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Information Asymmetry, Regulations and Equilibrium Outcomes: Theory and Evidence from the Housing Rental Market

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We explore the role of information asymmetry and regulations on equilibrium outcomes in rental markets to show that while landlords price the cost of regulations into rent, they also invest in tenant screening to alleviate information asymmetry, thus restricting access to rental housing. We are the first to document this additional tenant screening in response to regulations.

Residential leases are contracts that give tenants the right to use (enjoy) real property in exchange for payment of a consideration to the property owner. As a contract, the lease spells out the rights and responsibilities of all parties. In addition, leases are governed by state laws in the jurisdiction where the property is located. Historically, these laws recognized the special nature of residential leases in providing shelter to the tenant.[1] Whether enacted through statutes or established by courts, rental laws and regulations often strengthen tenant rights to the detriment of landlords, such as restricting landlord ability to evict bad tenants (Miron 1990), determine rent or gain possession of a property (through eviction procedures).[2] However, even the most well-intentioned regulation may have unforeseen consequences that could harm the intended beneficiaries.[3] For example, Figure 1 illustrates the potential

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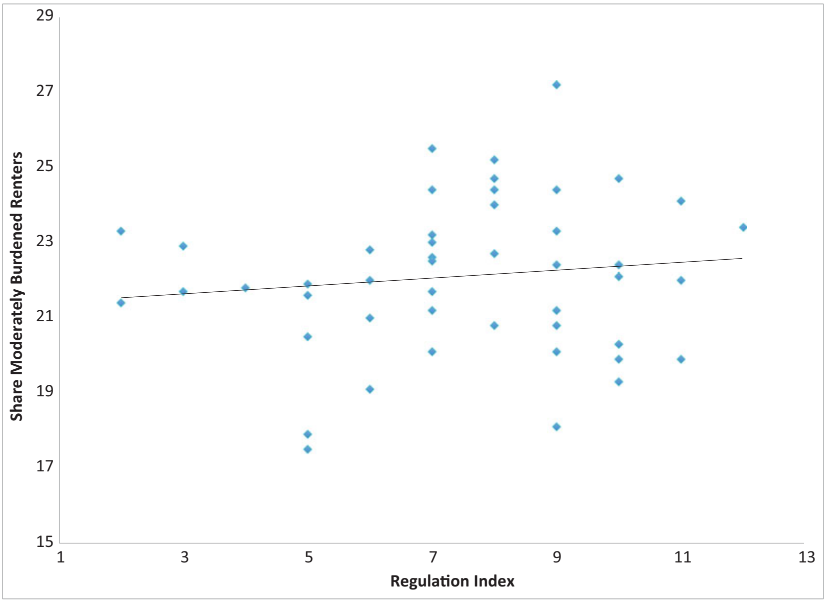
[1]Most regulations, particularly rent control and stabilization programs, were put in place in the 1970s during a period commonly referred to as the progressive era in landlord-tenant law (Rabin 1983; Goetz 1984).

[2]These regulations may also interfere in the right of landlords and tenants to decide the extent of landlord services (Rabin 1983). Although we use the term “regulations” loosely to refer to both local and state laws and regulations, our empirical analysis focuses on state regulations. Turner and Malpezzi (2003) provide an exhaustive review of the empirical literature on the costs and benefits associated with rent control.

[3]For example, Schuetz (2009) documents how zoning regulations in Massachusetts constrain development of rental housing and Glaeser, Gyourko and Saks (2005)

Figure 1 ■ Linear correlation between state rental regulation index and percentage of moderately burdened renters in 2014. Moderately burdened renters have rent greater than 30% of income. Source: Joint Center (2015). [Color figure can be viewed at wileyonlinelibrary.com]



connection between local rental regulations and housing affordability by plotting state landlord regulation index values against the percentage of state households moderately burdened by rents greater than 30% of their incomes.[4] The positive trend line supports the contention that areas with more regulations face greater problems with affordable housing. In this article, we explore how landlord actions in response to the regulatory environment can exacerbate issues of rental affordability and supply.

It is well known that rental regulations increase landlord operating costs (Miron 1990) and are therefore priced into rents in equilibrium to the extent permitted by the elasticity of rental demand (*e.g.*, Hirsch, Hirsch and

attribute the high cost of housing in Manhattan to strict land use controls. In an international setting, Suzuki and Asami (2018) study how changes to the Japanese Tenant Protection Law had a significant effect on housing supply.

[4]The data section explains the construction of the landlord regulation index that captures a variety of state regulations designed to protect tenants. The terms “landlord regulations,” “rental regulations,” “lease regulations” and “landlord-tenant regulations” have the same meaning and are used interchangeably.

Margolis 1975; Miron 1990; Malpezzi 1996). All else being equal, this direct effect of regulations on rents should normally lead to more rent payment defaults. However, the resulting increase in tenant default is predictable and could lead to more screening of prospective tenants by landlords to reduce information asymmetry about tenant quality.[5] Although additional screening is costly, when regulation costs are high, screening and rejecting poor-quality lease applicants becomes a dominant strategy because the alternative would likely lead to higher defaults and lower profits.[6] We propose a simple model that shows the effect of rental market regulations on tenant screening, and ultimately rent defaults.

Our focus is on the effects of regulations that are similar to the habitability laws (namely, repair and deduct, rent withholding, receivership and retaliatory eviction) covered by Hirsch, Hirsch and Margolis (1975). However, we take a more comprehensive approach by examining how these regulations affect the landlords' trade-off between rent and tenant risk. Although Miron (1990) graphically describes this trade-off within the context of security of tenure, this problem has not been directly modeled or empirically tested.

We develop a model that assumes that landlords cannot directly observe the quality of a lease applicant. They receive a noisy signal about the applicant's quality, but can improve the strength of the signal by investing in screening. We use the term "regulations" loosely to refer to both local and state laws and regulations. *Holding rent constant*, we show that the return on investing in tenant screening increases with regulation costs, which *ex-post* should dampen the direct positive effect (through rent) of regulations on rent defaults. Intuitively, if regulation costs are high, the gain from screening out bad applicants may exceed its cost.[7] In contrast, the return from detailed tenant screening may be low or even negative if the regulatory environment allows landlords to swiftly and efficiently terminate leases and remove delinquent tenants. In this

[5]In residential leasing, landlords may be exposed to a self-selection problem if they cannot identify applicant risk and to moral hazard because the contracted fixed rent payments may incite tenants to overconsume housing, a problem referred to as the rental externality (Henderson and Ioannides 1983). Generally, landlords can alleviate the self-selection problem by investing in tenant screening. The moral hazard problem, which is not the focus of this study, is generally controlled via the lease contract. In dealing with the information asymmetry problem, landlords trade off screening and regulation costs.

[6]While lease applicants may be required to cover the cost of a credit check, landlords bear the cost of contacting previous lessors, verifying employment, etc.

[7]These gains include avoided rent losses, additional maintenance costs and legal expenses to collect past-due rents.

case, landlords may be more willing to approve riskier applicants and, possibly, to supply additional rental units to accommodate the resulting increase in rental demand. In summary, regulations have a positive first-order effect on rent, hence causing more rent defaults. In high-regulation states, landlords would not only invest in applicant credit screening, but they may also pass on regulation costs to tenants by increasing asking rents to the extent permitted by the elasticity of demand because the regulatory environment limits their ability to collect unpaid rent and expenses related to property damage.

Empirically, we verify the model's predictions by examining rent and tenant default using a national database of individual lease payment records. As documented in the literature, we find a positive relation between rent and regulations. However, we find no evidence of risk-based rent pricing by landlords. More importantly, we document a significant decrease in lease defaults in response to regulations. Although the majority of the regulations covered in this study were enacted in the 1980s or earlier, we recognize that they may have arisen in response to actions by market participants and that these behaviors could be persistent, hence potentially causing endogeneity between regulations and tenant risk. Thus, we adopt an instrumental variable (IV) approach for our default model to account for the possibility that regulations likely arise endogenously in response to rental market risk.

In addition to documenting evidence supportive of more tenant screening by landlords in response to regulations, we also show that landlord size matters. Despite charging higher rents, large properties experience fewer defaults. Their higher vacancy rates in high-regulation states are supportive of stricter tenant screening. But smaller landlords may have more incentive to minimize tenant turnover compared to larger landlords because vacancies are likely to have a larger effect on profit.[8]

Ours is the first study to explore the equilibrium interaction among rental regulation, equilibrium rent and lease default. Compared to the existing literature, our study also benefits from the use of microlevel rental lease performance data. Previous studies of rental regulations generally use survey rent data and fail to consider the tenant risk dimension due to data limitations.[9] Relying on a simple modeling framework, our study provides greater insight into the complex relations between rent, tenant risk and landlord screening. As a result, our findings should aid policy makers in evaluating the soundness of landlord regulations in the context of promoting housing affordability.

