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Eviction Risk of Rental Housing: Does It Matter How Your Landlord Finances the Property?

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Eviction Risk of Rental Housing: Does It Matter How Your Landlord Finances the Property? *

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ABSTRACT

We show, using a stylized model, how the financing choice of landlords can impact eviction decisions in rental markets. Since multifamily loans rely on timely cash flows from tenants, strict underwriting factors can increase the chances that landlords are able to weather income shocks. Lender provided relief may create further leeway for landlords to work out a deal with tenants who default on rental payments. Using comprehensive data on nationwide evictions in the U.S. and performance records on multifamily mortgages, we confirm predictions from our model by documenting a negative relation between evictions and the financing activity by government-sponsored enterprises (GSE) that impose strict underwriting criteria but generally offer borrowers relief during unprecedented income shocks. We also quantify the eviction risks induced by the COVID-19 pandemic for 12 U.S. cities using our empirical model.

JEL Classification: G28, R30, I38.

Keywords: Evictions, Rental Housing, Multifamily Mortgages, GSE, COVID-19.

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I. Introduction

The COVID-19 pandemic created unprecedented financial difficulties for workers, families, and businesses. A recent study by the Federal Reserve Bank of Philadelphia shows that Americans could owe an estimated $7.2 billion in unpaid rent by December 2020 because of COVID-19-related job losses (Reed and Divringi, 2020). With the expiration of government income assistance and the eviction moratoria, many policymakers and housing activists have raised concerns about an eviction crisis.[1] According to Benfer et al. (2020*b*), an estimated 30 million to 40 million people in America could be at risk of eviction when federal, state, and local protections and assistance expire. Therefore, it is urgent for policymakers to understand the drivers of eviction as well as potential mechanisms for mitigating eviction risk. In this paper, we explore a new channel linking credit supply with eviction risk and highlight potential spillover effects of the credit market to the real economy.

Prior research examining causal mechanisms of evictions focus almost exclusively on factors in the rental market, e.g., those impacting individuals' ability to pay (Desmond and Gershenson, 2017), the legal systems allocating property rights between tenants and owners (Manheim, 1989; Roesch-Knapp, 2020), local policies designed to deter landlord actions (Bradford and Bradford, 2020; Coulson, Le and Shen, 2020), and regional differences in poverty and infrastructure (Kang, 2019).[2] While these are undoubtedly important causal factors, 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; Ambrose et al., 2019). For example, Ambrose et al. (2019) note

[1]For example, see Durana and Alexander (2020), Layser et al. (2020), Benfer et al. (2020*a*), and Furth (2020).

[2]For example, Kang (2019) notes that variation in automobile dependence is important in explaining regional differences in eviction rates.

that landlord decisions with respect to how the property is financed interact to determine lease rates and tenant risk. Thus, based on the insights from this literature, we expand the discussion of the causal mechanisms of residential evictions by introducing the idea that financing choices by property owners can impact tenant eviction risks.

Our analysis begins with two observations about the financing of rental properties. First, 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. Clearly, the debt service pressure or leeway granted by the lender in making the required mortgage payments could affect how the landlord deals with the tenants, e.g., how accommodating she could be to the tenants in granting payment holidays or eviction suspensions. Second, the U.S. has a bifurcated rental financing system involving private and government entities. For example, Fannie Mae and Freddie Mac (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.[3] The GSEs have various public policy mandates to provide credit to underserved areas and support various affordable housing initiatives. 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, are providing mortgage forbearance to millions of Americans.[4] Thus, an interesting question is to what extent does the GSEs' support to the multifamily housing sector filter through to help the tenants in those properties, particularly by mitigating renter eviction risk.

[3]Trepp data show that the share of GSE multifamily CMBS loans increased from about 25 percent pre-crisis to over 90 percent in recent years.

[4]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).

To crystallize our reasoning, we present a simple model that highlights how the choice of financing (via either the agency or non-agency lender) can factor into landlord decisions in dealing with tenants. Our model explicitly incorporates two choices on the part of the landlord – the decision to evict the tenant and the decision to default on the debt – in the face of an underlying shock to the tenant's ability to make the rental payment. The impact of the GSEs could arise through two channels. First, the GSEs, due to their implicit or explicit government guarantee, provide cheaper financing to mortgage borrowers. Meanwhile, they usually maintain higher underwriting standards, e.g., in terms of loan-to-value (LTV) ratio or debt service coverage ratio (DSCR) requirements than other lenders. Therefore, for two identical multifamily properties, the one with a GSE loan would have a smaller loan amount and a lower interest rate, resulting in significantly smaller debt service relative to a similar property financed with a non-agency mortgage. 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. Thus, in the case of a similar income shock to the borrowers/landlords, e.g., a loss of rental payment due to tenant financial difficulties, the non-agency borrower, who faces a higher debt service, will be more likely to encounter a loan payment shortfall. In order to avoid a costly default/delinquency, the non-agency borrower has to evict the troubled tenant and seek an immediate replacement of the rental income so that he can make the mortgage payment. On the contrary, the agency borrower has less incentive to evict the tenant to get immediate replacement of rental income, given his lower debt service. A workout with the tenant, e.g., through a rental payment deferral, could be a better choice. We refer to this as the debt service channel of GSE impact.

The second channel through which the GSEs can have an impact on tenant eviction is via loan workout strategies in response to borrower default. In case of a large shock to the rental market (e.g., a large share of renters cannot make their rental payment), both the agency borrower and the non-agency borrower would face a loan payment shortfall. For the agency borrower, given that the GSE lender is usually willing to bear a larger share of the default costs, the optimal strategy could be to cope with the troubled tenant through a rental payment deferral and enter into a loan modification. In fact, in the current environment, the GSE lenders are giving forbearance to their borrowers, which is equivalent to bearing all the default costs. In that case, the agency borrower can be better off defaulting (as default costs are low to him) and not evicting the troubled tenant. In contrast, non-agency loans are usually placed in conduit commercial mortgage-backed securities (CMBS), which have pooling and serving agreements (PSAs) that provide the loan servicers with less freedom in sharing default losses or giving out forbearance. Accordingly, non-agency borrowers may have to evict the tenant in an effort to avoid a costly default. In this second case, we can see that GSE lenders are more likely to provide loan accommodations to borrowers and that part of the benefits received by the borrower, who is also the landlord, are passed through to the tenants in the form of a grace period on their rental payment or a pause on eviction, for example. In other words, the landlord's choice of financing could result in spillover effects to multifamily tenants.

Our model leads to a number of hypotheses regarding how GSE funding affects eviction risk of rental housing. To test these hypotheses, we obtain eviction data from the Princeton Eviction Lab, which include 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. We combine the eviction data with data on multifamily loans obtained from Trepp. This data contain information on over 92,000 multifamily loans that were performing between 2000 and 2016. We aggregate our data to the county-month level in order to calculate annual eviction rates and shares of agency multifamily loans in each county. We note significant variations in both eviction rate and the share of agency loans in the cross section and the time series. In addition, Figure 1 shows a clear negative correlation between the average eviction rate and agency loan share over time from 2000 to 2016.

Using a panel data model with fixed effects, our baseline regression results confirm the role of GSE lending in mitigating eviction risk and suggest that changing the agency market share from the 10^{th} percentile to the 90^{th} percentile would lower the eviction rate by approximately 7.6 percent in a given market. Our analysis also shows a positive relation between eviction rate and debt service burden, as our model predicts. Finally, we find a positive relation between eviction rate and unemployment rate shock, consistent with our model prediction that eviction risk increases with the size of the rental income shock. To alleviate concerns of potential endogeneity, we run a number of alternative specifications including an instrumental variable regression. Results are robust with the expanded specifications, and become even stronger in the case of the instrumental variable regression.

Existing studies document the effects of local regulations on rental markets (Coulson, Le and Shen, 2020; Ambrose and Diop, 2020). Along those lines, our model predicts that default costs affect landlord eviction decisions when the rental income shock is large. In that regard, we find that, despite the fact that eviction rate increases with a larger unemployment shock, incentives to evict should weaken in judicial states where default costs are lower for borrowers. Our model also predicts that, in areas with both agency loans and non-agency loans, the difference in debt service burden between the two types of loans could affect eviction rate. Our empirical results also confirm that prediction. Finally, we find an interactive effect among the agency loan share, the judicial state indicator, and the high unemployment rate indicator on eviction rate, consistent with our model prediction that the effect of an unemployment shock on evictions is lower in markets in which the default cost to the landlord is low and agency multifamily lenders are active.

The COVID-19 pandemic exposed many U.S. households to eviction risk. Fortunately, with eviction moratorium, we do not see many evictions. Equipped with the estimated eviction model, we conduct a counterfactual analysis to quantify the amount of eviction risk in the absence of eviction moratoria. Such an analysis provides insights into the effects of eviction moratorium as well as what could happen when eviction moratorium expires and government income support diminishes. Our results suggest that there could have been more than 39,000 evictions in the second quarter of 2020 in 12 large cities tracked by the Princeton Eviction Lab if there were no government interventions or memorandums. Our results further show that these cities would have experienced about 20% more evictions without GSE financing.

Our study adds to four streams of the literature. First, we provide a novel insight into how financing and, in particular, how the GSEs can impact tenant outcomes. To the best of our knowledge, this is the first study to examine the role of financing in the evictions. Raymond et al. (2016) provide evidence of differences in eviction rates across institutional owners of residential property. Kang (2019) provides evidence that regional factors, such as poverty and automobile dependency, influence differences in eviction rates across cities. Our results complement findings of those papers and highlight how eviction rates vary with the sources of financing.

Second, we expand the growing literature looking at the causes and consequences of evictions (Desmond and Gershenson, 2017; Evans, 2020; Bradford and Bradford, 2020; Roesch-Knapp, 2020; Coulson, Le and Shen, 2020; Garboden and Rosen, 2019; Lundberg et al., 2020; Lee and Evans, 2020; Immergluck et al., 2020; Kang, 2019; Cooper and Paton, 2019). For example, 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.

Third, we provide a novel channel to evaluate the role of the GSEs in meeting their federal charters to support the housing market.[5] As federally chartered financial institutions, the GSEs are required to meet affordable-housing goals set by the Department of Housing and Urban Development (HUD) that are designed to promote the supply of housing to moderate- and lower-income households.[6] The GSEs meet these goals via a variety of programs, including backing mortgages for multifamily properties.[7] Although the impact of these goals 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 the GSEs' operations in the multifamily market. Thus, our study provides new insights into how financing of multifamily properties can affect the housing outcomes of tenants in these properties.

Finally, our paper provides insights into the current nationwide eviction crisis arising as a result of the COVID-19 pandemic (Wolf, 2020; Benfer et al., 2020*b*,*a*; Layser et al., 2020; Furth, 2020). Our model enables us to make predictions of the scale of evictions we would likely see during the pandemic in the absence of federal and local eviction moratorium. It

[5]See Frame and White (2005) for a discussion of the GSEs and the controversies surrounding their role in the U.S. housing finance system.

