

[27] Table IA.5 displays a similar test regressing the outcome variable on size bins interacted with a time dummy; this test confirms that the change in violations was not driven by the largest buildings.

[28] To conduct this matching, I use a caliper of 1 instead of .5 to allow for a larger sample, since rental data are only available for a subset of buildings.

4.6.4. Are the Results Driven by New York City's Rental Market Conditions

To examine whether results could be driven by other rental market conditions, I conduct a placebo test using market rate buildings in New York City, which are subject to similar market conditions but not rent-stabilization laws. Results are shown in Table 8. In all specifications, it is not possible to reject the null hypothesis that $\beta_1 = 0$, implying that the change in code violations following the Rent Act was likely not due to other market conditions.

5. The Relationship between Financing Constraints and Maintenance Outside of New York

5.1. External Validity

The results in the preceding section show that after the Rent Act, code violations increased for affected rent-stabilized buildings in New York relative to controls, especially in the presence of financing constraints. While these findings are consistent with Hypothesis 1, they may not be generalizable to other markets. This is because in a market-rate setting, building owners may be able to alleviate credit constraints by increasing rent, which could offset the negative effects of credit constraints relative to the rent-controlled setting.

Figure 4 illustrates this point by displaying the relationship between code violations and building LTV ratios, for rent-stabilized buildings in New York City, and for all buildings in the 45-city panel.[29] LTV ratios and violations are residualized at the zip-code-by-year level to control for time-varying local characteristics. Residualized LTV ratios are then normalized to be between 0 and 1, and mortgages are sorted into 100 residualized LTV ratio bins (i.e., 0-0.01, 0.01-0.02, etc...). While there is a positive relationship between LTV ratios and violations in both subsamples, the relationship is stronger in New York's rent-stabilized

[29]In these plots I limit the sample to mortgages with LTV ratios between 0 and 1.

building stock.

Ideally, we could observe random variation in financial resources for market-rate buildings. While such random variation is not available, I can examine whether LTV ratios are related to building maintenance in the cross-section. Using the 45-city panel of data on mortgage LTV ratios and violations, I use panel regressions to examine whether buildings have lower maintenance when they face financing constraints (proxied by LTV ratios at origination) outside of New York City's rent-stabilized building stock. Although this test is not as cleanly identified as that in the natural experiment, more violations for buildings financed using mortgages with higher LTV ratios at origination would be consistent with the predictions of Hypothesis 1.

5.2. Panel Regressions

To examine the relationship between code violations and LTV ratios more formally, I implement the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}, \tag{3}$$

where $Violations_{it}$ is one of the violations outcome variables, and $LTVratio_{it-1}$ is the LTV ratio at origination for the mortgage financing building i in year $t-1$. LTV ratios are standardized by subtracting the sample mean and dividing by the sample standard deviation.

X_{it-1} is a vector of building, loan, lender, and real estate company controls. Building-level controls include the transaction price in millions; the age; an indicator variable to denote if the building is either a mid-rise or a high-rise, where RCA identifies mid- or high-rise buildings as having four floors or more; and the number of units. Controls at the real-estate-company-level include indicator variables to denote if the real estate company that owns the building is a public company, an institutional investor, or a joint venture, respectively, and an indicator variable to denote if there is a pre-existing relationship between the real estate company and the loan originator. Lender-level controls include an indicator variable to denote if a loan is held by a CMBS lender and an indicator variable to denote if the loan was made by a government lender. Loan-level controls include the loan interest rate, an indicator variable to denote if a loan is a refinance of a pre-existing loan, an indicator variable to denote if the mortgage is fixed rate, and the mortgage time to maturity. γ_{zt}, κ_v are zip-code-by-year and mortgage-origination-year fixed effects. Standard errors are clustered at the city level.

The regression coefficient β_1 can be interpreted as the predicted increase in code violations after an increase in a building's LTV ratio controlling for both zip-code-by-year and mortgage-origination-year fixed effects as well as building, real estate company, lender, and loan characteristics. $\beta_1 > 0$ would be consistent with Hypothesis 1.

Table 9 displays regression results. Column (1) shows estimates from a regression of the number of violations on the LTV ratio. A one standard deviation increase in LTV ratios (14.3 percentage points) predicts 0.100 more violations per year, or 9.7% of the sample mean. Given that the majority of buildings in the sample never have a violation, this is a substantial effect. Examining the control variables, older buildings incur more violations and more highly valued buildings incur fewer violations. Results are qualitatively similar when examining the number of violations per 100 units and the violation indicator.

The findings in this section are consistent with buildings financed with mortgages that have higher LTV ratios incurring more code violations in a broad sample of 45 US cities. Similar to the findings from the natural experiment, these results are consistent with the prediction from Hypothesis 1 that financing constraints lead to reduced building maintenance.[30,31]

[30]Table IA.18 displays results using violations related to repairs, which are qualitatively similar.
[31]Results for a battery of robustness checks are provided in Section IA.C.

6. Conclusion

This paper provides evidence that the way an apartment building is financed has implications for the building's tenants vis-a-vis habitability and building quality. These findings also shed light on the unintended consequences of rent control. Previous work has shown that rent control has numerous unintended consequences, including a reduction in building maintenance (Sims, 2007). By establishing that this reduction in building maintenance is especially acute in the presence of financing constraints, this paper shows that rent control's unintended consequences can be exacerbated by the building owner's financing decisions.

Policymakers will find the analyses in this paper useful as the White House considers implementing rent control for multifamily buildings at the federal level. The White House Plan would cap rent increases at 5% for real estate companies receiving multifamily tax breaks with over 50 units in their portfolios. To the extent that a real estate company's size does not capture the building owner's financing capacity, this proposal could lead to worsening maintenance for buildings with financially constrained owners. The analysis in this paper shows that rent-stabilized buildings receive more housing code violations after a negative cash flow shock if they face financing constraints. Moreover, the rental law change that I exploit targets buildings with more than 35 units, and the difference-in-differences analysis still shows an increase in violations for affected buildings relative to controls. These findings therefore imply that restricting the regulation to real estate companies with over 50 units is unlikely to avoid the aforementioned problem. Therefore, policymakers may want to consider this unintended consequence as they evaluate the rent cap proposal.

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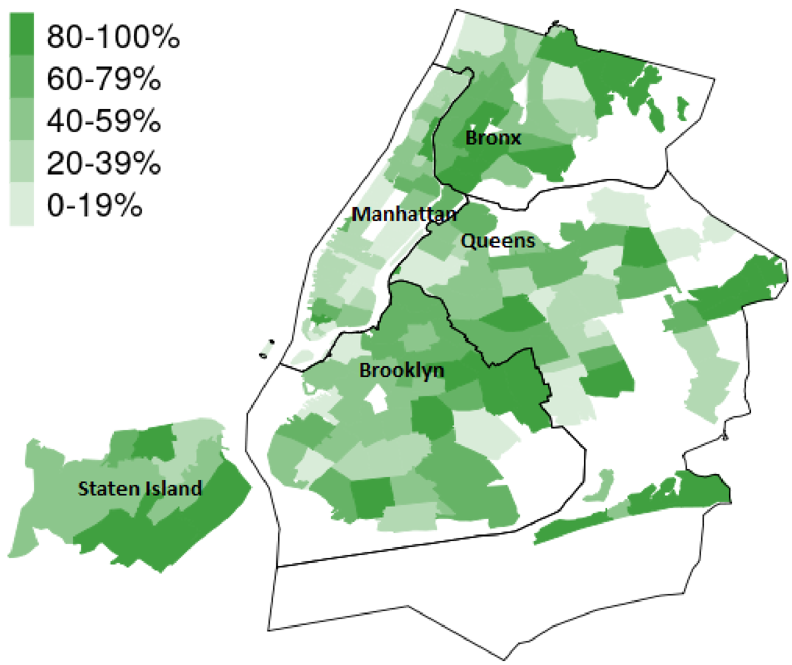
Fig. 1. Within Zip Code Variation in LTV – New York City

Average LTV ratio and capitalization rates across different zip codes in New York City. Building data are sourced from Real Capital Analytics.

(a) Average LTV ratios by NYC Zip Codes



(b) Average Capitalization Rates by NYC Zip Codes

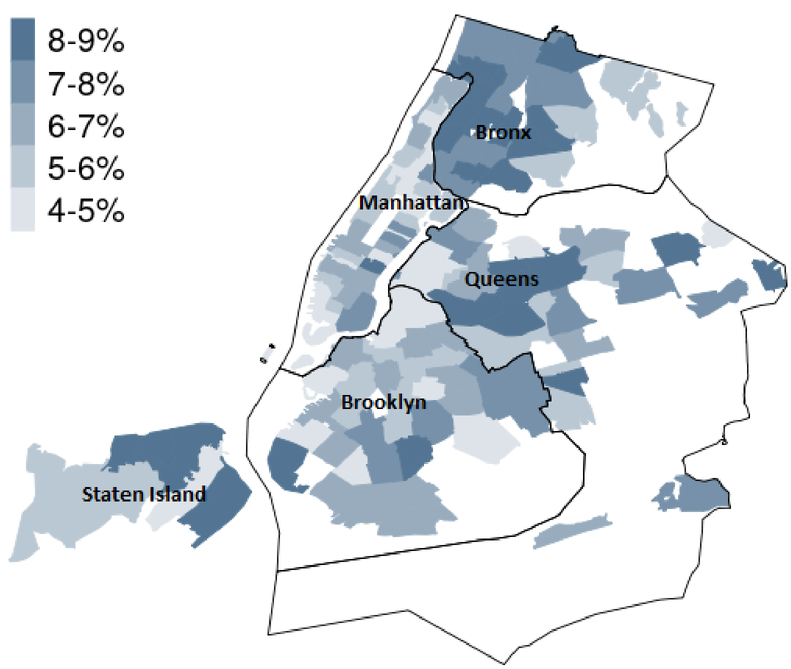


Fig. 2. Impact of Rent Act of 2011 on $5,000 Bathroom Renovation

This figure is meant to illustrate the effect of the Rent Act on the value of two hypothetical buildings: one with 35 or fewer units and the other with over 35 units. The illustration assumes an improvement equal to $5,000.

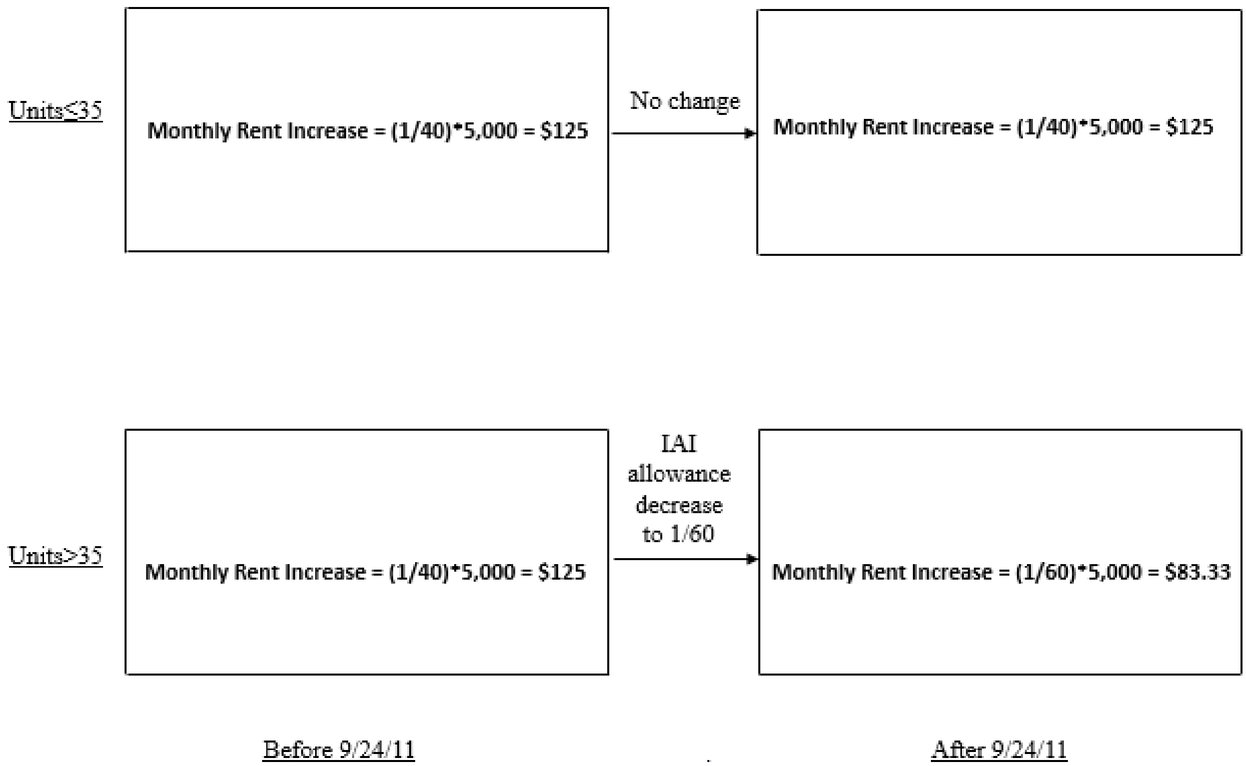
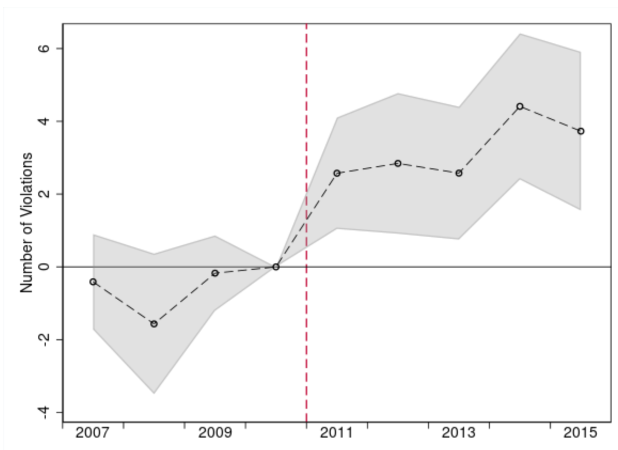