[8]See Downs (1996).

[9]See Hirsch, Hirsch and Margolis (1975).

The rest of the article is organized as follows. The next section presents a simple illustrative model of a landlord's profit maximization problem under asymmetric information. Then, we discuss the rental regulations and lease performance data sets used in the main empirical analysis presented in next two sections. Finally, we explore the potential for landlord heterogeneity to impact the analysis before concluding.

A Simple Tenant Screening Model

We present a simple one-period model that captures landlords' incentives to screen potential tenants in a perfectly competitive environment in reaction to increasing regulation costs. We assume that a tenant's quality θ can be either good ($\theta = 1$) or bad ($\theta = 0$) reflecting his propensity to default. Good (bad) tenants always (never) pay their rent in full. The proportion of bad tenants in the population is δ. Thus, the average expected or market default rate landlords face is δ. As a result, we assume that

$$\theta = \begin{cases} 1 & \text{with probability } 1 - \delta \\ 0 & \text{with probability } \delta \end{cases}. \tag{1}$$

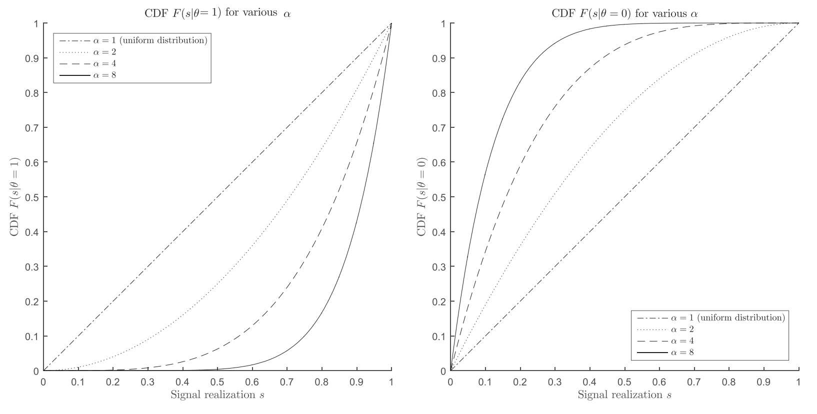
The quality of a prospective tenant is not directly observable by the landlord. Instead, the landlord receives a signal $s \in [0, 1]$ of the tenant's quality θ that represents an outside measure or hard information, such as a credit score about the tenant. These signals are drawn from the following conditional probability density function:

$$f(s|\theta) = \begin{cases} \alpha s^{\alpha-1} & \text{if } \theta = 1 \\ \alpha(1-s)^{\alpha-1} & \text{if } \theta = 0 \end{cases}, \tag{2}$$

where $\alpha \geq 1$ is the signal quality, as in Quint (2015). As Figure 2 shows, when $\alpha = 1$, the landlord's signal is completely uninformative about the tenant's quality θ. As α increases, the signal quality improves, allowing better identification of the tenant's quality. In the context of this article, α measures the landlord's investment in screening potential tenants. For example, a landlord may expend resources to check references only on applicants with a marginal signal above a minimum threshold. However, the incentive to expend additional resources may decline for applicants with exceptionally strong credit signals. Therefore, the landlord's level of investment in screening will be conditional on the signal s received, causing α to vary across applicants, and the riskiness of the rental population (δ)—the landlord's incentives to screen applicants also increase with the riskiness of the population. Thus, the joint distribution of s and θ is

$$f(s, \theta) = (1 - \delta)\alpha s^{\alpha-1} + \delta\alpha(1 - s)^{\alpha-1}. \tag{3}$$

Figure 2 ■ Conditional cumulative density functions of signal for various levels of screening.



For each prospective tenant, the landlord seeks to maximize the expected rent net of the cost of screening investment and other costs of operation. That is,

$$\begin{aligned}
&\max_{\alpha\geq 1} \mathbb{E}[Rent(Regulations)|s] - c(\alpha) - g(\mathbf{x}) \equiv \\
&\quad \max_{\alpha\geq 1}\left(\frac{\Pr(\theta=1)\cdot f(s|\theta=1)}{\Pr(\theta=1)\cdot f(s|\theta=1)+\Pr(\theta=0)\cdot f(s|\theta=0)}\right)\cdot 1\cdot Rent(Regulations) \\
&\quad +\left(\frac{\Pr(\theta=0)\cdot f(s|\theta=0)}{\Pr(\theta=1)\cdot f(s|\theta=1)+\Pr(\theta=0)\cdot f(s|\theta=0)}\right)\cdot 0\cdot Rent(Regulations) \\
&\quad - c(\alpha) - g(\mathbf{x}) \\
&\quad \equiv \max_{\alpha\geq 1}\left(\frac{(1-\delta)s^{\alpha-1}}{(1-\delta)s^{\alpha-1}+\delta(1-s)^{\alpha-1}}\right)\cdot Rent(Regulations) - c(\alpha) - g(\mathbf{x}), \qquad (4)
\end{aligned}$$

where $Regulations$ is a measure of the regulatory environment used in the empirical analysis (either the raw regulation index described in the data section or a standard normal transformation of the raw index), $Rent(Regulations)$ is a reduced-form relationship between monthly rent and regulations (as measured by our regulation index), $c(\alpha)$ is the total cost of investment in screening and $g(\mathbf{x})$ are rental costs due to a vector $\mathbf{x}$ of variables that do not depend on regulations or screening.[10] The first-order condition in α of the landlord's

[10]This formulation implies that regulation costs mainly affect the landlord in the event of tenant default. The landlord decides how much to invest in screening today in order to reduce the likelihood of default at the end of the period and not being able to collect the past-due rent because of tenant-friendly regulations. Without loss of generality, we assume that default leads to no payment.

profit maximization problem yields

$$Rent(Regulations) = c'(\alpha)\left[\frac{(1-\delta)^2 s^{2\alpha-2} + 2\delta(1-\delta)[s(1-s)]^{\alpha-1} + \delta^2(1-s)^{2\alpha-2}}{\delta(1-\delta)\ln(s)[s(1-s)]^{\alpha-1} - \delta(1-\delta)\ln(1-s)[s(1-s)]^{\alpha-1}}\right]. \tag{5}$$

As it is well documented in the literature that market rents typically increase when tenant-friendly regulations are imposed, we assume that $Rent$ is a strictly increasing and strictly concave function of $Regulations$.[11] Specifically, we use the function

$$Rent(Regulations) = \psi_0 + \psi_1\sqrt{Regulations}, \tag{6}$$

with ψ_0 and $\psi_1 > 0$ to describe this reduced-form relationship. Furthermore, we assume that the screening investment costs $c(\alpha)$ are strictly increasing and strictly convex in α so that the marginal cost is strictly increasing in α. Finally, we assume that $c(1) = 0$, because the landlord can always obtain a free uninformative signal. Thus, we use the function $c(\alpha) = (\alpha - 1)^2$.

We solve the model for the optimal level of screening investment numerically. To avoid issues with negative values, we first transform the regulation index using the standard normal cumulative distribution function ($\Phi(\cdot)$). We obtain the parameters ψ_0 and ψ_1 in Equation (6) from an ordinary least squares (OLS) regression of rent on a constant and the standardized regulation index. Specifically, $\psi_0 = 808.33$ and $\psi_1 = 219.06$. For various values of δ, the proportion of bad tenants in the population, we solve the model at four different values of the regulation index along a fine grid for s.[12]

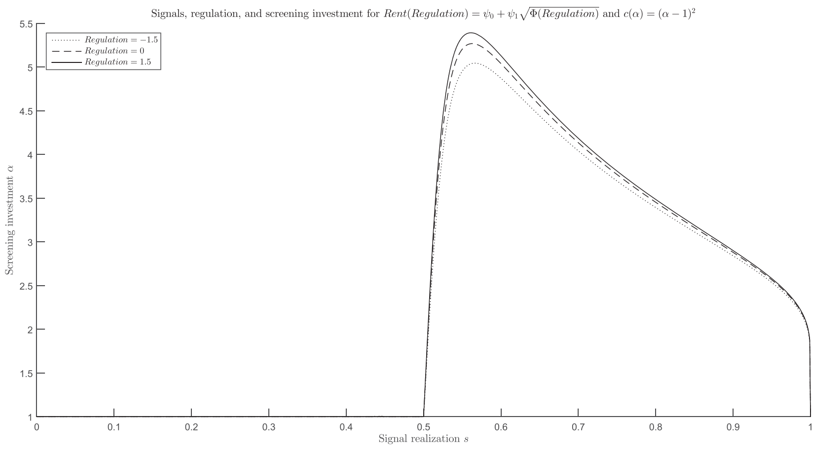
Figure 3 presents results for $\delta = 0.10$. Screening investment (α) is increasing in the level of regulation. Interestingly, no investment in screening occurs when $s \leq 0.5$; our interpretation is that when such a signal is received, the probability of the tenant being bad is so high that obtaining more information about the tenant is futile—the landlord would rather reject the tenant's application outright. Similarly, as s approaches one, the landlord's incentive to invest in screening decreases because the probability of facing a good tenant is very high. Thus, peak screening investment occurs at the greatest level of uncertainty about the tenant's quality, which is a signal $s \in (0.5, 0.8)$.[13]

[11] The pricing of regulation costs into rents has been widely documented (*e.g.*, Hirsch, Hirsch and Margolis 1975; Miron 1990, among others).