[6]See Ambrose and Thibodeau (2004) for a discussion of the creation of GSEs' affordable-housing goals and an early assessment of their effectiveness.

[7]The Federal Housing Finance Agency Affordable Housing and Community Investment webpage provides a description and discussion of the current GSE single-family and multifamily goals (`https://www.fhfa.gov/PolicyProgramsResearch/Programs/AffordableHousing/Pages/Fannie-Mae-and-Freddie-Mac-Housing-Goals-Performance.aspx`).

also enables us to quantify the difference in would-be evictions across cities due to different compositions of financing sources of multifamily properties.

The rest of the paper is organized as follows. We present a simple theoretical model in Section II. We explain our data in Section III and empirical results in Section IV. In Section V, we discuss our model implications to the eviction risks during the COVID-19 pandemic. Lastly, we provide our conclusions in Section VI.

II. Theoretical Framework

In this section, we construct a simple model to fix our ideas about how the financing channel and other factors may impact landlord propensity to pursue evictions. The model highlights two choices on the part of landlords: (1) the choice to evict a tenant and (2) the choice to default on the mortgage. Our model is a highly stylized representation of the multifamily rental market with a number of assumptions that remove inherent complexity while retaining the financial incentives associated with pursuing evictions. As such, many factors such as rental rates and interest rates are exogenous to the model.[8]

We begin by assuming that each tenant has an expected periodic income of W_t and enters into a two-period lease agreement with a landlord to secure one unit of housing at $t = 0$ with periodic rent payments of P_t due at $t = 1, 2$, where $P_t \leq W_t$.[9] To simplify the analysis and notation, we assume constant expected future income and rental payments ($W_1 = W_2; P_1 = P_2$). Furthermore, for the sake of simplicity, we assume tenants use all current period income to purchase housing ($P = W$) and the market discount rate is set to 0.

[8] While making such factors endogenous would move the model toward a general equilibrium setting, such complexity would not enhance the insights obtained from this simple representation.

[9] We can easily extend the two-period lease to more than two periods to gain the same insight.

Tenants face a random income shock λ at $t = 1$, where $0 \leq \lambda \leq 1$. In order to avoid strategic behavior by tenants, we assume that λ is beyond their control. In other words, they will always pay rent unless they are impacted by an exogenous event, such as an unemployment spell or medical crisis.[10] Thus, at $t = 1$, the landlord collects the minimum of the surviving wealth (λW) and rental payment (P) or Min[$\lambda W, P$]. Since λ is unknown at $t = 0$, the landlord cannot screen individual tenants for default risk. However, we assume that the overall average probability of an income shock across all prospective tenants (denoted as $\bar{\lambda}$) is known. Thus, the landlord's expected cash flow at $t = 1$ is $E_0[\bar{\lambda}P]$, where $E_0[]$ denotes $t = 0$ expectation. In addition, we note that the income shock occurs once at $t = 1$ and that income at $t = 2$ returns to W_2.[11]

At $t = 0$, the landlord also enters the credit market to secure a two-period mortgage with constant payments of l_i at $t = 1, 2$. Each period t loan payment is funded by period t rental income. We assume that mortgage payments are always made if rental income exceeds the contractual loan payment; on the contrary, mortgage payments cannot be made if rental income falls short of the contractual loan payment. Therefore at $t = 1$, the landlord's choice of whether to become delinquent on the loan (i.e., default) or make the required payment depends on the rental income, which is further determined by the level of tenant's income shock. If the landlord defaults at $t = 1$, then the payment plus default costs of Ψ are deferred to the next period. We also allow for lenders to share possible default losses, which may arise in the form of a loan modification or forbearance. Denote the portion of default losses shared by the lender as γ. Note, in this framework, default (delinquency) does not equal

[10] Desmond and Gershenson (2017) notes that job loss is one of the primary causal factors associated with evictions.

[11] We can allow income shocks in each period. It will provide the same insight with a more complicated representation.

foreclosure and there is a loan workout, which delays the payment one period.[12]

To focus on how the landlord's choice of financing can impact eviction, we note that property owners may select between two lenders ($i = A, C$), where lender A sells the mortgage to an agency, or government-sponsored enterprise (GSE), and lender C places the loan in a conduit commercial mortgage-backed security (CMBS). We assume that the GSE uses its affiliation with the federal government to provide funding at mortgage contract rates below conduit lenders (An, Deng and Gabriel, 2009).[13] As a result, $l_A < l_C \leq E_0[\bar{\lambda}P]$ at origination. Furthermore, the agency lender is required to meet various public policy mandates that conduit lenders do not. For example, policymakers often call on the GSEs to help financially constrained borrowers during periods of economics crisis by providing loan modifications or forbearance plans. We introduce this difference into the model by assuming that the agency loss sharing parameter is greater than the conduit lender, which we set to zero for convenience ($\gamma_A > \gamma_C = 0$).

In the event the tenant suffers an income shock of $\lambda < 1$, the landlord faces a shortfall in rent collection equal to $(1 - \lambda)P$. At this point, the landlord may evict the tenant by paying legal fees of F and leasing the unit to a new tenant who pays P.[14] In this case, total cash flows in the two periods $t = 1$ and $t = 2$ are $2P - F$. Alternatively, the landlord may allow the tenant to remain in the unit collecting a payment of λP at $t = 1$.[15] Then, at $t = 2$, the

[12] This reflects what usually happens in the real world in the commercial mortgage market.

[13] Also see Ambrose and Buttimer (2005) and Ambrose, LaCour-Little and Sanders (2004) for evidence and discussion of the rate spread advantage for single-family mortgages that meet the GSE conforming guidelines. In Section III below, we note that GSE multifamily loans in our sample have lower interest rate spreads and LTV ratios than conventional mortgages. This is consistent with evidence of the GSEs' effect on single-family mortgage terms (Kaufman, 2014).

[14] Note, since the income shock occurs after lease origination but prior to the first payment, all prospective period 1 replacement tenants have certain income. In order to highlight the eviction decision, we assume that landlords are not allowed to wait until after the income shock is realized to enter the market.

[15] In a survey of landlord strategies related to evictions, Garboden and Rosen (2019) find that eviction is costly to landlords and an outcome that is often avoided if possible.

landlord collects the recovery of the shortfall ($(1-\lambda)P$) along with a small penalty of δP and the period 2 payment P.[16] Thus, the $t = 2$ cash flow if the landlord does not evict is $[(1-\lambda+\delta)P + P]$.[17]

Table I describes the landlord cash flow positions reflecting the combination of lender and eviction/default decision under differing levels of income shock. In the simple case where $\lambda = 1$, which is not shown, the tenant suffers no income shock and makes the required lease payment. Thus, eviction does not occur and the landlord does not default. In contrast, cases 1 through 3 correspond to three possible income shocks (small, medium, and large) that reflect the various possible combinations of λP relative to period 1 loan payments, l_A and l_C. For each lender, the table describes the payoffs associated with the four possible outcomes: (a) Evict/No Default; (b) Evict/Default; (c) No Evict/No Default; and (d) No Evict/Default. However, if $\lambda P < l_i$ (Case 3), then outcome (c) No Evict/No Default is not an option since the period 1 rental income is insufficient to avoid delinquency.

Turning first to the evaluation of the outcomes for the agency and conduit loans under a small income shock (Case 1: $l_A < l_C < \lambda P$), we note that combination (c) is the dominate strategy and the landlord will not pursue eviction under either financing option (since $\delta P > -F$).

Next, we turn to Case 2 denoting a medium tenant income shock in markets characterized as having a large difference in agency and conduit financing costs such that $l_A < \lambda P < l_C$. Looking at the payoffs under the conduit financing option first, we note that combination (a) dominates (b) by avoiding the loss associated with default costs (Ψ). Next, setting (a)

[16]Setting δ equal 0 will not change our model results.

[17]Note, since we assumed that tenant income equals the required rental payments, our characterization of the eviction/no eviction decision requires an implicit assumption that the tenant has access to outside savings or endowment at $t = 2$ to cover the additional period 2 payment of $(1-\lambda+\delta)P$. Desmond (2016) notes that many low-income individuals facing eviction often turn to family or friends for help in making rent payments.

equal to (d), we see that combination (a) dominates as long as $F < \Psi - \delta P$. This is a reasonable assumption since default costs, including legal fees and the stigma effects, are usually very high and δP is relatively small. Furthermore, the costs of tenant eviction are usually lower than mortgage default costs in most jurisdictions. Therefore, tenant eviction is the most likely outcome when the landlord borrows from a conduit lender. In contrast, for the agency loan financing we note that (a) clearly dominates (b) and (c) dominates (d) as long as $\Psi > \gamma_A$, which is a reasonable assumption. Thus, comparing (a) and (c), we note that the no eviction / no default strategy always dominates since $\delta P > -F$. Thus, in Case 2 when there is a moderate income shock, the eviction rate will be lower as the proportion of landlords who select financing from the agency lender increases.

Finally, to complete the analysis, we examine Case 3, which reflects a large tenant income shock such that $\lambda P < l_A < l_C$. Under this scenario, the payoff positions for the conduit loan are unchanged and (a) (Evict / No Default) remains the dominate strategy. For the agency loan option, we now see that (c) is no longer available and (a) becomes the dominate strategy as long as $F < \Psi - \gamma_A - \delta P$. Thus, in the presence of a large income shock and significant default costs (large Ψ and small γ_A) to the borrower, tenant eviction is optimal regardless of financing choice. However, note that agency lenders could offer substantial loss sharing (γ_A), making the costs associated with default ($\Psi - \gamma_A$) relatively small. In fact, under the CARES Act, the GSE lenders are providing forbearance to borrowers of agency loans during the current pandemic, which essentially reduces default costs to almost zero. Thus, when default costs are low, (d) (No Evict /Default) is the dominant strategy for the landlord with an agency loan.

To summarize, the simple theoretical outline provides a number of testable predictions regarding how income shocks, landlord's debt service, landlord's choice of debt type (lender type), and variations in default costs may impact evictions. First, the eviction rate largely depends on the magnitude of the income shock. As we see in Table I, in the case of small income shocks, the landlord has no incentive to evict the tenant. As the shock gets larger (Cases 2 and 3), there are more scenarios under which eviction will be optimal for the landlord, holding the agency and non-agency loan mix constant.

Second, we note that the debt-service burden (the difference between l_i and λP) has a material impact on the landlord's eviction choice. When the debt service burden is small (λP is significantly greater than l_i), the odds are greater that a given income shock will have a small effect, and thus, the possibility of an eviction is small. In other words, holding the income shock and everything else constant, the smaller the debt service burden (or the greater the debt service coverage ratio), the less likely that eviction will be optimal.

