Credit Market Spillover Effects to the Real Economy: Evidence from Rental Housing Evictions*

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ABSTRACT

We study how landlords' credit contracts affect eviction decisions in rental housing markets. Using property-level eviction filings matched to loan-level data on multifamily mortgages, we show that properties financed with government-sponsored enterprise (GSE) loans are significantly less likely to file evictions than otherwise similar properties financed with private conduit loans or no debt. We identify two mechanisms. First, lower leverage and interest rates on GSE loans reduce debt service burdens, which are positively associated with eviction filings. Second, GSE lenders are more likely to provide forbearance or modifications during distress, reducing incentives to evict. A stylized model formalizes these mechanisms and predicts that the likelihood of eviction decreases with the probability of forbearance. Exploiting variation from the CARES Act, we find that eviction filings at GSE-financed properties fell by approximately 27 percent relative to non-GSE properties. Our results show that credit contract features and lender behavior play a central role in eviction decisions.

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I. Introduction

Public policymakers often intervene in credit markets to promote desired social outcomes. For example, the federal government promotes mortgage credit access through Fannie Mae and Freddie Mac to expand homeownership, while the Federal Reserve adjusts the federal funds rate and the interest rate on bank reserves to support economic growth and contain inflation. While a large literature examines the impact of credit market interventions (for example, see Agarwal et al., 2015; Gabriel and Lutz, 2017; Wu, Wu and Seshadri, Forthcoming 2025), a growing line of research has moved beyond program evaluations to study how interventions affect real economic activities, such as consumption, investment, and employment (Adelino, Schoar and Severino, 2025; Chodorow-Reich, 2014; Di Maggio and Kermani, 2017). However, understanding the mechanisms through which credit market interventions affect real outcomes is also important in facilitating effective policy design, as doing so advances our economic comprehension of how incentive structures mediate policy transmission and what frictions hinder the passthrough of their benefits. Against this backdrop, we study how a credit market intervention affects outcomes beyond those found in traditional credit market analyses.

The setting for our study is the bifurcated rental financing system in the U.S., involving private and government entities, which introduces heterogeneity in financing alternatives that allow for credit policies to have differential outcomes on borrowers and their customers. For example, Fannie Mae, Freddie Mac, and Ginnie Mae (together, the government-sponsored enterprises, or GSEs) are a critical source of financing to single-family and multifamily properties, especially in the post-Financial Crisis era.[1] As quasi-governmental entities, the GSEs have various public policy mandates to provide credit to underserved areas and support various affordable housing initiatives.[2] In addition, the GSEs are often called upon to provide relief to the housing market during periods of crisis. For example, during the COVID-19 pandemic, the GSEs, under the requirement of the Coronavirus Aid, Relief, and Economic Security (CARES) Act, provided mortgage forbearance to millions of

[1] While technically Ginnie Mae is a federal government agency, we follow industry data reporting standards and refer to it as a GSE in this paper. Trepp data show that the share of GSE multifamily CMBS loans increased from about 25% pre-crisis to over 90% in recent years.

[2] The literature concerning the GSE public policy mandates with respect to affordable housing is vast. See, for example, White, Richardson and Van Nieuwerburgh (2017) and Gete and Zecchetto (2018) for recent discussions of the impact of the GSEs on housing markets and the financial system. Ambrose and Thibodeau (2004) provide a discussion of the creation of GSEs' affordable-housing goals and an early assessment of their effectiveness.

Americans.[3] Thus, we examine to what extent the GSEs' support for the multifamily housing sector filters through to aid the tenants in those properties, particularly by mitigating renter eviction risk.

We propose and empirically distinguish two mechanisms through which mortgage financing can influence landlord eviction decisions. The first is a cash-flow (debt service) channel. Many landlords, both institutional and individual, finance their properties with mortgages and use cash flows from tenant rental payments to pay the mortgage debt service. As a result, the landlord's debt service requirements can create operational flexibility based on loan terms. The second mechanism is a loan workout channel, which operates through the lender's willingness to provide relief during periods of borrower financial distress.

To crystallize our reasoning, we present a simple model that highlights how mortgage financing terms can factor into landlord decisions in dealing with tenants. In our model, a landlord facing a tenant income shock chooses between evicting and retaining the tenant. The decision depends on two forces. First, higher mortgage payments increase the cost of carrying a nonpaying tenant, lowering the threshold of tenant risk at which eviction becomes optimal. Second, the expected loss mitigation policy of lenders (e.g., forbearance) interacts with this trade-off.[4] The model delivers two central predictions: (i) eviction filings should increase with debt service pressure and leverage, and (ii) conditional on observable underwriting, eviction filings should be lower for properties financed by lenders with more accommodative workout policies. Importantly, the model shows that, for empirically plausible parameter values, relatively small increases in the probability of forbearance can eliminate eviction incentives altogether.

For our empirical analysis, we build a national property-by-month panel linking eviction filings from the Princeton Eviction Lab to loan-level CMBS multifamily mortgage data from Trepp. The Princeton Eviction Lab has more than 80 million records on evictions and eviction filings collected from court records, state provided reports on landlord-tenant cases, and legacy datasets of public eviction records. Meanwhile, Trepp covers almost the entire universe of securitized multifamily mort-

[3]This is similar to the way the GSEs provided relief to many mortgage borrowers during the financial crisis through the Home Affordable Modification Program (HAMP) and the Home Affordable Refinance Program (HARP). See, for example, Maturana (2017) for a discussion of the effects of loan modification programs during the Great Financial Crisis.

[4]See Scharlemann and Shore (2016) and Maturana (2017) for evidence on the effectiveness of loss mitigation strategies in the single-family mortgage market.

gages in the United States.[5] Our matched sample comprises 3.76 million observations of eviction filing counts between January 2000 and June 2024, representing more than 13,000 properties, and 18,289 securitized mortgage loans associated with these properties, across 22 cities and 15 states. These properties have approximately 2 million rental units, accounting for about 52% of the rental supply in the census tracts represented in the sample. We observe detailed underwriting characteristics and can identify financing terms and the lender type for each property.

As mortgage financing changes over time with loans originating, maturing, or being refinanced, we can exploit within-building variation in our sample while controlling for rich time-varying mortgage financing characteristics and county-by-time fixed effects in a regression framework. We observe financing effects that are consistent with our model's predictions and proposed mechanisms. Properties with higher leverage and wider contract spreads exhibit higher eviction filing rates, showing evidence that cash flow pressures from overhanging debt influence landlord incentives. However, financing terms do not fully explain differences in filing rates between properties with and without agency loans, which are evident even in the pre-pandemic period subsample from 2010 through 2019, suggesting a loan workout channel.

The COVID-19 pandemic provides a unique setting to test the loan workout channel. The pandemic simultaneously increased tenant nonpayment risk and triggered unprecedented policy interventions in mortgage markets. Under the CARES Act, all GSE multifamily borrowers were granted universal forbearance eligibility, subject to a prohibition on tenant eviction during the forbearance period. The GSEs subsequently extended the forbearance program indefinitely. Private lenders also expanded forbearance offerings, but to a lesser extent and in a more heterogeneous manner, with less coordination. We exploit this policy environment in difference-in-differences and dynamic event study frameworks, comparing eviction filing rates across properties with different financing terms before and during the pandemic.

Our difference-in-differences results show that properties financed with an agency loan have 0.871 fewer annual eviction filings per 100 rental units than otherwise comparable non-agency properties during the post-treatment period. Our dynamic event-study estimates show no pre-trend differential and a pronounced post-treatment decline of 160 basis points in the eviction filing rate, on average.

[5]These data contain information on more than $1.8 trillion in securitized mortgage loans that are collateralized by over 158,000 multifamily properties.

The largest response occurs in the second year after treatment, when the eviction moratoria had mostly expired, and the GSE forbearance program remained active. Cohort-adjusted estimates that account for staggered treatment, following the modeling approach of Sun and Abraham (2021), are similar to our baseline estimates but further show that the decline is concentrated among properties that remain with an agency loan, while eviction filings rise after treated properties exit agency status (i.e., payoff) and become ineligible for GSE forbearance. Back-of-the-envelope calculations indicate that the 87.1 basis point decline in the filing rate corresponds to a 27 percent reduction relative to the average rate, and the peak decline in the second year exceeds 50 percent of the average rate. Interestingly, the response is persistent across neighborhoods and is strongest for mid-size to large residential rental properties.

Taken together, the results show that the transmission of credit market interventions to housing outcomes depends not only on statutory renter protections but also on borrower financing structure, leverage, and continued exposure to flexible lender loss-mitigation policies. In sum, our findings reveal previously undocumented transmission mechanisms through which credit market policies affect real economic outcomes.

Our paper contributes to the growing literature on the real effects of financial frictions. While prior research examines how credit supply affects investment (Chodorow-Reich, 2014) and employment (Giroud and Mueller, 2017), we show that credit market interventions also affect day-to-day decisions that extend beyond the borrowing firm to its stakeholders (Wu, Wu and Seshadri, Forthcoming 2025). This conceptually resembles how pension obligations affect corporate investment (Rauh, 2006) or how debt overhang influences employment decisions (Giroud and Mueller, 2017), but operates instead through the lender's workout policies during borrower distress.

We also provide new insights into the growing literature that examines the role of GSEs in housing policy. Although the impact of these policies in the single-family residential market is a source of considerable controversy and debate (Bhutta, 2012; An and Bostic, 2008; Bostic and Gabriel, 2006; Passmore, Sherlund and Burgess, 2005; Ambrose and Buttimer, 2005; Ambrose, LaCour-Little and Sanders, 2004), few studies have examined the effects of GSE participation in the multifamily market.[6] Thus, our study provides new insights into how financing of multifamily properties can affect the

[6]See Frame and White (2005) for a discussion of the GSEs and the controversies surrounding their role in the U.S. housing finance system. White, Richardson and Van Nieuwerburgh (2017), Elenev, Landvoigt and Van Nieuwerburgh (2016), and Gete and Zecchetto (2018) discuss the impacts of potential GSE reforms on the housing and rental markets.

housing outcomes of tenants in these properties.

We also connect with the growing literature on the causes and consequences of evictions (Desmond, 2012; Desmond and Gershenson, 2017; Evans, 2021; Bradford and Bradford, 2020; Roesch-Knapp, 2020; Coulson et al., 2025; Garboden and Rosen, 2019; Lundberg et al., 2021; Lee and Evans, 2020; Immergluck et al., 2020; Kang, 2021; Cooper and Paton, 2021). While the pandemic drew greater attention to the problem of evictions, it is essential to emphasize that tenant evictions occur frequently in normal times and that research clearly documents that they can exacerbate negative social and economic stresses on tenants.[7] In explaining why evictions occur, existing research focuses almost exclusively on factors in the rental market, e.g., those impacting individuals' ability to pay (Desmond and Gershenson, 2017), legal systems allocating property rights between tenants and owners (Manheim, 1989; Roesch-Knapp, 2020), local policies designed to deter landlord actions (Diamond, McQuade and Qian, 2019; Bradford and Bradford, 2020; Coulson et al., 2025), regional differences in poverty and infrastructure (Kang, 2021), and differences in eviction rates across institutional owners of residential property (Raymond et al., 2016). In addition, growing evidence from the credit market highlights how endogenous credit choices on the part of landlords and tenants can affect observed lease outcomes (Ambrose and Yildirim, 2008; Agarwal et al., 2011*a*; Ambrose et al., 2019). For example, Ambrose et al. (2019) note that landlord decisions regarding how the property is financed interact to determine commercial lease rates and tenant risk. Our results complement these findings and highlight how eviction rates vary across financing sources. Furthermore, our study demonstrates how factors identified by Desmond and Gershenson (2017), such as job loss, neighborhood crime, and family size, can interact with landlord financing choices to predict evictions. Thus, we introduce a credit-supply perspective into the study of eviction, showing that contractual features of mortgage finance, instead of tenant income shocks alone, play a central role in eviction decisions.

In doing so, we contribute to a broader literature on how financial contracts affect real economic activity. The connection between the supply of mortgage credit and housing outcomes is well documented. For example, Gabriel and Rosenthal (2010) provide evidence on the extent to which GSE activity impacts the supply of credit during various economic environments. In a study of the 1930s predecessor of the modern GSEs, Fishback et al. (2011) provide evidence that the Home Owners'

[7]For example, evictions are associated with increased violence in communities (Sampson and Sharkey, 2008), lower educational attainment (Pribesh and Downey, 1999), and lasting negative health outcomes (Dong et al., 2005).

Loan Corporation (HOLC) increased the supply in the rental market. In addition, Gete and Reher (2018) link the supply of mortgage credit with outcomes in the rental market, while Gete and Zecchetto (2018) and Elenev, Landvoigt and Van Nieuwerburgh (2016) discuss the implications of removing the GSEs from the mortgage market. Ambrose and Diop (2014) provide direct evidence linking credit expansion in the single-family mortgage market with tenant risk in the rental market. Based on these insights, we expand this literature by introducing the idea that financing choices by property owners can affect tenant eviction risks. Specifically, we identify and empirically demonstrate that loan workout policies transmit to tenant outcomes through mortgage choice.

While our analysis focuses on multifamily rental housing, the mechanisms we document are likely relevant in other settings where borrowers rely on third-party payments to service debt, and lenders differ in workout practices. Examples include small business lending, where business owners rely on customer payments; non-residential commercial real estate, where property owners rely on tenant rents; and corporate lending, where firms rely on customer revenues more broadly. In these environments, credit market structure may have first-order implications for real economic outcomes beyond traditional investment and default margins (Agarwal et al., 2011*a*).

The remainder of the paper proceeds as follows. In Section II, we describe the institutional background of multifamily mortgage finance. In Section III, we present a simple theoretical model on the impact of lender types on the landlord's choice to evict a tenant. In Section IV, we explain our data and present reduced-form evidence on eviction, lender type, and mortgage characteristics. In Section V, we exploit pandemic-era policy variation to identify the loan workout channel. Lastly, in Section VI, we conclude.

II. Background

Our focus is on multifamily rental housing, which encompasses a range of structures, from mid-rise apartment complexes to skyscrapers, as well as facilities for student, low-income, and senior housing. According to the 2019 American Community Survey (1-year estimates), the US has approximately 26.4 million multifamily units, which account for about half of all US rental housing units and approximately 19% of total housing units. Generally, the owner of a multifamily property has the right to collect rental payments from tenants in exchange for the use of the dwelling units. In turn,

owners use the rental income to pay operating expenses associated with ownership. The owner may also rely on rental income to make monthly payments on any loan for which the property is pledged as collateral.