[12] Strictly speaking, α is not a function of s because the signal realization s is drawn from a distribution parameterized by α. Rather, in the results that follow, we interpret the relationship between s and α as an *ex-post* relationship.

[13] Results from raw regulation index scores are indistinguishable from those using the standardized regulation index. Also, our results are unchanged when rent and

Figure 3 ■ Results from the two specifications using standardized values for the regulation index with $\delta = 0.1$. When $Regulation = -1.5$, screening investment at its peak (where $s = 0.5660$) is $\alpha = 5.0454$, and when $Regulation = 1.5$, screening investment at its peak (where $s = 0.5610$) is $\alpha = 5.3930$, a 6.9% increase in screening investment.



As expected, a higher proportion of risky tenants in the market (or higher expected rental default rate, δ) increases the level of investment in screening (α) for a given credit quality signal (s) over the range $0.5 \leq s \leq 1$. Figure 4 shows the screening investment α as a function of the population's true default probability δ assuming $s = 0.55$. We see that screening investment increases as the tenant pool becomes riskier and as regulations increase.[14]

To summarize, our model suggests that it will be optimal for landlords to invest more in tenant screening in high-regulation rental markets for two reasons: (i) to lower expected higher tenant default rates in those areas due to the pricing of regulations into rents and (ii) to mitigate the impact of higher tenant default costs in those areas on landlords' profit. Thus, we will formally test the following two hypotheses:

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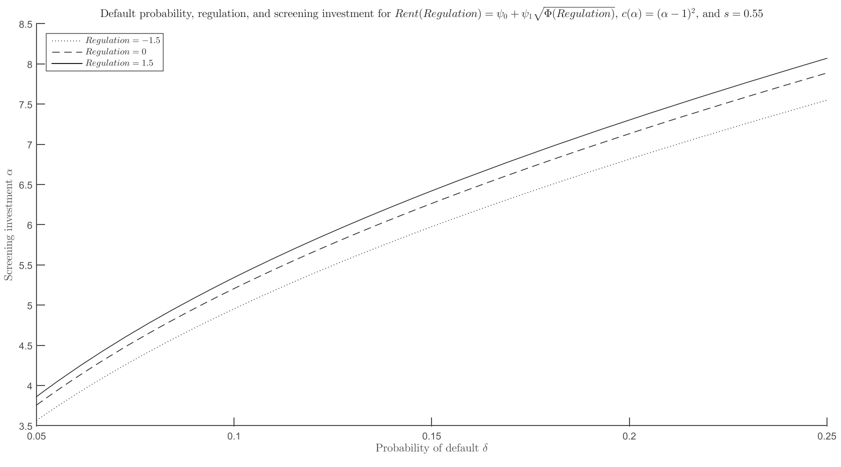
total cost are modeled using log and exponential functions, receptively, as follows: $Rent(Regulations) = \beta_0 + \beta_1 \ln(Regulation)$ and $c(\alpha) = \exp(\alpha - 1) - 1$.

[14]As a robustness check, we abstract away from the full default model by allowing partial defaults on rent. That is, we set up the model so that a good tenant θ_g always pays his rent in full (so that $\theta_g = 1$) but that a bad tenant θ_b only pays a fraction of his rent (*i.e.*, $\theta_b = 0.5$ or 0.75). The results do not change substantively. As there is less risk for the landlord in a partial default model, incentives to invest in screening are not as high, and thus less screening occurs at all regulation scores and signal realizations. However, the general shape of the investment functions is unchanged.

Figure 4 ■ Screening as a function of the true probability of default for the two specifications using standardized values for the regulation index and $s = 0.55$.



H1: As documented for similar regulations, the pricing of rental regulations by landlords will lead to higher rents in high regulations compared to less-regulated rental markets.[15]

H2: Due to more tenant screening by landlords to mitigate rent losses, rent defaults in high-regulation markets will be comparable to defaults in less-regulated markets after controlling for rent.

As discussed in the next section, we do not empirically observe landlords' tenant screening efforts, but rather the outcome of those efforts. As increased screening of lease applicants should lead to lower expected defaults, *ceteris paribus*, we empirically examine the marginal effects of regulations on rents and the likelihood of lease default. Our empirical analysis that follows takes advantage of the heterogeneity in state landlord regulations.

Data

Regulations

As real property is generally the purview of local jurisdictions, significant heterogeneity exists in the laws and regulations pertaining to residential lease contracts. We compiled and summarized current state laws and regulations

[15]For the sake of model simplicity, this is an assumption rather than a direct prediction of our model.

governing residential lease contracts for the U.S. states and the District of Columbia from Nolo, a private legal data and service provider.[16] The regulations are coded in state statutes or established by legal precedence and cover many tenant-landlord contractual aspects, from security deposit related issues to conditions under which landlords may unilaterally terminate leases without prejudice. We categorize these regulations into the following four summary groups:

- *Termination for Lease Violation*: The minimum number of days a landlord must give notice to a tenant before unilaterally ending a lease in case of serious violation of contract terms. Longer notice periods protect tenants and increase regulation costs to landlords.
- *Right to Withhold Rent*: Regulations that allow tenants to withhold rent to force landlords to perform repairs and maintenance.
- *Security Deposit Return*: The maximum number of days a landlord may wait before refunding security deposits, with longer waiting periods favoring landlords to the detriment of tenants.
- *Small-Claims Court Limit*: The maximum dollar amount a landlord can sue a tenant for in small-claims courts. This limit effectively caps tenant liability and may be viewed as an indicator of the regulatory environment.

For comparison and aggregation purposes, we recode the regulation variables using a linear scoring system that increases with the level of landlord regulations. With the exception of the *Right to Withhold Rent*, which is coded as a dummy variable, we assign scores ranging from 0 to 3 to individual regulations. Regulations granting the greatest flexibility to landlords have the lowest score (0) and those that seriously restrict landlord rights receive the highest score (3). For the *Right to Withhold Rent* group, states that do not grant tenants this right are assigned 0 and those that do receive 1. Next, we combine the individual regulation scores into an index that is then standardized to the standard normal distribution across the sample (Figure 5).[17] We compiled rental regulations for the 50 continental states and the District of Columbia. Figure 6 shows the geographic distribution of state rental regulations. Table 1

[16]Nolo is a wholly owned subsidiary of Interest Brands. More information about the data and Nolo can be found at http://www.nolo.com/legal-encyclopedia/state-landlord-tenant-laws. We use current landlord regulations because they are generally stable over time. We compare the regulations from Nolo to the ones listed by Landlordology (https://www.landlordology.com/state-laws/), another residential rental information provider, and find a high degree of correlation between the two. We thank Joseph Ooi for bringing this website to our attention.

[17]To give *Right to Withhold Rent* regulation its full weight in the index, we assign it a value of 0 for states that do not allow rent withholding and 3 for states that allow rent withholding.