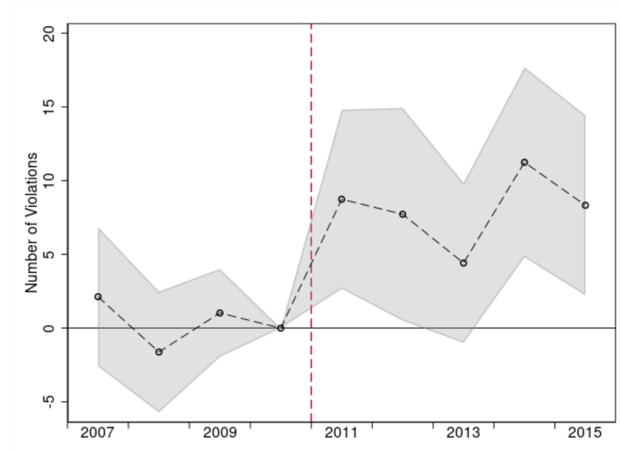
Fig. 3. Dynamic Difference-in-Differences Results – All Code Violations

Regression coefficients from dynamic difference-in-differences regressions comparing trends in code violations for treated buildings (i.e., rent-stabilized buildings with over 35 units) relative to control buildings (i.e., rent-stabilized buildings with 35 or fewer units). Regressions are run at an annual frequency. Coefficients to the right of the red dotted line are for 2011 or later. The year 2010 is excluded from the regression, so estimates can be interpreted as differences in the change in code violations from 2010 until year j for treated relative to control buildings. The shaded region is the 95% confidence interval. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent-stabilized buildings with over 35 units) to control buildings (i.e., rent-stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to one if a building was owned by an institutional investor, and zip-code-level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

(a) Number of Violations



(b) Violations per 100 units



(c) Violation Indicator

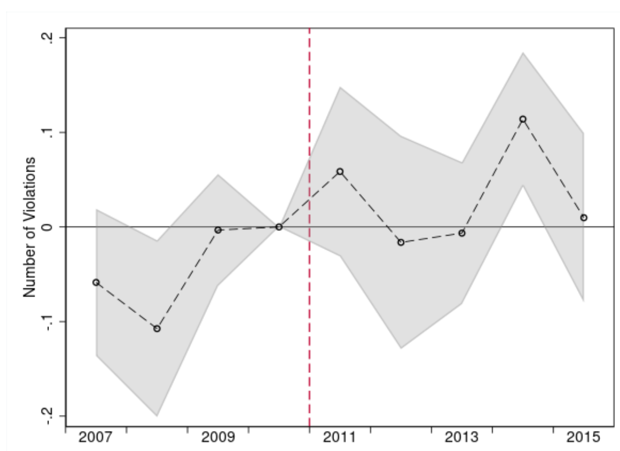
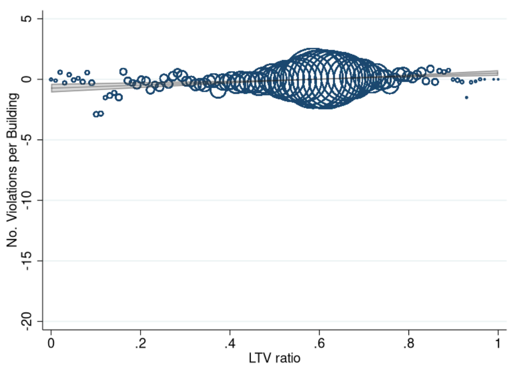


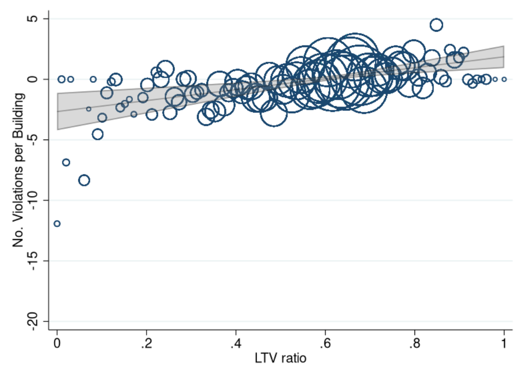
Fig. 4. Correlation between LTV and Code Violation for NYC 2011 Rent-Stabilized Buildings and Other Buildings

Code violations (measured using the number of code violations in a given year, the number of code violations per 100 units in a given year, or an indicator variable equal to one if a building incurs a code violation in a given year) graphed in 100 LTV ratio percentile bins, where the y-axis shows average code violations in a given percentile bin. The size of each dot indicates the number of observations in each bin. Both LTV ratios and code violations are residualized at the zip-code-by-year level. The black lines are from regressions of each code violations outcome on LTV ratios, and the shaded region is the 95% confidence interval. Both scatterplots and lines weighted by number of observations in each bin. Building data are sourced from Real Capital Analytics and code violations data are provided by various municipal governments. Sample for panels (b), (d), and (f) is limited to New York's rent-stabilized building stock in 2011.

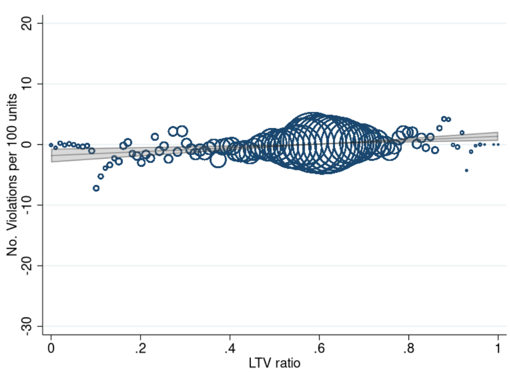
(a) # Violations (All Buildings)



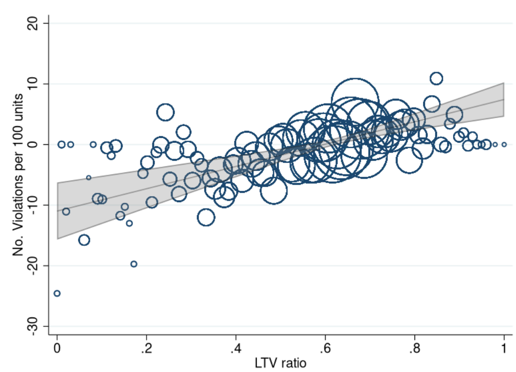
(b) # Violations (NYC RC)



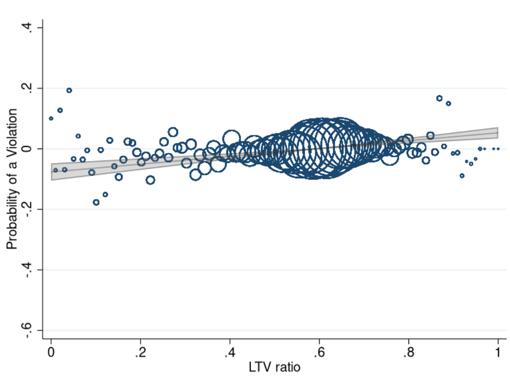
(c) Violations/100 units (All Buildings)



(d) Violations/100 units (NYC RC)



(e) Violation Indicator (All Buildings)



(f) Violation Indicator (NYC RC)

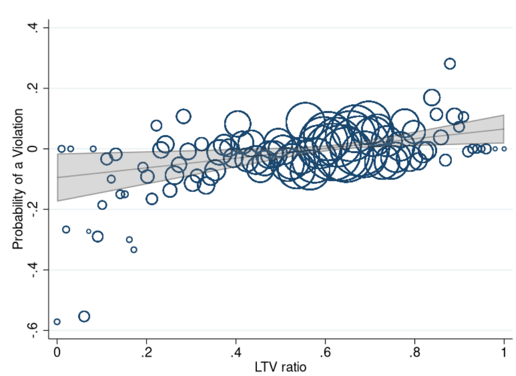


Table 1: Summary Statistics

Number of violations, number of violations per 100 units, number of repair violations, number of repair violations per 100 units, LTV ratios, combined LTV ratios, interest rates, number of units per building, building ages, Zillow index, DSCR and occupancy rates are winsorized at the 1% and 99% levels. Data are at the building-by-year level. Building data are provided by Real Capital Analytics, and code violations data are from various municipal governments.

Variable	Obs	Mean	Std. Dev.	Min	Max
Number of Violations	62,628	1.029	4.321	0.000	36
Violations per 100 Units	62,628	2.817	13.433	0.000	106.667
Violation Indicator	62,628	0.140	0.347	0.000	1.000
Number of Repair Violations	55,856	0.502	2.566	0.000	23
Repair Violations per 100 Units	55,856	1.501	8.004	0.000	66.667
Repair Violation Indicator	55,856	0.075	0.263	0.000	1.000
LTV Ratio at Origination	62,628	0.654	0.143	0.052	1.259
Combined LTV Ratio	62,628	0.663	0.155	0.052	1.457
Amortized LTV Ratio	62,628	0.620	0.155	0.037	1.256
DSCR	60,399	1.548	0.744	0.000	9.290
Transaction Price (MM)	62,628	12.728	17.874	0.654	107.5
Building Age	62,628	50.463	32.941	1.000	120
Mid/High Rise Indicator	62,628	0.320	0.467	0.000	1.000
Number of Units in Building	62,628	120.709	131.942	5.000	628
Public Owner	62,628	0.009	0.093	0.000	1.000
Institutional Owner	62,628	0.091	0.287	0.000	1.000
Joint Venture	62,628	0.056	0.231	0.000	1.000
Real Estate Company-Originator Relationship	62,628	0.424	0.494	0.000	1.000
CMBS Indicator	62,628	0.587	0.492	0.000	1.000
Loan Held by Government Lender	62,628	0.571	0.495	0.000	1.000
Refinance Indicator	62,628	0.759	0.428	0.000	1.000
Fixed-Rate Indicator	62,628	0.947	0.224	0.000	1.000
Interest Rate	62,628	0.051	0.011	0.023	0.079
Time to Maturity	62,628	7.039	5.358	0.000	40.417
Time Since Most Recent Renovation	19,362	10.72	11.582	0.000	127
Property Capitalization Rate at Origination	34,499	0.062	0.015	0.011	0.130
Property Occupancy Rate at Origination	53,969	0.945	0.061	0.300	1.000
Zip Code Zillow Index	55,975	446,626	389,381.3	34,400	3,338,500

Table 2: Change in Code Violations After the Rent Act of 2011.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t, or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35 units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent-stabilized buildings with over 35 units) to control buildings (i.e., rent-stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip-code-level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results using all code violations and Panel B displays results using only those code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units, and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
$Treat_i \times After_t$	3.764***	7.708***	0.074***
	(0.710)	(2.109)	(0.027)
Adjusted R^2	0.480	0.446	0.620
Observations	5,526	5,526	5,526
Panel B – Repair Violations			
$Treat_i \times After_t$	2.541***	5.600***	0.093***
	(0.472)	(1.387)	(0.027)
Adjusted R^2	0.464	0.440	0.581
Observations	5,526	5,526	5,526
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building