Since the Great Financial Crisis (GFC), government entities (Fannie Mae, Freddie Mac, and Ginnie Mae, or GSEs) have significantly expanded their multifamily housing financing. In the early 2000s, US chartered depository institutions were the dominant lenders in the multifamily mortgage market, while GSEs accounted for less than 20%.[8] In contrast, in 2024, GSE multifamily loan acquisitions accounted for 64.8% of new multifamily mortgage credit (Board, 2025).[9] One of the reasons for this growth is the strong performance of the GSEs' multifamily loan guarantee business, especially in contrast to its single family business, during the GFC. Another reason is the collapse of private-label securitization (PLS) during the GFC and the subsequent dearth of credit supply from PLS.

Fannie Mae and Freddie Mac are not direct lenders but instead purchase and securitize loans that meet certain underwriting criteria in the secondary mortgage market. Similarly, Ginnie Mae securitizes multifamily loans insured by the Federal Housing Administration (FHA). Generally, GSE borrowers must be a single-purpose entity with US ownership. However, the loans the GSEs purchase are typically non-recourse, meaning that if a mortgage becomes delinquent, the lender may repossess the property but cannot seek a deficiency judgment against the borrower to recover any outstanding mortgage debt. As a result, the underwriting focus is on the collateral.

For example, a financially healthy multifamily property should have net operating income (NOI) sufficiently high to more than cover debt service. If the debt service coverage ratio (DSCR), defined as NOI divided by mortgage payments, falls below 1, the lender faces the risk of loan delinquency or default, as it indicates that the borrower does not have sufficient net income to make the mortgage payment. Fannie Mae and Freddie Mac set the minimum DSCR at 1.25 for new fixed-rate mortgage originations. However, the exact criteria may vary. For example, the DSCR underwriting constraint may be lower for multifamily properties that accept HUD Section 8 housing vouchers or rental assistance payments.[10]

[8] Bradley, Nothaft and Freund (1998) discuss the composition of multifamily financing from 1980 to 1997.

[9] The multifamily mortgage market grew from $736.4 billion in 2007Q1 to $2.32 trillion in 2025Q1 (in nominal terms).

[10] For further details on underwriting criteria for Freddie Mac see https://mf.freddiemac.com, for Fannie Mae see

The goals of Fannie Mae and Freddie Mac have been to provide liquidity to banks through the secondary mortgage market by and, in part, to pass on lower credit costs to borrowers, by directly or indirectly insuring multifamily property financing against default on debt service payments (Green and Wachter, 2005). In addition, low- and moderate-income households are emphasized in efforts to promote access to mortgage credit. For instance, GSEs securitize purchase and refinance mortgages on single-family and multifamily properties that support their housing affordability goals.

Although GSE-backed lenders typically have strict underwriting standards, they often offer lower interest rates due to the GSE advantages stemming from their relationship with the federal government (Kerrigan, 2022*a*); and they differ from conventional lenders in their loan workout strategies in response to borrower default.[11] Other private multifamily lenders include private US chartered depository institutions, life insurance companies, real estate investment trusts, private pension funds, and issuers of asset-backed securities, who place a subset of their loan portfolios in conduit commercial mortgage-backed securities (CMBS), which have pooling and serving agreements (PSAs) that provide loan servicers with less freedom in sharing default losses or offering forbearance (Kerrigan, 2022*b*). We examine the implications of choosing between agency and conduit financing on landlord eviction decisions.

III. A Model of Eviction

In this section, we construct a stylized rational expectations model to fix our ideas about the impact of lender types and mortgage characteristics on landlord eviction decisions.

A. Model Set Up

We assume that a landlord leases a housing unit to a tenant with a constant rent payment of X, and we explicitly incorporate three key features. First, landlords may finance the property with

https://multifamily.fanniemae.com, and for Ginnie Mae see https://www.ginniemae.gov.

[11] See Scharlemann and Shore (2016) and Maturana (2017) for evidence on the effectiveness of loss mitigation strategies in the single-family mortgage market. In fact, in the current environment, GSE lenders are providing forbearance to their borrowers, effectively bearing all default costs. In the single-family loan setting, Agarwal et al. (2011*b*) show that the probability of modification is higher for GSE loans than for private-label securitized loans in the single-family.

a mortgage originated from either a GSE (type G) or a conduit CMBS lender (type N) that has a fixed payment of M^i, $i \in \{G, N\}$.[12]

Second, we further introduce loan heterogeneity by assuming that type N and G mortgages differ in the probability of obtaining mortgage payment forbearance (θ^i) in the event of mortgage default, and in the amount of forbearance offered (χ^i).[13] Mortgages are thus differentiated by the set (θ^i, χ^i). In the single-family market, Adelino, Gerardi and Willen (2013) and Agarwal et al. (2011*b*) note that, relative to non-GSE securitized mortgages, those securitized via the GSEs have (a) a higher ex ante probability of receiving forbearance or modifications ($\theta^G > \theta^N$) and, (b) conditional on being granted forbearance, a higher loan payment forgiveness ($\chi^G > \chi^N$).

Third, we introduce risk into the analysis by assuming that tenants face a probability λ of job loss, such that if the shock is realized, they are unable to pay the lease payment. If the tenant realizes a job loss, then in the next period she has a probability ψ of recovering and being able to resume making the required rental payment, or she remains in default with probability $1 - \psi$.[14]

In the event of tenant job loss, the landlord has the choice to either evict or retain the tenant. Landlords can evict tenants by paying fixed eviction costs of C_E and immediately releasing the unit to a new tenant, who faces a similar probability of job loss in the next period. Alternatively, the landlord can retain the current tenant by forbearing rent for one period. If the tenant remains in default, the landlord faces a new option to either evict the tenant or continue with retention. If the tenant recovers, then she resumes making the contractually obligated rent payment plus the missed payment and a penalty of ϕ percent of the rent. This process proceeds until either the defaulting tenant is evicted or recovers.

To determine the landlord's optimal eviction decision, we derive the value functions for each tenant rent payment position: paying rent (V_P), defaulting and being evicted (V_E), and defaulting but retained (V_R).[15] We start by defining the value when the tenant pays the rent on time (i.e., a paying tenant) as:

$$V_P = (X - M^i) + \delta \left[(1 - \lambda) V_P + \lambda W \right], \tag{1}$$

[12] Landlords rely solely on rental income to cover the mortgage payment and operating expenses, i.e. $X \geq M^i$.
[13] If χ^i is very large, then forbearance is similar to a principal write-down loan modification.
[14] For simplicity, we assume that $\lambda < \psi$.
[15] To ease the notation burden, we do not include a time subscript.

where δ is the discount factor and W represents the value function for the tenant default state. The first term on the right-hand side is the landlord's current period net of financing payment cash flow. The second term represents the present value of the possibility that the tenant may suffer a job loss with probability λ in the next period. Finally, W captures the landlord's decision to evict or retain the tenant. After collecting terms and simplifying, Equation (1) yields

$$V_P(1-\delta(1-\lambda)) \quad = \quad (X - M^i) + \delta\lambda W. \tag{2}$$

Next, we define the value functions if the tenant realizes a job loss (the default state). First, we define the value of eviction as

$$V_E \quad = \quad -C_E + V_P. \tag{3}$$

Equation (3) implicitly assumes that eviction allows the landlord to immediately replace the defaulting tenant by paying fixed costs of C_E. Equation (3) also recognizes that the new tenant may default in the future since V_P explicitly incorporates the probability of job loss in the next period.

Second, the value of retaining the defaulted tenant is given as

$$V_R \quad = \quad -M^i \left[1 - \theta^i \chi^i\right] + \delta \left[\psi(V_P + (1+\phi)X) + (1-\psi)W\right]. \tag{4}$$

Equation (4) recognizes that the costs of retention include the financing payment net of forbearance ($M^i[1-\theta^i\chi^i]$) in the current period and the present value of the weighted average of the probability that the tenant recovers and the probability that the tenant continues in default in the next period, in which case the landlord must decide again whether to evict or retain the tenant for another period. Thus, the second term is the present value of the weighted average payoffs associated with tenant recovery or continued default. Finally, we note that the optimal default value is

$$W \quad = \quad \max\left[V_E, V_R\right]. \tag{5}$$

Equations (2) - (5) provide a system that allows for a recursive analysis of the landlord's optimal

eviction decision, conditional on the choice of financing. If the tenant experiences a job loss, the landlord will evict when V_E exceeds V_R. The equality $W = V_E = V_R$ provides the indifference point between eviction and retention. Thus, substituting $W = V_E$ in (4) and simplifying, we obtain

$$V_E(1 - \delta(1 - \psi)) = M^i(1 - \theta^i\chi^i) + \delta\psi V_P + \delta\psi(1 + \phi)X. \tag{6}$$

Next, we can substitute $-C_E + V_P$ into equations (6) and (2) and simplifying to get

$$\begin{aligned} V_P(1 - \delta) &= -M^i(1 - \theta^i\chi^i) + \delta\psi(1 + \phi)X + C_E(1 - \delta(1 - \psi)) & (7) \\ V_P(1 - \delta) &= (X - M^i) - \delta\lambda C_E. & (8) \end{aligned}$$

Equating equations (7) and (8) yields

$$K^i = X[1 - \delta\psi(1 + \phi)] - M^i\theta^i\chi^i - C_E[(1 - \delta(1 - \psi)) + \delta\lambda] = 0 \tag{9}$$

which characterizes the landlord's indifferent point between evicting or retaining a tenant who defaults on their rent payment, conditional on financing with mortgage i. Equation (9) highlights how the parameters associated with mortgage financing (M^i, θ^i, χ^i) interact with tenant risk (λ, ψ) factors and eviction costs (C_E, ϕ) to affect the probability of eviction.

B. Empirical Predictions

To derive empirical predictions, we focus on defining the threshold tenant risk (λ^*) that determines the landlord's indifference point between eviction and retention. To do so, we first differentiate Equation (9) with respect to λ to obtain

$$\frac{\partial K^i}{\partial \lambda} = -\delta C_E < 0 \tag{10}$$

revealing that $K^i(\lambda)$ is strictly decreasing in λ. Defining λ^* as the threshold point for $K^i(\lambda) = 0$ leads to the decision rule to evict if $\lambda \geq \lambda^*$ and to retain if $\lambda < \lambda^*$. Assuming that tenant risk is distributed with a cumulative density function (CDF) F and probability density function (pdf) f,

then we can write the decision rule as

$$p \equiv Pr(evict) \quad = \quad Pr(\lambda \geq \lambda^*) = 1 - F(\lambda^*). \tag{11}$$

If tenant risk increases, then first-order stochastic dominance (FOSD) implies that

$$p' = 1 - F'(\lambda^*) \quad \geq \quad 1 - F(\lambda^*) = p. \tag{12}$$

In addition, we can differentiate equation (11) with respect to M^i to obtain:

$$\frac{\partial p}{\partial M^i} = -f(\lambda^*)\frac{\partial \lambda^*}{\partial M^i} \quad = \quad f(\lambda^*)\frac{\theta^i \chi^i}{\delta C_E} \geq 0. \tag{13}$$

The derivative reveals that an increase in the mortgage payment level leads to a rise in the eviction rate.[16] The intuition is that higher mortgage payment levels lower the landlord's tenant risk threshold (λ^*), thereby increasing the eviction region and the probability of eviction. As discussed in Section II, we note that GSEs have more conservative underwriting standards than conduit lenders, which implies that conduit loans would have higher loan amounts for the same properties, all else equal. In addition, conduit loans usually carry higher interest rates, partially due to private conduit lenders higher funding costs. Thus, with larger loan amounts and high interest rates, private conduit loans would have higher mortgage payments, i.e., $M^N > M^G$, for similar properties. This debt service difference can lead to differences in eviction rates between GSE and conduit loans.

We now turn to an analysis of how mortgage forbearance and debt modification policies interact to affect the probability of eviction. Given the complex, non-linear nature of these interactions, we examine their impact on evictions through a numerical simulation of a representative tenant residing

[16]The derivative $\frac{\partial p}{\partial M^i}$ follows by substituting λ^* for λ in equation (9) and solving for λ^* to obtain:

$$\lambda^* \quad = \quad \frac{X(1 - \delta\psi(1+\phi)) - M^i\theta^i\chi^i - C_E(1 - \delta(1-\psi))}{\delta C_E}.$$

Thus,

$$\frac{\partial \lambda^*}{\partial M^i} \quad = \quad -\frac{\theta^i \chi^i}{\delta C_E}.$$

in Atlanta. In keeping with estimates from the Consumer Financial Protection Board (CFPB) that the overall rental delinquency rate over the period from September 2021 to November 2024 ranged between 18 to 30 percent (Witzen, January 2025), we calculate the probability of eviction in a Monte Carlo framework assuming the tenant risk distribution reflects an average 20 percent chance of tenant nonpayment, i.e., $\bar{\lambda} = 20\%$.[17] We use the simulation to highlight how differences in the probability of mortgage forbearance (θ^i), debt forgiveness (χ^i), and tenant risk (λ) impact the probability of eviction.

In Figure 1, we plot a surface map showing the probabilities of eviction, which shows that the greater the probability that the landlord/borrower receives forbearance, the less likely they are to pursue eviction. Importantly, the model shows that for empirically plausible parameter values, landlords optimally choose tenant retention in most states of the world, and relatively small increases in forbearance probability can eliminate eviction incentives altogether. For example, when forbearance probability increases from 20% to 30%, the eviction probability decreases from 100% to 0% (assuming a 30% forgiveness). This result highlights loan workouts as a potentially powerful—and underappreciated—policy lever for reducing evictions. A small push on lenders to grant forbearance could result in a huge gain for tenants.

Figure 1 also illustrates that the amount of forbearance offered is a crucial factor in determining whether evictions are pursued. For example, even if the probability of forbearance is nearly certain ($\theta^G = 0.95$), the amount of forbearance offered (χ^G) would need to be greater than 25% for the landlord to forgo evictions. In contrast, if the amount of mortgage payment forgiveness offered is less than 15%, then landlords have almost no incentive to retain tenants (Pr(Eviction)=98%).

Finally, to highlight the interaction effects of θ^i and χ^i, Figure 2 shows the contour curve associated with combinations of θ^i and χ^i necessary to hold the probability of eviction constant at approximately 25%. For example, a lender forbearance probability of 70% in conjunction with a 40% payment forgiveness is required to produce a probability of eviction of about 25%. Figure 2 clearly shows the expected inverse relation between the benefits derived from forbearance (χ^i) versus the likelihood of receiving forbearance (θ^i). In other words, when borrowers (landlords) anticipate a high degree of debt forgiveness or loan modification in the event of default, they require a lower

[17] Further supporting our assumption setting $\bar{\lambda} = 20\%$, the Federal Reserve (May 2024) reports that 19 percent of renters indicated that they were in arrears on rent at some point in 2023. We simulate the tenant income shocks using a beta distribution with $\alpha = 2, \beta = 8$ to approximate a mean income shock probability of approximately 20%.

probability of actually obtaining that forbearance in order to forgo evicting tenants who suffer an income shock.