Third, the theoretical framework predicts a potential divergence in the landlord's decision to evict based on the choice of financing (agency versus conduit (non-agency) loan). For example, in Case 2, agency borrowers are better off not evicting while non-agency borrowers find eviction optimal. Therefore, eviction rate will decrease as the share of agency loans increases. The same applies in Case 3 when default costs are high. Certainly, in Case 1 and in the low default costs scenario of Case 3, there is no such divergence. However, we can conclude that, on average, a higher share of agency loans is associated with a lower likelihood of eviction, everything else equal.

Fourth, we notice that the wedge between agency loan debt service burden and non-agency debt service burden, $l_C - l_A$, could matter. Assuming that $l_A < l_C < E[\bar{\lambda}P]$ at loan origination, then the odds increase for a given income shock to result in Case 2 versus Cases 1 or 3 as the debt service coverage wedge widens. Case 2 demonstrates the contrast in eviction choice between agency and non-agency borrowers, leading to the prediction that the likelihood of eviction will decrease as the agency loan share increases. We therefore note a potential interactive effect between agency loan share and the debt service coverage wedge on eviction rates – the eviction rate difference between agency and non-agency loans is more prominent when the debt service coverage wedge is larger.

Another interesting prediction highlighted in Table I is that default costs impact eviction choice, but only in Case 3, i.e., when the income shock is large. From another perspective, despite the fact that eviction rate increases with a larger rental income shock, incentives to evict should weaken when default costs are low as the agency loan borrower would find default and no eviction to be a better choice. Therefore, we expect an interactive effect on eviction rates from default cost heterogeneity and the magnitude of the income shock. By the same token, heterogeneity in default costs across markets can compound differences across markets in agency loan share to affect eviction rates. Thus, the theory suggests the potential for interactive effects from default cost heterogeneity and the agency loan share.

Finally, conditioning on both large income shocks and high borrower default costs (as in Case 3), we see that the eviction rate is inversely related to the share of agency loans, as Case 3 shows. This suggests an interactive effect on eviction rate of the magnitude of the shock, default cost heterogeneity, and agency loan share.

As we can see, within this simple theoretical framework, we are able to incorporate a number of eviction risk factors ranging from income shocks, to debt types as well as the terms of the debt (e.g., debt service burden), to derive a rich set of predictions between eviction rates and those risk factors. Furthermore, we note that some of those factors can have compound effects.

III. Data

We use data on multifamily loans from the Trepp database and retain a sample of more than 92,000 securitized multifamily loans that were performing between 2000 and 2016. Trepp provides detailed information on underwriting factors and mortgage characteristics, which come from pooling and servicing agreements (PSA). Trepp also provides information from periodic performance reports crafted by mortgage servicers or trustees. Table A.1 in the online Appendix reports summary statistics for the sample of multifamily loans, describing underwriting factors, mortgage terms, collateral characteristics, and CMBS attributes at the time of securitization by deal type. The sample consists of 27,488 non-agency loans and 65,473 agency loans that were originated throughout 1,399 U.S. counties. Out of all the agency loans in our sample, 30% are in Freddie Mac CMBSs, 20% are in Fannie Mae CMBSs, and 40% are in Ginnie Mae CMBSs.

We aggregate the multifamily loan performance records to the month-county-level and merge them with year-county eviction data from the Princeton Eviction Lab. The eviction data include more than 80 million records on evictions and eviction filings, which were collected from court records, state provided reports on landlord-tenant cases, and legacy datasets of public eviction records.[18]

Table II reports summary statistics at the month-county-level for the merged sample by agency loan share bucket (0-20%, 20%-40%, 40%-60%, 60%-80%, and 80%-100%), excluding observations with missing fields. The final sample covers 1,111 U.S. counties (80% of the counties available in the Trepp data). The average eviction rate measured as the annual number of evictions per 100 renter-occupied housing units in the county is 2.98, which is similar to the mean eviction rate reported by Kroeger and Mattina (2020). In other words,

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

about 3 out of every 100 renters are evicted, on average. We also see in Table II that the eviction rate decreases with the agency share. As the agency share increases from the bottom to top bucket, the average eviction rate decreases from 2.91 to 2.51, representing a decline of about 13.7%. A similar pattern is evident with the eviction filing rate, which is similarly measured as the number of eviction filings per 100 renter-occupied housing units. Figure 1 overlays the agency share with the eviction rate and filing rate for the U.S. annually from 2000 to 2016. The figure shows that the eviction filing rate and the eviction rate are concave, whereas the agency share is convex.

Figure 2 illustrates the variation in our sample in the county-level eviction rate and agency share across the United States in 2005, 2010, and 2015. A dark shade of red indicates that the county features a high eviction rate or large agency share of multifamily loans. We see that over time the intensity of evictions decrease while the dominance of agency financing increases, particularly in large states such as California, Texas, New York, Illinois, and Florida.

We observe a correlation between the agency share and weighted-average debt service coverage ratio (WA-DSCR), too. We weigh within every month-county panel the non-missing DSCR for each loan in our sample using the loan size.[19] The average DSCR increases from 1.12 to 1.26, as the average share of multifamily loans in agency CMBS increases from 4 percent to 91 percent. We do not observe differences in the weighted-average loan-to-value, which is constant at about 68 percent. Demographic variables reported in Table II, i.e., the poverty rate, renter-occupied percent, Hispanic percent, African American percent, and Asian percent, do not show any obvious correlations with agency share.

[19] We winsorize the DSCR at the 1 percent level and measured it excluding only loans with missing DSCR 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.

To examine differences among the underlying loans between agency and non-agency deals, for every non-agency loan, we find an agency loan securitized during the same time with collateral of similar age, occupancy, size, renovation status, and location.[20] The matching process allows us to factor out differences in the underlying collateral risk. We then compare the loan characteristics by deal type. Table A.2 reports for several characteristics the mean value and mean difference across deal type along with the corresponding t-statistic to gauge statistical significance and Cohen's d-statistic to gauge economic significance. We see that once accounting for the underlying risk of collateral, the average agency loan features stricter underwriting criteria than the average non-agency loan in terms – the average agency loan has a higher DSCR and lower LTV than the average non-agency loan. The contract rate is also smaller for agency loans than non-agency loans, on average. The mean differences of these variables (DSCR, LTV, and contract rate) across deal type are statistically or economically meaningful. These findings are consistent with what we discuss in Section II about the differences between agency and non-agency loans.

IV. Empirical Analysis

A. *Model Specification*

We employ a panel data model with fixed effects to identify the relation between evictions and the credit market. The county-level, cross-sectional variation overtime in evictions shown

[20]Specifically, for every non-agency loan, we find a comparable loan using a standard propensity scores matching approach. Propensity scores are estimated using a Probit regression at the loan level. The dependent variable is an indicator for whether the loan is in an agency loan. The independent variables include the collateral's (or building's) age, a flag for whether the collateral includes multiple buildings, the occupancy rate, the log number of rental units, an indicator for whether the collateral was recently renovated, and year-month securitization date dummies. We then force matching at the ZIP code level with a caliper of 0.01. We allow repeated sampling, which results in non-agency loans matched to more than one agency loan.

in Figure A.1 allows us to construct a fixed effects model that accommodates a continuous treatment variable, which in our case is the share of loans in a county that are in an agency CMBS deal. Specifically, we estimate the following model:

$$Y_{it} = \alpha + \beta_1 A_{it} + \beta_2 D_{it} + \beta_3 U_{it} + \gamma X_{it} + \tau_t + \zeta_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} stands for the eviction rate in county i at time t, A_{it} is the share of agency loans in county i in period t; D_{it} is the orthogonalized weighted-average debt coverage ratio ($DSCR$) in county i in period t; [21] U_{it} represents the standardized unemployment rate shock, which serves as a proxy for the income shock; X_{it} is a matrix of county-level control variables, both time-varying and time-invariant; and ε_{it} stands for the error term. The coefficient β_1 is the treatment effect of agency share on evictions. The DSCR is the opposite of debt service burden, and thus, the coefficient β_2 provides for a test of the hypothesis that the eviction rate is negatively (positively) related to debt-service coverage (debt-service burden). The coefficient β_3 provides for a test of the predictions concerning the relation between eviction rates and tenant income shocks. The county-level control variables include the log median household income, the log population, the poverty rate, the percent of renter-occupied homes, and demographic variables reflecting the percent Hispanic, Black, and Asian residing in the county. We cluster the standard errors by county to mitigate concerns that the panel setup introduces serial correlation that affects statistical inference of the independent variable of interest (see Bertrand, Duflo and Mullainathan (2004)).

We remove unobserved confounding factors from cross-sectional and common time series differences by including fixed effects for the year-month time (τ_t) and county location (ζ_i)

[21] The orthogonalize weighted-average debt coverage ratios are the residuals from the regression of the county average DSCR on the county-level agency loan share.

in our model. Therefore, our identification strategy relies on within-county mean differences that differ from nationwide time trends in both the eviction rate and agency share. The key identifying assumption of equation (1) is that ε_{it} does not contain any factors that simultaneously affect both the eviction rate and agency share. This is a reasonable assumption because the framework of equation (1) factors out constant cross-sectional differences that affect both the eviction risk and agency share, and nationwide common time trends that could also influence both the eviction risk and agency share. Later in the paper, we will discuss how we further address this endogeneity concern.

B. Baseline Results

Table III reports the coefficient estimates of equation (1) using the county-level monthly panel from January 2001 to December 2016. Columns (1)-(3) test separately the predictions concerning the relationship between market eviction rates and the share of GSE loans (Agency), debt levels relative to income (DSCR), and the size of tenant income shocks (as captured through changes in the unemployment rate). Each regression includes the full set of county control variables and fixed effects. The unemployment rate shock is measured at the year-county-level as the difference between the current unemployment rate and the average unemployment rate during the past five years. To simplify interpretation, we standardize the unemployment shock using the average and variation in the cross-sectional unemployment shock measure observed in the same year.

Turning first to the effect of GSE credit on evictions, we see in column (1) that the estimated coefficient of -0.255 is statistically significant at the 1% level. This is a large effect as Table II shows that the average eviction rate is 2.98 percent. The coefficient implies that if the agency share in a given market changed from the 10^{th} percentile to the 90^{th} percentile, then the eviction rate would decrease by 7.6 percent.[22] Framed differently, increasing the agency share by one standard deviation (or 32 basis points) decreases the eviction rate by about 2.78% (=0.32×0.255/2.93).

In column (2), the negative and statistically significant (at the 1% level) coefficient of the DSCR is consistent with the theoretical predictions that eviction rates will decline as borrowers have greater excess cash flow to withstand income shocks. The negative coefficient is consistent with our theoretical prediction that areas with mortgages having higher underwriting standards (higher DSCR) will have lower eviction rates. The estimated coefficient of -0.127 implies that moving the DSCR in a given market from the 10^{th} percentile to the 90^{th} percentile results in about a 4% decrease in the average eviction rate.[23]

In column (3), we introduce the standardize unemployment rate shock as a measure of economic shock or uncertainty. The estimated coefficient is positive and statistically significant at the 10% level indicating that evictions are approximately 1.5% (= 0.045/2.98) higher in areas experiencing a one standard deviation increase in the unemployment rate shock (a negative income shock). This is consistent with the predictions that evictions should become the dominate strategy for both agency and conduit lenders as the income shock increases.