Figure 5 ■ Raw regulation index density distribution and fitted normal density. [Color figure can be viewed at wileyonlinelibrary.com]

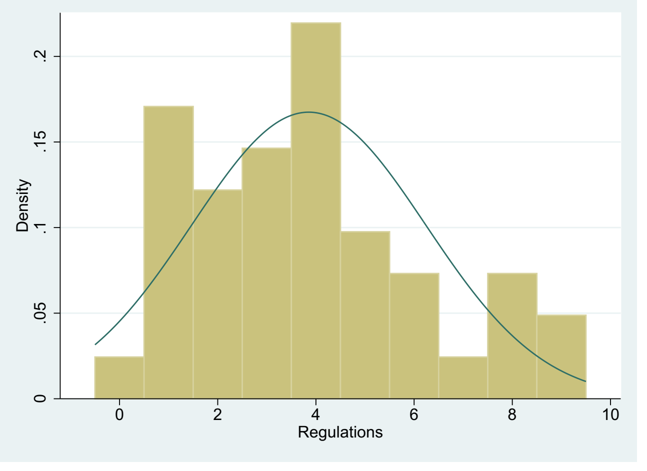
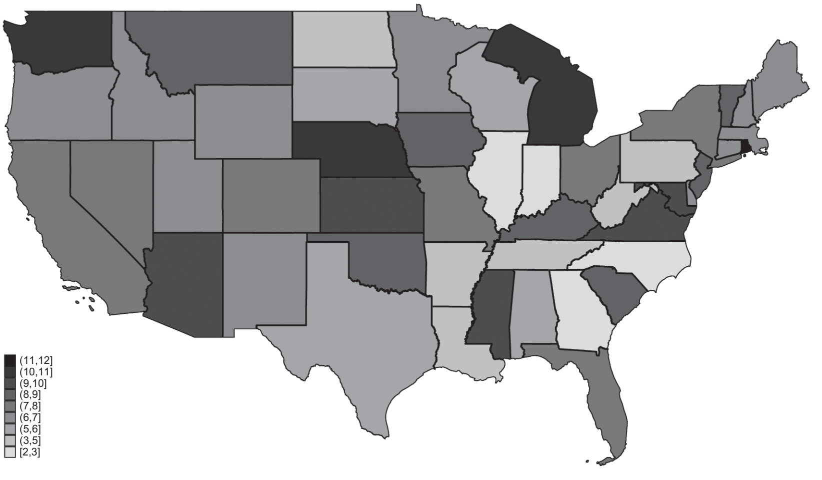


Figure 6 ■ State landlord regulation map (raw regulation index).



summarizes individual regulations and derived index values for the 34 states making our final sample.[18] Michigan has the toughest landlord regulation

[18]As noted later, our final study sample drops to 34 states after the addition of the rent performance and other data.

Table 1 ■ Raw regulations.

	Security Deposit Return (Days)	*Termination Lease Violation (Days)*	*Right to Withhold Rent*	*Small-Claims Court Limit*	*Raw Regulation Index*
Georgia	30	0	No	$25,000	3
Illinois	45	0	No	$10,000	3
Arkansas	60	0	No	$5,000	4
Indiana	45	0	No	$6,000	4
Nortch Carolina	30	0	No	$10,000	4
Tennessee	180	14	Yes	$25,000	5
Louisiana	30	0	Yes	$25,000	6
Pennsylvania	30	0	Yes	$12,000	6
Wisconsin	21	0	Yes	$25,000	6
Idaho	21	3	No	$5,000	7
Minnesota	21	0	Yes	$10,000	7
Texas	30	0	Yes	$10,000	7
Alabama	35	14	No	$3,000	8
California	21	3	Yes	$10,000	8
Florida	60	7	Yes	$5,000	8
New York	180	10	Yes	$5,000	8
Utah	30	3	Yes	$10,000	8
Colorado	30	3	Yes	$7,500	9
Kentucky	60	15	Yes	$2,500	9
Missouri	30	0	Yes	$5,000	9
Nevada	30	3	Yes	$7,500	9

(*Continued*)

Table 1 ■ Continued.

	Security Deposit Return (Days)	*Termination Lease Violation (Days)*	*Right to Withhold Rent*	*Small-Claims Court Limit*	*Raw Regulation Index*
Ohio	30	0	Yes	\$3,000	9
Oregon	31	14	Yes	\$10,000	9
Arizona	14	5	Yes	\$3,500	10
Iowa	30	7	Yes	\$5,000	10
Oklahoma	30	10	Yes	\$7,500	10
South Corolina	30	14	Yes	\$7,500	10
Kansas	30	14	Yes	\$4,000	11
Maryland	45	30	Yes	\$5,000	11
Mississippi	45	30	Yes	\$3,500	11
Nebraska	14	14	Yes	\$3,500	11
Virginia	45	21	Yes	\$5,000	11
Washington	14	10	Yes	\$5,000	11
Michigan	30	30	Yes	\$5,000	12

Note: This table presents raw individual regulations and the raw regulation index for the 34 states in our study sample. The index was computed by classifying states in quartile groups for each regulation and assigning states in each quartile a value from 0 to 3 in increasing order of landlord regulation. For *Right to Withhold Rent*, No is coded as 0 and Yes as 3. Small-claims court limit was capped at \$25,000 when missing.

environment. In contrast, Georgia and Illinois are the most landlord-friendly states.

Table 2 presents the correlation matrix of landlord regulations across the states. The variables are not strongly correlated, indicating heterogeneity in landlord/tenant regulations. This heterogeneity in landlord state regulations also revealed by Figures 5 and 6 should permit identification of the effect of such regulations on landlord behavior. Table 3 gives the summary statistics of states' regulation variables and raw regulation scores. We see that most states require that security deposits be returned within 30 days, even though some states allow as much as 180 days. On average, landlords may terminate leases within eight days, but the majority of states permit almost immediate lease termination in four days or less for serious lease violations. The small-claims court limits range from $2,500 to $25,000, with a mean of roughly $8,600.[19] As the average small-claims court limit is more than nine times the average rent of $938 (from Table 5) and the typical residential lease is 12 months, this regulation may affect how landlords treat delinquent tenants. The majority of states in our sample allow tenants the right to withhold rent in the event a landlord fails to perform repairs and maintenances required under the lease. Again, the regulation scores reported in the bottom half of Table 4 are computed such that higher scores correspond to stricter regulations from the landlord's perspective. The states' raw regulation scores range from 3 to 12 with a mean of 8.1. As identification is achieved by examining variations across states, we normalize this index for use in the subsequent analysis—the standardized scores range from -2.16 to 1.62 with a mean of -0.04. Even though we present the results based on the standardized index values, estimations using the raw index scores produce similar results. Again, we do not observe changes in regulations over time at the state level. Consequently, identification is achieved across states, which explains the omission of location fixed effects in the reduced-form rent and default models that follow.

Rental Data

Our empirical analysis uses multifamily rental data from January 2000 to November 2009 compiled by Experian RentBureau.[20] Ambrose and Diop

[19]We arbitrarily assign $25,000, which is almost twice the maximum amount in our sample, to states that do not set a limit. This is just for ranking purposes and does not affect our findings. The average falls to $5,000 if we omit those states.

[20]We obtained the data from the Wharton Research Data Service (WRDS). Unfortunately, WRDS has not updated the data.

Table 2 ■ Correlation matrix landlord regulations.

	Security Deposit Return	*Termination for Lease Violation*	*Right to Withhold Rent*	*Small-Claims Court Limit*
Security Deposit Return	1.00			
Termination for Lease Violation	−0.17	1.00		
Right to Withhold Rent	−0.05	0.32	1.00	
Small-Claims Court Limit	−0.17	−0.33	−0.05	1.00

Note: This is the correlation matrix of the four raw regulation variables. "*Security Deposit Return*" is the maximum time allowed to return security deposits. "*Termination for Lease Violation*" is the minimum time allowed before eviction due to serious lease violation. "*Right to Withhold Rent*" indicates whether rent withholding is allowed in the state. "*Small-Claims Court Limit*" is the maximum dollar amount landlords can sue for in small-claims courts.

Table 3 ■ Descriptive statistics of landlord regulation variables.

	No. of Obs.	*Mean*	*Std. Dev.*	*Min.*	*Median*	*Max*
Regulation variables						
Security Deposit Return (days)	34	41	37	14	30	180
Termination Lease Violation (days)	34	8	9	0	4	30
Right to Withhold Rent (dummy)	34	0.79	0.41	0	1	1
Small-Claims Court Limit	34	\$8,559	\$6,609	\$2,500	\$5,500	\$25,000
Regulation scores						
Security Deposit Return (score)	34	2.50	0.90	0	3	3
Termination Lease Violation (score)	34	1.18	1.06	0	1	3
Small-Claims Court Limit (score)	34	2.00	1.15	0	2.5	3
Regulation Index (raw)	34	8.06	2.55	3	8.5	12
Regulation Index (standardized)	34	−0.04	1.07	−2.16	0.15	1.62

Note: This table gives the distributional characteristics of the raw regulation variables and the derived regulation scores. For each regulation, expect for the binary "*Right to Withhold Rent*" variable, states are ranked in increasing order and assigned a score from 0 to 3. Each state's scores are then aggregated and the resulting regulation index is then standardized across the states.