IV. Eviction Filings and Mortgage Financing

A. Data

To empirically test the insights gained from the theoretical analysis, we identify multifamily eviction filings at the property level using data from the Eviction Lab at Princeton. The Eviction Lab data contain information on more than 80 million individual eviction cases across the United States, which were registered in court records, state provided reports on landlord-tenant disputes, and legacy datasets of public eviction records.[18] In a joint effort with the Eviction Lab, we aggregated data on evictions by multifamily landlords into property-level longitudinal eviction filing counts, covering January 2000 to June 2024 (excluding 2019).[19] Since the data are anonymized per IRB requirements, we only observe (i) the "cluster id," which is a token that identifies the building address, and (ii) the monthly count of new eviction filings based on court filing dates. Furthermore, we focus on 22 cities across 15 states where the Eviction Lab confines they have strong and consistent property level coverage of eviction filings.[20]

We linked each apartment building to Trepp CMBS mortgage data using exact property addresses. The Trepp database contains information on 158,466 multifamily properties, which supply over 25.2 million rental units and serve as collateral for more than $1.86 trillion in securitized commercial mortgage debt. The Trepp data allow us to observe property characteristics such as the number of residential units in each apartment building and whether one or more mortgages are outstanding at any given time. Time-varying characteristics include the outstanding loan balance, the most recent net operating income, mortgage debt service payments, the most recent appraised value, the coupon rate, and whether a loan is past due. Importantly, we can tell whether each loan is an agency loan or a private conduit loan: If the loan is part of a commercial securitization deal classified as "agency"

[18] More information about the Eviction Lab at Princeton is available at `https://evictionlab.org/`.

[19] The Princeton Eviction Lab does not have eviction filing data for 2019.

[20] Albuquerque, Boston, Charleston, Cincinnati, Cleveland, Columbus, Dallas, Fort Worth, Greenville, Houston, Indianapolis, Kansas City, Las Vegas, Memphis, Milwaukee, Minneapolis, Phoenix, Providence, South Bend, St. Louis, Tampa, and Wilmington.

(or the issuer of the loan's securitization deal is Freddie Mac, Fannie Mae, or Ginnie Mae), then the loan is considered an agency loan; otherwise, the loan is considered a conduit loan.

In cases where a building is the collateral for more than one loan at once, we weight the non-missing key underwriting factors such as the debt service coverage ratio (DSCR) and loan-to-value (LTV) ratio by loan size.[21] Specifically, we compute the weighted-average DSCR at the property level as

$$\text{DSCR}_{it} = \frac{\sum_k \text{NOI}_{kit}}{\sum_k DS_{kit}}$$

where NOI_{kit} is the property's net operating income reported for loan k in building i at time t, and DS_{kt} is the annual debt service of loan k in building i at time t. Similarly, we compute the weighted-average LTV at the property level as

$$\text{LTV}_{it} = \frac{\sum_k BAL_{kit}}{\sum_k VAL_{kit}}$$

where BAL_{kit} is the outstanding mortgage balance of loan k for property i at time t, and VAL_{kt} is the most recent appraised value of the collateral property of loan k on property i at time t. Thus, the DSCR and LTV reflect the monthly performance of both new and existing multifamily loans. We similarly compute the average spread on the contract rate. Additionally, we compute the within-building mortgage delinquency rate as the share of multifamily loans with debt service payments 30 days or more past due. Lastly, we determine each month whether an agency loan is outstanding on the property, as a loan can be paid off over time. In the panel dataset, the loan variables are set to zero when there is no outstanding loan on the property.

For each property, we calculate the annual eviction filing rate per 100 units ($E_{i,t}$) as

$$E_{i,t} = 12 \times \frac{Filings_{i,t}}{Units_i} \times 100$$

where $Filings_{i,t}$ is the monthly number of eviction filings at property i at time t, and $Units_i$ is the number of rental units in the property. We obtain the unit count from the median number of rental

[21] We winsorize the DSCR and LTV at the 1% tails and measure them excluding only loans with missing DSCR or LTV at the loan level. The DSCR at the loan level is measured using the most recent DSCR, net operating income, and/or debt service estimates. The LTV is measured using the most recent outstanding loan amount and property value estimates.

units reported across all Trepp loan records linked to the property. To avoid an undefined eviction filing rate, we exclude sample properties with an unknown unit count (fewer than 3%).

We merge tract-level data from the US Census Bureau American Community Survey 5-year estimates (2016-2020) to obtain neighborhood characteristics. We import the Population, Median Income, Median Rent, Hispanic Share, Black Share, Asian and Pacific Islander (API) Share, White Share, Vacancy Rate, and Tenant-to-Owner Ratio.

We link a total of 13,320 apartment buildings in the Eviction Lab sample to 18,289 multifamily loans (or about $267 billion in origination balances) in the Trepp dataset. These properties account for approximately 2 million rental units. In the census tracts where these properties are located, there are 3.8 million renter-occupied units, according to the American Community Survey 5-year estimates (2016-2020). Hence, our sample accounts for 52% of the rental supply in the observed neighborhoods. Since not all rental units are located in multifamily properties (e.g., single-family rentals), our sample likely captures the majority of multifamily apartments in the same neighborhoods.

B. Summary Statistics

In Panel A of Table I, we describe property and neighborhood characteristics for unique buildings in the sample. Most buildings are matched to 1 to 4 mortgages over 20 years. The average property has 153 rental units, with a 10th-90th percentile range of 26 to 342 units. The bulk of the sample includes properties built between 1955 and 2003. The final sample comprises 13,320 apartment buildings, resulting in approximately 3.76 million building-year-month observations.

For each property, we observe the financing cycle, including dates before a loan was originated, while a loan is outstanding, and when a loan is paid off.[22] In terms of financing type, Figure 3 exhibits the market share by the type of loan over time, revealing a gain in market share in the multifamily debt market by the GSEs over the past decade that peaked in 2021/2022.

In Panel B of Table I, we focus on building-year-month observations when there is an outstanding loan on the property, which account for 29% of the full sample. The average combined loan amount outstanding is $17.97 million with a LTV ratio of 68% and DSCR of 1.37. As a measure of distress, we observe a mortgage delinquency rate of 3%. Approximately 42% of the mortgage observations are for

[22] A caveat here is that we do not observe non-CMBS loans in the data.

agency loans. Freddie Mac and Fannie Mae account for 29% and 13% of the mortgage observations, respectively. The rest are conduit loan observations.[23]

In Panel C of Table I, we include all observations in the panel dataset to examine the eviction rate. We report an annual eviction filing rate of 3.24 per 100 rental units, with a 10th-90th percentile distribution ranging from 0 to 8.41 yearly filings per 100 rental units. In Figure 4, we show the annualized monthly and yearly eviction filing rate by whether the property is financed by an agency loan or a conduit loan. The eviction filing rate is higher for properties with outstanding loans than for those without an agency or conduit CMBS loan. The eviction filing rate appears even higher for private conduit loans than for agency loans.

C. Baseline Analysis

As a first pass in our empirical analysis, we quantify the baseline average effect of lender type and mortgage characteristics on eviction outcomes by estimating the following two-way fixed effects model:

$$E_{i,t} = \delta_0 \cdot \mathbb{1}Agency_{i,t} + X_{i,t} \cdot \beta + \tau_{c,t} \times \mathbb{1}\text{Loan}_{i,t} + \rho_i + \varepsilon_{i,t} \tag{14}$$

where $E_{i,t}$ is the annualized eviction rate per 100 rental units at building i at time t. $X_{i,t}$ represents a subset of time-varying financing terms, including the DSCR or LTV, contract spread, and mortgage delinquency, which we measure as the share of active loans attached to the property that are 30 days or more past due. $\mathbb{1}Agency_{i,t}$ is the time-varying treatment variable that takes the value of one when an agency loan on the property is outstanding. $\mathbb{1}Agency_{i,t}$ is zero if the agency loan is paid off, the property has only a non-agency loan outstanding, or the property has no securitized loans outstanding. δ_0 captures the average response of eviction filings to holding an agency loan. The error term is the parameter $\varepsilon_{i,t}$.

Our model includes *County* $\times$ *Time* fixed effects ($\tau_{c,t}$) and *Building* fixed effects (ρ_i). The county-time component of the fixed effects accounts for location specific monthly time trends from the pandemic or local economic environment (e.g., unemployment, eviction moratoriums, government shutdowns, the spread of COVID-19 infections, or LIHTC properties) that may uniquely influence

[23] Approximately 1% of the mortgage observations involved a property with both an agency loan and a conduit loan outstanding simultaneously.

eviction filing decisions through mechanisms like income shocks. $\mathbb{1}Loan_{i,t}$ is an indicator variable for whether a loan on property i is outstanding. By interacting the county-specific time trends with $\mathbb{1}Loan_{i,t}$, we account for potential time-varying local confounding factors that may affect leveraged properties differently from properties with overhanging debt (e.g., differences in liquidity access or market interest rates). The building fixed effects in the regression are meant to account for property-specific and cross-sectional spatial variation in tenant risk, which, based on the existing literature, influences eviction risk (e.g., tenant rights, property quality/size, neighborhood density). Through these controls, we exploit within-property variation in mortgage financing to isolate the association between lender type and landlord eviction decisions.

Table II reports the marginal effect of an outstanding mortgage by lender type on the eviction filing rate. Column (1) shows that the eviction filing rate is 49.8 basis points higher when a CMBS loan is outstanding than when no CMBS loan is outstanding, representing a 15.1% relative increase in the eviction filing rate. In addition, we find that the eviction filing rate is 53.2 basis points lower when an agency loan is outstanding. In column (2), the association remains similar in the post-2010 sample, reducing any possible power or noise concerns from the fact that the agency market share was negligible to non-existent (below 2% per year) before 2010, as shown in Figure 3. In column (3), we include the interacted county-time fixed effects, absorbing the standalone loan indicator, and observe a larger coefficient on agency. Our results thus indicate that eviction filings are lower at properties with an agency loan than at similar properties with conduit financing in the same county during the same time. These findings are consistent with our theoretical predictions that (i) mortgage financing can lead to higher eviction rates, and (ii) there are differences in eviction rates between properties with GSE vs conduit loans.

As discussed previously, agency loans and conduit loans differ in many respects, including underwriting criteria and pricing, which, in turn, may influence mortgage payments and, thus, the eviction rate. For instance, Figure 5 exhibits differences in the average underwriting characteristics by lender type over time. One potential reason for the discrepancies could be the GSEs' ability to offer lower cost financing to mortgage borrowers through their implicit government guarantee.[24] However, the benefits associated with the GSEs are not without controversy (Jeske, Krueger and Mitman, 2013).

[24]See Hancock and Passmore (2011) and Hurst et al. (2016) for a discussion of the GSEs' effects on the mortgage market during the Great Financial Crisis.

Additionally, they usually maintain higher underwriting standards, e.g., LTV or DSCR requirements, than other lenders. Therefore, for two identical properties, the one with a GSE loan would have a smaller loan amount and a lower interest rate, resulting in lower debt service than a similar property financed with a non-agency mortgage.[25]

Yet, we continue to observe lower eviction filing rates with an agency loan than with a conduit loan, even after controlling for time-varying loan characteristics. In particular, column (4) shows that although DSCR is negatively associated with the eviction filing rate (but statistically insignificant), the agency effect remains virtually unchanged. In column (5), in lieu of the DSCR, we include the LTV ratio and interest rate spread. We also include the delinquency rate as a control.[26] We find that both LTV and contract spread are positively associated with eviction risk and are statistically significant. An increase in LTV from 40% to 90% is associated with a 46 basis point (14.2% relative) increase in eviction filings. A one percentage point increase in the spread is associated with a 21.6 basis point (or 6.7% relative) increase in eviction filings. The delinquent rate likewise has a positive effect, but it is statistically insignificant. Meanwhile, the difference in eviction rates between agency and private conduit loans becomes slightly smaller but does not disappear, remaining negative and statistically significant at the 1% level.

D. Challenges to Identifying the Causal Mechanism

Distinguishing Compliance from Financing Effects

Our theoretical framework suggests that lower eviction rates result from stricter loan underwriting, enhanced monitoring, and superior access to forbearance programs. These mechanisms should persist regardless of specific policy mandates. However, a potential concern with our analyses is that they potentially conflate two distinct channels: (1) compliance with legal mandates on evictions during the pandemic, and (2) fundamental differences in property risk characteristics that influence landlord eviction incentives independent of other regulations.

[25] Table A.2 in the Appendix provides empirical support for this by showing that the LTV and DSCR for agency-backed loans differ from non-agency-backed debt.

[26] Inspired by the literature that shows borrowers' inability to pay significantly affects mortgage delinquency/default (see e.g., Foster and Van Order, 1985; Elmer and Seelig, 1999; Goldberg and Capone, 2002; Bhutta, Dokko and Shan, 2017; Gerardi et al., 2018), we conjecture that debt service pressure faced by multifamily landlords/borrowers can affect not only their delinquency decisions but also their eviction decisions.

To address these concerns, we note that our empirical analysis accounts for compliance with legal mandates through multiple angles. First, our empirical models include *county* by *year-month* fixed effects, which allows us to rule out possible time-varying local economic and policy factors that could drive evictions. For example, although most of the states in our sample implemented their own eviction moratoriums, our rich set of fixed effects captures trends, such as policy changes, that are specific to counties within each state. Second, while the pandemic eviction moratoriums imposed an administrative stop to evictions for nonpayment of rent, they did not apply for other causes associated with tenant behavior (e.g. damage to property, etc.). As a result, evictions they were not perfectly suspended. For instance, Figure 4(a) shows that although monthly eviction filings declined during the first few months of 2020, they did not reach zero.

To address concerns that the pandemic policies created a mechanical relationship linking GSE forbearance to evictions, we restrict the sample to observations from 2010 to 2018, excluding both the Great Financial Crisis and the COVID-19 pandemic, reflecting a period of financial stability and growth (column (6) in Table II). We find that the eviction rate on properties financed with agency loans remains negative and statistically significant. We also observe that the underlying factors, including LTV, delinquency, and spread, become statistically insignificant. During this period GSE policies did not restrict landlord eviction actions even if the GSE had granted forbearance. Thus, the results suggest that our findings are not unique to the post-COVID policies and economic environment. Because the eviction moratoriums were not in effect during this decade, any observed eviction discount for GSE properties cannot be attributed to compliance with pandemic-era mandates. Hence, our analysis provides compelling evidence that the agency effect is a structural feature rather than a transitory response to federal or local eviction regulations, as the loan workout channel should operate independently of any legal mandate.