We also note that the effects of agency share, DSCR, unemployment shock are robust to the joint inclusion of the three variables (column 4). The negative and statistically significant (at the 1% level) coefficient for agency share continues to indicate that evictions are lower in markets with a greater percentage of agency multifamily loans financing rental units, even after controlling for the DSCR and presence of an income shock.

[22] 0.076=(.89x0.255)/2.98
[23] -0.04=(-0.127x0.95)/2.98

C. *Endogeneity concerns*

A concern with our specification in equation (1) is that the county eviction rate could be endogenous to the percentage of multifamily loans backed by the GSEs. This endoegenous relation could arise if the GSEs engage in risk-based pricing such that only landlords in lower risk areas select mortgages backed by the GSEs. This could lead to a spurious correlation between the eviction rate and GSE multifamily market share. As a result, the endogeneity concern arises through the cross sectional nature of our empirical analysis – the GSEs potentially selecting less risky areas to lend.[24] Unfortunately, as with most empirical research in economics, it is difficult to completely eliminate the possibility of an endogenous relation. However, we present a series of econometric methods and specifications that, on the whole, demonstrate a preponderance of evidence consistent with a causal link between GSE multifamily lending and rental eviction risk.

First, we note that our estimation of equation (1) includes a variety of control variables designed to capture differences in local economic risk, and the estimated coefficient for agency share is robust to the introduction of these variables.[25] Since the endogeneity issue arises mostly from the cross section, our use of county fixed effects should eliminate much of this concern. We also show that the estimation results are robust to a variety of model specifications as demonstrated in columns (1) through (4) of Table III. Thus, we take comfort in the robustness of the estimate of β_1.

Second, we account for potential endogeneity between agency share and eviction rate by lagging agency share, DSCR, and unemployment shock under the assumption that the

[24]To the extent that endogeneity arises in the time series, it would mostly arise from possible large refinancing waves. However, we note that 87% of the multifamily loans have yield maintenance penalties or prepayment lockout provisions, which significantly curtail the ability or incentive to refinance.

[25]We report the estimation results introducing various control variables in Table A.3 in the Appendix and note that the estimated coefficients are robust to various specifications.

error terms are not correlated over time. We report results of this exercise in Table A.3 column (5) in the Appendix. Again, we find that the estimated coefficients are robust to this specification.

Third, we expand the empirical specification to include the securitized multifamily delinquency rate, and the lagged 1-year eviction rate. Since eviction filings occur prior to actual evictions, the lagged eviction filing rate is a strong proxy for the within-county eviction risk that changes over time. The mortgage delinquency rate also varies over time and across space and thus captures changes in the underlying market conditions and risks. We report the results from the expanded regression estimation in Table III column (5). The lagged eviction filing rate is positive, and statistically significant at the 1% level, indicating persistence in eviction rates over time.[26] However, we note that the delinquency rate is positive but not statistically significant. Thus, it does not appear that eviction rates are directly associated with mortgage delinquencies but rather are correlated with the underlying causes that could trigger delinquencies such as an unemployment shock. This is an interesting result as it confirms our model predictions in Table I showing that eviction is not always associated with loan distress. Nonetheless, after controlling for these measures of underlying area economic risk, we note that the estimated coefficients for our variables of interest (agency loan share, DSCR, and unemployment shock) remain economically and statistically significant at conventional levels and suggest qualitatively the same effect as the baseline results.

Our final method of controlling for the potential endogenous relation between the eviction rate and GSE market share is to employ a two-stage instrumental variable (IV) approach. The IV method requires identifying valid instruments that capture the growth in agency share but are uncorrelated with current eviction risk. To do so, we follow standard practice

[26] We note that the number of observations in column (5) declines due to missing eviction data in some counties in 2000.

in the literature to use the lagged explanatory variable as an instrument. We also instrument the agency market share on the differences in the relative costs of GSE-backed multifamily mortgages and loans destined for conduit CMBS deals (the spread gap).[27] We expect that the agency share is time dependent, and that an increase in the spread gap increases the incentive borrowers face to seek agency financing. Thus, in the first stage, we predict each county's agency share using the one-year lagged agency share for that same county and the difference in funding costs as instruments. In the second stage, we then use the predicted agency share in our baseline model as the independent variable of interest. Since evictions are often a result of current economic factors and arise quickly with non-payment of rent (unlike mortgage foreclosures that often take 12 months or more following borrower default), the lagged agency share meets the exclusion restriction under the plausible assumption that the agency share from the prior year does not directly affect the eviction risk in the subsequent years. Furthermore, although local risks that might cause evictions may impact the overall cost of debt, these risks would impact both agency and non-agency loans alike. Thus, the lagged spread gap should not reflect current eviction risk. However, we acknowledge that identifying a pure causal instrument is virtually impossible. As a result, we offer the discussion of the IV estimation as a supporting robustness check and leave it to the reader's discretion to whether the IV estimation aligns with the preponderance of the evidence.

In the first stage regression (reported in Table A.4 in the Appendix), the coefficients on the lagged agency share and spread gap are positive and statistically significant at the 1% level, providing evidence of the relevance criteria. Both instruments affect the agency share positively at a statistically significant level, indicating that the instruments are relevant.[28]

[27]We construct the spread gap every month for each state as the weighted-average spread on the contract rate of conduit loans less the weighted-average spread on the contract rate of agency loans.

[28]Table A.4 in the online Appendix reports the first stage results.

In the second stage regression (reported in Table III, column 6), the estimated coefficient for the agency share is statistically significant at the 1% level and is even larger in magnitude than previously estimated, suggesting that moving the agency market share from the 10^{th} percentile to the 90^{th} percentile would lower the average eviction rate by 15.3%.[29] In addition, we also note that the estimated coefficients for the control variables are consistent with prior specifications, giving confidence that the specification is stable.

To summarize, we provide a number of alternative strategies and econometric methods to address the potential endogenous relation between GSE market share and eviction risks. Although we acknowledge that each is less than perfect, we take comfort in the preponderance of the evidence across these methods that is consistent with our primary specification.

D. Market segmentation

We are cognizant of the potential effects of market segmentation in the multifamily rental market on our model estimates. In particular, we note that the Princeton Eviction Lab data represent a census of eviction filings across all rental properties (single-family rentals, small multifamily properties, and larger multifamily properties), whereas our data on multifamily mortgages mainly cover larger properties. As a result, the estimated coefficient of our focus variable captures a weighted average effect of the impact of agency loan share on the larger properties covered by our multifamily mortgage data and that of agency loan share on smaller properties. In cases in which single-family rentals or smaller multifamily properties do not rely on debt financing from the CMBS market, there will be less variation in eviction rates due to financing differences. Therefore, our estimated coefficient on agency market share has a downward bias (toward zero).

[29] ($.153 = 0.89 \times .514/2.98$)

This certainly creates a challenge on how we interpret our results. However, on the other hand, it provides an opportunity for us to conduct some causal inference because, if what we identify in the prior regressions is really the effect of agency financing on eviction rate, we would expect the effect to be weaker in markets that have a larger share of smaller rental properties.

We thus segment the data into quintiles based on Trepp coverage of the market.[30] Markets with high Trepp coverage represent areas with relatively few smaller rental properties, whereas markets in the bottom quintile are dominated by smaller rental properties that are not financed by mortgages contained in the Trepp data. In column (7) of Table III, we report the estimated coefficients for the specification that includes the indicator variables for markets in which Trepp is in the bottom and top quintile. We interact these indicator variables with agency share. We notice that the estimated coefficient of the bottom quintile is smaller than the top quintile. Meanwhile, we note that the estimated coefficient for the interaction of agency share with the top coverage indicator variable is negative and statistically significant. The negative coefficient confirms the theoretical predictions that GSE lending activity has a negative impact on eviction rates and that the effect is stronger in markets in which there are more larger multifamily properties.

Therefore, the results in Table III clearly confirm the primary prediction of an inverse relation between agency loan market share and eviction rates that is derived from the theoretical arguments outlined in Section II. Moreover, the additional tests provide us comfort that the relation is not spurious.

[30] We define Trepp coverage by dividing the sum of rental units in properties collateralizing mortgages reported in Trepp by the total number of rental units in the market. The coverage at the bottom quintile is less than 1% while the coverage at the top quintile is about 13.5%.

E. Falsification test

We further conduct a falsification test to confirm that our finding of a negative relation between agency mortgage share and eviction is not spurious. We preform two versions of this test. First, we randomly assign each county an agency market share based on a normal distribution truncated between 0 and 1 with the same mean and standard deviation as the full sample agency share. Second, we randomly assign an agency share to each county based on a normal distribution using the actual December 2016 agency share mean and standard deviation, again truncated between zero and 1. We then apply a constant monthly time trend to deflate the assigned agency shares back to the starting period. Table A.5 in the Appendix reports the results replicating the specification in Table III, column (4) with these randomly assigned agency shares. As expected, the estimated coefficients are not statistically significant, confirming the validity of the observed negative effect in Table III. Thus, the falsification tests support our contention that the results reported earlier are not spurious.

F. Relative debt-service burden, income shocks, and default costs

The negative and statistically significant coefficients for DSCR in Table III indicate that evictions are inversely linked to the ability of landlords to withstand income shocks relative to loan payments, as predicted. In Table IV, we expand on this finding to explore how evictions respond to changes in the landlord's debt-service coverage position via agency or conduit loans as well as to specific regional income shocks. To do so, we create a new variable, *DSCR Wedge*, that measures the difference in average agency and conduit orthogonalized DSCR in each county.[31] Thus, *DSCR Wedge* measures the relative difference in risk exposures landlords have to economic shocks, i.e., $l_C - l_A$ in Table I. A large wedge indicates a greater difference in risk exposure. Column (1) replicates the specification of column (4) in Table III with the addition of *DSCR Wedge* and interaction of *DSCR Wedge* with the *Agency Share* variable. We note that the wedge is positive and statistically significant (at the 10% level) indicating that eviction rates increase when the difference in DSCR ratios increases. Since a larger DSCR wedge more likely corresponds to Case 2 described in Table I, the positive coefficient for *DSCR Wedge* is consistent with the theory prediction that the eviction rate will be higher in Case 2 than in Case 1 for a given income shock. More importantly, we note that the coefficient for the agency share and DSCR wedge interaction is negative and statistically significant. This is exactly the interactive effect predicted by our model – the share of agency loans matters more when we are in Case 2 (than in Case 1 or 3).