(2014) use these data to examine the impact of recent mortgage credit expansion on the rental market. RentBureau maintains residential rental performance data collected nationally from property management companies. The database contains lease characteristics (lease start date, lease termination date, tenant move-in date, tenant move-out date, last transaction date), property location information (city, state and ZIP code) and rent payment records.[21] The company updates rent payment records every month, noting whether rent was paid on time or not, the type of payment delinquency, if applicable, the accrued number of late payments and any write-off on rent and nonrental expenses due. Ambrose and Diop (2014) more fully describe the data.

We restrict our sample to leases with rent between \$250 and \$5,000 and retain metropolitan statistical areas (MSAs) with at least 10 leases in any given month or 120 leases in a year. Table 4 summarizes the data by year. Our sample comprises 1,645,710 leases covering 2,531 properties spread

[21] In addition to the rent performance data, RentBureau also tracks collections on terminated leases. To maintain privacy, limited information is disclosed on individual tenants and property locations.

Table 4 ■ Number of leases, properties and MSA in our sample.

	2000	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*Average*	*Total*
Leases	5,909	20,289	30,564	51,581	84,106	150,692	246,498	397,230	348,168	310,673	164,571	1,645,710
Average Monthly Rent	684	696	695	754	732	863	997	974	1009	962	938	
Properties	39	163	228	386	637	857	1,405	1,707	1,825	1,797	904	2,531
Leases/Property	152	124	134	134	132	176	175	233	191	173	162	
MSAs	8	22	45	60	88	106	117	138	143	138	87	154
Leases/MSA	739	922	679	860	956	1,422	2,107	2,878	2,435	2,251	1,525	
Properties/MSA	5	7	5	6	7	8	12	12	13	13	9	
States	5	8	12	20	27	28	30	34	33	29	23	34
Leases/State	1,182	2,536	2,547	2,579	3,115	5,382	8,217	11,683	10,551	10,713	7,282	
Properties/States	8	20	19	19	24	31	47	50	55	62	40	

Note: The lease data are from RentBureau. Our sample excludes leases with rents less than \$250 or greater than \$5,000. We only keep MSAs with at least 10 (120) leases in any given month (year).

over 154 MSAs and 34 states. RentBureau greatly expanded its geographic coverage over time. Consequently, our sample increases from 5,909 leases in 39 properties located in eight MSAs and five states in 2000 to 310,673 leases in 1,797 properties located in 138 MSAs and 29 states by the end of 2009. The average property size is roughly 162 units. Therefore, our sample is composed primarily of large residential buildings. We do not expect the net increase in geographic coverage over time to impact our findings because identification is achieved across states and the sample is geographically diverse throughout the sample period.[22] Average rent increased roughly from $680 in 2000 to $960 in 2009, with a median of $805.

RentBureau reports rent payments of tenants in 24-digit vectors, recording each tenant's historical payments over the last 24 months ending the month of reporting or the month the lease ended. The reported payment records are therefore left censored because records older than 24 months are missing.[23] Monthly rent payments in the RentBureau data are coded as P (on-time payment), L (late payment), N (insufficient funds or a bounced check), O (outstanding balance at lease termination), W (write-off of rent at lease termination) or U (write-off of nonrent amount owed at lease termination).

We use the payment vectors to generate a monthly payment time series for each lease, keeping only populated payment records.[24] We label any month that is not coded as on-time payment (P) or late payment (L) as a default event. We then generate monthly 0/1 default variables taking the value of 1 if the record is not coded as P or L. Next, we use these default variables to compute (*i*) three- and six-month lease default binary variables, indicating whether tenants have missed at least one payment over the last three and six months, respectively, and (*ii*) MSA-level 12-month moving average default rates and 12-month default forecasts using ARIMA(1,1) used as control variables in our estimations. We summarize the descriptive statistics of lease defaults and MSA default forecasts in the top section of Table 5. The average three- and six-month default on leases in our sample are 5% and 11%, respectively, representing roughly 2% per month. This figure is similar to the average MSA monthly default forecasts of 3%. However, the distributional characteristics show significant heterogeneity in tenant risk across MSAs. As noted earlier, the relation between rent and default is an empirical question.

[22] In the Appendix, we report the results from a robustness check controlling for the change in geographic coverage.

[23] As most residential leases are short term in nature (a year or less), issues associated with the left censoring of tenant payment records are minimized because the leases of problem tenants are generally not renewed.

[24] Payment vectors sometimes contain missing records. Following Ambrose and Diop (2014), missing payment records located between populated cells are recoded as P.

Table 5 ■ Descriptive statistics of rent defaults and control variables.

	No. of Obs.	*Mean*	*Std. Dev.*	*Min*	*Median*	*Max*
Three-Month Default (lease level)	1,645,710	0.05	0.22	0	0	1
Six-Month Default (lease level)	1,645,710	0.11	0.31	0	0	1
MSA Monthly Lease Default (12-Month Forecast)	1,645,710	0.03	0.01	0	0.03	0.18
MSA Monthly Lease Default (12-Month Moving Average)	1,625,696	0.03	0.01	0	0.03	0.17
Monthly Rent (lease level)	1,645,710	$938	$441	$250	$805	$5,000
Fair Market Rent (MSA)	125	$719	$210	$391	$652	$1,448
Unemployment (MSA)	125	0.05	0.01	0.03	0.05	0.10
House Price Index (MSA)	125	188.9	38.8	130.8	177.2	310.7
HOI (MSA)	2,018	61.9	21.7	2.6	68.7	97.5
Inflation (Region)	38	190.3	16.5	163.6	189.7	225.1
Vacancy Rate (State)	226	0.11	0.03	0.04	0.11	0.18
Renter Population (State)	226	0.21	0.01	0.18	0.21	0.26
Affordable Housing Supply State (units)	226	3,379	3,368	19	2,331	16,742
Median Income (State)	226	$52,963	$6,766	$38,666	$52,686	$72,678
Rental Supply State (units)	226	13,481	14,533	797	7,828	78,088
Leading Market Indicator (MSA)	7,517	1.06	0.16	0.63	1.06	1.79
Vacancy Rate (Property)	8,586	0.14	0.12	0.00	0.10	0.83

Note: The lease data are from RentBureau. Our sample excludes leases with rents less than $250 or greater than $5,000. We only keep MSAs with at least 10 leases in any given month or 120 leases during a year. We define a missed rent payment as an event of default. The 6-, 12-, and 24-month defaults indicate whether an event of default has occurred during the relevant time period. Property and MSA average monthly defaults are the averages of individual lease defaults.

Empirical Method

In this section, we explore the impact of landlord regulations on equilibrium rent and defaults. As our regulation measure is ordinal, our analysis focuses on comparing average rents and default rates in high- and low-regulation areas, rather than using a continuous regulation variable in our empirical models.

Rent and Regulations

As noted in the first hypothesis, by imposing nonnegligible costs on landlords, rental regulations become an important consideration in the landlords' profit maximization problem. The costs considered here are those stemming broadly from limitations on the landlords' ability to terminate leases and recover past-due rent payments, property damages and legal fees. Most landlords have the ability to accurately assess and price tenant risk and associated default costs. However, they are generally reluctant to do so because tenant risk may be highly correlated with personal characteristics covered by the Fair Housing Act of 1968, which could expose landlords to lawsuits based on disparate impact.[25] As a result, landlords basically face a choice between accepting or rejecting lease applicants at the posted rents, which normally reflect the weight of existing regulations and general conditions of the rental market.[26]

As previously noted, the pricing of various regulations into rent is widely documented. Thus, landlord regulations should also affect equilibrium rents. As implied by the positive estimated regulations parameter (ψ_1) in Equation (6), we expect contract rent to be lower in less-regulated states due in part to lower regulation costs, the ability of landlords to swiftly remove delinquent tenants before rent delinquencies accumulate and the higher probability of collecting past due rents at lease termination.[27] On the other hand, stringent regulations may impose considerable costs, resulting in rents reflecting those costs and possibly landlords adopting more conservative leasing policies by lowering $\bar{\theta}$, the maximum tenant risk (*i.e.*, default rate) acceptable. To confirm this prediction, we examine the regulation–rent relation by estimating

[25]The Fair Housing Act prohibits discrimination in the sale, rental and financing of dwellings, and in other housing-related transactions. While the law does not specifically prohibit risk-based pricing in residential leasing, it does prohibit discrimination based on race, color, national origin, religion, sex, familial status and disability (Source: https://www.justice.gov/crt/fair-housing-act-2).

[26]This leads to rationing in rental markets as suggested by Stiglitz and Weiss (1981).