Table 3: Change in Code Violations After the Rent Act of 2011 by LTV Ratio.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t, or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35 units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent-stabilized buildings with over 35 units) to control buildings (i.e., rent-stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip-code-level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results examining buildings in the bottom tercile of LTV ratios, Panel B displays results examining buildings in the middle tercile of LTV ratios, and Panel C displays results examining buildings in the top tercile of LTV ratios. LTV ratio terciles are assigned based on the LTV ratio of buildings as of 2010. Number of violations, number of repair violations, number of violations per 100 units, and number of repair violations per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Violation type	All Violations			Repair Violations		
Variable	# Violations	Violations/ 100 units	Has Violation	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A – Bottom LTV Tercile, N=1,746						
$Treat_i \times After_t$	1.583	0.487	0.046	1.279*	1.468	0.044
	(1.302)	(3.949)	(0.043)	(0.762)	(2.249)	(0.051)
Adjusted R^2	0.473	0.441	0.569	0.451	0.428	0.531
Panel B – Mid LTV Tercile, N=1,494						
$Treat_i \times After_t$	4.342***	9.059***	0.059	2.769***	6.329***	0.123***
	(1.045)	(2.553)	(0.043)	(0.635)	(1.573)	(0.038)
Adjusted R^2	0.457	0.403	0.611	0.432	0.404	0.590
Panel C – Top LTV Tercile, N=1,620						
$Treat_i \times After_t$	5.762***	13.548***	0.119***	3.722***	8.801***	0.118**
	(1.314)	(3.696)	(0.046)	(0.931)	(2.609)	(0.047)
Adjusted R^2	0.531	0.490	0.647	0.515	0.475	0.598
FE	Building	Building	Building	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building	Building	Building	Building

Table 4: Change in Code Violations After Rent Act of 2011 – Match Within Real Estate Company.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t, or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35 units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent-stabilized buildings with over 35 units) to control buildings (i.e., rent-stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, and zip-code-level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Matching is conducted within real estate company. Panel A displays results using all code violations, and Panel B displays results using only those code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units, and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A: All Violations			
$Treat_i \times After_t$	3.821**	8.196*	0.035
	(1.527)	(4.410)	(0.053)
Adjusted R^2	0.541	0.521	0.611
Observations	1,098	1,098	1,098
Panel B: Repair Violations			
$Treat_i \times After_t$	2.711***	6.202**	0.073
	(0.897)	(2.544)	(0.061)
Adjusted R^2	0.518	0.494	0.632
Observations	1,098	1,098	1,098
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E. Cluster	Building	Building	Building

Table 5: Change in Code Violations After Rent Act of 2011 – With Size Restrictions.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t, or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35 units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent-stabilized buildings with over 35 units) to control buildings (i.e., rent-stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip-code-level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results using buildings with 10 to 60 units, Panel B displays results using buildings with 15 to 55 units, Panel C displays results using 20 to 50 units, Panel D displays results using 25 to 45 units and Panel E displays results using 30 to 40 units. Number of violations, number of violations requiring repairs, number of violations per 100 units, and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – 10-60 units, N=4,635			
$Treat_i \times After_t$	3.335***	7.225**	0.072**
	(0.881)	(2.828)	(0.036)
Adjusted R^2	0.463	0.456	0.615
Panel B – 15-55 units, N=4,075			
$Treat_i \times After_t$	3.708***	8.427***	0.100***
	(0.986)	(3.134)	(0.037)
Adjusted R^2	0.458	0.459	0.621
Panel C – 20-50 units, N=3,492			
$Treat_i \times After_t$	2.996***	7.534**	0.097**
	(1.060)	(3.453)	(0.041)
Adjusted R^2	0.451	0.471	0.607
Panel D – 25-45 units, N=2,187			
$Treat_i \times After_t$	1.958	4.013	0.099**
	(1.336)	(4.016)	(0.042)
Adjusted R^2	0.451	0.451	0.596
Panel E – 30-40 units, N=1,435			
$Treat_i \times After_t$	3.802**	10.097**	0.110**
	(1.668)	(4.819)	(0.048)
Adjusted R^2	0.488	0.488	0.624
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E. Cluster	Building	Building	Building

Table 6: Change in Code Violations After Rent Act of 2011 – Controlling for Rent

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it}.$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t, or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35 units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent-stabilized buildings with over 35 units) to control buildings (i.e., rent-stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, zip-code-level occupancy rates, and building rent as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results examining all violations; Panel B displays results examining repair violations. Number of violations, number of repair violations, number of violations per 100 units, and number of repair violations per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Property data are provided by Real Capital Analytics, rent data are provided by CoStar Group, and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
$Treat_i \times After_t$	4.002***	8.837***	-0.001
	(0.834)	(2.284)	(0.036)
Adjusted R^2	0.596	0.556	0.706
Observations	1,170	1,170	1,170
Panel B – Repair Violations			
$Treat_i \times After_t$	2.311***	4.951***	0.009
	(0.544)	(1.557)	(0.030)
Adjusted R^2	0.592	0.556	0.687
Observations	1,170	1,170	1,170
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building

Table 7: Change in Code Violations After Rent Act of 2011 – Control for Building Permits

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t, or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35 units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent-stabilized buildings with over 35 units) to control buildings (i.e., rent-stabilized buildings with 35 or fewer units) according to issuance of building permits, LTV, most recent transaction price, building age, and zip-code-level occupancy rates as covariates. All covariates are taken from the most recent transaction data as of 2010, except building permits, which are based on 2007-2010. Panel A displays results using all code violations, and Panel B displays results using only those code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units, and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A: All Violations			
$Treat_i \times After_t$	3.513***	7.170***	0.071***
	(0.720)	(2.085)	(0.026)
Adjusted R2	0.496	0.473	0.646
Observations	5,634	5,634	5,634
Panel B: Repair Violations			
$Treat_i \times After_t$	2.347***	5.134***	0.092***
	(0.479)	(1.376)	(0.026)
Adjusted R2	0.477	0.462	0.599
Observations	5,634	5,634	5,634
FE	Building Pair-Year	Building Pair-Year	Building Pair-Year
S.E. Cluster	Building	Building	Building

Table 8: Placebo Test Using Market-Rate Buildings in New York

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t, or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35 units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent-stabilized buildings with over 35 units) to control buildings (i.e., rent-stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, and zip-code-level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results using all code violations, and Panel B displays results using only those code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units, and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
$Treat_i \times After_t$	1.109	1.577	-0.031
	(0.843)	(2.332)	(0.021)
Adjusted R^2	0.439	0.352	0.674
Observations	1,836	1,836	1,836
Panel B – Repair Violations			
$Treat_i \times After_t$	0.765	1.354	-0.008
	(0.502)	(1.383)	(0.023)
Adjusted R^2	0.409	0.322	0.647
Observations	1,836	1,836	1,836
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building

Table 9: Relationship Between LTV Ratios at Origination and Code Violations.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to one if building i incurs a code violation in year t. $LTVratio_{it-1}$ is the LTV ratio at origination for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v and are zip-code-by-year and mortgage-origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Number of violations, number of violations per 100 units, LTV ratios, transaction prices, building age, number of units per building, and interest rates are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
LTV Ratio	0.100***	0.294***	0.006**
	(0.016)	(0.093)	(0.002)
Building Controls			
Transaction Price	-0.007**	-0.030**	-0.001***
	(0.003)	(0.012)	(0.000)
Building Age	0.005***	0.023***	0.000***
	(0.001)	(0.007)	(0.000)
Mid/High Rise Indicator	0.421**	0.209	0.031***
	(0.204)	(0.628)	(0.010)
Number of Units in Building	0.001**	-0.003	0.000***
	(0.001)	(0.002)	(0.000)
Real Estate Company Controls			
Public Owner	0.019	-0.036	-0.013
	(0.165)	(0.448)	(0.024)
Institutional Owner	-0.025	0.376	0.004
	(0.040)	(0.276)	(0.007)
Joint Venture	0.326*	1.054*	0.034**
	(0.186)	(0.546)	(0.015)
Real Estate Company-Originator Relationship	0.064**	0.156*	0.006
	(0.030)	(0.082)	(0.004)
Lender Controls			
CMBS Indicator	-0.144***	-0.129	-0.001
	(0.049)	(0.111)	(0.007)
Loan Held by Government Lender	-0.326**	-0.368	-0.010*
	(0.137)	(0.375)	(0.006)
Loan Controls			
Interest Rate	4.096	13.338	0.608*
	(2.699)	(11.141)	(0.335)
Refinance Indicator	-0.245	-0.658	-0.017*
	(0.196)	(0.479)	(0.009)
Fixed-Rate Indicator	-0.124	0.237	-0.008
	(0.093)	(0.300)	(0.006)
Time to Maturity	-0.012***	0.013	-0.002***
	(0.003)	(0.014)	(0.000)
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
SE Cluster	City	City	City
Adjusted R^2	0.153	0.145	0.208
Observations	62,628	62,628	62,628

Internet Appendix

IA.A. Other Data Information

Violations Relating to Repairs

I collect data on housing code violations for 45 cities.[1] For 41 of these cities, there is a description of the violations. In some cases, this is the actual text of the violation, while in others, there is an ordinance number given referring to the relevant ordinance in the city code of ordinances. I read through several hundred descriptions to determine words indicating that the violation is due to a need to make repairs. The words I identify are:

Improve	Repair	
Improve	Battered	Heat
Install	Boiler	Heater
New	Broken	Heating system
Reconstruct	Busted	Hot water
Rehabilitate	Collapsed	Janitor
Rehabilitation	Crack	Leak
Renovate	Crumbled	Lighting
Renovation	Crumbling	Maintenance
Replace	Crushed	Neglected
Restore	Damaged	Paint
	Decaying	Pave
	Decrepit	Ramshackle
	Defective	Repair
	Demolished	Rickety
	Derelict	Run down
	Dilapidated	Run-down
	Dingy	Seedy
	Electricity	Water in basement
	Fractured	Water supply
	Fragmented	Wreck

To be classified as a violation requiring repairs I also require that a violation is not classified as a violation requiring improvements so as to address endogeneity concerns in the difference-in-differences analysis in section 4. I parse through the text to check for the appearance of any of the above strings. If no description is available but instead an ordinance is provided, I read through the code of ordinances for the city to identify violations of ordinations including these strings. For Seattle, Greenville SC, Cleveland, although there is neither a detailed description nor is the ordinance included, a vague descriptor or the

[1] For example, the NYC data can be found at https://data.cityofnewyork.us/Housing-Development/Housing-Maintenance-Code-Violations/wvxf-dwi5.

department that handled the violation is included. If this is the case, I designate violations as relating to repairs as well as possible.

Note that as some of the violation descriptions in the data are very vague, it is inevitable that some violations related to building maintenance will be classified as unrelated to repairs. This is apparent when examining the examples of code violations provided in subsection 3.1. The first example is clearly related to building maintenance, and would be classified as such because it contains the word "repair". On the other hand, the second violation is unrelated to building maintenance, and accordingly would not be classified as requiring repairs. However, the third violation contains no useful information about the content of the violation, and could either be related to building maintenance or unrelated to building maintenance. Nonetheless, it will be classified as not requiring repairs as it does not contain any words indicating a repair must be made. For this reason, separately examining violations not requiring repairs is not an informative test.

IA.B. Drivers of Apartment Financing Decision

In this section, I examine what drives the apartment financing decision. The key takeaway from this analysis is that building-owners use more mortgage debt to finance buildings that they expect to have lower returns to maintenance. Therefore, building-owners choose to preserve less financial capacity for buildings with lower returns to maintenance.

Figure 1 shows that buildings in zip codes with high capitalization rates tend to have higher LTV ratio mortgages, but these results raise the question of what explains variation in LTV ratios within zip codes. I argue that building-owners anticipate investing less in lower quality buildings as those buildings have lower returns to investment.

To further examine the cross-sectional determinants of financing constraints, I run regressions of LTV ratios at-origination on hypothesized drivers of the LTV ratio choice:

$$LTVratio_{it} = \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 X_{3,it} + \beta_4 X_{4,it} + FE + \epsilon_{it}, \tag{4}$$

where $LTVratio_{it}$ is the LTV ratio for the mortgage originated for building i in year t, $X_{1,it}$ are building characteristics, $X_{2,it}$ are local zip code level characteristics, $X_{3,it}$ are building-owner characteristics, and $X_{4,it}$ are loan characteristics. LTV ratios and control variables are measured at the time of mortgage-origination. The vector $X_{1,it}$ includes building age, the number of units in a building, an indicator variable equal to 1 if a building is a mid or high-rise and the most recent transaction price for a building. In one specification I also include the time since the most recent renovation, although I exclude it in other specifications as it is not well-populated. $X_{2,it}$ includes the zip code level capitalization rate, the zip code level occupancy rate and the zip code level Zillow Home Values Index (ZHVI). $X_{3,it}$ includes an indicator variable equal to one if building i is owned by a public company and an indicator variable equal to one if building i is owned by an institutional investor. $X_{4,it}$ includes an indicator variable equal to one if the mortgage was made by a government lender, an indicator variable equal to one if a mortgage is fixed-rate, an indicator variable equal to one if a mortgage was a refinancing of a pre-existing mortgage, the mortgage time to maturity and the mortgage interest rate.