The predictions outlined in Table I vary based on the magnitude of the income shock and the costs associated with mortgage default. Thus, in columns (2) and (3) of Table IV we further explore the predictions outlined by Case 3 in Table I in relation to large or small economic shocks and variation in default costs. To do so, we classify each market based on whether it is in a state that requires a judicial foreclosure proceeding or a non-judicial process.[32] In general, judicial foreclosure is a more costly process for lenders to resolve default and requires more time to foreclose. As a result, judicial foreclosure states are often referred to as "borrower friendly" in that they provide greater protections to borrowers and thus make default less costly for borrowers. In contrast, a non-judicial foreclosure state

[31] We construct the DSCR Wedge at the county-level as the difference in the weighted average DSCR for agency loans minus the weighted average DSCR for non-agency loans. The WA-DSCR for either agency or non-agency loans are set to zero in counties where there are no agency or no non-agency loans.

[32] We consider loans with collateral in the District of Columbia and following states to be judicial: DE, FL, HI, IA, IL, IN, KS, KY, NJ, LA, ME, ND, NM, NY, OH, OK, PA, SC, VT, and WI.

allows the lender to foreclose on a defaulted mortgage without seeking a judge's approval. As a result, the costs of foreclosure are lower to the lender and these states are viewed as less borrower friendly. Thus, in the context of our predictions, judicial foreclosure states have lower default costs to the borrower.

In column (2), we introduce the interaction of the unemployment shock with an indicator for judicial states. The interaction of unemployment rate with judicial is negative and statistically significant at the 1% level. This finding is commensurate with the predictions that, despite the fact that eviction rate increases with a larger unemployment shock, incentives to evict should weaken for both agency and conduit borrowers as the cost to default lessens, and in turn the borrower/landlord has the option to default to withstand the greater tenant income shocks.

In column (3), we further interact judicial with the agency share and unemployment shock in a triple interaction style and include a set of two-way interactions among the variables in order to further test the predictions in Case 3 of Table I regarding the interaction of default costs, income shocks, and financing choice. We see that the coefficient on the triple interaction of agency share, judicial foreclosure, and unemployment shock is negative and statistically significant (at the 5% level). The results confirm that the effect of an unemployment shock on evictions is lower in markets in which the default cost to the landlord is low and agency multifamily lenders are active. These results reinforce the role of financing choice in lowering the impact of negative income shocks on the eviction rate when the default cost to the landlord decreases. This is consistent with the predictions in Case 3 in Table I that when default costs are low, the eviction rate will be inversely related to the agency loan share.

V. Discussion on Eviction Risks During the COVID-19 Pandemic

In early March 2020, many U.S. state governors declared state of emergencies and issued "stay-at-home" orders that required non-essential businesses to reduce operations or close down, along with recommending that individuals minimize non-essential travel. These shutdown orders and travel restrictions created consumption shocks that significantly impacted businesses and the employees of those businesses reliant on face-to-face interactions (see Alexander and Karger, 2020; Chetty et al., 2020). In response to the economic distress caused by the coronavirus pandemic and concurrent government mandated mitigation efforts, the federal government quickly passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act to help households and businesses. Among the policy interventions, the CARES Act included a four-month eviction memorandum that temporarily blocked residential evictions until July 2020. The Centers for Disease Control and Prevention later extended the eviction moratorium to the end of December 2020.[33] Moreover, some state and local governments imposed additional restrictions on evictions. For example, the State of New York issued a memorandum that immediately halted eviction proceedings and pending eviction orders, and declared that hearings on landlord lockouts, serious housing code violations, and related housing disputes are essential functions of the state courts.[34]

To understand the potential impact of the COVID-19 pandemic on tenant eviction risk, we predict the eviction rates for 12 cities covered by the Princeton Eviction Lab's current

[33] For further details, see `https://www.federalregister.gov/documents/2020/09/04/2020-19654/temporary-halt-in-residential-evictions-to-prevent-the-further-spread-of-covid-19`.

[34] Details are available at `https://d3n8a8pro7vhmx.cloudfront.net/righttocounselnyc/pages/23/attachments/original/1584479372/Updated_Protocol.pdf.pdf?1584479372`.

data on weekly eviction filings from December 2019 to June 2020.[35] Using the eviction rate model coefficients (β_1 through β_3 from column 4 of Table III) with current monthly data on unemployment rates (U_{it}), DSCR (D_{it}), and agency loan market shares (A_{it}) through June 2020, we estimate the expected monthly eviction rate for each city as:

$$\widehat{ER_{it}} = \overline{ER_i} \times (1 + \beta_1(A_{it} - A_{i0}) + \beta_2(D_{it} - D_{i0}) + \beta_3(U_{it} - U_{i0})), \tag{2}$$

where the $\overline{ER_i}$ is the unconditional expected monthly eviction rate based on the eviction filings in 2020Q1 and the historical filings-to-evictions conversion rate for city i;[36] and A_{i0}, D_{i0} and U_{i0} are the agency share, DSCR, and unemployment rate, respectively, observed in December 2019 for city i. Thus, the predicted month t eviction rate reflects the evolution in each city's updated change in the GSE market share, DSCR, and unemployment rate. We also predict the monthly eviction rate assuming only agency financing ($\widehat{ER^A_{it}}$) and non-agency financing ($\widehat{ER^C_{it}}$) as:

$$\widehat{ER^A_{it}} = \overline{ER_i} \times (1 + \beta_1(1 - A_{it}) + \beta_2(D_{it} - D_{i0}) + \beta_3(U_{it} - U_{i0})) \tag{3}$$

$$\widehat{ER^C_{it}} = \overline{ER_i} \times (1 - \beta_1(A_{it}) + \beta_2(D_{it} - D_{i0}) + \beta_3(U_{it} - U_{i0})). \tag{4}$$

Figure 3 plots the predicted eviction rates ($\widehat{ER_{it}}$, $\widehat{ER^A_{it}}$, and $\widehat{ER^C_{it}}$) for Boston, Columbus, Houston, Jacksonville, Milwaukee, and Pittsburgh.[37] We note that the actual GSE market

[35] Data are available for Austin, Boston, Cincinnati, Cleveland, Columbus, Houston, Jacksonville, Kansas City, Milwaukee, Pittsburgh, Richmond, and St. Louis. Eviction filings are the precursor to actual evictions. Unfortunately, the Princeton Eviction Lab does not report actual eviction counts after 2016.

[36] The 2020Q1 eviction rate equals the sum of eviction filings from January to March 2020 divided by the renter-occupied households, which is then divided by three to express as a monthly rate. We then multiply the average filing rate by the historical filing-to-eviction conversion rate to obtain the baseline eviction rate. The historical filing-to-eviction conversion rate is the average conversion rate observed for each city over the 2000 to 2016 period.

[37] To conserve space, we report the predicted eviction counts and filings for the 12 cities covered by the

share in each city is very high (above 90%) and thus the difference between $\widehat{ER_{it}}$ and $\widehat{ER_{it}^A}$ is small. In other words, we would not expect a significant change in predicted evictions if all loans were backed by the GSEs. However, Figure 3 clearly shows the significant gap in predicted evictions that would result if all loans were originated by non-agency lenders illustrating the impact of GSE financing in reducing potential evictions. To put this in perspective, Table V reports the expected number of evictions from January to June 2020 based on the predicted monthly eviction rates.[38] For example, our estimates indicate that Boston should have experienced 3,226 evictions between January and June 2020. Since over 97% of the loans financing multifamily properties in Boston are backed by GSEs, we estimate that evictions would have been approximately 17.6% greater if all Boston multifamily properties were financed with non-agency loans. Across all 12 markets, our model indicates that evictions would be 20.4% higher if all properties were financed with non-agency debt.

We can also use our model predictions to study the potential impact of the COVID-19 pandemic on the rental market. For example, we see in Figure 3 a sizable increase across all markets in the predicted eviction rates starting in April 2020. This corresponds to the surge in unemployment associated with various government-ordered business shutdowns and stay-at-home orders. As reported in Table A.6, we projected an average of 8,235 evictions per month across the 12 cities during the pre-pandemic first quarter of 2020. However, following the surge in business closings in April, predicted evictions increase 59.7% to an average of 13,148 per month. As the various eviction moratorium enacted at the onset of the pandemic effectively reduced the number of evictions to zero, our projections provide an indication of the number of potentially impacted tenants. For example, assuming the 2020Q1 predictions

Princeton Eviction Lab in Table A.6 in the Appendix.

[38]Table A.6 in the Appendix reports the monthly eviction counts and renter-occupied households underlying the estimated eviction rates.

reflect a baseline for the "normal" number of expected evictions, then the pandemic would have resulted in an average of 4,913 more evictions per month during 2020Q2 than in the absence of the pandemic. These are sizable differences and provide credence to the claims raised that the surge in unemployment and business closing would have resulted in a wave of evictions. We do not know the number of actual evictions that occurred in January through March 2020, and thus, we do not claim that all predicted evictions were impacted by the eviction moratoriums. However, we note that our predictions are roughly consistent with the number of eviction filings reported by the Princeton Eviction Lab for the 12 cities. Thus, we take comfort that our predictions are within a reasonable range of what should have been expected in the absence of the moratoriums.

VI. Conclusion

The COVID-19 pandemic exposed many U.S. households to eviction risk. Many policymakers and housing activists have raised concerns about an eviction crisis. While the pandemic has certainly drawn greater attention to the problem of evictions, it is important to stress that tenant evictions occur frequently during normal times and research clearly documents that they can compound negative social and economic stresses on tenants.[39]

We bring to the literature a new angle on evictions, which is to study how financing choices by property owners can impact tenant eviction risk. Specifically, we examine the impact of GSE financing on evictions. A stylized model reveals the linkage between credit supply and eviction risk – having a GSE loan could lead to a lower likelihood for the landlord to pursue evictions. In the empirical analysis, using a sample of nationwide multifamily loans

[39]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).

that were securitized between 2001 and 2016, we find lower eviction rates in counties with a larger share of multifamily loans that are insured by Fannie Mae, Freddie Mac, or Ginnie Mae than in counties with a smaller share of multifamily loans insured by the three GSEs. Our study highlights the spillover effects of the credit market to the real economy.

Our analysis contributes to the current debate surrounding the future of the GSEs (Layton, 2020). By highlighting a new channel demonstrating how the GSEs' role providing multifamily credit supply can impact tenant housing outcomes during periods of economic stress, we provide a new metric for evaluating how the GSEs' are meeting their affordable housing mandates.

Finally, we use our estimated model of eviction rates to provide evidence of the magnitude of potential evictions results from various government policies implemented to curb the COVID-19 pandemic. Our findings suggest that evictions are more likely to be prevalent in areas where most multifamily loans are originated via non-agency lenders.