Nonetheless, in the next section, we further examine how the response to the forbearance policy varies over time and document that the agency effect is largest after the first year of treatment, suggesting that differences in forbearance policies have a limited effect on reducing eviction filings when universal eviction moratoriums are in effect.

Origination Effects and Property Risk

Although building fixed effects should capture the underlying property risk (e.g., tenant profile), we address the concern that observed differences in eviction rates may arise from temporal variation in property risk characteristics that are correlated with financing choice. To do so, we note that our data allows us to track the eviction filings for properties prior to the loan origination. That is, for a property that has a loan origination (either a new loan or a refinance of an existing loan) at date t, we can observe its eviction rate over the six or twelve months prior to t.

We then estimate the following regression

$$\mathrm{E}_{it} \quad = \quad \gamma \cdot \mathbb{1}\{\text{Agency Origination}\}_{i,t+v} + \tau_{c,t} + \zeta_i + \varepsilon_{it} \tag{15}$$

where E_{it} is the eviction rate for property i at month t and $\mathbb{1}\{\textit{Agency Origination}\}_{i,t+v}$ is the forward looking indicator for the type of loan that is originated within v months, where v equals six-months or one-year after t. For example, $\mathbb{1}\{\textit{Agency Origination}\}_{i,t+v}$ equals 1 when a GSE loan will be outstanding between $t+1$ and $t+6$ (or $t+12$) months following the eviction observation, and is 0 otherwise. The control group consists of properties that will have a conduit loan originated over the same window. Lastly, instead of property fixed effects, we use census tract fixed effects (ζ_i) to capture neighborhood risk since the building fixed effect would otherwise absorb the agency origination variable. This set-up allows us to test for differences in eviction rates prior to loan origination. If variance exists across properties in tenant risk characteristics based on whether the landlord utilizes a GSE or conduit loan, then we would expect to see these risk differences manifest in heterogeneous eviction rates.

Columns (1) and (2) of Table III presents the results for the eviction filings 6 and 12 months prior to loan origination, respectively. The coefficients are not statistically significant, indicating that we cannot observe a significant difference in the eviction filing rates across properties regardless of whether the property originated a GSE or conduit loan. In Column (3), we observe similar results when excluding refinance loans from the sample. This result confirms that property risk characteristics, in terms of eviction priors, are similar across properties.

V. Evictions During the Pandemic

The mortgage financing effects on evictions we identified are intuitive and consistent with our theoretical insights. But what explains the remaining difference in eviction rates between agency- and conduit-financed properties? As we discussed previously, in addition to underwriting and interest rate differences, GSE loans differ from private conduit loans in terms of distress management and loss mitigation. Specifically, GSE borrowers are more likely to receive forbearance or modifications during times of distress (see, e.g., Adelino, Gerardi and Willen, 2013; Agarwal et al., 2011*b*). We thus posit that, because they face a higher likelihood of receiving forbearance or forgiveness, landlords with GSE loans are more tolerant of tenant nonpayment and thus engage in fewer costly evictions. We define this as the loan workout channel.

The COVID-19 pandemic provides a unique setting to study the loan workout channel in evictions, as it simultaneously increased tenant nonpayment risk and triggered unprecedented policy interventions in mortgage markets. We thus study evictions during the pandemic in this section.

A. CARES Act and Eviction Moratoriums

In response to the unprecedented economic disruptions caused by government responses to the COVID-19 pandemic, Congress passed the CARES Act (Congress, 2020) (Public Law 116-136, 2020) to provide relief to mortgage holders, along with other provisions. Certain provisions of the CARES Act specifically targeted financial relief to multifamily borrowers. For example, the law notes that "a multifamily borrower with a Federally backed multifamily mortgage loan experiencing a financial hardship due, directly or indirectly, to the COVID-19 emergency may request a forbearance under the terms outlined in this section." However, this forbearance is not without costs as the CARES Act also stipulates that a borrower receiving forebearance "may not, for the duration of the forbearance (1) evict or initiate the eviction of a tenant from a dwelling unit located in or on the applicable property solely for nonpayment of rent or other fees or charges; or (2) charge any late fees, penalties, or other charges to a tenant described in paragraph (1) for late payment of rent." The CDC extended the federal eviction moratorium multiple times, including one targeting communities with a high risk of COVID-19 contagion, until the US Supreme Court intervened in late August 2021. Although most CARES Act provisions expired as the pandemic became endemic, Freddie Mac announced

in September 2021 that it would continue offering the forbearance program (with its associated eviction moratoria) indefinitely (Freddie Mac, 2021). Fannie Mae similarly extended its multifamily forbearance program (Fannie Mae, 2021). As a result, the passage of the CARES Act in March 2020 marks an apparent shift in the flexibility of lenders to multifamily borrowers.

B. Policy Interventions and Eviction

Within the context of our eviction model in Section III, the GSEs followed federal regulatory and policy guidelines during the pandemic, altering their mortgage default policies to grant automatic forbearance upon request. This corresponds to setting $\theta^G = 1$, compared to $\theta^G << 1$ pre-pandemic. In Figure 6, we demonstrate how this increase in the forbearance probability could have lowered eviction probabilities. The solid line shows the eviction probability as a function of the forbearance probability for a representative tenant in Atlanta, assuming the landlord finances the unit with a GSE mortgage. As we can see, the landlord has no incentive to evict if the probability of forbearance is above 50 percent. Thus, if the probability of receiving forbearance from the GSEs was relatively high (above 50 percent) prior to the pandemic, then the new policy linking forbearance to an eviction moratorium was unnecessary, as high forbearance rates on their own reduce the economic incentives to evict. Thus, even without the federal government's mandatory retention policy, we can imagine that landlords with GSE loans would not pursue evictions. In other words, the mandatory retention policy during the pandemic did not cause a market distortion in this case.

We know that during the pandemic, many private lenders, including conduit lenders, followed the GSEs' lead in granting forbearance to their borrowers. In this regard, we are also interested in learning how the eviction probability for conduit loans has changed, especially compared to that of GSE loans. We thus include in Figure 6 the simulated eviction probabilities for a unit financed with a conduit mortgage (the dashed line). The difference between the solid and dashed lines represents the wedge in eviction probabilities between a GSE and a conduit loan (shown on the inverse axis).

To isolate the effect of lender forbearance policies, we assume that both mortgages have the same terms (loan amount, interest rate, maturity, and payment). In addition, we follow Glancy, Kurtzman and Loewenstein (2022) in assuming that GSE mortgages have higher mortgage payment forgiveness than conduit lenders ($\chi^G = 0.55, \chi^N = 0.45$). The comparison between the solid and dashed lines

in Figure 6 shows that, under the counterfactual in which both GSE and conduit loans have a 20 percent probability of forbearance, tenant eviction probabilities converge, with both reaching 100 percent. In contrast, when the GSE forbearance probability reached 100 percent (e.g., during the COVID-19 pandemic), the wedge could have ranged from 80% to 0, depending on whether the conduit forbearance probability was below 45% or above 80%. Since we do not observe the forbearance probability of conduit lenders, nor do we know the percentage of payment forgiveness of either conduit or GSE lenders, the wedge of eviction probability between conduit and GSE loans during the pandemic remains an empirical question.

C. DID Analysis

Empirically, we use the passage of the CARES Act (and the introduction of the GSE forbearance program) in March 2020 as an exogenous shock to isolate the change in the eviction probability between conduit and GSE loans during the pandemic. This shock increased the probability of receiving forbearance for properties with a GSE loan, but not necessarily for those without one. Initially, the CARES Act stipulated that properties eligible for forbearance must have obtained an agency loan by February 2020. Subsequently, the GSEs adopted policy changes that indefinitely extended the forbearance program, allowing multifamily borrowers with new agency loans originated after the CARES Act to qualify. The program effectively increases the likelihood that a property with GSE financing is offered forbearance.

We thus define the treatment group as properties that held an agency loan during or after March 2020, representing 6,971 of 13,320 unique multifamily properties in our sample. Figure 7 shows the share of multifamily properties by treatment timing cohorts. Approximately 37% of the properties in the sample, grouped as Cohort 1, had either a federally backed or agency loan outstanding in March 2020, when the CARES Act was enacted. Cohort 2, which includes properties that obtained an agency loan within the first twelve months following the Act's passage, accounts for 7% of the sample. Properties in Cohorts 3 and 4 that obtained an agency loan two and three years after enactment, respectively, make up another 8% of the sample combined. The remaining 48% are properties considered Never Treated, meaning they did not have an outstanding agency loan during the post-CARES Act period. These properties include those that were never financed, obtained a

non-agency private loan alone, or had an agency loan but paid it off before the start of the treatment period.

One challenge in our analysis is that qualified agency properties are not continuously treated. Landlords can refinance or pay off an agency loan, thereby limiting their exposure to the forbearance program and reducing the lender's influence on eviction filings. The dynamic nature of mortgage financing choices gives rise not only to differences in treatment timing but also to variations in treatment duration. In our context, the forbearance program should influence eviction filing decisions after the passage of the CARES Act, but only while an agency loan is outstanding on the property.

In light of these concerns, we first quantify the baseline average effect of the lender choice on eviction outcomes by estimating the following two-way fixed effects model:

$$E_{i,t} = \delta_1 \cdot (\mathbb{1}Post_{i,t} \times \mathbb{1}Agency_{i,t}) + \delta_0 \cdot \mathbb{1}Agency_{i,t} + X_{i,t} \cdot \beta + \tau_{c,t} \times \mathbb{1}\{\text{Loan}_{i,t}\} + \rho_i + \varepsilon_{i,t} \quad (16)$$

where $E_{i,t}$ is the eviction rate, and $\mathbb{1}Agency_{i,t}$ is the agency loan indicator, as previously defined. The post treatment indicator, $\mathbb{1}Post_{i,t}$, takes a value of one if the observation for property i is on or after March 2020; it is zero otherwise. We interact $\mathbb{1}Post_{i,t}$ with $\mathbb{1}Agency_{i,t}$, while the standalone $\mathbb{1}Post_{i,t}$ is absorbed by the time fixed effects. The remaining controls and array of fixed effects are the same as in our baseline model (equation (14)).

The validity of causal inference depends on the standard parallel trends assumption. In our model, we assume that the evolution of the eviction filing rate at qualified agency-leveraged properties would have been the same as the observed trend in eviction filings at unqualified properties with similar financing had neither group been affected by the CARES Act. We condition our assumption on loan characteristics ($X_{i,t}$), including the LTV ratio, the contract spread, and mortgage delinquency. The choice of variables is consistent with insights from our theoretical model. Our rich set of property- and location-specific time-fixed effects allows us to further qualify the parallel trends assumption by controlling for properties within the same neighborhoods and exposed to the same dynamic local economic trends and liquidity constraints.

We test for a divergence in the pre-trend effects between the treated and never treated properties, and model the marginal effect of having an agency loan for every 12 months before and after

treatment:

$$E_{i,t} = \sum_{l \in L} [\delta_1^l \cdot (\mathbb{1}D_{i,t}^l \times \mathbb{1}Agency_{i,t}) + \delta_0^l \cdot \mathbb{1}D_{i,t}^l] + \delta_0 \cdot \mathbb{1}Agency_{i,t} + X_{i,t} \cdot \beta + \tau_{c,t} \times \mathbb{1}\text{Loan}_{i,t} + \rho_i + \varepsilon_{i,t} \quad (17)$$

where $\mathbb{1}D_{i,t}^l$ is one for property i at time l years from treatment, such that $l \in L \equiv \{\leq -6\} \cup \{-5, -4, -3, -2, 0, 1, \ldots 4\}$. $\mathbb{1}D_{i,t}^l$ is zero whenever $l \neq t - t_i^*$ and for properties that are never treated. The treatment date for property i occurs at time t_i^*, and the twelve months immediately preceding treatment ($t - t_i^* = -1$) is the reference period. For example, if property i is treated in March 2020, and an agency loan is outstanding at the time of the CARES Act's passage, the reference pre-treatment period is from March 2019 to February 2020. For a property that obtained an agency loan in April 2022, becoming first treated on this date, the reference pre-treatment year is from April 2021 to March 2022. We combine the event time dummy variables that capture periods of 6 years or more preceding treatment. We obtain estimates of the treatment response dynamics across time by interacting the relative event time indicators with the $\mathbb{1}Agency_{i,t}$ indicator to capture treatment duration.

An additional concern is that properties selected into the program by obtaining an agency loan after passage of the CARES Act may introduce cohort-specific trends that could bias the leads and lags of the dynamic TWFE model. We adopt the interacted-weighted (IW) estimator of Sun and Abraham (2021) to address this concern. We segment properties into cohorts by their agency loan origination date (i.e., first treatment) and estimate the following model:

$$E_{i,t} = \sum_{l \in L} \sum_{c \in C} \mathbb{1}\{C_i = c\} \cdot [\delta_1^{l,c} \cdot (\mathbb{1}D_{i,t}^{l,c} \times \mathbb{1}Agency_{i,t}) + \delta_2^{l,c} \cdot (\mathbb{1}D_{i,t}^{l,c} \times (1 - \mathbb{1}Agency_{i,t}))] + \delta_0 \cdot \mathbb{1}Agency_{i,t} + X_{i,t} \cdot \beta + \tau_{c,t} \times \mathbb{1}\text{Loan}_{i,t} + \rho_i + \varepsilon_{i,t} \quad (18)$$

where $\mathbb{1}\{C_i = c\}$ is an indicator function for whether loan i belongs to cohort $c \in C \equiv \{$March 2020, April 2020 - March 2021, April 2021 - March 2022, April 2022 - March 2023$\}$. We consider mortgages first treated in March 2020 as Cohort 1, those from April 2020 to March 2021 as Cohort 2, those from April 2021 to March 2022 as Cohort 3, and so on. Furthermore, we enhance the

model to separately estimate the time trend for loans treated when an agency loan is outstanding versus when it is not. As a result, Equation (18) produces two $L \times C$ matrices of time-varying cohort specific ATRs for each setting ($\hat{\delta}_1^{l,c}$) and ($\hat{\delta}_2^{l,c}$). This allows us to decompose the program's impact by examining dynamic changes in agency financing coverage. Furthermore, we derive the interacted-weighted estimator of the ATR of retaining agency status vs removing it at relative time l as

$$ATR^l = \sum_{c \in C} w^{l,c} \cdot (\hat{\delta}_1^{l,c} - \hat{\delta}_2^{l,c}) \tag{19}$$

where $w^{l,c}$ is the weight of cohort c at event time l, and $(\hat{\delta}_1^{l,c} - \hat{\delta}_2^{l,c})$ is the marginal effect of gaining agency status during the post treatment era. The weight $w^{l,c}$ is set as the sample share of each cohort in C in the relative time period (Sun and Abraham, 2021).