Table IA.29 displays cross-sectional regression results. Column (1) displays results with no fixed effects. Older buildings have higher LTV ratio mortgages, perhaps because the returns to investing in older buildings are lower. Mortgages on larger buildings also have higher LTV ratios, possibly because buildings with more units have more diversified cash flows. Examining the effect of local economic characteristics, buildings in higher capitalization rate zip codes tend to have bigger mortgages. Surprisingly though, buildings in zip codes with higher occupancy rates tend to have larger mortgages. This could be since those investments may be less risky since they have a more stable cash flow stream, reducing costs of borrowing and therefore allowing borrowers to take on more debt. Lastly, buildings in zip codes with higher home values tend to have smaller mortgages, consistent with buildings owners using more debt to finance buildings that they anticipate having lower returns to investment. Owner characteristics are displayed below, where buildings owned by public companies tend to have lower LTV ratio mortgages. This could be since those investors have other sources of capital to choose from, and therefore need to rely less on mortgage financing.

Column (2) adds zip code and mortgage origination-year fixed effects to the regression in order to control for time-varying macroeconomic conditions at the time the mortgage was originated and local time-invariant characteristics. For the most part, the results are very similar. The coefficient on the mid/high rise indicator is also now negative and statistically significant, perhaps because these buildings tend to be luxury apartments which may have higher returns to investment. In this specification, the effects of the age, units and government lender indicator on the mortgage LTV ratios are now statistically insignificant.

The results in columns (1) and (2) make it clear that time-varying zip code level characteristics are an important determinant of building financing, so column (3) includes zip-code-by-year fixed effects to control for these zip code level time trends. When using zip-code-by-year fixed effects, the estimates of the effects of transaction prices are now negative and statistically significant. The coefficient on the number of units is also once again positive and statistically significant. Furthermore, the R^2 of the regression increases from 0.423 in column (2) to 0.619 in column (3), indicating that a significant portion of the variation in apartment mortgage LTV ratios are explained by zip code time trends. For this reason, including zip-code-by-year fixed effects significantly improves the reliability of the panel regressions. This indicates that by controlling for zip-code-by-year fixed effects it is possible to control for a significant amount of unobserved heterogeneity in LTV ratios. Lastly, in Column (4), the time since the most recent renovation is included to better proxy for building quality. Buildings that have been renovated less recently tend to be financed with lower LTV ratio mortgages. This could be since building-owners borrow to finance renovations.[2]

Columns (1) through (4) display results using all of the mortgages in RCA. Columns (5) through (8) only display results for the portion of the sample for which there is code violations data available (i.e. cities referenced in Table IA.1). For the most part, the results are qualitatively similar. The only exceptions are that the estimates on the number of units and the ownership indicators are statistically insignificant in all specifications. This is likely due to the reduced sample size when limiting the data to cities where information on code

[2]While there are some differences in the results in this column relative to others, this is largely due to the significant decrease in the sample size when including the time since renovation variable.

violations is available.

Overall, the findings in this section provide evidence that LTV ratios are not chosen randomly. In particular, zip code level characteristics are an important determinant of building LTV ratios, as are the building's size, age, owner, and quality. Therefore, a shock is necessary to test how building financing constraints affect maintenance.

IA.C. Other Robustness Checks

IA.C.1. Difference-in-differences analysis

A battery of robustness checks are included to ensure the results are not sensitive to empirical choices made in implementing the difference-in-differences design. To consider whether the choice to proxy for financing constraints with the LTV ratio at origination is driving the results in the subsample analysis, results are presented using alternative measures. Table IA.6 displays results using the DSCR, Table IA.7 displays results using the combined LTV ratio and Table IA.8 displays results using an amortized LTV ratio. In all tests, the change in violations after the Rent Act is absent in the least financially constrained tercile, and in most cases it is strongest in the top tercile.

I conduct a test where I match on a building's effective age, defined as the time since the most recent building renovation when available and a building's age otherwise. Results are displayed in Table IA.9, and are qualitatively similar to those in the main specification, providing evidence that the results are not driven by differences in building quality for treated and control buildings.

While the results provide evidence that code violations increase in the presence of financing constraints, it is not clear whether this is due to access to external capital, or due to reductions in internal capital (i.e. either the building's current income, or retained income). I next explicitly test whether access to external capital is driving the results by matching within real estate company-originator relationship, as within each relationship, it should be equally easy to obtain additional financing. Results from a test using such a match are displayed in Table IA.10, which are consistent with the main results, indicating that access to external financing is not driving the results. This implies that the change in violations is primarily due to decreases in access to internal capital (i.e. lower rent collections from the Rent Act).

As the number of violations is a count variable, tests using it as a dependent variable may have reduced efficiency (Cohn et al., 2022). Although using the violations per 100 units helps with this, Table IA.11 includes results of the difference-in-differences analysis using a

Poisson regression, and the conclusions are broadly similar.

The results from Section 4 use buildings from the RCA database, which only covers buildings sold in transactions worth over \$2.5 million, which could introduce selection bias. To examine a more general sample of buildings, I merge code violations with a list of all buildings required to register with the New York Department of Housing Preservation and Development (HPD). The list contains the number of units in each building, allowing me to conduct the analysis using all rental buildings in New York City. Results are displayed using all rent stabilized buildings registered with the HPD in Table IA.12. For all outcome variables, the results are qualitatively similar to those in the main specifications, showing the findings generalize to a broad population of buildings.

Additionally, the results in the difference-in-differences regressions are robust to variations in the empirical design. For instance, Table IA.13 displays tests using several different time windows. Table IA.14 displays results on the full unmatched sample. Lastly, Table IA.15 shows results clustering standard errors at the zip-code-level instead of the building-level, while Table IA.16 shows results double-clustering standard errors at the building and year levels. In all of these cases, the conclusions are qualitatively similar.

To more formally compare treatment effects along the dimension of building financing constraints, I implement a triple-difference regression comparing the change in code violations for treated buildings after the Rent Act, between buildings in the top LTV tercile and those in the bottom LTV tercile in Table IA.17. The regression results show statistically significant and negative estimates for the triple-difference coefficient in four out of six specifications, providing further evidence that changes in code violations for treated buildings after the Rent Act is sensitive to building financing constraints.

IA.C.2. Panel Regressions

Noting that LTV ratios at origination may not be the only way to capture whether a building faces financing constraints, I consider several other proxies for the existence of financing constraints. Table IA.19 uses debt-service coverage ratios (DSCR) instead. I also include results using several other calculations of the LTV ratio. To consider the effect of second mortgages, Table IA.20 includes results using combined LTV ratios. Additionally, Table IA.21 displays regression results using estimated amortized LTV ratios from information provided by RCA. Using all these different proxies for the existence of financing constraints, the results are similar to those using LTV ratios at origination, providing further evidence that buildings tend to be less well maintained when they face financing constraints.

Several tests are included to consider whether sample selection may drive the results. To account for concentration of data in certain cities, results using inverse probability weighting by the number of observations in each city are shown in Table IA.22. Table IA.23 also shows results excluding the four most widely represented cities (New York, Los Angeles, Houston and Chicago) from the sample. Likewise, to examine whether greater availability of code violations data in larger years are driving the results, Table IA.24 displays results only including observations from 2012 and earlier, Table IA.25 displays results only including observations from 2013 and later, and Table IA.26 includes results double-clustering by city and year. All results are broadly similar to the baseline, indicating the findings are not driven by the composition of the sample.

Note that since code violations are a count variable, efficiency loss can occur in a regression of code violations on LTV ratios (Cohn et al., 2022). While the regressions using violations per 100 units help correct for this problem, Table IA.27 includes results of a Poisson regression of code violations on LTV ratios, and the conclusions are similar.

Lastly, to better control for the quality of a building, Table IA.28 displays regression results using the building's effective age, defined as the time since the building's most recent renovation when available and the building's age otherwise, as a control in place of the building's age, and the results are similar to the baseline.

IA.D. Additional Results

Fig. IA.1. Geographic Distribution of Data

Map displaying the geographic composition of the data. The size of each point is proportional to the number of observations in that MSA. The shade of blue corresponds to the number of code violations per observations (i.e. cities with more code violations are darker shades of blue). Code violations data are from various municipal governments.

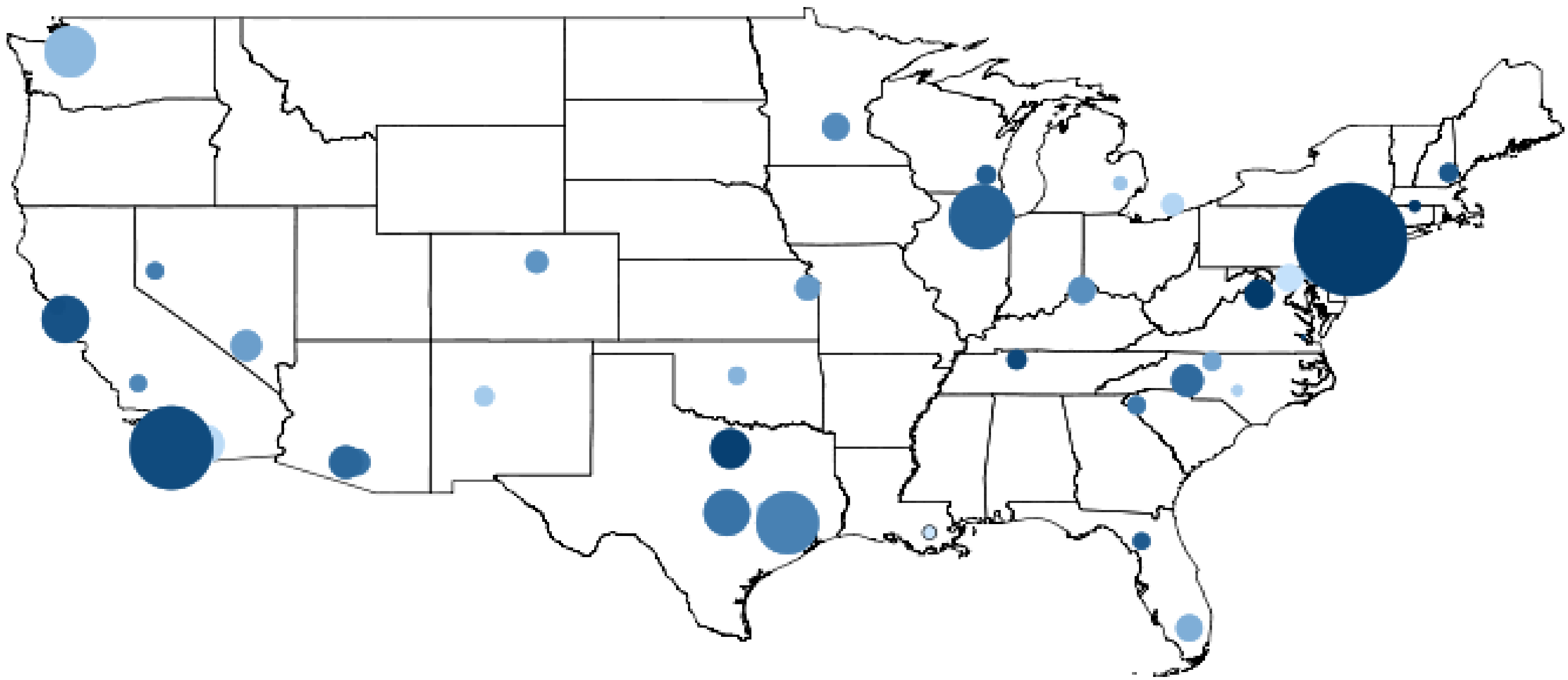


Fig. IA.2. Code Violations over Time

Number of code violations observed in the data per year. Code violations data are from various municipal governments.