[27]We note that fewer landlord regulations alone do not guarantee lower rents. Rather, competition is needed to ensure that landlords do not use their superior bargaining power to the detriment of tenants.

the following model:

$$\ln(Rent_{i,t}) = \alpha_R + \beta_R\, High\, Regulations + \gamma_R\, E[Default_{MSA}] + \mathbf{X}'\,\delta_R + \xi_i, \tag{7}$$

where the dependent variable $Rent_{i,t}$ is the individual lease i's contracted rent in year t; *High Regulations* is an indicator variable representing states with tenant/landlord regulation indexes above the median;[28] $E[Default_{MSA}]$ is the MSA-level average 12-month lease default forecast; X represents a set of variables controlling for differences in property-level characteristics, local rental market conditions, macroeconomic conditions and lease-year fixed effects. The last term, ξ_i, is the estimation error component.[29]

As assumed in the theory section, we expect a positive relation between tenant regulations and rents. However, the effect of expected defaults on rents is unclear. At the individual lease level, risk-based pricing dictates a positive relation between lease default and rent. Our model assumption of no information asymmetry about tenant risk should reinforce this prediction. However, higher rent is likely to lead to more defaults. As a result, increasing rents in response to defaults may not be the most optimal course of action for all landlords. When faced with mounting defaults, landlords may also ration credit by expelling delinquent tenants. Therefore, it is unclear that the best response to deteriorating tenant risk is further rent increases. We measure expected default at the MSA level, rather than at the individual lease level using a rolling 12-month forecast of MSA-level tenant defaults. In summary, the relation between expected default and rent is an empirical question.

Screening and Regulations

Next, we consider our main hypothesis concerning the relation between regulations and tenant default. Increasing rents to account for rental regulation costs is likely to lead to more defaults. Consequently, this *direct effect* of rental regulations on defaults through rent implies a positive relation between default and regulations. As a result of the projected increase in defaults, it may be worthwhile for landlords to take preemptive actions by more carefully screening lease applicants in order to lower tenant risk. This is the negative *indirect effect* of regulations on defaults stemming from the additional tenant

[28]This choice is somewhat arbitrary. The results are unchanged if we use the mean regulation value as cutoff.

[29]We estimate Equation (7) using OLS with standard errors clustered at the property level because rent level and tenant screening decisions are made at the property management level.

screening by landlords in response to regulations predicted by our model. In summary, landlords have two levers at their disposal to control the effects of costly rental regulations: rent adjustments and tenant screening. While the effect of regulations on rent is unequivocally positive, their net effect on observed lease defaults is unclear because it is not necessarily the case that the *positive direct effect* of regulations on defaults will dominate the *negative indirect effect* stemming from tenant screening by landlords.

Conditional on the regulatory environment and the state of the rental market, we assume that each landlord's profit maximization problem dictates an optimal threshold of acceptable tenant risk ($\bar{\theta}$) he is willing to bear. The less restrictive (or less costly to landlords) regulations become, the higher $\bar{\theta}$ and the higher the observed average risk of approved lease applicants, which should translate into more lease defaults *ex post*.[30] Everything else the same, a high $\bar{\theta}$ strategy becomes optimal when regulation costs are low because the regulatory system allows landlords to efficiently deal with tenant defaults. In contrast, restrictive landlord regulations may result in significantly less risk taking by landlords (*i.e.*, lower $\bar{\theta}$s), which is tantamount to credit rationing. Again, we do not observe direct tenant screening by landlords or their chosen $\bar{\theta}s$. However, we observe tenant defaults that are positively related to $\bar{\theta}$, allowing us to analyze the relation between regulations and defaults using the following model:

$$\Pr(Default_{i,t}) = \alpha_D + \beta_D\, High\,Regulations + \gamma_D\, Rent_{MSA} + \mathbf{X}'\,\delta_D + \omega_{it}, \quad (8)$$

where $Default_i$ is a 0/1 variable indicating whether lease i defaulted during the time period t (the first three or six months). *High Regulations* and X have the same meanings as in Equation (7); $Rent_{MSA}$ is the average MSA rent at t; and ω_i represents the estimation error term. Our model predicts that landlords have a greater propensity to screen lease applicants when regulations are high. Equation (8) allows us to directly gauge the effect of such screening efforts by comparing average default rates in low-regulation and high-regulation states. The estimated value of β_D indicates the difference in average rent defaults between the two regulatory environments and we expect β_D to be nonpositive if landlords' tenant screening efforts are productive.

Although the majority of rental regulations covered in this study were enacted in the 1980s or earlier and they tend to be persistent (Rabin 1983; Goetz 1984), we recognize that these regulations may have arisen endogenously in response to the behaviors of market participants and that these behaviors may

[30]In addition, the more competitive the rental market, the higher $\bar{\theta}$ should become.

be persistent.[31] Thus, to address this potential endogeneity concern between regulations and tenant risk, we estimate Equation (8) using an IV approach. In order to achieve identification, we instrument on the 2000 state-level estate tax rates.[32] The intuition behind this instrument is that citizens in states with higher levels of regulations tend to favor larger government involvement, and thus these states are likely to have higher taxes than states with populations that prefer more limited government. We instrument on estate tax rates because they should be exogenous to rental market outcomes. The rational is that changes in estate tax rates are unlikely to affect the population residing in rental housing (demand) or the institutional investors supplying the rental housing covered in our data.

Control Variables

Table 5 reports the summary statistics of the various control variables (X) capturing differences in property characteristics, local market conditions and the macroeconomic environment. Contract rents reflect the restrictions applied to our sample. Even though half of the leases in our sample have rents of \$805 or less, a significant number of properties have much higher rents. The locality and macroeconomic control variables proxy for factors driving the rental market and the general economy. For example, MSA fair market rents (FMRs) capture changes in local rents.[33] We also control for rental vacancy at the property level derived from the RentBureau data and locally using state rental vacancy rates. To account for the overall growth in the supply of rental housing, we include the number of building permits for rental units and the affordable housing supply proxied by the number of low income housing tax credit (LIHTC) units built during the year in each state.[34] The percentage of the state's population in the 20-year to 34-year age group relative to the state's population controls for shifts in rental demand.

Local and national economic conditions affect the riskiness of the rental market and therefore landlords' decisions. Thus, we include median income

[31]For example, increased rental market risk may lead landlords to lobby for weaker tenant protections. Alternatively, soaring rent may lead to tenants calling for stronger tenant rights.

[32]This variable measures 2000 estate tax receipts as a percentage of total tax receipts by state (Source: U.S. Census Bureau – http://www.census.gov/govs/www/statetax.html).

[33]FMR data are produced by the U.S. Department of Housing and Urban Development (HUD; http://www.huduser.org/portal/datasets/fmr.html).

[34]We include affordable housing supply because the availability of affordable housing should attract risker tenants, hence leading to lower rental default. LIHTC is a program run by HUD to provide resources for the supply of affordable housing to low-income households in the United States (https://www.huduser.gov/portal/datasets/lihtc.html).

and housing affordability as additional explanatory variables in the default and rent models. We control for housing affordability to capture the effect of tenure choice decisions on rental market outcomes, particularly rental market risk (Ambrose and Diop 2014). We use the Housing Opportunity Index (HOI) developed by the National Association of Home Builders (NAHB) and Wells Fargo to control for geographic differences in housing affordability. HOI compares the median family income to median house prices quarterly at the MSA level. Thus, the more affordable a market, the higher HOI.[35]

Results

Rent and Regulations

As we noted in Hypothesis H1, a cross-sectional analysis should reveal that higher regulation costs lead to higher rent in equilibrium.[36] To confirm this prediction, we begin by reporting in Table 6 the OLS estimation results of Equation (7). The variable of interest (*High Regulations*) indicates states with above median standardized aggregate regulation indexes.[37] In column (1), we proxy expected lease default measured at the MSA level using monthly 12-month ARIMA(1,1) default forecasts and cluster standard errors at the tenant level.[38] But since rents are set by property owners in response to the regulatory environment and market conditions, we cluster the standard errors at the property level in columns (2) and (3). Also, our measure of expected MSA rental default risk in column (1) is somewhat arbitrary. Hence, we provide an alternative default rate specification in column (3) where expected rental default is the 12-month moving average MSA default rates.