We summarize these estimates across all post (and pre) treatment periods as:

$$\overline{ATR} = \frac{1}{N} \cdot \sum_{l \geq 0} ATR^l \tag{20}$$

following the methodology of Callaway and Sant'Anna (2021) and Sun and Abraham (2021). N is the number of post (or pre) treatment ATR estimators to compare estimates across alternative model specifications consistently. Agarwal et al. (2024) employ a similar strategy.

D. DID Results

Table IV reports ordinary least squares (OLS) estimates of the forbearance program on eviction filings and t-statistics based on standard errors clustered by building ID. The coefficient estimates in columns (1) and (3) correspond to equation (16), whereas the coefficient estimates in columns (2) and (4) correspond to equation (17). Column (1) indicates that the eviction filing rate on properties with an agency loan outstanding post-CARES Act is 87.1 basis points lower than that of similar properties without an agency loan. The average treatment response (ATR) is statistically significant at the 1% level. The results suggest that the forbearance program reduces the likelihood of eviction by approximately 27% from 3.24 to 2.37 filings per 100 rental units, on average.

Column (2) of Table IV reports the event study results, while Figure 8 plots them overlying the

baseline ATR estimate from column (1). We observe that the eviction filing rate of treated properties is not statistically different than that of non-treated properties prior to treatment. The coefficient on each interaction of the agency indicator and pre-treatment time indicator (D^l) is statistically insignificant. Moreover, the average pre-trends differential is less than 1% of the average eviction filing rate and statistically insignificant. These statistics support the parallel trends assumption. In contrast, the post-treatment time interactions with the agency indicator are statistically significant at conventional levels with a mean post-trend effect of -1.6 (or 160 basis points), which is statistically significant at the 1% level. The effect is greatest during the second year of treatment, with a reduction in the eviction filing rate of 170 basis points, representing a 52% decrease in the average filing rate for properties with an agency loan compared to properties without an agency loan.

In the last two columns of Table IV, we restrict the sample to observations from January 2010 onward, as relatively few properties prior to 2010 had outstanding agency loans, which could introduce noise into the analysis. Furthermore, limiting the sample period excludes observations from the previous financial crisis. The main results remain qualitatively similar to those of the full sample, and consistent with our findings in Table II. Overall, the results suggest that the forbearance program was most effective during the second year, after the Federal eviction moratoriums expired or were overturned by the Supreme Court, leaving the GSE forbearance program as the primary deterrent to eviction filings.

E. Decomposition of Cohort Adjusted Effects

In Table A.3 in the appendix, we limit the treatment group by cohort using post-2010 observations. We find that properties in Cohorts 1 and 2 mostly drive the effects. The interaction term between agency and post remains negative but statistically insignificant when the control group is set to Cohort 3 or 4 alone. However, the lack of significance may be due to a power issue, as Cohorts 3 and 4 each represent less than 5% of the sample. Hence, we estimate the Sun and Abraham (2021) model (equation (18)) to better account for dynamic cohort effects.

Figure 9 plots the coefficient estimates of equation (18) with 95% and 90% confidence intervals using observations from 2010 to 2024. We decompose and examine the differences in the coefficient estimates across three panels. Panel A shows the $\hat{\delta}_1^l$ coefficients, representing the trend of treated

properties when they retain an agency loan over time. Panel B displays the $\hat{\delta}_2^l$ coefficients, which represent the trend of treated properties when they pay off their existing agency loan and do not refinance into another agency loan. Panel C displays the difference between the coefficients $\hat{\delta}_1^l$ and $\hat{\delta}_2^l$, illustrating the cohort-adjusted average treatment response of the eviction filing rate from the forbearance program. The results in Panel C are similar to those reported in Figure 8, indicating that staggered treatment and cohort-specific effects do not materially affect the event study analysis.

The results provide an insightful decomposition of the average treatment response. Panel A suggests that the eviction filing rate of treated agency properties relative to control properties decreases immediately after treatment with a decreasing intensity, conditional on remaining treated up to that date. Meanwhile, Panel B shows that the eviction rate on treated properties increases after the first year, once they pay off the outstanding agency loan, and the forbearance program is effectively no longer available. The reversal in the eviction rate filing rate for treated properties paying off debt exceeds that of control properties. The results suggest that eviction filings are delayed by the forbearance program but are not necessarily eliminated, particularly among properties with maturing agency loans.

In Table A.4, in the Appendix, we examine which treated properties (among Cohort 1 only) exit agency using a linear probability model of agency on property and neighborhood characteristics, with county and year-month fixed effects. The sample is limited to observations from March 2020 to June 2024. We observe that multifamily borrowers (in Cohort 1) with few rental units were likelier to exit agency. Likewise, properties in neighborhoods with a high share of minorities exit agency more often. Interestingly, agency exit is also associated with properties in neighborhoods with high median household income.

F. Heterogeneity

We examine whether the average treatment response to the forbearance program for eviction filings varies across neighborhood dimensions and property characteristics. We begin by interacting demographic variables from the 5-year ACS at the census tract level with the agency and post indicator variables in equation (16). Specifically, we examine the share of minorities (i.e., Hispanics and Blacks), the tenant-to-owner ratio, the median household income, and the median rent. We

report the results in Table V using post-2010 observations. ACS variables are standardized into z-scores. The ATR does not vary significantly with the ACS variables, suggesting that the results are consistent throughout neighborhoods, within the same counties.

In Table VI, we report estimates of the ATR by subsamples defined by the number of rental units at the multifamily property. The baseline specification is equation (16). Column (1) shows the results for small properties with 25 or fewer rental units, whereas column (2) shows the results for large properties with 339 or more. Column (3) shows the results for properties with 25 to 338 rental units. The interaction term is statistically insignificant for small multifamily properties but not for those with more rental units. The results suggest that the GSE forbearance program is most effective in reducing eviction filings at median- to large-sized multifamily properties, but not at small ones.

VI. Conclusion

The COVID-19 pandemic exposed many US households to eviction risk, raising concerns about an impending eviction crisis. In response, the federal government followed a well used playbook of credit market intervention in an attempt to limit this crisis. Our study examines how landlords responded to these changes which linked linked loan forbearance with eviction moratorium. Thus, we highlight the spillover effects of the credit market on the real economy, showing how financing choices by property owners can affect tenant eviction risk.

Specifically, we study the impact of GSE financing on evictions, focusing on differences in underwriting and loan workout policies across lenders. We provide a stylized model that reveals the linkage between credit supply and eviction risk—having a GSE loan could lead to a lower likelihood that a landlord will pursue evictions. In the empirical analysis, using a sample of nationwide multifamily loans securitized between 2000 and 2024, we find lower eviction rates in properties financed with mortgages insured by Fannie Mae, Freddie Mac, or Ginnie Mae compared to properties financed with non-GSE conduit debt. Importantly, our study reveals that relatively small changes in the probability of lender forbearance can significantly reduce landlord incentives to evict tenants.

Additionally, our analysis contributes to the current debate surrounding the future of the GSEs (Layton, 2020; White, Richardson and Van Nieuwerburgh, 2017; Elenev, Landvoigt and Van Nieuwerburgh, 2016; Frame and White, 2005). By highlighting a new channel demonstrating how the GSEs'

role in providing multifamily credit can impact tenant housing outcomes, we offer a new metric for evaluating how the GSEs meet their affordable housing mandates.

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Table I Descriptive Statistics of Multifamily Properties

This table displays summary statistics for multifamily properties from January 2000 to June 2024 (excluding 2019). Panel A describes property and neighborhood characteristics at the multifamily building level. Panel B displays mortgage characteristics at the building-year-month level when a mortgage on the property is outstanding. Panel C displays eviction filings for all multifamily building-year-month level observations. Property and mortgage characteristics are obtained from Trepp, LLC. Neighborhood characteristics are obtained from the 2020 American Community Survey, 5-year estimates. Eviction filings are obtained from the Princeton Eviction Lab.

Panel A: Unique Building Level Observations					
	Mean	**SD**	**P10**	**P90**	**N**
Property					
Building Units	153.47	146.18	26.00	342.00	13,320
Total Matched Mortgages	1.82	1.38	1.00	4.00	13,320
Year Built	1975.21	23.58	1955.00	2003.00	13,123
Neighborhood Census Tract					
Population (Thousands)	4.25	1.56	2.32	6.28	13,320
Income ($Thousands)	71.98	36.42	35.24	116.63	12,995
Home Value ($Thousands)	222.31	140.90	97.10	374.30	12,291
Monthly Rent ($)	1067.73	293.51	774.00	1434.00	13,285
Hispanic Share	0.24	0.23	0.03	0.61	13,320
Black Share	0.20	0.21	0.02	0.52	13,320
Asian Share	0.06	0.07	0.00	0.14	13,320
White Share	0.47	0.27	0.10	0.83	13,320
Other Race Share	0.04	0.04	0.01	0.08	13,320
Vacancy Rate	0.10	0.07	0.02	0.18	13,320
Tenant-to-Owner Ratio	6.35	37.79	0.34	8.09	12,994
Panel B: Building-Year-Month Level Observations with an Outstanding Mortgage					
	Mean	**SD**	**P10**	**P90**	**N**
Concurrent Loans Outstanding	1.26	0.59	1.00	2.00	1,095,762
$\mathbb{1}$Agency	0.42	0.49	0.00	1.00	1,095,762
$\mathbb{1}$Loan Type: Freddie Mac	0.29	0.45	0.00	1.00	1,095,762
$\mathbb{1}$Loan Type: Fannie Mae	0.13	0.33	0.00	1.00	1,095,762
$\mathbb{1}$Loan Type: Ginnie Mae	0.00	0.02	0.00	0.00	1,095,762
$\mathbb{1}$Loan Type: Conduit	0.59	0.49	0.00	1.00	1,095,762
Loan Amount ($Millions)	17.97	59.45	1.06	38.37	1,095,762
Loan-to-Value Ratio	0.68	0.12	0.52	0.79	1,093,003
Debt Service Coverage Ratio	1.37	0.75	0.56	2.16	1,033,274
Contract Rate	0.06	0.02	0.04	0.08	1,095,762
Contract Rate Spread	0.02	0.01	0.01	0.04	1,095,762
Loan Age (Years)	4.30	2.86	1.00	8.00	1,095,762
Delinquency Rate	0.03	0.18	0.00	0.00	1,095,762
$\mathbb{1}$(Agency and Conduit Loans Outstanding)	0.01	0.08	0.00	0.00	1,095,762
Panel C: All Building-Year-Month Level Observations					
	Mean	**SD**	**P10**	**P90**	**N**
Eviction Filing Rate (annualized per 100 units)	3.24	13.23	0.00	8.41	3,756,240
Eviction Filings Counts (monthly)	0.42	1.65	0.00	1.00	3,756,240

Table II Financing Effects on Eviction Filings

This table displays OLS estimates of the relation between mortgage financing and eviction filings at multifamily properties from January 2000 to June 2024 (excluding 2019). The dependent variable is the annualized eviction filing rate per 100 rental units. 𝟙Agency is 1 when a Freddie Mac, Fannie Mae, or Ginnie Mae loan is outstanding and is 0 otherwise. 𝟙Freddie Mac and 𝟙Fannie Mae identify the respective GSE issuer. LTV and DSCR are the property's most recent loan-to-value ratio and debt service coverage ratio, respectively. Delinquency is the share of outstanding loans 30 days or more past due. Spread is the mortgage contract rate minus the 10-year treasury yield in percentage points. In parentheses, t-statistics based on standard errors within building clusters are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	**Eviction Filing Rate per 100 Units**					
𝟙Loan	0.498***	0.422***				
	(7.589)	(4.583)				
𝟙Agency	-0.532***	-0.640***	-0.693***	-0.693***	-0.483***	-0.600***
	(-5.546)	(-5.812)	(-5.606)	(-5.483)	(-3.629)	(-3.490)
LTV					0.921**	0.028
					(2.193)	(0.048)
Delinquency					0.333	0.382
					(1.171)	(1.322)
Spread (%)					0.216***	-0.039
					(4.426)	(-0.501)
DSCR				-0.069		
				(-1.612)		
Subsample:	2000-2024	2010-2024	2010-2024	2010-2024	2010-2024	2010-2018
Building FE	✓	✓	✓	✓	✓	✓
County × Year-Month F.E.	✓	✓				
𝟙Loan × County × Year-Month F.E.			✓	✓	✓	✓
Observations	3,748,062	2,153,142	2,147,890	2,127,952	2,145,814	1,430,293
R^2	0.189	0.211	0.214	0.214	0.214	0.267

Table III Eviction Filings During Mortgage Underwriting

This table displays OLS estimates of the agency origination effect on eviction filings at multifamily properties from January 2010 to June 2024 (excluding 2019), for the 6 or 12 months preceding a loan origination. The dependent variable is the annualized eviction filing rate per 100 rental units. $\mathbb{1}$Agency Origination is 1 when a Freddie Mac, Fannie Mae, or Ginnie Mae loan will be outstanding and is 0 otherwise. The control group consists of properties within 6 or 12 months of a conduit origination. The third column excludes observations with an outstanding loan. In parentheses, t-statistics based on standard errors within building clusters are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
Outcome:	**Eviction Filing Rate per 100 Units**		
	6 Months	12 Months	12 Months
Variables	New/Refi Loan	New/Refi Loan	New Loan
$\mathbb{1}$Agency Origination	0.293	0.273	0.308
	(0.932)	(0.990)	(1.106)
Census Tract F.E.	✓	✓	✓
County × Year-Month F.E.	✓	✓	✓
Observations	83,114	154,777	153,141
R^2	0.282	0.258	0.259