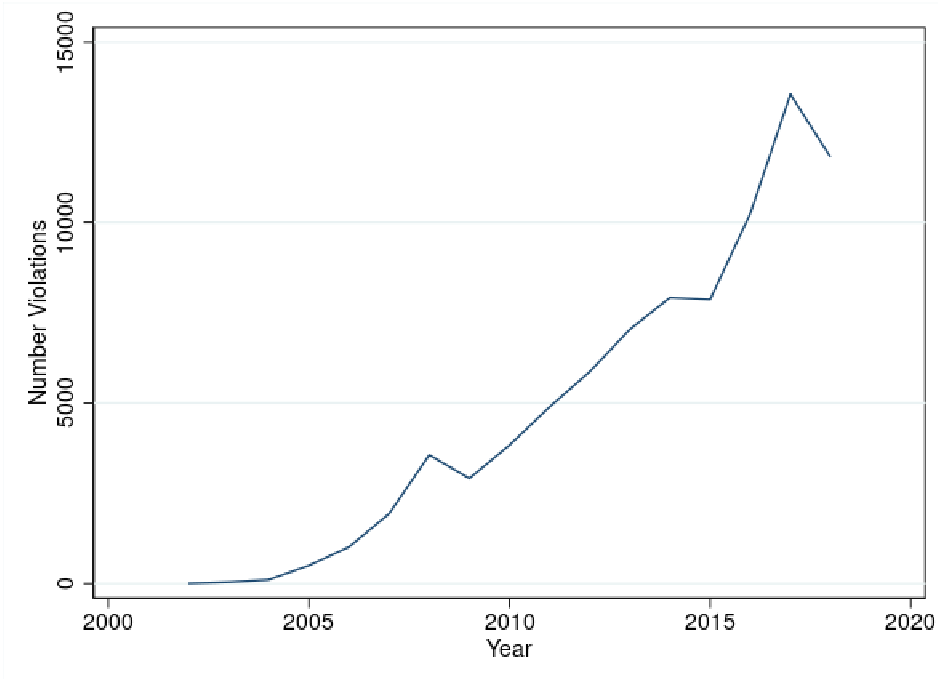


Fig. IA.3. Change in Capitalization Rates After the Rent Act

Average capitalization rates for treated buildings (i.e., rent stabilized buildings with over 35-units) relative to control buildings (i.e., rent stabilized buildings with 35 or fewer units). Sample constructed using one-to-one nearest neighbor matching of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to one if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

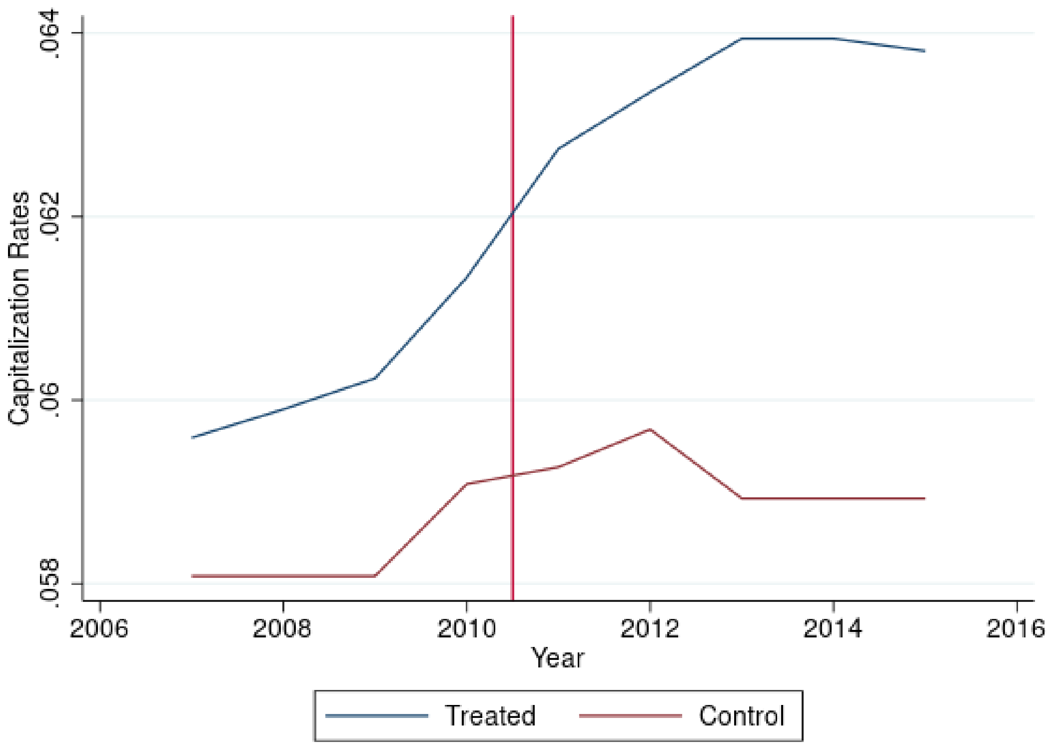
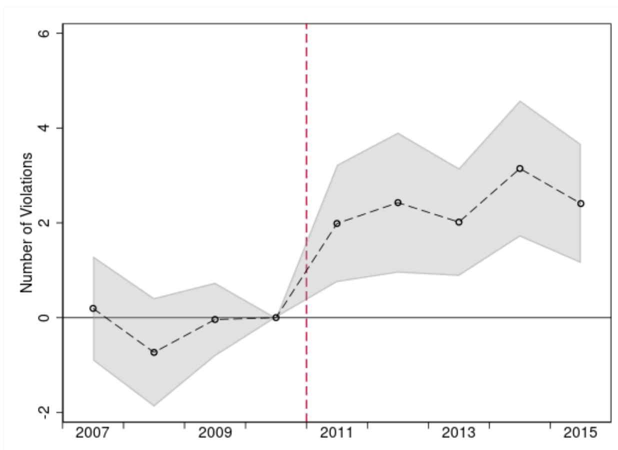


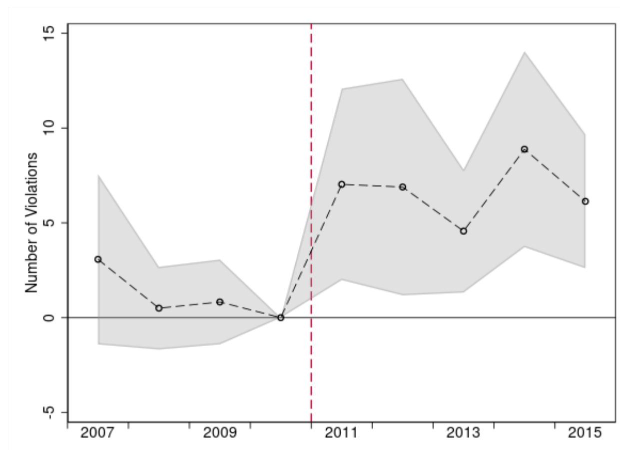
Fig. IA.4. Dynamic Difference-in-Differences Results – Code Violations Requiring Repairs

Regression coefficients from dynamic difference-in-differences regressions comparing trends in code violations requiring repairs for treated buildings (i.e., rent stabilized buildings with over 35-units) relative to control buildings (i.e., rent stabilized buildings with 35 or fewer units). Regressions are run at the annual frequency. Coefficients to the right of the red-dotted line are for 2011 or later. 2010 is excluded from the regression, so estimates can be interpreted as differences in the change in code violations from 2010 until year j for treated relative to control buildings. The shaded region is the 95% confidence interval. Sample constructed using one-to-one nearest neighbor matching with replacement to assign NYC rent stabilized buildings with more than 35-units to those with 35 or fewer units according to average building LTV ratios over the pre-period, most recent transaction prices as of 2010, building ages as of 2010, and indicator variable equal to 1 if a building was owned by an institutional investor in 2010, an indicator variable equal to 1 if the mortgage on a building in 2010 was a refinance, and zip code level occupancy rates as of 2010. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

(a) Number of Repair Violations



(b) Repair Violations per 100 units



(c) Repair Violation Indicator

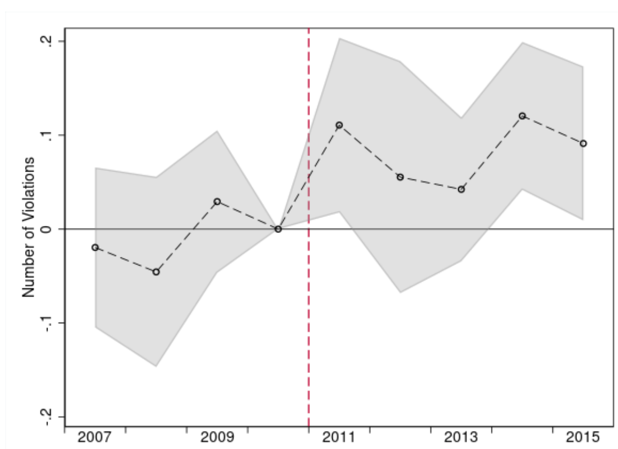
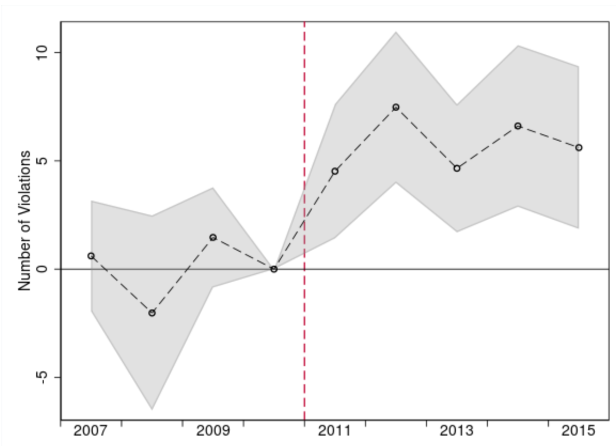


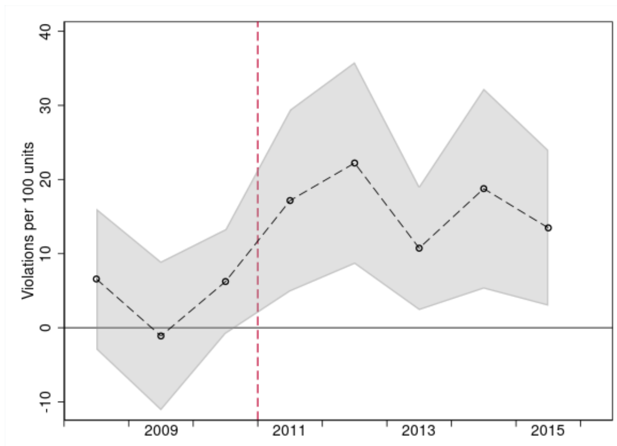
Fig. IA.5. Dynamic Difference-in-Differences Results – Top LTV Tercile

Regression coefficients from dynamic difference-in-differences regressions comparing trends in code violations for treated buildings (i.e., rent stabilized buildings with over 35-units) relative to control buildings (i.e., rent stabilized buildings with 35 or fewer units) in the top LTV tercile. Regressions are run at the annual frequency. Coefficients to the right of the red-dotted line are for 2011 or later. 2010 is excluded from the regression, so estimates can be interpreted as differences in the change in code violations from 2010 until year j for treated relative to control buildings. The shaded region is the 95% confidence interval. Sample constructed using one-to-one nearest neighbor matching with replacement to assign NYC rent stabilized buildings with more than 35-units to those with 35 or fewer units according to average building LTV ratios over the pre-period, most recent transaction prices as of 2010, building ages as of 2010, and indicator variable equal to 1 if a building was owned by an institutional investor in 2010, an indicator variable equal to 1 if the mortgage on a building in 2010 was a refinance, and zip code level occupancy rates as of 2010. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

(a) Number of Violations



(b) Violations per 100 units



(c) Violation Indicator

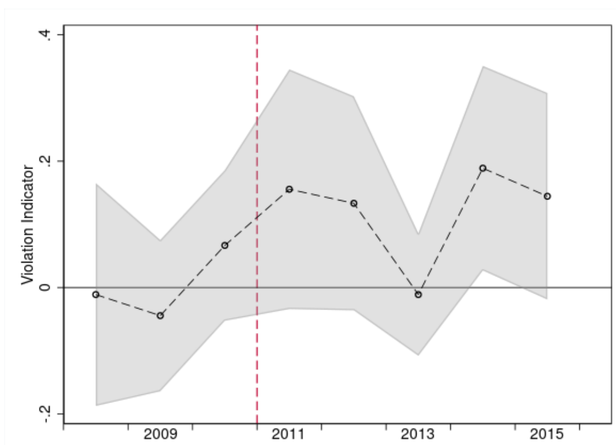


Table IA.1: Cities with Data on Code Violations.

The number of observations is the number of building-year observations observed in each city. The number of observations with a violation is the number of building-year observations with a violation occurring. The number of buildings is number of buildings observed in data. The number of buildings with a violation is number of buildings for which a violation is observed at some point in data. Other cities are those with under 1,000 observations, which includes Baltimore MD, Minneapolis MN, Cincinnati OH, Dallas TX, Tacoma WA, Kansas City MO, Anaheim CA, Greensboro NC, Fort Lauderdale FL, Oklahoma City OK, Cleveland OH, Albuquerque NM, Aurora CO, Milwaukee WI, Nashville TN, Tempe AZ, Greenville SC, Mesa AZ, College Station TX, Gainesville FL, Reno NV, Boston MA, Bakersfield CA, Fayetteville NC, Burbank CA, Santa Rosa CA, El Cajon CA, Hartford CT, New Orleans LA, Detroit MI and Virginia Beach VA. Code violations data are from various municipal governments.

City	No. Obs	No. Obs with Viol	No. Bldgs	No Bldgs w. Viol	Earliest Year	Latest Year
New York	11,522	2,315	2,240	797	2002	2018
Los Angeles	7,883	946	1,343	460	2003	2018
Houston	6,318	323	941	172	2003	2018
Chicago	4,933	655	1,132	328	2006	2018
Austin	2,971	422	487	164	2003	2018
Seattle	2,604	84	472	61	2004	2018
San Francisco	2,215	292	348	133	2003	2018
Philadelphia	2,209	180	317	80	2007	2018
San Diego	1,867	33	326	27	2004	2018
Washington	1,289	253	229	124	2007	2018
Charlotte	1,229	91	220	67	2007	2018
Tucson	1,209	359	205	109	2008	2018
Fort Worth	1,197	738	200	154	2006	2018
Las Vegas	1,107	51	283	33	2012	2018
Other	14,075	2,001	2,893	863	N/A	N/A
Total	62,628	8,743	11,636	3,572	N/A	N/A

Table IA.2: NYC Summary Statistics – Before Matching.