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Table I

Comparison of Landlord Decisions and Payoffs

Lender	**Decision**	**Payoff**	**Dominant Strategy**
Case 1: Small Income Shock ($l_A < l_C < \lambda P$)			
Conduit	(a) Evict / No Default	$2P - F - 2l_C$	
	(b) Evict / Default	$2P - F - 2l_C - \Psi + \gamma_C$	
	(c) No Evict / No Default	$2P + \delta P - 2l_C$	✓
	(d) No Evict / Default	$2P + \delta P - 2l_C - \Psi + \gamma_C$	
Agency	(a) Evict / No Default	$2P - F - 2l_A$	
	(b) Evict / Default	$2P - F - 2l_A - \Psi + \gamma_A$	
	(c) No Evict / No Default	$2P + \delta P - 2l_A$	✓
	(d) No Evict / Default	$2P + \delta P - 2l_A - \Psi + \gamma_A$	
Case 2: Medium Income Shock ($l_A < \lambda P < l_C$)			
Conduit	(a) Evict / No Default	$2P - F - 2l_C$	✓
	(b) Evict / Default	$2P - F - 2l_C - \Psi + \gamma_C$	
	(c) No Evict / No Default	Not Applicable	
	(d) No Evict / Default	$2P + \delta P - 2l_C - \Psi + \gamma_C$	
Agency	(a) Evict / No Default	$2P - F - 2l_A$	
	(b) Evict / Default	$2P - F - 2l_A - \Psi + \gamma_A$	
	(c) No Evict / No Default	$2P + \delta P - 2l_A$	✓
	(d) No Evict / Default	$2P + \delta P - 2l_A - \Psi + \gamma_A$	
Case 3: Large Income Shock ($\lambda P < l_A < l_C$)			
Conduit	(a) Evict / No Default	$2P - F - 2l_C$	✓
	(b) Evict / Default	$2P - F - 2l_C - \Psi + \gamma_C$	
	(c) No Evict / No Default	Not Applicable	
	(d) No Evict / Default	$2P + \delta P - 2l_C - \Psi + \gamma_C$	
Agency	(a) Evict / No Default	$2P - F - 2l_A$	✓ when $(\Psi - \gamma_A)$ large
	(b) Evict / Default	$2P - F - 2l_A - \Psi + \gamma_A$	
	(c) No Evict / No Default	Not Applicable	
	(d) No Evict / Default	$2P + \delta P - 2l_A - \Psi + \gamma_A$	✓ when $(\Psi - \gamma_A)$ small

Table II

Summary Statistics at Month-County-Level by Agency Share Bucket

Variables	All	A $\leq$ 0.2	$0.2 < A \leq 0.4$	$0.4 < A \leq 0.6$	$0.6 < A \leq 0.8$	$A \geq 0.8$
Eviction rate	2.98	2.91	3.35	3.12	3.04	2.51
	(2.53)	(2.59)	(2.74)	(2.48)	(2.48)	(2.15)
Filing rate	6.48	6.11	7.00	6.60	7.13	5.89
	(7.27)	(6.66)	(7.35)	(7.07)	(7.07)	(7.93)
Conversion rate	0.61	0.64	0.61	0.61	0.58	0.59
	(0.27)	(0.27)	(0.26)	(0.26)	(0.26)	(0.26)
Agency share	0.41	0.04	0.29	0.49	0.69	0.91
	(0.32)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)
WA-DSCR (winsorized)	1.13	1.12	1.08	1.10	1.13	1.26
	(0.41)	(0.42)	(0.33)	(0.40)	(0.40)	(0.47)
WA-LTV (winsorized)	0.68	0.69	0.69	0.68	0.68	0.68
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)
Delinquency rate	0.02	0.02	0.03	0.03	0.02	0.01
	(0.08)	(0.11)	(0.07)	(0.08)	(0.08)	(0.03)
Poverty rate	0.11	0.11	0.11	0.11	0.11	0.10
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Renter-occupied percent	0.31	0.30	0.33	0.32	0.32	0.32
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Hispanic percent	0.10	0.10	0.11	0.09	0.10	0.11
	(0.13)	(0.14)	(0.13)	(0.12)	(0.12)	(0.12)
African American percent	0.10	0.09	0.11	0.11	0.11	0.10
	(0.13)	(0.12)	(0.13)	(0.14)	(0.14)	(0.12)
Asian percent	0.02	0.02	0.03	0.02	0.02	0.03
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Observations	131,567	41,204	24,412	24,550	19,097	22,304

This table reports summary statistics for county-level variables for the full sample and by agency share A bucket. The sample covers the period from January 2001 to December 2016. "A" stands for agency share and ranges from 0 to 1.

Table III

Sensitivity of Evictions to CMBS Factors

Dep. var.: Eviction rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model:	OLS	OLS	OLS	OLS	OLS	2SLS	OLS
Agency share	-0.255***			-0.292***	-0.258***	-0.514***	-0.267***
	(-2.978)			(-3.285)	(-2.861)	(-3.737)	(-2.846)
Orthogonal WA-DSCR		-0.127***		-0.128***	-0.108***	-0.134***	-0.122***
		(-3.936)		(-3.861)	(-3.277)	(-3.882)	(-3.716)
Unemp. shock (z-score)			0.045*	0.045*	0.046*	0.050*	0.046*
			(1.766)	(1.768)	(1.861)	(1.916)	(1.818)
Delinquency rate					0.163		
					(1.177)		
Eviction filing rate, lagged 1-yr					0.063***		
					(4.875)		
Bottom coverage							0.044
							(0.463)
Top coverage							0.101
							(1.082)
Bottom coverage × Agency share							0.108
							(0.769)
Top coverage× Agency share							-0.267*
							(-1.795)
Observations	131,567	131,567	123,683	123,683	116,366	120,845	123,683
R-squared	0.046	0.047	0.049	0.052	0.073	n/a	0.053
Number of Counties	1,111	1,111	1,107	1,107	1,073	1,076	1,107
County Controls	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓

This table reports coefficient estimates for an unbalanced county-level monthly panel from January 2001 to December 2016. The dependent variable is the Eviction Rate, which is the annual number of evictions per 100 renter households. Agency share is the proportion of multifamily loans that were issued by Fannie Mae, Freddie Mac, or Ginnie Mae (in decimal form). Orthogonal WA-DSCR is the residual of the correlation between the WA-DSCR and agency share. Unemp. shock (z-score) is the standardized difference between the current unemployment rate and average unemployment rate from the past five years. Delinquency rate is the share of multifamily loans 30 days or more past due on debt service (in decimal form). Filing Rate is the annual number of eviction filings per 100 renter households. The controls include the annual county-level log median household income, log population, poverty rate, percent renter-occupied homes, percent Hispanic, percent Black, and percent Asian. Column (6) reports the estimates from the second-stage 2SLS instrumental variables (IV) specification using the lagged agency share and lagged differences in agency and conduit mortgage loan rate spreads as instruments. The results from the first-stage regression are reported in Table A.4 in the Appendix. In column (7), bottom and top coverage are indicator variables identifying markets in the bottom and top quintiles, respectively, for the sum of rental units in properties collateralizing mortgages reported in Trepp divided by the total number of rental units in the market. The t-statistics are reported in parentheses, which are robust and clustered by county. The stars *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table IV

DSCR Differences, Unemployment Shocks, and Default Costs

	(1)	(2)	(3)
Dep. var.: Eviction rate			
Orthogonal WA-DSCR wedge	0.119**		
	(2.262)		
Agency share × Orthogonal WA-DSCR wedge	-0.148*		
	(-1.758)		
Judicial × Unemp. shock (z-score)		-0.165***	-0.038
		(-3.558)	(-0.596)
Judicial × Agency share			0.107
			(0.840)
Agency share × Unemp. shock (z-score)			0.074
			(0.725)
Agency share × Judicial × Unemp. shock (z-score)			-0.287**
			(-2.176)
Agency share	-0.278***	-0.290***	-0.335***
	(-3.102)	(-3.292)	(-2.796)
Orthogonal WA-DSCR	-0.081**	-0.128***	-0.127***
	(-2.104)	(-3.922)	(-3.936)
Unemp. shock (z-score)	0.045*	0.112***	0.081
	(1.775)	(3.038)	(1.455)
Observations	123,683	123,683	123,683
R-squared	0.053	0.056	0.057
Number of Counties	1,107	1,107	1,107
County Controls	✓	✓	✓
Year-Month FE	✓	✓	✓
County FE	✓	✓	✓

This table reports coefficient estimates for an unbalanced county-level monthly panel from January 2001 to December 2016. The dependent variable is the Eviction Rate, which is the annual number of evictions per 100 renter households. Agency share is the proportion of multifamily loans that were issued by Fannie Mae, Freddie Mac, or Ginnie Mae (in decimal form). Orthogonal WA-DSCR is the residual of the correlation between the WA-DSCR and agency share. Unemp. shock (z-score) is the standardized difference between the current unemployment rate and average unemployment rate from the past five years. Judicial is an indicator variable for whether the state follows a judicial foreclosure state. The controls include the annual county-level log median household income, log population, poverty rate, percent renter-occupied homes, percent Hispanic, percent Black, and percent Asian. The t-statistics are reported in parentheses, which are robust and clustered by county. The stars *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table V

Predicted Evictions for January to June 2020

City	Predictions by GSE Assumption			Difference
	As-is	Agency only	Non-agency only	
Austin	4,251	4,208	5,166	-959
Boston	3,226	3,211	3,794	-582
Cincinnati	2,980	2,963	3,595	-632
Cleveland	2,520	2,470	2,912	-442
Columbus	5,581	5,505	6,711	-1,206
Houston	21,576	21,121	25,892	-4,771
Jacksonville	4,024	4,024	4,956	-932
Kansas City	2,555	2,520	3,102	-582
Milwaukee	4,799	4,771	5,778	-1,007
Pittsburgh	3,062	3,052	3,697	-645
Richmond	3,506	3,506	4,309	-803
St. Louis	6,071	6,007	7,334	-1,327
Total	64,151	63,356	77,246	-13,889

This table reports the predicted evictions for the first six months of 2020 by city. We use the coefficient estimates from the model in Table III, column 4, and the most recent data on eviction filings from the Princeton Eviction Lab. The monthly time series is reported in Table A.6.

Figure 1. U.S. Evictions, Filings, and Agency CMBS Multifamily Loans

This figure plots the annual U.S. share of agency multifamily loans (right axis) and the annual U.S. eviction and filing rate per 100 renter-occupied homes from 2000 to 2016 (left axis). Actual mix is the eviction rate predicted based on the actual agency share. Agency only is the eviction rate predicted based on the assumption of 100% GSE financing. Non-agency only is the eviction rate predicted based on the assumption of 0% GSE financing.