Consistent with findings reported in the literature (Hirsch, Hirsch and Margolis 1975; Miron 1990), the results across the specifications confirm that rents are higher in more regulated cities (the estimated coefficients are

[35]The HOI is defined as the share of homes sold in an MSA that would have been affordable to a family earning the MSA median income, based on standard mortgage underwriting criteria. NAHB assumes that a family can afford to spend 28% of its gross income on housing. HOI is the share of houses sold in a metropolitan area for which the monthly median income available for housing is at or above their monthly mortgage costs. http://www.nahb.org/reference_list.aspx?sectionID=135

[36]Lower regulations may also enhance competition by facilitating market entry, leading to lower rent in equilibrium and limiting the ability of landlords to increase rent in the future.

[37]The standardized index ranges from −2.16 to 1.62 with a standard deviation of 1.

[38]We compute average MSA lease defaults using the RentBureau data. Next, we forecast MSA default rates for the next 12 months using ARIMA(1,1) and then take the average of monthly default forecasts as the MSA's expected default.

Table 6 ■ Rent estimation results.

	(1) *Log Rent*	*(2)* *Log Rent*	*(3)* *Log Rent*
High Regulations	0.0934***	0.0934***	0.0939***
	(0.0008)	(0.0184)	(0.0183)
MSA Lease Default (12-Month Forecast)	−2.8984***	−2.8984***	
	(0.0274)	(0.5324)	
MSA Lease Default (12-Month Moving Average)			−2.8028***
			(0.5290)
FMR MSA (log)	0.7463***	0.7463***	0.7398***
	(0.0016)	(0.0372)	(0.0368)
Median Income State (log)	0.6227***	0.6227***	0.6322***
	(0.0038)	(0.0847)	(0.0844)
Vacancy Rate (State)	−2.0945***	−2.0945***	−2.0820***
	(0.0117)	(0.2322)	(0.2286)
Renter Population (State)	−0.9959***	−0.9959	−0.9790
	(0.0270)	(0.6416)	(0.6415)
House Price Index (MSA)	0.0002***	0.0002	0.0002
	(0.0000)	(0.0002)	(0.0002)
Affordable Housing Supply State (log)	0.0214***	0.0214**	0.0231**
	(0.0005)	(0.0094)	(0.0093)
Rental Supply State (log)	0.0063***	0.0063	0.0053
	(0.0005)	(0.0104)	(0.0103)
Lease-Year FE	Yes	Yes	Yes
SE Clusters	Tenant	Property	Property
Observations	*1,645,710*	*1,645,710*	*1,645,710*
Adjusted R^2	*0.449*	*0.449*	*0.449*

Note: These are OLS estimation results of log rent following the model specification in Equation (7). Our variable of interest, *High Regulations*, is an indicator variable that is equal to 1 for states whose regulation index (as defined in this article) is greater or equal to the sample median and equal to 0 otherwise. The figures in parentheses are property clustered standard errors, with *, ** or *** indicating statistical significance at 10%, 5% or 1%.

statistically significant at the 1% level), providing evidence that regulations ostensibly designed to help renters ultimately hurt the intended beneficiaries. Furthermore, the economic effect is large. The estimated coefficient indicates that average rents in high-regulation states are 9.3% higher than in less-regulated locations. To place this in perspective, we note that the average annual rent in 2009 is $11,544.[39] Thus, the estimated coefficient implies that if an area moved from below the median to above the median in tenant regulations, then landlords would respond by increasing annual rents by $1,078. As the 2009 median household income for all renters was $31,463, a 9.3%

[39]From Table 3 $962 × 12 = $11,544.

increase in the average 2009 rent level (from \$11,544 to \$12,622) would increase the mean rent-to-income ratio (a measure of housing affordability) from 36.7% to 40.1%.[40]

We use average 12-month rent default forecasts to proxy for changes in credit risk at the MSA level in columns (1) and (2). The negative and statistically significant (at the 1% level) coefficient confirms that higher default rates have negative impacts on rent. The estimated coefficient for the default variable implies that a one-point increase in the predicted default rate is associated with a 2.9% decline in the average monthly rent. Although prices are generally expected to adjust positively to increases in risk, the significantly negative coefficient on rental default implies that landlords respond to a deterioration in credit risk by slightly lowering rent, rather than risk-adjusting rent upward, which might cause more defaults and higher income losses.[41] As a robustness check, we also estimate the model using a 12-month moving average of the prior MSA default rate and note that the results are qualitatively the same.

We also see that most of the control variables, which are lagged relative to the dependent variable, display the expected influence on rent.[42] For example, contracted rents are positively correlated with local rent proxied by FMR and income. As expected, rents decrease with vacancy rate and increase with house prices. The other control variables show no significant effect on rent in columns (2) and (3). The fact that our model is able to reproduce most of these intuitive results gives us comfort about the predicted positive relation between rents and regulations and the negative relation between rents and expected defaults.

In addition to the lease-level rent estimations discussed earlier, we also performed property-level estimations where our dependent variable is logged property-averaged rents. Normally, the pricing of regulations into rents confirmed by lease-level regressions should also materialize in property-level rent regressions, although the statistical significance of the estimate may be weaker. Property-level rent estimation results reported in column (1) of

[40]The median household income is obtained from the *Current Population Survey* (CPS) Annual Social and Economic (ASEC) Supplement for 2010, accessed at http://www.census.gov/data/tables/time-series/demo/income-poverty/cps-hinc/hinc-01.2009.html.

[41]Kim (2018) shows that it may be optimal for landlords to give rent discounts to delinquent tenants to lower payment delinquencies.

[42]The results are consistent with the findings of Bracke (2015) and Verbrugge *et al.* (2017) with respect to the relationship between rent and vacancy rates and house prices.

Table A1 of the Appendix confirm the positive relation between rent and regulations derived from the lease-level analysis. The magnitudes of the effect are comparable (0.0934 vs. 0.0739), with the estimated coefficient still significant at 1% confidence level. We also derive additional comfort from the rent estimation result controlling for the expansion in RentBureau's geographic coverage result reported in column (1) of Table A2 of the Appendix.[43] To confirm that changes in our sample composition over time do not drive our finding, we restrict our rent estimation to the 89 MSAs represented in our sample during the first five years from 2000 to 2004. We find from this restricted estimation that rent is still positively correlated with regulations. In summary, these results confirm the pricing of regulations by landlords.

Screening and Regulations

Table 7 reports the average marginal effects from the two-stage least squares (2SLS) estimation of regulations on the likelihood of three- and six-month lease defaults (Equation 8). Again, we instrument on the state estate tax rates. Columns (1) and (2) report the results for where the dependent variable is the individual lease-level three- and six-month default rate, respectively, with standard errors clustered at the tenant level, while columns (3) and (4) report the standard errors clustered at the property level. The first-stage results are reported in the Appendix (Table A3). As discussed, our instrument likely meets the exogeneity requirement needed for a valid IV and as the first-stage regression shows state estate taxes and regulations are strongly correlated with an adjusted R^2 of 0.63. Furthermore, our 2SLS exogeneity test unequivocally rejects the exogeneity of regulations (p-value $= 0.000$).

Consistent with the prediction from our main hypothesis H2, the estimated coefficient of our variable of interest (*High Regulations*) is negative and statistically significant. The results confirm the prediction that high-regulation states experience lower default rates than low-regulation states. On average, tenants in high-regulation states experienced a 22% lower default rate over six months. This effect is consistent with our theoretical prediction that landlords are more likely to screen lease applicants in highly regulated markets, which results in significantly lower lease default rates. In contrast, landlords may be more willing to accept riskier tenants in less-constraining rental markets. Even though such a strategy results in more defaults *ex-post*, the associated costs are relatively low because landlords can easily remove delinquent tenants and release the units.

[43]RentBureau expanded its geographic coverage from 8 to 138 MSAs (Table 3). In addition to expanding its geographic coverage, RentBureau also significantly increased market penetration.

Table 7 ■ Two-stage least squares (2SLS) estimation results of three-month and six-month lease defaults.