Summary statistics comparing treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units). Number of violations, number of violations per 100 units, number of repair violations, number of repair violations per 100 units, LTV ratio, building age, and unemployment rate winsorized at the 1% and 99% levels. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are provided by the New York City government.

Variable	Treated		Control		Difference
	Mean	St. Dev	Mean	St. Dev	
Number of Violations	3.136	7.610	0.997	3.560	2.139***
Violations per 100 Units	5.322	14.005	4.640	16.827	0.682
Violation Indicator	0.293	0.455	0.129	0.336	0.164***
LTV Ratio	0.552	0.221	0.598	0.218	-0.046***
Transaction Price (MM)	11.0	17.1	4.500	5.200	6.500***
Building Age	79.633	17.121	91.797	18.399	-12.164***
Mid/High Rise Indicator	0.986	0.118	0.980	0.140	0.006
Public Owner	0.002	0.045	0.000	0.000	0.002
Institutional Owner	0.100	0.301	0.063	0.243	0.037**
Property Capitalization Rate at Origination	0.056	0.016	0.058	0.013	-0.002
Occupancy %	0.883	0.284	0.936	0.179	-0.053

Table IA.3: Summary Statistics – Matched Sample.

Summary statistics comparing treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units). Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Number of violations, number of violations per 100 units, number of repair violations, number of repair violations per 100 units, LTV ratio, building age, and unemployment rate winsorized at the 1% and 99% levels. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are provided by the New York City government.

Variable	Treated		Control		Difference
	Mean	St. Dev	Mean	St. Dev	
Number of Violations	3.573	7.904	2.459	5.802	1.114**
Violations per 100 Units	6.669	16.054	9.405	22.534	-2.736*
Violation Indicator	0.342	0.475	0.202	0.402	0.140***
LTV Ratio	0.558	0.203	0.557	0.199	0.001
Transaction Price	5.506	4.619	4.563	4.384	0.942***
Building Age	84.564	8.622	85.476	8.405	-0.912
Mid/High Rise Indicator	0.997	0.057	0.997	0.057	0.000
Public Owner	0.000	0.000	0.000	0.000	0.000
Institutional Owner	0.052	0.223	0.052	0.223	0.000
Building Capitalization Rate at Origination	0.061	0.016	0.059	0.013	0.002
Occupancy %	0.853	0.329	0.903	0.219	-0.050
$N_{control} = N_{treated} = 307$					

Table IA.4: Change in Appraised Values Following the Rent Act of 2011.

This table displays results from the following regression:

$$ApprValperUnit_{it} = \beta_1 Treat_i + \beta_2 After_t + \beta_3 Treat_i \times After_t + FE + \epsilon_{it},$$

where $ApprValperUnit_{it}$ is the appraised value of building i in year t divided by the number of units in building i, $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units and $After_t$ is an indicator variable equal to 1 if year t is 2012. Appraised values per unit winsorized at the 1% and 99% levels. The sample includes all appraisals for all rent stabilized buildings in New York City from 2010 and 2012. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively.

	(1)	(2)	(3)	(4)
$Treat_i \times After_t$	-2772.529***	-2837.047***	-2919.856***	-991.047**
	(365.696)	(368.024)	(361.011)	(435.299)
$Treat_i$	-49488.358***	-26232.860***		
	(830.084)	(906.135)		
$After_t$	8264.906***			
	(290.541)			
FE		Year	Year	
			Building	Building
				Zip-Year
S.E. Cluster	Building	Building	Building	Building
Adjusted R^2	0.092	0.439	0.947	0.952
Observations	39,344	39,344	39,304	39,294

Table IA.5: Change in Code Violations After Rent Act of 2011 by Size-Bin.

This table displays results from the following regression:

$$\begin{aligned} Violations_{it} = &\beta_1[\mathbb{1}(35 < Units \leq 45)] \times After_t + \beta_2[\mathbb{1}(45 < Units \leq 55)] \times After_t \\ &+ \beta_3[\mathbb{1}(55 < Units \leq 65)] \times After_t + \beta_4[\mathbb{1}(65 < Units \leq 75)] \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it}, \end{aligned} \quad (5)$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $\mathbb{1}(35 < Units \leq 45)$ is an indicator variable equal to 1 if building i has more than 35-units and 45 or fewer units, $\mathbb{1}(45 < Units \leq 55)$ is an indicator variable equal to 1 if building i has more than 45 units and 55 or fewer units, $\mathbb{1}(55 < Units \leq 65)$ is an indicator variable equal to 1 if building i has more than 55 units and 65 or fewer units and $\mathbb{1}(65 < Units \leq 75)$ is an indicator variable equal to 1 if building i has more than 65 units and 75 or fewer units. $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. Sample limited to buildings with 75 or fewer units. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
$\mathbb{1}(35 < Units \leq 45) \times After_t$	3.359***	8.416**	0.104**
	(1.074)	(3.352)	(0.042)
$\mathbb{1}(45 < Units \leq 55) \times After_t$	4.170***	8.232***	0.063
	(1.112)	(3.172)	(0.041)
$\mathbb{1}(55 < Units \leq 65) \times After_t$	1.477	2.192	0.020
	(1.126)	(3.212)	(0.039)
$\mathbb{1}(65 < Units \leq 75) \times After_t$	3.145**	6.908	0.046
	(1.522)	(4.640)	(0.048)
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E. Cluster	Building	Building	Building
Adjusted R^2	0.477	0.459	0.628
Observations	5,067	5,067	5,067

Table IA.6: Change in Code Violations After the Rent Act of 2011 by DSCR.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results examining buildings in the bottom-tercile of DSCR, Panel B displays results examining buildings in the middle-tercile of DSCR and Panel C displays results examining buildings in the top-tercile of LTV ratios. DSCR terciles are assigned based on the DSCR of buildings prior to 2011. Number of violations, number of repair violations, number of violations per 100 units and number of repair violations per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Violation type	All Violations			Repair Violations		
Variable	# Violations	Violations/ 100 units	Has Violation	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A – Bottom DSCR Tercile, N=180						
$Treat_i \times After_t$	9.060***	21.662**	0.205*	6.200**	14.197**	0.150
	(2.854)	(7.811)	(0.113)	(2.087)	(5.846)	(0.111)
Adjusted R^2	0.539	0.461	0.374	0.510	0.410	0.519
Panel B – Mid DSCR Tercile, N=54						
$Treat_i \times After_t$	-0.433	-1.130	-0.083	-0.550	-1.477	-0.050
	(0.272)	(0.685)	(0.126)	(0.473)	(1.202)	(0.106)
Adjusted R^2	0.304	0.308	0.284	0.151	0.154	0.301
Panel C – Top DSCR Tercile, N=90						
$Treat_i \times After_t$	4.740	15.165	-0.010	3.130	8.874	-0.010
	(4.634)	(14.825)	(0.010)	(3.060)	(8.675)	(0.010)
Adjusted R^2	0.452	0.396	0.628	0.441	0.416	0.628
FE	Building	Building	Building	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building	Building	Building	Building

Table IA.7: Change in Code Violations After the Rent Act of 2011 by Combined LTV Ratio.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results examining buildings in the bottom-tercile of combined LTV ratios, Panel B displays results examining buildings in the middle-tercile of combined LTV ratios and Panel C displays results examining buildings in the top-tercile of combined LTV ratios. Combined LTV ratio terciles are assigned based on the combined LTV ratio of buildings prior to 2011. Number of violations, number of repair violations, number of violations per 100 units and number of repair violations per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Violation type	All Violations			Repair Violations		
Variable	# Violations	Violations/ 100 units	Has Violation	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A – Bottom CLTV Tercile, N=1,620						
$Treat_i \times After_t$	1.208	-0.434	0.066	1.045	0.883	0.045
	(1.370)	(4.160)	(0.043)	(0.794)	(2.347)	(0.053)
Adjusted R^2	0.479	0.452	0.566	0.453	0.434	0.529
Panel B – Mid CLTV Tercile, N=1,314						
$Treat_i \times After_t$	3.740***	7.732***	0.031	2.442***	5.530***	0.095***
	(0.940)	(2.335)	(0.041)	(0.597)	(1.527)	(0.035)
Adjusted R^2	0.466	0.418	0.650	0.432	0.411	0.627
Panel C – Top CLTV Tercile, N=1,458						
$Treat_i \times After_t$	4.504***	10.361***	0.099**	2.986***	6.822***	0.096**
	(1.360)	(3.739)	(0.042)	(0.953)	(2.570)	(0.044)
Adjusted R^2	0.502	0.461	0.639	0.481	0.444	0.600
FE	Building	Building	Building	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building	Building	Building	Building

Table IA.8: Change in Code Violations After the Rent Act of 2011 by Amortized LTV Ratio.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results examining buildings in the bottom-tercile of amortized LTV ratios, Panel B displays results examining buildings in the middle-tercile of amortized LTV ratios and Panel C displays results examining buildings in the top-tercile of amortized LTV ratios. Amortized LTV ratio terciles are assigned based on the amortized LTV ratio of buildings prior to 2011. Number of violations, number of repair violations, number of violations per 100 units and number of repair violations per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Violation type	All Violations			Repair Violations		
Variable	# Violations	Violations/ 100 units	Has Violation	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A – Bottom Amortized LTV Tercile, N=1,566						
$Treat_i \times After_t$	2.126	1.974	0.066	1.605**	2.398	0.071
	(1.314)	(3.869)	(0.042)	(0.782)	(2.220)	(0.047)
Adjusted R^2	0.462	0.422	0.557	0.449	0.420	0.522
Panel B – Mid Amortized LTV Tercile, N=1,494						
$Treat_i \times After_t$	5.173***	11.060***	0.074*	3.233***	7.355***	0.128***
	(1.097)	(2.758)	(0.042)	(0.690)	(1.754)	(0.038)
Adjusted R^2	0.460	0.380	0.627	0.434	0.372	0.594
Panel C – Top Amortized LTV Tercile, N=1,548						
$Treat_i \times After_t$	5.448***	12.983***	0.090	3.587***	8.753***	0.094
	(1.443)	(4.214)	(0.060)	(1.051)	(3.062)	(0.058)
Adjusted R^2	0.536	0.512	0.667	0.518	0.496	0.619
FE	Building	Building	Building	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building	Building	Building	Building

Table IA.9: Impact of Rent Act on Code Violations – Match on Effective Age.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building effective age, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results using all code violations and Panel B displays results using only code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, code violations and building deeds data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
$Treat_i \times After_t$	2.893***	4.668**	0.031
	(0.732)	(2.267)	(0.026)
Adjusted R^2	0.502	0.463	0.646
Observations	6,066	6,066	6,066
Panel B – Repair Violations			
$Treat_i \times After_t$	2.070***	3.977***	0.056**
	(0.430)	(1.313)	(0.028)
Adjusted R^2	0.488	0.465	0.600
Observations	6,066	6,066	6,066
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building

Table IA.10: Change in Code Violations After Rent Act of 2011 – Match Within Owner-Originator.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, building age and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Matching is conducted within building-owner-by-originator pair. Panel A displays results using all code violations and Panel B displays results using only those code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A: All Violations			
$Treat_i \times After_t$	3.785**	8.570**	0.057
	(1.654)	(4.015)	(0.077)
Adjusted R2	0.606	0.558	0.582
Observations	486	486	486
Panel B: Repair Violations			
$Treat_i \times After_t$	2.563**	5.712**	0.111
	(1.141)	(2.831)	(0.074)
Adjusted R2	0.570	0.537	0.599
Observations	486	486	486
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E. Cluster	Building	Building	Building

Table IA.11: Impact of Rent Act on Code Violations – Poisson Regression.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t or the number of repair violations for building i in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results using all code violations and Panel B displays results using only code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, code violations and building deeds data are provided by the New York City government.