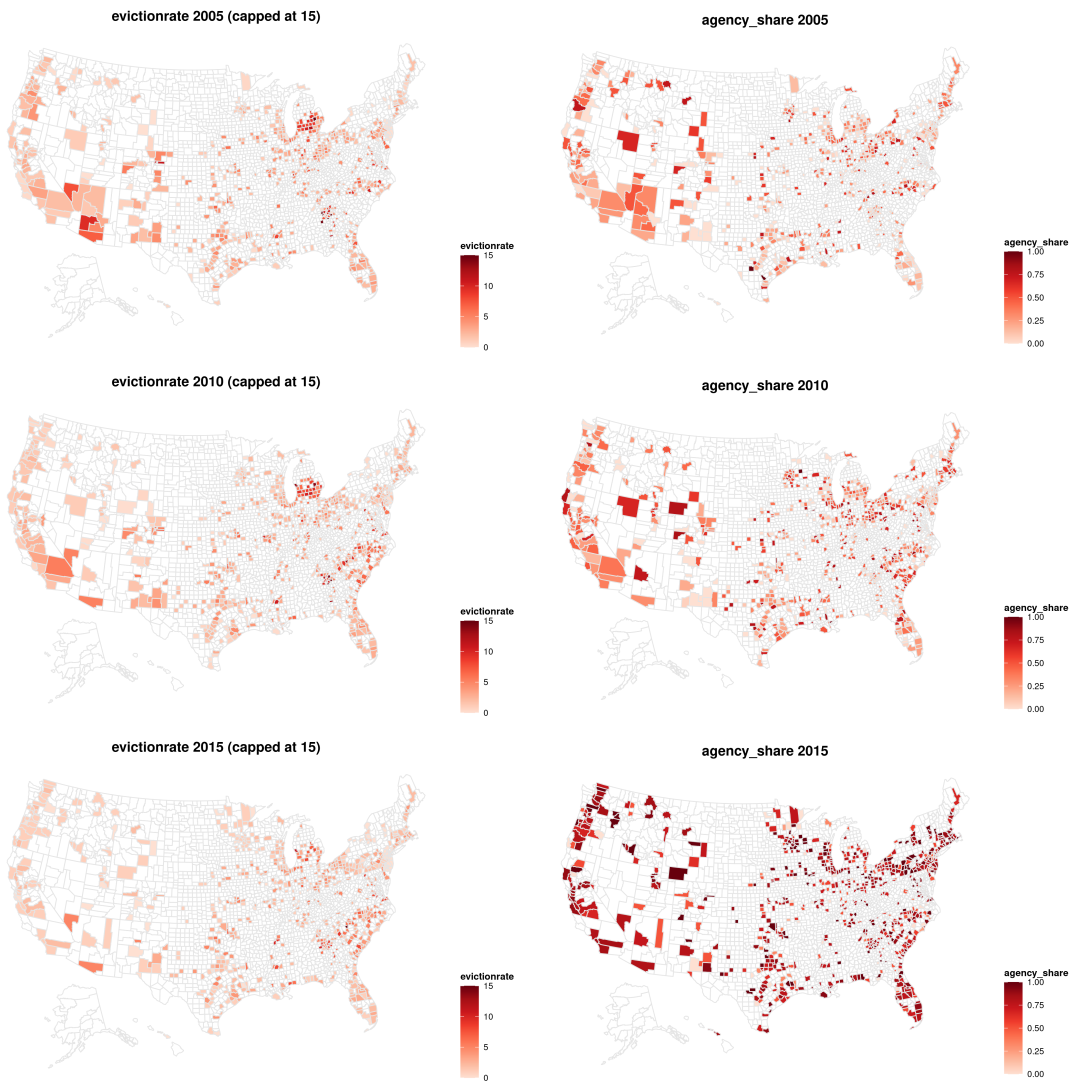

Figure 2. Eviction Rate and Agency Share by U.S. Counties

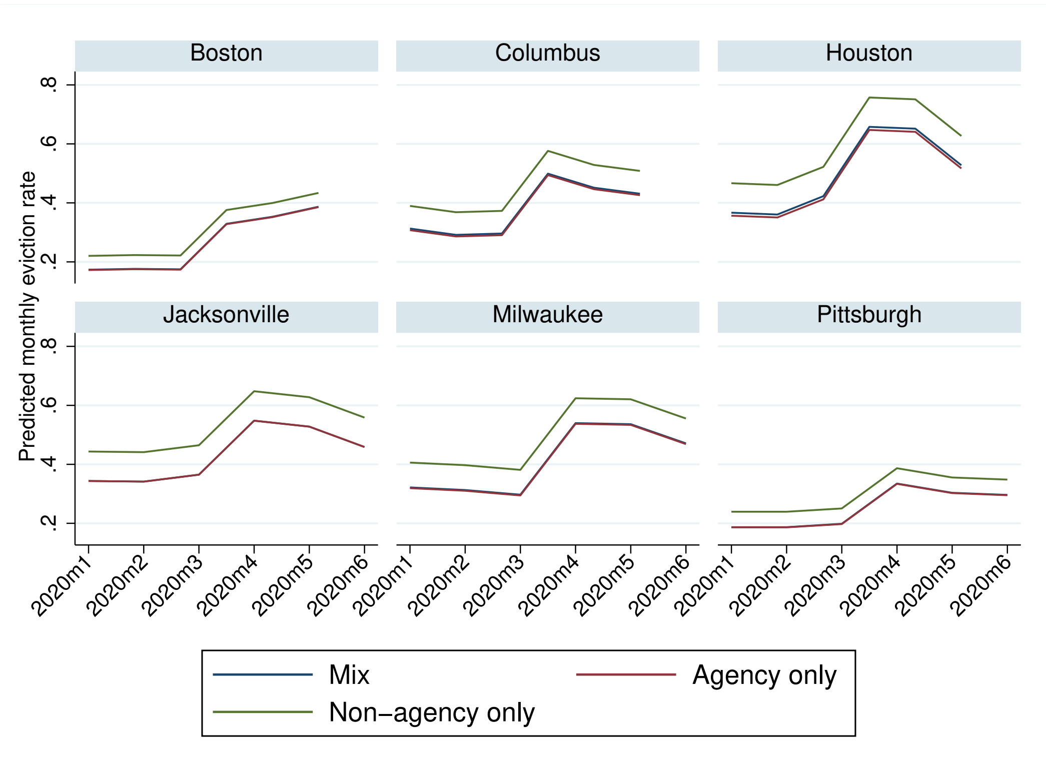

Figure 3. Predicted U.S. Evictions by City

This figure plots the predicted eviction rate by city from January to June 2020. The monthly eviction rate is the predicted number of evictions in a month divided by the most recent number of renter-occupied households times 100. Mix represents predicted evictions using the actual GSE share for each city. Agency only denotes predicted evictions assuming the city contains only agency loans for multifamily properties. Non-agency only is predicted evictions assuming the city contains only non-agency loans for multifamily properties.

Appendix

Table A.1

More Summary Statistics

A. Non-Agency Loans					
Variables	N	Mean	Sdv	Min	Max
Becomes 30+ days delinquent (within 60 months)	27488	0.2	0.4	0.0	1.0
Modified (within 60 months)	27488	0.0	0.1	0.0	1.0
DSCR (winsorized)	27140	1.6	0.9	0.5	5.9
LTV (winsorized)	27067	68.0	15.7	7.9	82.3
Outstanding loan balance (in $millions)	27488	6.9	16.3	0.0	1500.0
Remaining term	27487	126.3	71.3	1.0	499.0
Contract rate (winsorized)	27342	6.5	1.2	2.6	8.9
Spread (winsorized)	27342	1.7	0.9	0.1	5.4
Origination year	26173	2003.1	5.0	1981.0	2016.0
Building age (winsorized)	26786	19.7	21.1	0.0	102.0
Multiple buildings	27488	0.0	0.1	0.0	1.0
Occupancy rate (winsorized)	25912	1.0	0.0	0.8	1.0
Rental units (winsorized)	26245	155.0	143.2	6.0	792.0
Building renovation	27476	0.3	0.5	0.0	1.0
Deal current balance (in $millions)	27488	1519.7	1078.1	10.0	7903.5
Deal current asset count	27488	208.0	115.2	1.0	664.0
Securitization year	27488	2003.5	4.8	1994.0	2016.0
B. Agency Loans					
Variables	N	Mean	Sdv	Min	Max
Becomes 30+ days delinquent (within 60 months)	65473	0.0	0.2	0.0	1.0
Modified (within 60 months)	65473	0.0	0.1	0.0	1.0
DSCR (winsorized)	31248	1.6	0.7	0.5	5.9
LTV (winsorized)	33594	66.1	13.3	7.9	82.3
Outstanding loan balance (in $millions)	65473	8.3	13.8	0.0	878.0
Remaining term	65469	255.3	169.7	1.0	516.0
Contract rate (winsorized)	65281	4.7	1.3	2.6	8.9
Spread (winsorized)	65281	2.0	1.0	0.1	5.4
Origination year	65386	2011.2	4.8	1971.0	2016.0
Building age (winsorized)	31478	23.8	22.5	0.0	102.0
Multiple buildings	65473	0.0	0.0	0.0	1.0
Occupancy rate (winsorized)	22284	1.0	0.0	0.8	1.0
Rental units (winsorized)	32323	189.5	157.3	6.0	792.0
Building renovation	65157	0.1	0.3	0.0	1.0
Deal current balance (in $millions)	65454	658.2	491.9	0.3	2665.0
Deal current asset count	65454	93.8	48.0	1.0	321.0
Securitization year	65473	2011.9	4.6	1993.0	2016.0
Freddie Mac	65473	0.3	0.5	0.0	1.0
Fannie Mae	65473	0.2	0.4	0.0	1.0
Gennie Mae	65473	0.4	0.5	0.0	1.0

This table reports additional summary statistics for multifamily loans in the sample at time of securitization. Loans in the sample were performing between 2001 and 2016.

Table A.2

Propensity Score Matched Multifamily Loans at Securitization by Deal Type

Variables	Agency	Conduit	Difference	t-stat	d-stat
Becomes 30+ days delinquent (within 60 months)	0.00	0.06	0.1	8.4	0.3
Modified (within 60 months)	0.02	0.01	0.0	-2.3	-0.1
DSCR (winsorized)	1.61	1.50	-0.1	-7.8	-0.3
LTV (winsorized)	66.83	69.36	2.5	7.2	0.2
Outstanding loan balance (in $millions)	13.75	7.78	-6.0	-11.4	-0.4
Remaining term	105.11	104.05	-1.1	-0.8	0.0
Contract rate (winsorized)	4.42	6.45	2.0	40.3	1.1
Spread (winsorized)	1.71	1.72	0.0	0.4	0.0
Origination year	2011.53	2004.00	-7.5	-31.1	-0.9
Building age (winsorized)	17.41	20.66	3.3	5.4	0.2
Multiple buildings	0.00	0.00	0.0	1.0	0.0
Occupancy rate (winsorized)	0.95	0.95	0.0	3.4	0.1
Rental units (winsorized)	227.35	183.21	-44.1	-8.7	-0.3
Building renovation	0.38	0.19	-0.2	-13.9	-0.4
Deal current balance (in $millions)	1,082.10	1,173.23	91.1	4.7	0.2
Deal current asset count	88.72	183.23	94.5	24.8	0.8
Securitization year	2012.56	2004.59	-8.0	-34.3	-1.0
Observations	1,241	3,720			

This table reports summary statistics for multifamily loans in the sample at time of securitization. Loans in the sample were performing between 2001 and 2016. Agency loans are matched with non-agency loans on the basis of property characteristics, securitization year-month, and ZIP code property location.