Table IV Eviction Filings Before and After CARES Act

This table displays OLS estimates of the effect of mortgage finance type on eviction filings at multifamily properties from January 2000 to June 2024 (excluding 2019). The dependent variable is the annualized eviction filing rate per 100 rental units. $\mathbb{1}$Agency is 1 when a Freddie Mac, Fannie Mae, or Ginnie Mae loan is outstanding and is 0 otherwise. $\mathbb{1}$Post is 1 for months after the enactment of the CARES Act (i.e., March 2020) and 0 for prior months. The $\mathbb{1}D^l$s are indicators for the year (in 12 month increments) from treatment time t^* for each treated property. The $\mathbb{1}D^l$s are always zero for never-treated properties. LTV and DSCR are the property's most recent loan-to-value ratio and debt service coverage ratio, respectively. Delinquency is the share of outstanding loans 30 days or more past due. LTV, DSCR, and Delinquency are 0 when no loans are outstanding on the property. In parentheses, t-statistics based on standard errors within building clusters are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Outcome:	**Eviction Filing Rate per 100 Units**			
Subsample:	2000-2024		2010-2024	
$\mathbb{1}$Agency × $\mathbb{1}$Post	-0.871***		-0.875***	
	(-3.791)		(-3.886)	
$\mathbb{1}$Agency × $\mathbb{1}D^{-6^+}$		0.027		0.170
		(0.100)		(0.664)
$\mathbb{1}$Agency × $\mathbb{1}D^{-5}$		-0.209		0.008
		(-0.895)		(0.032)
$\mathbb{1}$Agency × $\mathbb{1}D^{-4}$		-0.222		0.009
		(-0.956)		(0.039)
$\mathbb{1}$Agency × $\mathbb{1}D^{-3}$		0.050		0.263
		(0.189)		(0.944)
$\mathbb{1}$Agency × $\mathbb{1}D^{-2}$		-0.361		-0.278
		(-1.140)		(-0.864)
$\mathbb{1}$Agency × $\mathbb{1}D^{0}$		-1.086***		-0.897***
		(-3.320)		(-2.681)
$\mathbb{1}$Agency × $\mathbb{1}D^{1}$		-1.889***		-1.718**
		(-2.783)		(-2.481)
$\mathbb{1}$Agency × $\mathbb{1}D^{2}$		-1.766***		-1.483***
		(-5.024)		(-4.216)
$\mathbb{1}$Agency × $\mathbb{1}D^{3}$		-1.822***		-1.419***
		(-4.655)		(-3.635)
$\mathbb{1}$Agency × $\mathbb{1}D^{4}$		-1.433***		-1.005**
		(-3.231)		(-2.264)
$\mathbb{1}$Agency	0.179	0.221	-0.108	-0.091
	(1.170)	(1.221)	(-0.715)	(-0.481)
LTV	0.886**	0.897**	0.863**	0.864**
	(2.376)	(2.408)	(2.057)	(2.056)
Delinquency	0.470**	0.474**	0.405	0.417
	(2.068)	(2.080)	(1.418)	(1.454)
Spread (%)	0.233***	0.223***	0.214***	0.210***
	(5.200)	(4.956)	(4.395)	(4.273)
Standalone D^l Indicators		✓		✓
Building FE	✓	✓	✓	✓
$\mathbb{1}$Loan × County × Year-Month F.E.	✓	✓	✓	✓
Observations	3,736,360	3,736,360	2,145,814	2,145,814
R^2	0.192	0.192	0.214	0.214

Table V Cross Sectional Tests by Neighborhood Traits

This table displays cross-sectional OLS estimates of the effect of mortgage financing type on eviction filings at multifamily properties from January 2010 to June 2024 (excluding 2019) across neighborhoods. The dependent variable is the annualized eviction filing rate per 100 rental units. 𝟙Agency is 1 when a Freddie Mac, Fannie Mae, or Ginnie Mae loan is outstanding and is 0 otherwise. 𝟙Post is 1 for months after the enactment of the CARES Act (i.e., March 2020) and 0 for prior months. *Variable* is a static neighborhood tract characteristic defined in the column sub-header, demeaned and normalized by the sample standard deviation (i.e., z-score). LTV and DSCR are the property's most recent loan-to-value ratio and debt service coverage ratio, respectively. Delinquency is the share of outstanding loans 30 days or more past due. LTV, DSCR, and Delinquency are 0 when no loans are outstanding on the property. In parentheses, t-statistics based on standard errors within building clusters are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Outcome:	**Eviction Filing Rate per 100 Units**			
Interacted Variable (in z-scores):	*Minority Share*	*Tenant-to-Owner Ratio*	*Median Household Income*	*Median Rent*
𝟙Agency	-0.089	-0.071	-0.114	-0.105
	(-0.591)	(-0.459)	(-0.718)	(-0.679)
𝟙Agency × 𝟙Post	-0.944***	-0.935***	-0.901***	-0.940***
	(-4.228)	(-4.058)	(-3.927)	(-4.097)
Variable × 𝟙Post	-0.285***	0.093	0.169***	0.357***
	(-3.637)	(0.792)	(2.815)	(4.928)
𝟙Agency × Variable	-0.240***	-0.017	0.162**	0.180**
	(-2.683)	(-0.246)	(2.128)	(2.331)
𝟙Agency × Variable × 𝟙Post	0.208	-0.167	-0.088	-0.108
	(1.596)	(-1.419)	(-0.839)	(-0.936)
LTV	0.905**	0.945**	0.871**	0.945**
	(2.167)	(2.218)	(2.042)	(2.247)
Delinquency	0.376	0.394	0.326	0.367
	(1.318)	(1.348)	(1.126)	(1.286)
Spread (%)	0.214***	0.217***	0.218***	0.217***
	(4.395)	(4.340)	(4.356)	(4.442)
Building F.E.	✓	✓	✓	✓
𝟙Loan × County × Year-Month F.E.	✓	✓	✓	✓
Observations	2,145,814	2,093,051	2,093,274	2,140,163
R^2	0.214	0.213	0.216	0.214

Table VI Cross Sectional Tests by Property Size

This table displays cross-sectional OLS estimates of the effect of mortgage financing type on eviction filings at multifamily properties from January 2010 to June 2024 (excluding 2019), using different subsamples defined by the number of rental units available at each multifamily property. The dependent variable is the annualized eviction filing rate per 100 rental units. 𝟙Agency is 1 when a Freddie Mac, Fannie Mae, or Ginnie Mae loan is outstanding and is 0 otherwise. 𝟙Post is 1 for months after the enactment of the CARES Act (i.e., March 2020) and 0 for prior months. LTV and DSCR are the property's most recent loan-to-value ratio and debt service coverage ratio, respectively. Delinquency is the share of outstanding loans 30 days or more past due. LTV, DSCR, and Delinquency are 0 when no loans are outstanding on the property. In parentheses, t-statistics based on standard errors within building clusters are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
Outcome:	**Eviction Filing Rate per 100 Units**		
Subsample:	Rental Units $\leq$ 25	25 $<$ Rental Units $\leq$ 338	Rental Units $\geq$ 339
𝟙Agency	-1.118	-0.042	-0.002
	(-1.503)	(-0.239)	(-0.006)
𝟙Agency × 𝟙Post	0.645	-1.007***	-1.065**
	(0.706)	(-3.769)	(-2.028)
LTV	2.293	0.923*	0.673
	(1.090)	(1.936)	(0.771)
Delinquency	-0.123	0.258	0.772
	(-0.099)	(0.789)	(1.343)
Spread (%)	-0.165	0.261***	0.099
	(-0.601)	(4.509)	(1.000)
Building F.E.	✓	✓	✓
𝟙Loan × County × Year-Month F.E.	✓	✓	✓
Observations	208,841	1,712,971	214,199
R^2	0.129	0.250	0.377

Figure 1. Sensitivity of Eviction Probability to Changes in Lender Forbearance (θ) and Payment Forgiveness (χ).

This figure illustrates the probability of eviction for properties financed with a GSE mortgage under differing assumptions about the probability that the lender provides mortgage payment forbearance (θ) and the amount of mortgage payment forgiveness (χ) in the event of a tenant income shock. The eviction probabilities are derived from a Monte Carlo simulation of tenant income risk, which is assumed to follow a beta distribution ($\alpha = 2, \beta = 8$) that has a mean income shock probability of approximately 20%. The other parameters are: Monthly rent (X) = \$955, discount factor (δ) = 0.95, probability that the tenant recovers after job loss (ψ) = 0.5, penalty rate on missed rent payment (ϕ) = 0.1, and eviction costs (C_E) = \$250.

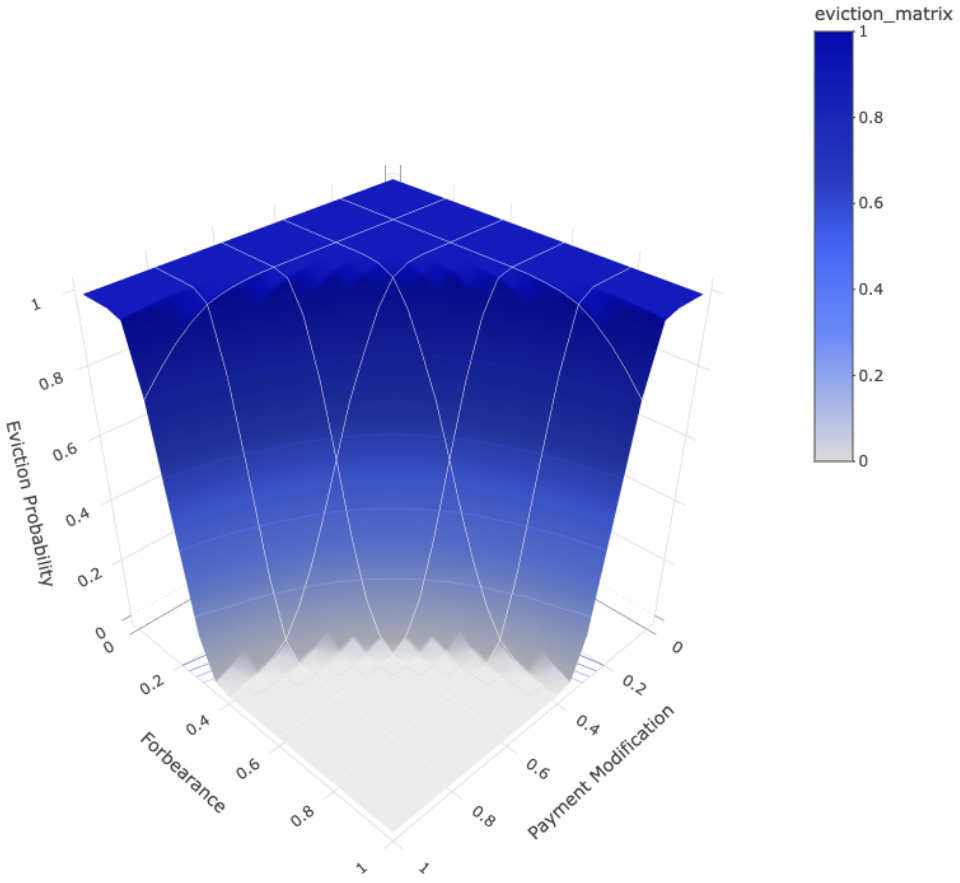


Figure 2. Eviction Probability = 25% Corresponding to Various Lender Forbearance (θ) and Payment Forgiveness (χ) Values.

This figure illustrates the trade-off between mortgage payment forbearance (θ) and mortgage payment forgiveness (χ) required to achieve an eviction probability of approximately 25%. The eviction probability is derived from a Monte Carlo simulation of tenant income risk, which is assumed to follow a beta distribution ($\alpha = 2, \beta = 8$) that has a mean income shock probability of approximately 20%. The other parameters are: Monthly rent (X) = \$955, discount rate (δ) = 0.95, probability tenant that the recovers after job loss (ψ) = 0.5, penalty rate on missed rent payment (ϕ) = 0.1, and eviction costs (C_E) = \$250.

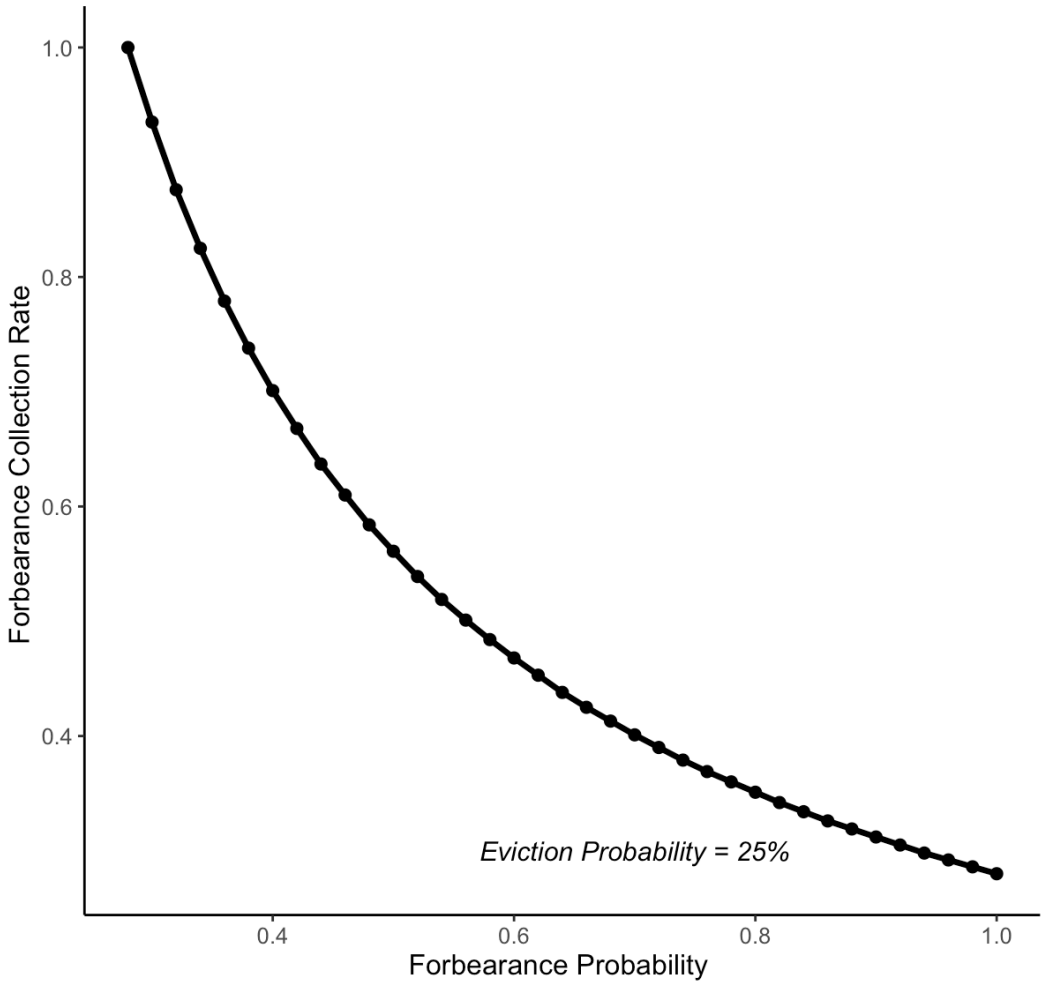


Figure 3. Market Share Over Time

This figure shows the evolution of financing type for multifamily properties in the sample from January 2000 to June 2024. Unlevered represents the share of multifamily properties with no securitized loans outstanding. Freddie Mac represents the share of multifamily properties with an outstanding loan issued by the Federal Home Loan Mortgage Corporation. Fannie Mae represents the share of multifamily properties with an outstanding loan issued by the Federal National Mortgage Association. Ginnie Mae represents the share of multifamily properties with an outstanding loan issued by the Government National Mortgage Association within the U.S. Department of Housing and Urban Development. Conduit represents the share of multifamily properties with an outstanding loan issued by a non-agency conduit lender.