Variable	# Violations	# Repair Violations
	(1)	(2)
$Treat_i \times After_t$	0.932***	1.068***
	(0.217)	(0.269)
FE	Building	Building
	Pair-Year	Pair-Year
S.E Cluster	Building	Building
Psuedo R^2	0.675	0.603
Observations	1,114	922

Table IA.12: Change in Code Violations After Rent Act of 2011 – All Buildings Registered with HPD.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_t + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_t are building and year fixed effects. Panel A displays results using all code violations and Panel B displays results using only code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Code violations data are provided by the New York City government and New York apartments data are provided by the New York Department of Housing Preservation and Development.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
$Treat_i \times After_t$	4.623***	0.812	0.068***
	(0.146)	(0.521)	(0.005)
Adjusted R^2	0.409	0.305	0.386
Observations	189,603	189,603	189,603
Panel B – Repair Violations			
$Treat_i \times After_t$	2.864***	1.773***	0.116***
	(0.091)	(0.323)	(0.005)
Adjusted R^2	0.397	0.288	0.369
Observations	189,603	189,603	189,603
FE	Building Year	Building Year	Building Year
S.E Cluster	Building	Building	Building

Table IA.13: Change in Code Violations After Rent Act of 2011 – Alternate Time Windows.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to LTV, most recent transaction price, an indicator variable equal to 1 if a building was owned by an institutional investor, and zip code level occupancy rates as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results using a time window of 2007-2014, Panel B displays results using a time window of 2006-2015, Panel C displays results using a time window of 2006-2016, Panel D displays results using a time window of 2007-2016 and Panel E displays results using a time window of 2009-2012. Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Bulding data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Violation Type	All Violations			Repair Violations		
Variable	# Violations	Violations/ 100 units	Has Violation	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2007-2014, N=4,848						
$Treat_i \times After_t$	3.649***	7.720***	0.082***	2.548***	5.796***	0.100***
	(0.790)	(2.442)	(0.029)	(0.529)	(1.631)	(0.028)
Adjusted R^2	0.448	0.417	0.606	0.432	0.413	0.554
Panel B: 2006-2015, N=4,300	2.805***	4.194	0.069*	1.956***	3.305*	0.088**
	(0.967)	(3.209)	(0.041)	(0.577)	(1.853)	(0.042)
Adjusted R^2	0.497	0.499	0.613	0.476	0.483	0.572
Panel C: 2006-2016, N=4,928						
$Treat_i \times After_t$	2.946***	4.408	0.067**	2.053***	3.511**	0.088**
	(0.890)	(2.904)	(0.033)	(0.536)	(1.706)	(0.039)
Adjusted R^2	0.496	0.496	0.643	0.478	0.483	0.607
Panel D: 2007-2016, N=6,720						
$Treat_i \times After_t$	3.250***	5.662***	0.041	2.202***	4.318***	0.076***
	(0.714)	(2.156)	(0.027)	(0.453)	(1.375)	(0.028)
Adjusted R^2	0.510	0.492	0.648	0.493	0.488	0.629
Panel E: 2009-2012, N=3,376						
$Treat_i \times After_t$	2.835***	8.182***	0.045	2.114***	6.600***	0.072*
	(0.731)	(2.870)	(0.043)	(0.543)	(2.333)	(0.043)
Adjusted R^2	0.388	0.310	0.584	0.360	0.295	0.520
FE	Building	Building	Building	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year	Pair-Year
S.E. Cluster	Building	Building	Building	Building	Building	Building

Table IA.14: Change in Code Violations After Rent Act of 2011 – No Matching.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + Controls + \gamma_i + \kappa_t + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i are building fixed effects. κ_t are year fixed effects. Controls are all taken as of 2010 Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Violation Type	All Violations			Repair Violations		
Variable	# Violations	Violations/ 100 units	Has Violation	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A – No Controls						
$Treat_i \times After_t$	3.075***	4.914***	0.052***	1.917***	3.193***	0.077***
	(0.458)	(1.247)	(0.016)	(0.285)	(0.768)	(0.016)
Adjusted R^2	0.499	0.431	0.654	0.482	0.423	0.618
Obs	7,209	7,209	7,209	7,209	7,209	7,209
Panel B – With Controls						
$Treat_i \times After_t$	2.959***	5.044***	0.034*	1.862***	3.394***	0.057***
	(0.525)	(1.450)	(0.018)	(0.328)	(0.889)	(0.019)
$Price_i \times After_t$	-0.067***	-0.179***	-0.002***	-0.041***	-0.109***	-0.002***
	(0.009)	(0.023)	(0.000)	(0.006)	(0.015)	(0.000)
$InstOwner_i \times After_t$	1.092	3.144	0.055	0.840	2.215	0.049
	(1.019)	(2.609)	(0.034)	(0.669)	(1.682)	(0.036)
$Age_i \times After_t$	-0.029**	-0.056*	-0.002***	-0.018**	-0.027	-0.002***
	(0.012)	(0.030)	(0.001)	(0.008)	(0.017)	(0.001)
$ZipOccupancy_i \times After_t$	-2.225	-4.196	-0.117**	-1.622*	-3.249	-0.129**
	(1.501)	(3.815)	(0.051)	(0.958)	(2.353)	(0.054)
Adjusted R^2	0.510	0.445	0.670	0.494	0.438	0.630
Obs	6,291	6,291	6,291	6,291	6,291	6,291
FE	Building	Building	Building	Building	Building	Building
	Year	Year	Year	Year	Year	Year
SE	Building	Building	Building	Building	Building	Building

Table IA.15: Change in Code Violations After Rent Act of 2011 – Cluster at Zip Code Level.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to average building LTV ratios over the pre-period, most recent transaction prices as of 2010, building ages as of 2010, an indicator variable equal to 1 if a building was owned by an institutional investor in 2010, an indicator variable equal to 1 if the mortgage on a building in 2010 was a refinance and zip code level occupancy rates as of 2010 as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results using all code violations and Panel B displays results using only code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are clustered at the zip code level. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
$Treat_i \times After_t$	3.764***	7.708***	0.074***
	(0.756)	(2.212)	(0.028)
Adjusted R^2	0.480	0.446	0.620
Obs	5,526	5,526	5,526
Panel B – Repair Violations			
$Treat_i \times After_t$	2.541***	5.600***	0.093***
	(0.507)	(1.473)	(0.028)
Adjusted R^2	0.464	0.440	0.581
Obs	5,526	5,526	5,526
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building

Table IA.16: Change in Code Violations After Rent Act of 2011 – Double-Cluster at Building and Year Levels.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, and $After_t$ is an indicator variable equal to 1 if year t is 2011 or later. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching with replacement of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to average building LTV ratios over the pre-period, most recent transaction prices as of 2010, building ages as of 2010, an indicator variable equal to 1 if a building was owned by an institutional investor in 2010, an indicator variable equal to 1 if the mortgage on a building in 2010 was a refinance and zip code level occupancy rates as of 2010 as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results using all code violations and Panel B displays results using only code violations requiring repairs. Number of violations, number of violations requiring repairs, number of violations per 100 units and number of violations requiring repairs per 100 units are winsorized at the 1% and 99% levels. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are double-clustered at the building and year levels. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
$Treat_i \times After_t$	3.764***	7.708***	0.074*
	(0.630)	(1.763)	(0.035)
Adjusted R^2	0.480	0.446	0.620
Obs	5,526	5,526	5,526
Panel B – Repair Violations			
$Treat_i \times After_t$	2.541***	5.600***	0.093***
	(0.387)	(1.197)	(0.023)
Adjusted R^2	0.464	0.440	0.581
Obs	5,526	5,526	5,526
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building
	Year	Year	Year

Table IA.17: Triple-Difference – Impact of Rent Act on Violations for Top LTV Tercile Buildings Relative to Bottom LTV Tercile Buildings.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 Treat_i \times After_t + \beta_2 TopLTV_i \times After_t + \beta_3 Treat_i \times TopLTV_i \times After_t + \gamma_i + \kappa_{pt} + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $Treat_i$ is an indicator variable equal to 1 if building i has more than 35-units, $After_t$ is an indicator variable equal to 1 if year t is 2011 or later, and $TopLTV_i$ is an indicator variable equal to 1 if building i is in the top tercile of LTV ratios and 0 if it is in the bottom tercile. γ_i, κ_{pt} are building and matched-pair-by-year fixed effects. Sample constructed using one-to-one nearest neighbor matching of treated buildings (i.e., rent stabilized buildings with over 35-units) to control buildings (i.e., rent stabilized buildings with 35 or fewer units) according to average building LTV ratios over the pre-period, most recent transaction prices as of 2010, building ages as of 2010, an indicator variable equal to 1 if a building was owned by an institutional investor in 2010, an indicator variable equal to 1 if the mortgage on a building in 2010 was a refinance and zip code level occupancy rates as of 2010 as covariates. LTV ratios and transaction prices for the matching are taken from the most recent transaction data as of 2010. Panel A displays results examining all code violations, Panel B displays results examining code violations requiring repairs. LTV ratio terciles are assigned based on the LTV ratio of buildings prior to 2011. We include the top and bottom terciles of LTV ratios in the test sample. Number of violations, number of repair violations, number of violations per 100 units and number of repair violations per 100 units are winsorized at the 1% and 99% levels. Standard errors, clustered at the building level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics and code violations data are provided by the New York City government.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
$Treat_i \times TopLTV_i \times After_t$	4.179**	13.061**	0.074
	(1.847)	(5.399)	(0.062)
$Treat_i \times After_t$	1.583	0.487	0.046
	(1.300)	(3.942)	(0.042)
Adjusted R^2	0.507	0.470	0.612
Obs.	3,366	3,366	3,366
Panel B – Repair Violations			
$Treat_i \times TopLTV_i \times After_t$	2.443**	7.333**	0.075
	(1.201)	(3.438)	(0.069)
$Treat_i \times After_t$	1.279*	1.468	0.044
	(0.761)	(2.245)	(0.050)
Adjusted R^2	0.491	0.459	0.568
Obs.	3,366	3,366	3,366
FE	Building	Building	Building
	Pair-Year	Pair-Year	Pair-Year
S.E Cluster	Building	Building	Building

Table IA.18: Relationship between LTV Ratios at Origination and Code Violations Requiring Repairs.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it},$$

where $Violations_{it}$ is either the number of violations requiring repairs for building i in year t, the number of violations requiring repairs per 100 units for building i in year t or an indicator variable equal to one if building i incurs a code violation requiring repairs in year t. $LTVratio_{it-1}$ is the LTV ratio at origination for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Number of violations, number of violations per 100 units, LTV ratios, transaction prices, building age, number of units per building and interest rates are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are provided by Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations (1)	Violations/ 100 units (2)	Has Violation (3)
LTV Ratio	0.057***	0.193***	0.003**
	(0.014)	(0.061)	(0.002)
Building Controls			
Transaction Price	-0.001	-0.012**	-0.000***
	(0.002)	(0.005)	(0.000)
Building Age	0.002***	0.013***	0.000***
	(0.000)	(0.004)	(0.000)
Mid/High Rise Indicator	0.255*	0.242	0.032***
	(0.140)	(0.435)	(0.009)
Number of Units in Building	0.000	-0.002	0.000*
	(0.000)	(0.001)	(0.000)
Real Estate Company Controls			
Public Owner	-0.017	-0.010	0.005
	(0.072)	(0.147)	(0.016)
Institutional Owner	-0.005	0.273	0.002
	(0.019)	(0.198)	(0.006)
Joint Venture	0.224*	0.720**	0.031**
	(0.124)	(0.344)	(0.013)
Real Estate Company-Originator Relationship	0.050**	0.113***	0.008***
	(0.020)	(0.036)	(0.002)
Lender Controls			
CMBS Indicator	-0.081***	-0.032	0.003
	(0.029)	(0.079)	(0.005)
Loan Held by Government Lender	-0.148	-0.044	0.002
	(0.091)	(0.204)	(0.004)
Loan Controls			
Interest Rate	2.061	8.264	0.400*
	(1.267)	(6.815)	(0.222)
Refinance Indicator	-0.188	-0.525	-0.016
	(0.129)	(0.335)	(0.010)
Fixed-Rate Indicator	-0.038	0.222	-0.006
	(0.028)	(0.188)	(0.004)
Time to Maturity	-0.007***	0.011	-0.001***
	(0.001)	(0.007)	(0.000)
FE	Zip-Year	Zip-Year	Zip-Year
	Origination-Year	Origination-Year	Origination-Year
SE Cluster	City	City	City
Adjusted R^2	0.158	0.133	0.146
Observations	55,856	55,856	55,856

Table IA.19: Relationship Between DSCR and Code Violations.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 DSCR_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. $DSCR_{it-1}$ is the DSCR for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v and are zip-code-by-year and mortgage origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Number of violations, number of violations per 100 units, DSCR, transaction prices, building age, number of units per building and interest rates are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
DSCR	-0.101***	-0.195**	-0.006**
	(0.024)	(0.078)	(0.003)
Adjusted R^2	0.150	0.143	0.206
Observations	60,399	60,399	60,399
Panel B – Repair Violations			
DSCR	-0.066***	-0.162***	-0.004**
	(0.012)	(0.031)	(0.002)
Adjusted R^2	0.153	0.129	0.143
Observations	53,760	53,760	53,760
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City	City	City