Table A.3

Regressions on Eviction Rate

Dep. var.: Eviction rate	(1)	(2)	(3)	(4)	(5)
Agency share	-0.262**	-0.320**	-0.178	-0.292***	
	(-2.004)	(-2.348)	(-0.926)	(-3.285)	
Orthogonal WA-DSCR	-0.549***	-0.341***	-0.327***	-0.128***	
	(-5.371)	(-4.403)	(-3.950)	(-3.861)	
Unemp. shock (z-score)	0.301***	0.177***	0.181***	0.045*	
	(6.731)	(4.441)	(4.427)	(1.768)	
ln(Population)		0.413***	0.419***	-0.754*	-0.929**
		(5.671)	(5.568)	(-1.900)	(-2.226)
ln(Income)		-0.624	-0.713	-0.718	-0.375
		(-1.510)	(-1.408)	(-1.332)	(-0.692)
Poverty rate		-5.610**	-5.512*	1.396	1.211
		(-2.110)	(-1.939)	(1.146)	(0.913)
Pct renter-occupied		-2.013*	-2.090*	-1.480	-0.717
		(-1.827)	(-1.826)	(-1.028)	(-0.473)
Pct Hispanic		-0.695	-0.735	-4.052**	-4.897***
		(-1.496)	(-1.542)	(-2.468)	(-2.734)
Pct Asian		-11.684***	-11.444***	-7.579**	-6.571*
		(-5.242)	(-4.968)	(-2.129)	(-1.773)
Pct Af-Am.		9.692***	9.631***	-1.076	-3.369
		(10.853)	(10.717)	(-0.442)	(-1.403)
Agency share, lagged 1-year					-0.305***
					(-3.023)
Orthogonal WA-DSCR, lagged 1-year					-0.109***
					(-3.253)
Unemp. shock (z-score), lagged 1-year					0.077***
					(2.739)
Observations	123,683	123,683	123,683	123,679	112,485
R-squared	0.021	0.261	0.265	0.860	0.864
Year-Month FE			✓	✓	✓
County FE				✓	✓

This table reports coefficient estimates for an unbalanced county-level monthly panel from January 2001 to December 2016. The dependent variable is the Eviction Rate, which is the annual number of evictions per 100 renter households. Agency share is the proportion of multifamily loans that were issued by Fannie Mae, Freddie Mac, or Ginnie Mae (in decimal form). Orthogonal WA-DSCR is the residual of the correlation between the WA-DSCR and agency share. Unemp. shock (z-score) is the standardized difference between the current unemployment rate and average unemployment rate from the past five years. Delinquency rate is the share of multifamily loans 30 days or more past due on debt service (in decimal form). Filing Rate is the annual number of eviction filings per 100 renter households. The t-statistics are reported in parentheses, which are robust and clustered by county. The stars *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4

IV Analysis of Evictions and CMBS Factors

	(1)	(2)
Stage:	First	Second
Dep. var.:	Agency Share	Eviction Rate
Agency share hat		-0.514***
		(-3.737)
Agency share, lagged 1-yr	0.640***	
	(63.045)	
Spread gap, lagged 1-yr	2.440***	
	(3.367)	
Orthogonal WA-DSCR	-0.019***	-0.134***
	(-5.070)	(-3.882)
Unemp. shock (z-score)	0.001	0.050*
	(0.684)	(1.916)
ln(Population)	0.033	-0.747*
	(1.041)	(-1.854)
ln(Income)	-0.007	-0.732
	(-0.149)	(-1.325)
Poverty rate	-0.106	1.475
	(-0.967)	(1.189)
Pct renter-occupied	0.125	-1.227
	(0.981)	(-0.840)
Pct Hispanic	0.266*	-3.985**
	(1.889)	(-2.375)
Pct Asian	0.692***	-7.283**
	(3.039)	(-2.002)
Pct Af-Am	0.206*	-0.835
	(1.660)	(-0.347)
Observations	120,845	120,845
R-squared	0.820	n/a
Number of Counties	1,076	1,076
Year-Month FE	✓	✓
County FE	✓	✓

This table reports coefficient estimates for an unbalanced county-level monthly panel from January 2001 to December 2016. In column 1, the dependent variable is agency share. In column 2, the dependent variable is the Eviction Rate, which is the annual number of evictions per 100 renter households. Agency spread hat is the predicted agency spread using the coefficients from column 1. Spread gap is the conduit-to-agency gap in the weighted average contract rate spread at the state-month level. Orthogonal WA-DSCR is the residual of the correlation between the WA-DSCR and agency share. Unemp. shock (z-score) is the standardized difference between the current unemployment rate and average unemployment rate from the past five years. The t-statistics are reported in parentheses, which are robust and clustered by county. The stars *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.5

Falsification Tests

	(1)	(2)
Dep. var.: Eviction rate		
Random agency share (v1)	-0.004	
	(-0.450)	
Random agency share (v2)		-0.726
		(-0.968)
Orthogonal WA-DSCR	-0.121***	-0.131***
	(-3.592)	(-3.766)
Unemp. shock (z-score)	0.044*	0.047*
	(1.818)	(1.690)
Observations	123,683	118,123
R-squared	0.050	0.052
Number of Counties	1,107	1,007
County Controls	✓	✓
Year-Month FE	✓	✓
County FE	✓	✓

This table reports coefficient estimates for an unbalanced county-level monthly panel from January 2001 to December 2016. The dependent variable is the Eviction Rate, which is the annual number of evictions per 100 renter households. Random agency share (v1) is a randomly assigned number based on a normal distribution with the same mean and standard deviation as the full sample of agency share but truncated between 0 and 1. Random agency share (v2) is a randomly assigned number based on a normal distribution with the same mean and standard deviation as the sample of agency share in December 2016 but truncated between 0 and 1; each preceding value is discounted by a constant monthly time trend. Orthogonal WA-DSCR is the residual of the correlation between the WA-DSCR and agency share. Unemp. shock (z-score) is the standardized difference between the current unemployment rate and average unemployment rate from the past five years. The t-statistics are reported in parentheses, which are robust and clustered by county. The stars *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.6

Predicted Monthly Eviction Counts by City

Panel A: Predicted monthly evictions

City	Austin	Boston	Cincinnati	Cleveland	Columbus	Houston	Jacksonville	Kansas City	Milwaukee	Pittsburgh	Richmond	St. Louis
Dec-19	548	333	361	253	689	2727	533	333	576	369	459	758
Jan-20	552	351	392	275	765	2649	535	345	623	380	469	815
Feb-20	543	357	380	283	713	2605	532	335	606	380	459	778
Mar-20	578	354	391	321	724	3053	568	353	575	403	476	787
Apr-20	932	666	654	615	1220	4751	853	527	1045	680	747	1194
May-20	899	714	600	555	1104	4707	822	531	1038	617	686	1291
Jun-20	748	783	564	471	1054	3811	714	463	912	602	669	1206

Panel B: Predicted monthly evictions assuming 100% GSE financing

City	Austin	Boston	Cincinnati	Cleveland	Columbus	Houston	Jacksonville	Kansas City	Milwaukee	Pittsburgh	Richmond	St. Louis
Dec-19	540	330	358	245	676	2653	533	327	571	368	459	749
Jan-20	544	349	389	267	752	2575	535	340	618	379	469	804
Feb-20	537	354	377	275	700	2532	532	329	601	379	459	767
Mar-20	570	351	388	312	711	2976	568	347	570	401	476	777
Apr-20	925	664	652	607	1208	4675	853	522	1040	678	747	1183
May-20	891	712	597	546	1092	4629	822	525	1034	615	686	1280
Jun-20	741	781	561	463	1042	3733	714	457	907	600	669	1195

Panel C: Predicted monthly evictions assuming 0% GSE financing

City	Austin	Boston	Cincinnati	Cleveland	Columbus	Houston	Jacksonville	Kansas City	Milwaukee	Pittsburgh	Richmond	St. Louis
Dec-19	699	428	464	318	877	3448	688	424	739	475	593	971
Jan-20	704	446	494	341	953	3370	690	437	786	486	603	1026
Feb-20	696	452	482	348	901	3327	687	426	769	486	593	988
Mar-20	730	449	493	386	912	3771	724	444	738	509	610	998
Apr-20	1085	761	757	681	1409	5470	1009	619	1208	786	880	1404
May-20	1051	809	702	620	1293	5424	977	622	1201	722	820	1501
Jun-20	901	878	666	537	1243	4528	870	554	1075	708	803	1417

Panel D: renter-occupied households

City	Austin	Boston	Cincinnati	Cleveland	Columbus	Houston	Jacksonville	Kansas City	Milwaukee	Pittsburgh	Richmond	St. Louis
Total	231,718	202,385	149,446	230,156	244,520	722,230	155,668	112,495	193,601	203,148	48,327	80,582

This table reports predicted eviction counts under various assumptions about the share of GSE financing by city and over time.

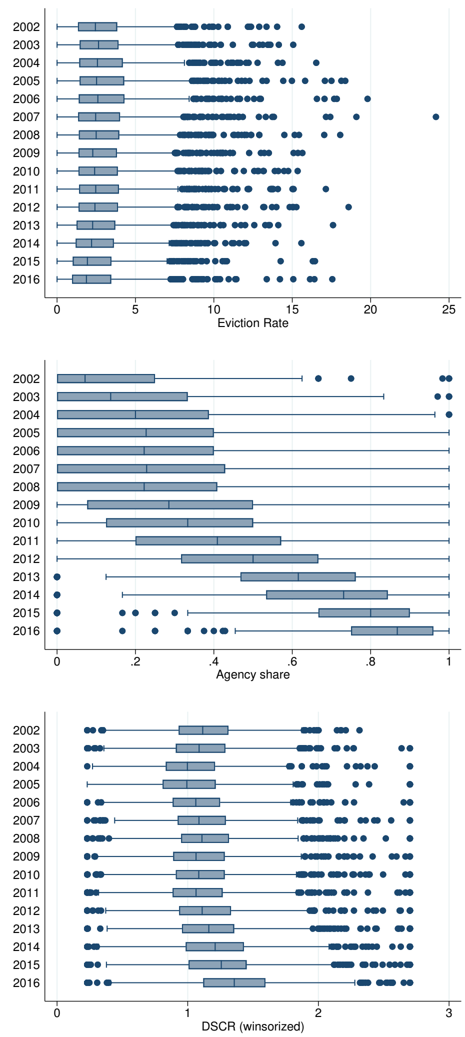

Figure A.1. Distribution by Year

This figure shows the box plot distribution of the Eviction Rate, Agency Share, and WA-DSCR by year.