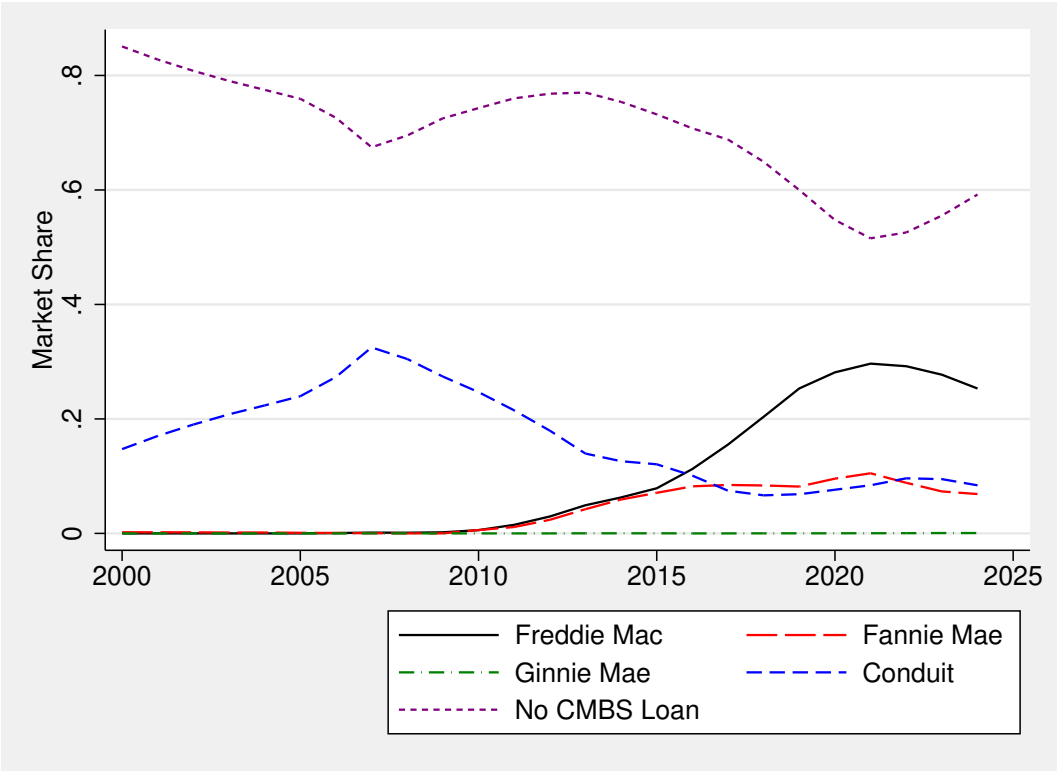
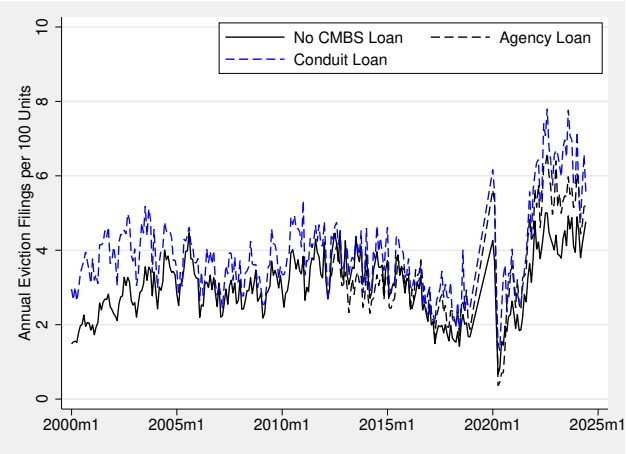
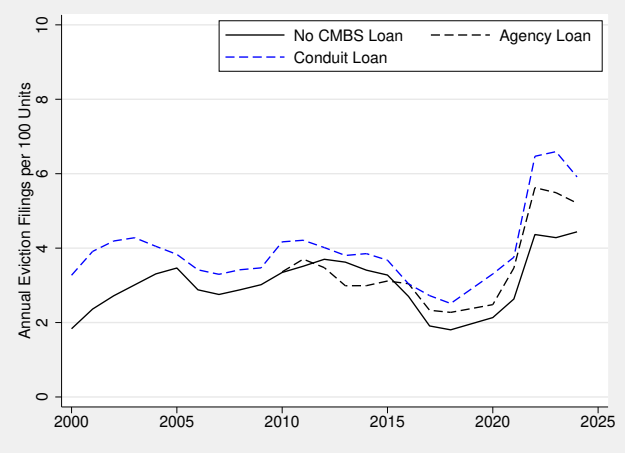


Figure 4. Eviction Filings

This figure illustrates the average annualized eviction filing rate per 100 rental units at multifamily properties from January 2000 to June 2024 (excluding 2019) by whether the property is unlevered, has an agency loan outstanding, or has only non-agency conduit loans outstanding. The eviction filings are reported monthly in Panel A and yearly in Panel B. We exclude agency observations before 2010 as fewer than 50 properties have an agency loan during this period, and thus, produce noisy estimates.



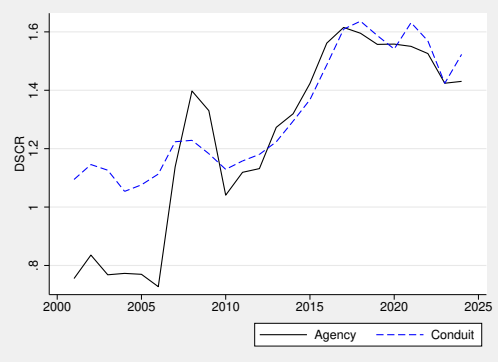
(a) Monthly



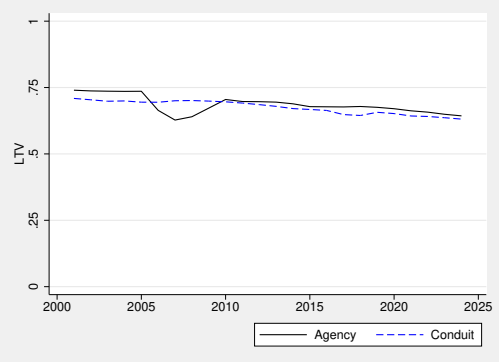
(b) Yearly

Figure 5. Multifamily Mortgage Characteristics

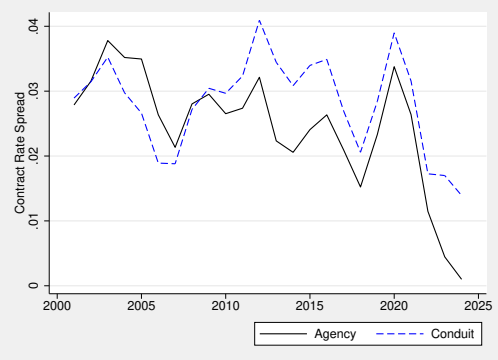
This figure shows the average value of mortgage characteristics for multifamily properties in the sample from January 2000 to June 2024, by whether a GSE lender or a non-agency conduit lender issues the loan. GSEs include Freddie Mac, Fannie Mae, and Ginnie Mae.



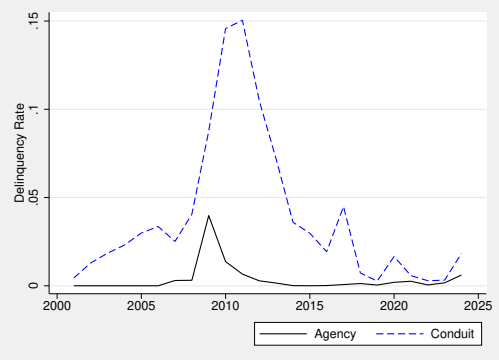
(a) DSCR



(b) LTV



(c) Contract Rate Spread



(d) Mortgage Delinquency

Figure 6. Probability of Eviction: GSE vs. Conduit Mortgages

This figure illustrates the probability of eviction for properties financed with a GSE or Conduit mortgage under differing assumptions regarding the probability that the lender provides mortgage payment forbearance in case of tenant income shock. The eviction probabilities are derived from a Monte Carlo simulation of tenant income risk, which is assumed to follow a beta distribution ($\alpha = 2, \beta = 8$) that has a mean income shock probability of approximately 20%. To isolate the role of lender forbearance, we assume that GSE and Conduit loan terms are identical ($M^G = M^N$). The Wedge plots the difference in eviction probabilities between GSE and non-GSE loans over the range of forbearance probabilities. The simulation follows Glancy, Kurtzman and Loewenstein (2022) in assuming that GSE mortgages have higher mortgage payment forgiveness than Conduit lenders, conditional on forbearance being offered ($\theta^G = 0.55, \theta^N = 0.45$). The other parameters are: Monthly rent (X) = \$955, discount rate (δ) = 0.95, probability tenant that the recovers after job loss (ψ) = 0.5, penalty rate on missed rent payment (ϕ) = 0.1, and eviction costs (C_E) = \$250.

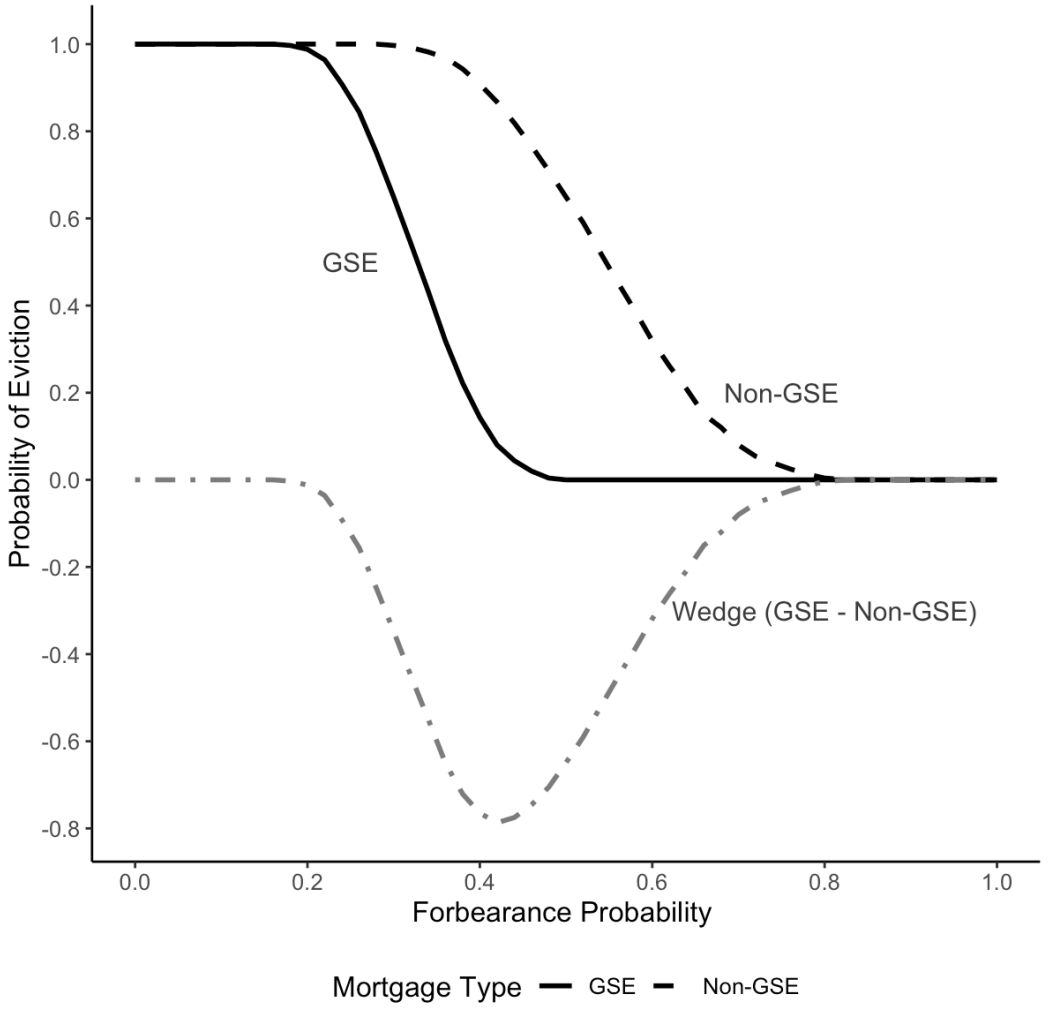


Figure 7. Treatment Timing Distribution

This figure displays the share of unique multifamily properties in the sample by treatment type. Never Treated are multifamily properties that did not have an agency loan outstanding during the post-treatment period (March 2020 - June 2024). Cohort 1 is multifamily properties with an outstanding agency loan in March 2020. Cohort 2 is multifamily properties that are not in Cohort 1 but obtained an agency loan between April 2020 and March 2021. Cohort 3 is multifamily properties that are not in Cohorts 1 or 2 but obtained an agency loan between April 2021 and March 2022. Cohort 4 is multifamily properties that are not in Cohorts 1 - 3 but obtained an agency loan between April 2022 and March 2023. Cohorts 2 - 4 properties became treated at the origination of their respective agency loan.