Table IA.20: Relationship Between Combined LTV Ratios and Code Violations.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. Panel A uses all code violations and Panel B uses only code violations requiring repairs. $LTVratio_{it-1}$ is the combined LTV ratio (calculated using both first and second mortgages) for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. Combined LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Regression controls the same as in Table 9. Number of violations, number of violations per 100 units, LTV ratios, transaction prices, building age, number of units per building, and interest rates are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
LTV Ratio	0.098***	0.251**	0.006***
	(0.019)	(0.103)	(0.002)
Adjusted R^2	0.153	0.145	0.208
Observations	62,628	62,628	62,628
Panel B – Repair Violations			
LTV Ratio	0.054***	0.165**	0.003**
	(0.017)	(0.067)	(0.001)
Adjusted R^2	0.158	0.133	0.146
Observations	55,856	55,856	55,856
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City	City	City

Table IA.21: Relationship Between Amortized LTV Ratios and Code Violations.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. Panel A uses all code violations and Panel B uses only code violations requiring repairs. $LTVratio_{it-1}$ is the amortized LTV ratio for building i in year $t-1$, where the LTV ratio of the building accounting for amortization is calculated using information provided in the RCA Data. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. Amortized LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Regression controls the same as in Table 9. Number of violations, number of violations per 100 units, amortized LTV ratios, interest rates, number of units per building and building ages are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
LTV Ratio	0.055***	0.164***	0.003
	(0.014)	(0.049)	(0.003)
Adjusted R^2	0.152	0.144	0.208
Observations	62,628	62,628	62,628
Panel B – Repair Violations			
LTV Ratio	0.025***	0.095***	0.000
	(0.007)	(0.032)	(0.002)
Adjusted R^2	0.158	0.132	0.145
Observations	55,856	55,856	55,856
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City	City	City

Table IA.22: Relationship between LTV Ratios at Origination and Code Violations – Probability Weight by City.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. Panel A uses all code violations and Panel B uses only code violations requiring repairs. $LTVratio_{it-1}$ is the LTV ratio at origination for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Observations are probability weighted by the inverse of the number of observations in each city in running the regressions. Regression controls the same as in Table 9. Number of violations, number of violations per 100 units, LTV ratios, transaction prices, building age, number of units per building and interest rates are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
LTV Ratio	0.073***	0.217***	0.009***
	(0.026)	(0.079)	(0.003)
Adjusted R^2	0.213	0.245	0.386
Observations	62,628	62,628	62,628
Panel B – Repair Violations			
LTV Ratio	0.031**	0.100*	0.003***
	(0.014)	(0.057)	(0.001)
Adjusted R^2	0.151	0.122	0.136
Observations	55,856	55,856	55,856
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City	City	City

Table IA.23: Relationship between LTV Ratios at Origination and Code Violations – Drop Four Largest Cities.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. Panel A uses all code violations and Panel B uses only code violations requiring repairs. $LTVratio_{it-1}$ is the LTV ratio at origination for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. All buildings located in either New York City, Los Angeles, Houston, or Chicago are dropped from the sample. Regression controls are the same as in Table 9. Number of violations, number of violations per 100 units, LTV ratios, transaction prices, building age, number of units per building, and interest rates are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
LTV Ratio	0.096***	0.222**	0.010***
	(0.030)	(0.104)	(0.002)
Adjusted R^2	0.124	0.139	0.259
Observations	31,971	31,971	31,971
Panel B – Repair Violations			
LTV Ratio	0.039*	0.121	0.004***
	(0.020)	(0.086)	(0.001)
Adjusted R^2	0.096	0.045	0.081
Observations	25,200	25,200	25,200
FE	Zip-Year	Zip-Year	Zip-Year
	Origination-Year	Origination-Year	Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City	City	City

Table IA.24: Relationship Between LTV Ratios at Origination and Code Violations – Exclude Sample After 2012.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. Panel A uses all code violations and Panel B uses only code violations requiring repairs. $LTVratio_{it-1}$ is the LTV ratio for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Regression controls the same as in Table 9. Number of violations, number of violations per 100 units, LTV ratios, interest rates, number of units per building and building ages are winsorized at the 1% and 99% levels. Standard errors, double-clustered at the city and year levels, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
LTV Ratio	0.060*	0.165**	0.004
	(0.030)	(0.065)	(0.003)
Adjusted R^2	0.117	0.099	0.220
Observations	21,830	21,830	21,830
Panel B – Repair Violations			
LTV Ratio	0.030***	0.128***	0.004
	(0.010)	(0.040)	(0.003)
Adjusted R^2	0.119	0.090	0.128
Observations	19,673	19,673	19,673
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City	City	City

Table IA.25: Relationship Between LTV Ratios at Origination and Code Violations – Include Sample from 2013 and Later.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. Panel A uses all code violations and Panel B uses only code violations requiring repairs. $LTVratio_{it-1}$ is the LTV ratio for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Regression controls the same as in Table 9. Number of violations, number of violations per 100 units, LTV ratios, interest rates, number of units per building and building ages are winsorized at the 1% and 99% levels. Standard errors, double-clustered at the city and year levels, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations (1)	Violations/ 100 units (2)	Has Violation (3)
Panel A – All Violations			
LTV Ratio	0.126***	0.389**	0.007**
	(0.042)	(0.190)	(0.003)
Adjusted R^2	0.171	0.166	0.204
Observations	40,797	40,797	40,797
Panel B – Repair Violations			
LTV Ratio	0.072**	0.235*	0.002*
	(0.032)	(0.118)	(0.001)
Adjusted R^2	0.178	0.153	0.156
Observations	36,182	36,182	36,182
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City	City	City

Table IA.26: Relationship Between LTV Ratios at Origination and Code Violations – Double-Cluster by City and Year.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. Panel A uses all code violations and Panel B uses only code violations requiring repairs. $LTVratio_{it-1}$ is the LTV ratio at origination for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Regression controls the same as in Table 9. Number of violations, number of violations per 100 units, LTV ratios, interest rates, number of units per building and building ages are winsorized at the 1% and 99% levels. Standard errors, double-clustered at the city and year levels, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
LTV Ratio	0.100***	0.294***	0.006**
	(0.013)	(0.087)	(0.002)
Adjusted R^2	0.153	0.145	0.208
Observations	62,628	62,628	62,628
Panel B – Repair Violations			
LTV Ratio	0.057***	0.193***	0.003*
	(0.015)	(0.061)	(0.002)
Adjusted R^2	0.158	0.133	0.146
Observations	55,586	55,586	55,586
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City Year	City Year	City Year

Table IA.27: Poisson Regression of Code Violations on LTV Ratios at Origination.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t or the number of repair violations for building i in year t. $LTVratio_{it-1}$ is the LTV ratio at origination for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. Regression controls the same as in Table 9. Number of violations, number of violations per 100 units, LTV ratios, interest rates, number of units per building and building ages are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	# Repair Violations
	(1)	(2)
LTV Ratio	0.098***	0.103***
	(0.017)	(0.018)
Psuedo R^2	0.344	0.332
Observations	35,278	22,299
FE	Zip-Year	Zip-Year
	Origination-Year	Origination-Year
Building Controls	X	X
Loan Controls	X	X
Real Estate Company Controls	X	X
Lender Controls	X	X
S.E. Cluster	City	City

Table IA.28: Relationship between LTV Ratios at Origination and Code Violations – Define Age using Effective Age.

This table displays results from the following regression:

$$Violations_{it} = \beta_1 LTVratio_{it-1} + X_{it-1}\Gamma + \gamma_{zt} + \kappa_v + \epsilon_{it}.$$

$Violations_{it}$ is either the number of violations for building i in year t, the number of violations per 100 units for building i in year t or an indicator variable equal to 1 if building i incurs a code violation in year t. Panel A uses all code violations and Panel B uses only code violations requiring repairs. $LTVratio_{it-1}$ is the LTV ratio at Origination for building i in year $t-1$. X_{it-1} are control variables for building i as of year $t-1$. γ_{zt}, κ_v are zip-code-by-year and mortgage origination-year fixed effects. LTV ratios are standardized by subtracting the mean and dividing by the standard deviation. The regression controls are the same as in Table 9, except effective age (defined as the time since the most recent building renovation if available and the building's age otherwise) is used instead of the building's age. Number of violations, number of violations per 100 units, LTV ratios, transaction prices, building age, number of units per building and interest rates are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics, and code violations data are from various municipal governments.

Variable	# Violations	Violations/ 100 units	Has Violation
	(1)	(2)	(3)
Panel A – All Violations			
LTV Ratio	0.101***	0.297***	0.006**
	(0.015)	(0.090)	(0.003)
Adjusted R^2	0.152	0.144	0.208
Observations	62,628	62,628	62,628
Panel B – Repair Violations			
LTV Ratio	0.058***	0.197***	0.003**
	(0.013)	(0.060)	(0.002)
Adjusted R^2	0.158	0.132	0.146
Observations	55,856	55,856	55,856
FE	Zip-Year Origination-Year	Zip-Year Origination-Year	Zip-Year Origination-Year
Building Controls	X	X	X
Loan Controls	X	X	X
Real Estate Company Controls	X	X	X
Lender Controls	X	X	X
S.E. Cluster	City	City	City

Table IA.29: Cross-Sectional Variation in LTV at Origination.

This table displays results from the following regression:

$$LTVratio_{it} = \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 X_{3,it} + \beta_4 X_{4,it} + FE + \epsilon_{it},$$

where $LTVratio_{it}$ is the LTV ratio for the mortgage originated on building i in year t, $X_{1,it}$ are building characteristics, $X_{2,it}$ are local zip code level characteristics, $X_{3,it}$ are real estate company characteristics, $X_{4,it}$ are loan characteristics, and fixed effects vary according to specification and are indicated at the bottom of the table. Data are taken at time of mortgage origination. Age, units, and the time since the most recent renovation are standardized by subtracting the mean and dividing by the standard deviation for all observations. LTV ratios, ages, number of units, transaction price, interest rates and DSCR are winsorized at the 1% and 99% levels. Standard errors, clustered at the city level, are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Building data are sourced from Real Capital Analytics.

Sample	All RCA Data				Code Violations Sample			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Building Characteristics								
Building Age	0.002*	0.003	0.003	0.008***	0.003	0.003	0.001	0.010***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.003)
Number of Units in Building	0.006***	0.002	0.003**	0.011***	0.010***	0.005*	0.005	0.017***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Mid/High Rise Indicator	-0.002	-0.005**	-0.004	-0.004	-0.002	-0.001	-0.000	0.003
	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Transaction Price	-0.004	-0.001	-0.003**	-0.011***	-0.011***	-0.007**	-0.007***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.006)
Time Since Renovation				-0.003***				-0.004**
				(0.001)				(0.002)
Local Economic Characteristics								
Zip Code Capitalization Rate	2.096***	1.961***			2.297***	2.350***		
	(0.138)	(0.152)			(0.492)	(0.536)		
Zip Code Occupancy Rate	0.128***	0.074***			0.183***	0.047		
	(0.022)	(0.019)			(0.045)	(0.042)		
Zip Code Zillow Index	-0.029***	-0.013**			-0.024***	-0.005		
	(0.003)	(0.005)			(0.004)	(0.006)		
Real Estate Company Characteristics								
Public Owner	-0.014***	-0.021***	-0.017***	-0.035***	-0.011	-0.021*	-0.023	-0.056**
	(0.004)	(0.004)	(0.006)	(0.013)	(0.012)	(0.011)	(0.016)	(0.021)
Institutional Owner	0.002	0.002	0.005	0.011	-0.005	-0.007	0.006	0.014
	(0.005)	(0.005)	(0.004)	(0.007)	(0.019)	(0.015)	(0.009)	(0.014)
Loan Characteristics								
Loan Held by Government Lender	-0.016***	0.002	-0.002	0.036**	-0.005	0.002	-0.004	0.037
	(0.004)	(0.005)	(0.009)	(0.015)	(0.012)	(0.013)	(0.020)	(0.026)
Fixed-Rate Indicator	-0.004	-0.004	-0.013**	-0.028***	0.016	0.009	0.001	-0.039***
	(0.005)	(0.004)	(0.006)	(0.004)	(0.012)	(0.009)	(0.011)	(0.005)
Refinance Indicator	-0.049***	-0.046***	-0.046***	-0.037***	-0.046***	-0.042***	-0.042***	-0.038***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)
Time to Maturity	-0.001***	-0.001***	-0.001***	0.000	-0.001	-0.001***	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Interest Rate	-0.374	0.168	0.488	1.522***	-0.675	-0.463	-0.139	1.578**
	(0.233)	(0.226)	(0.350)	(0.358)	(0.641)	(0.559)	(0.714)	(0.681)
FE	N/A	Zip	Zip-Year	Zip-Year	N/A	Zip	Zip-Year	Zip-Year
	N/A	Year	N/A	N/A	N/A	Year	N/A	N/A
S.E. Cluster	City	City	City	City	City	City	City	City
R^2	0.257	0.423	0.619	0.656	0.255	0.403	0.586	0.643
Observations	39,780	38,277	32,589	7,584	10,320	10,206	10,793	3,584