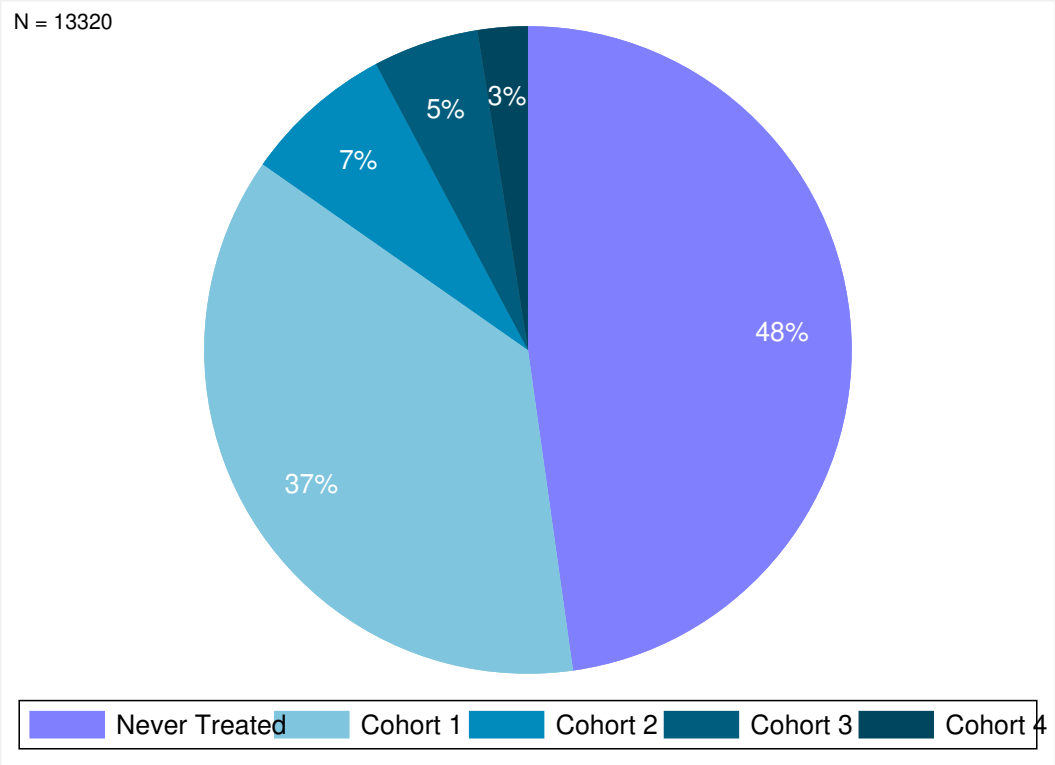


Figure 8. Effect of Agency Financing on Eviction Filings

This figure plots the event study estimates of the effect of financing choice on eviction filings reported in Columns (1) and (2) of Table IV. The baseline average treatment response (ATR) estimate pertains to the interaction term of $\mathbb{1}$Agency and $\mathbb{1}$Post in equation (16), while the individual ATR(l) estimates pertain to the interaction terms between $\mathbb{1}$Agency and the $\mathbb{1}D^l$ indicators in equation (18). The standard errors are clustered at the building level.

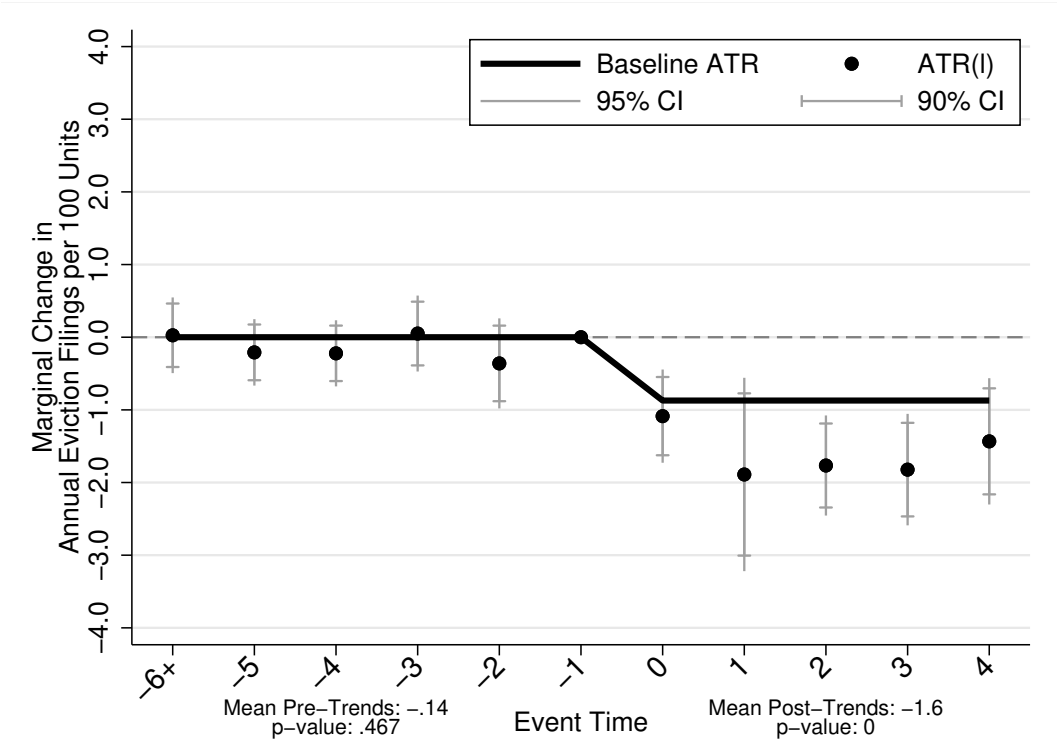
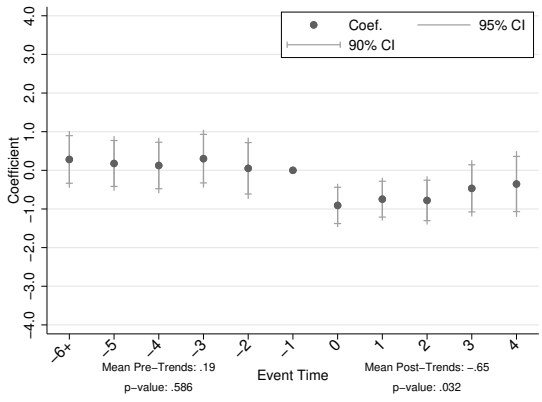
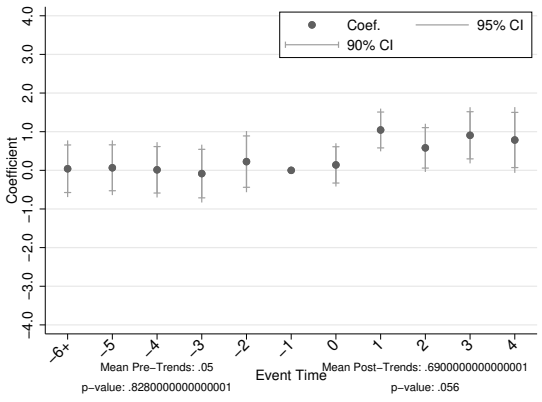


Figure 9. Staggard Treatment Effect of Agency Financing on Eviction Filings

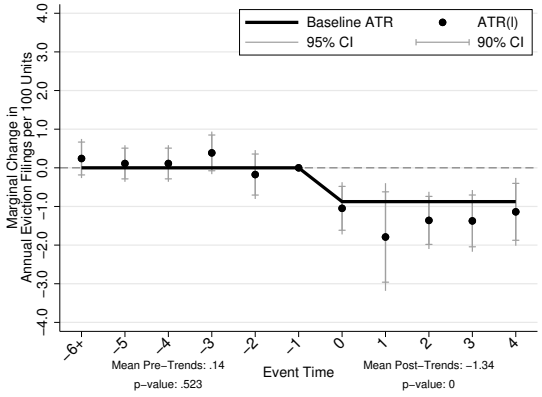
This figure plots the event study estimates of the effect of financing choice on eviction filings reported using the Sun and Abraham (2021) approach to account for potential bias from staggered treatment. Panel A reports the cohort weighted average estimates of the δ_1^l coefficients in equation (18), representing the effect of holding onto an agency on eviction filings following the CARES Act. Panel B reports the cohort weighted average estimates of the δ_2^l coefficients in equation (18), representing the effect of paying off an existing agency loan on eviction filings following the CARES Act. Panel C reports the average treatment response defined as the difference between the δ_1^l and δ_2^l coefficients (see equation (19)). The baseline average treatment response (ATR) estimate pertains to the interaction term of $\mathbb{1}$Agency and $\mathbb{1}$Post in equation (16). The standard errors are clustered at the building level.



(a) Treated Agency Loan Outstanding ($\hat{\delta}_1^l$)



(b) Treated Agency Loan Paidoff ($\hat{\delta}_2^l$)



(c) Average Treatment Response ($\hat{\delta}_1^l - \hat{\delta}_2^l$)

Appendix

Appendix A. Tables

Table A.1 Multifamily Properties by Treatment Cohort

This table reports the average value for various property and neighborhood characteristics for unique multifamily properties in the sample by cohort group. Neighborhood characteristics come from the 2020 American Community Survey 5-year estimates. Property characteristics come from the Trepp multifamily data.

Variable	Never Treated	Cohort 1	Cohort 2	Cohort 3	Cohort 4
Property Characteristics					
Total Matched Mortgages	1.37	2.37	2.00	1.73	1.74
Residential Units	152.38	161.65	155.99	118.53	125.30
Year Built	1974	1977	1975	1975	1978
Neighborhood Characteristics					
Population (Thousands)	4.27	4.26	4.24	4.23	3.89
Income ($Thousands)	71.70	73.34	68.51	70.46	70.66
Home Value ($Thousands)	220.86	229.77	211.89	210.14	200.29
Monthly Rent ($)	1056.53	1095.17	1042.82	1033.79	1022.76
Hispanic Share	0.24	0.25	0.27	0.27	0.22
Black Share	0.20	0.19	0.19	0.18	0.20
Asian Share	0.06	0.06	0.05	0.05	0.05
White Share	0.47	0.47	0.46	0.47	0.49
Other Race Share	0.04	0.04	0.04	0.04	0.04
Vacancy Rate	0.10	0.10	0.10	0.09	0.11
Tenant-to-Owner Ratio	5.67	7.89	5.22	4.52	3.85
N (unique buildings)	6,349	4,929	994	700	348
N (building-year-month)	952,350	739,350	149,100	105,000	52,200

Table A.2 Multifamily Mortgage Observations

This table reports summary statistics for multifamily mortgage observations from January 2010 to June 2024 (excluding 2019) at the building-year-month level. Observations for when there is no outstanding mortgage on the property are excluded. Treatment indicates that the property is the collateral of an agency multifamily loan sometime during the post-CARES Act period, whereas Never Treated indicates that the property is never used as collateral for an outstanding agency loan during the post-CARES Act period.

Variable	Never Treated	Treated	Difference	t-stat	$\|d\|$-stat
Loans	1.08	1.43	0.35	325.78	0.59
Loan Amount ($Millions)	12.92	22.73	9.81	86.63	0.17
Loan-to-Value	0.68	0.67	-0.01	-24.94	0.05
Debt Service Coverage Ratio	1.27	1.47	0.20	137.20	0.27
Contract Rate	0.06	0.05	-0.01	-506.66	0.87
Contract Rate Spread	0.03	0.02	-0.01	-273.26	0.51
Loan Age (Years)	4.78	3.84	-0.94	-175.55	0.33
Delinquency	0.05	0.02	-0.03	-91.25	0.17
Loan Type: Freddie Mac	0.04	0.53	0.49	661.09	1.07
Loan Type: Fannie Mae	0.06	0.19	0.13	215.52	0.40
Loan Type: Ginnie Mae	0.00	0.00	0.00	17.05	0.03
Loan Type: Conduit	0.90	0.29	-0.62	-837.11	1.25
N (building-year-month)	531,932	563,830			

Table A.3 Cross Sectional Tests by Treatment Cohort

This table displays cross-sectional OLS estimates of the financing choice effect on eviction filings at multifamily properties from January 2010 to June 2024 (excluding 2019) using different cohorts as the treatment group and never treated properties as the control group. The dependent variable is the annualized eviction filing rate per 100 rental units. 𝟙Agency is 1 when a Freddie Mac, Fannie Mae, or Ginnie Mae loan is outstanding and is 0 otherwise. 𝟙Post is 1 for months after the enactment of the CARES Act (i.e., March 2020) and 0 for prior months. LTV and DSCR are the property's most recent loan-to-value ratio and debt service coverage ratio, respectively. Delinquency is the share of outstanding loans 30 days or more past due. LTV, DSCR, and Delinquency are 0 when no loans are outstanding on the property. In parentheses, t-statistics based on standard errors within building clusters are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Outcome:	**Eviction Filing Rate per 100 Units**			
Treatment Group:	Treatment Cohort 1	Treatment Cohort 2	Treatment Cohort 3	Treatment Cohort 4
𝟙Agency	-0.074	-0.046	-0.080	-0.095
	(-0.467)	(-0.219)	(-0.362)	(-0.432)
𝟙Agency × 𝟙Post	-0.854***	-0.785**	-0.610	-0.497
	(-3.558)	(-2.045)	(-1.307)	(-0.840)
LTV	0.494	1.052*	0.910	0.579
	(1.159)	(1.744)	(1.548)	(0.982)
Delinquency	0.455	0.308	0.210	0.244
	(1.495)	(1.014)	(0.680)	(0.776)
Spread (%)	0.205***	0.319***	0.263***	0.234***
	(3.772)	(4.763)	(3.910)	(3.299)
Building FE	✓	✓	✓	✓
𝟙Loan × County × Year-Month FE	✓	✓	✓	✓
Observations	1,816,007	1,179,036	1,131,939	1,074,564
R^2	0.220	0.227	0.225	0.227

Table A.4 Agency Treatment Exit Analysis

This table displays OLS estimates of the relation between property or neighborhood characteristics and the likelihood of paying off an outstanding agency loan from March 2020 to June 2024. The sample consists of observations for multifamily properties with an outstanding agency loan in March 2020. The dependent variable is $\mathbb{1}$Agency, which is 1 when a Freddie Mac, Fannie Mae, or Ginnie Mae loan is outstanding and is 0 otherwise. Units is the number of rental units at the property. Minority Share is the share of Black and Hispanic households in the tract. Median Household Income is the median household income in the tract. Median Rent is the median rent in the tract. Tenant-to-Owner is the ratio of tenant-occupied households to owner-occupied households in the tract. All control variables are demeaned and normalized by the sample standard deviation. In parentheses, t-statistics based on standard errors within building clusters are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)
Outcome:	**$\mathbb{1}$Agency**
Units (z-score)	-0.023***
	(-5.605)
Minority Share (z-score)	0.021***
	(2.894)
Median Household Income (z-score)	0.017***
	(2.597)
Median Rent (z-score)	-0.007
	(-1.145)
Tenant-to-Owner Ratio (z-score)	-0.002
	(-0.829)
County F.E.	✓
Year-Month F.E.	✓
Observations	243,828
R^2	0.168