	(1) *Three-Month Default*	*(2)* *Six-Month Default*	*(3)* *Three-Month Default*	*(4)* *Six-Month Default*
High Regulations	−0.0902***	−0.2202***	−0.0902***	−0.2202***
	(0.0054)	(0.0077)	(0.0340)	(0.0795)
FMR MSA (log)	−0.0126***	−0.0236***	−0.0126	−0.0236
	(0.0018)	(0.0025)	(0.0087)	(0.0185)
Median Income State (log)	−0.1875***	−0.4180***	−0.1875***	−0.4180***
	(0.0077)	(0.0111)	(0.0522)	(0.1199)
Renter Population (State)	1.7664***	4.2191***	1.7664***	4.2191***
	(0.0988)	(0.1423)	(0.6416)	(1.5065)
Vacancy Rate (Property)	0.0261***	0.0256***	0.0261***	0.0256
	(0.0021)	(0.0029)	(0.0093)	(0.0188)
House Price Index (MSA)	−0.0003***	−0.0009***	−0.0003*	−0.0009**
	(0.0000)	(0.0000)	(0.0002)	(0.0004)
HOI (MSA)	0.0006***	0.0012***	0.0006***	0.0012***
	(0.0000)	(0.0000)	(0.0002)	(0.0004)
Affordable Housing Supply State (log)	−0.0126***	−0.0345***	−0.0126***	−0.0345***
	(0.0008)	(0.0011)	(0.0046)	(0.0106)
Rental Supply State (log)	0.0201***	0.0535***	0.0201**	0.0535***
	(0.0013)	(0.0018)	(0.0079)	(0.0184)
Lease-Year FE	Yes	Yes	Yes	Yes
SE Clustering	Tenants	Tenants	Properties	Properties
Observations	*1,207,712*	*1,207,712*	*1,207,712*	*1,207,712*
Wald Chi-squared	*3,552.99*	*7,214.49*	*198.18*	*238.54*

Note: These are 2SLS estimation results of three-month and six-month lease defaults. We instrument for regulations using 2000 state estate taxes (Source: U.S. Census Bureau – http://www.census.gov/govs/www/statetax.html). The estimates' standard errors in parentheses are clustered at the tenant level in columns (1) and (2), and at the property level in columns (1') and (2'). The superscripts *, ** or *** stars indicate statistical significance at 10%, 5% or 1%, respectively.

To make sure we identify the true effect of regulations on lease default, we include various control variables in our model. In addition to lease-year fixed effects, we employ a battery of control variables likely to explain defaults, namely, market rent, income, vacancy, rental supply and housing affordability. The effects of most of these variables on defaults are intuitively predictable. For example, higher state median income, a proxy for credit risk, is strongly associated with fewer defaults. As expected, high vacancy at the property level is associated with more defaults as landlords relax credit screening in order to increase absorption. As homeownership is a substitute to renting, housing affordability measured by HOI has a negative effect on the rental market as better quality renters move into homeownership, leaving behind a riskier rental pool, a fact documented by Ambrose and Diop (2014). Finally, an expansion in affordable housing, as indicated by the number of LIHTC units built in the state, is correlated with fewer defaults, *ceteris paribus*, possibly by attracting a larger share of riskier tenants into subsidized housing and altering the tenant credit-risk profile in institutional grade properties.

We also check whether property-level regression would yield similar results. The results reported in columns (2) and (3) of the Appendix (Table A1) also yield negative coefficients for *High Regulations*.[44] We also confirm that changes in the sample composition over time do not affect our default results. Despite the resulting limited geographic coverage, the six-month default estimation results restricted to earlier (2000–2004) MSAs in columns (2) and (3) of Table A2 also depict a negative relation between regulation and defaults.

In summary, our rent and default results lead to the conclusion that tenant-friendly regulations may actually harm the intended beneficiaries. First, the associated costs are passed on to tenants in the form of higher rents due to the relative inelasticity of rental demand. Second, landlords are likely to screen out risky tenants leading to the classic Stiglitz and Weiss (1981) credit rationing story in rental markets.

The Importance of Landlord Size

Until now, we have abstracted from the issue of landlord heterogeneity. Our theoretical model does not cover this aspect of the rental market, but a general equilibrium analysis of the rental market is likely to lead to separating equilibria made up of numerous submarkets, each characterized by relatively

[44]In this instance, property-level default variables are not binary, but rather continuous over [0,1]. We regress average lease default at the property level on regulations using the same set of control variables as in Table 7.

homogeneous landlords and renters (Miron 1990). Thus, our previous landlord optimization analysis remains valid in this context as our sample is characteristic of the multifamily submarket predominantly composed of large rental properties.

However, even within the submarket defined by our sample, heterogeneity exists across landlords. Thus, in this section, we explore the effects of landlord heterogeneity on rent and default. As the RentBureau data do not include landlord or property owner identifiers, we use property size as a proxy.[45] We measure property size as the maximum of the number of leases observed in the RentBureau data every month during the study period.[46]

Table 8 presents the results from our extended rent and default models that include a large property size dummy and its interaction with regulations. *Large Property* takes the value of 1 if the size of the property is above the sample's median size.[47] Column (1) shows that large properties generally have significantly higher rents of about 2.4% on average, after controlling for various market and macroeconomic factors. While we cannot definitely identify the source of this higher rent, the most plausible explanation lies with larger apartment complexes generally having higher quality amenities.[48] However, rent adjustments to regulations, which are positive, are largely identical for small and large properties, as evidenced by the insignificant coefficient of the regulations–large property interaction term. As noted previously, column (1) of Table 8 confirms the reluctance of landlords to adopt risk-based rent pricing.

Despite commanding higher rents, larger properties experience fewer defaults as evidenced by the significant negative coefficient of the large property dummy in column (2) of Table 8. This result supports our amenities-based theory as the most plausible explanation of higher rents for larger

[45] Although some landlords are likely to own several properties in each market they operate, it is likely that they will consider the profitability of each property separately.

[46] This measure has some shortcomings. It may lead lower vacancy rates by not reflecting normal vacancy rates because it is based on occupied units. Furthermore, it does not allow changes in property size over time.

[47] We perform the property size sorting only once. However, our findings are unchanged if we perform the sorting annually, for example.

[48] Other possible explanations include higher bargaining power for larger landlords (Gilderbloom 1989) or strategic behavior of smaller landlords to lower vacancy (Downs 1996). Downs argues that smaller owners wish to avoid vacancies and thus may be unwilling to quickly increase rents to market-clearing levels. Gilderbloom hypothesizes that rents tend to be higher in markets dominated by a few large landlords. We also note that Verbrugge *et al.* (2017) raise concerns about using rent levels to infer quality.

Table 8 ■ Effects of landlord size on rent and default.

	(1) *Log Rent* *OLS*	*(2)* *Six-Month Default* *2SLS*
High Regulations	0.0973***	−0.2143***
	(0.0182)	(0.0793)
Large Property	0.0241**	−0.0195***
	(0.0117)	(0.0067)
High Regulations x Large Property	−0.0140	−0.0221
	(0.0204)	(0.0166)
MSA Lease Default (12-Month Forecast)	−2.8745***	
	(0.5285)	
FMR MSA (log)	0.7435***	−0.0221
	(0.0369)	(0.0190)
Median Income State (log)	0.6149***	−0.4187***
	(0.0841)	(0.1195)
Vacancy Rate	−2.1200***	0.0203
	(0.2341)	(0.0190)
Renter Population (State)	−0.9905	4.2119***
	(0.6412)	(1.4983)
House Price Index (MSA)	0.0002	−0.0009**
	(0.0002)	(0.0004)
Affordable Housing Supply State (log)	0.0203**	−0.0332***
	(0.0093)	(0.0105)
Rental Supply State (log)	0.0070	0.0526***
	(0.0104)	(0.0182)
HOI (MSA)		0.0012***
		(0.0004)
Lease-Year FE	Yes	Yes
SE Clustering	Properties	Properties
Observations	*1,645,710*	*1,207,712*
R-squared/Chi-squared	*0.449*	*309*

Note: This table presents OLS rent estimation and 2SLS estimation of six-month lease default controlling for property size. Large Property is a binary variable set to 1 if property size is greater that the sample's median property size. The figures in parentheses are property-clustered standard errors with *, ** or *** indicating statistical significance at 10%, 5% or 1%, respectively.

properties.[49] Also, the default estimation implies that larger properties are not more likely to implement stricter tenant screening rules in reaction to regulations. Again, default appears to be negatively related to rent at the MSA level, which likely proxies for property and/or tenant quality. The

[49]See Beracha *et al.* (2018) for evidence regarding the pricing of amenities in housing markets.

Table 9 ■ Landlord size and vacancy rates.

	(1) *Vacancy Rate*
High Regulations	−0.0029
	(0.0022)
Large Property	−0.0051
	(0.0043)
High Regulations × Large Property	0.0168**
	(0.0067)
Property Lease Default (Lag 12-mo Average)	0.0059
	(0.0206)
MSA Lease Default (Lag 12-mo Average)	−0.0803
	(0.0758)
Rent Property (log)	−0.0079*
	(0.0041)
FMR MSA (log)	0.0022
	(0.0073)
Median Income State (log)	0.0023
	(0.0138)
Growth Rental Demand (State)	−0.4332***
	(0.1411)
Rental Supply State (log)	0.0051***
	(0.0014)
Lease-Year FE	Yes
Observations	*5,748*
R-squared	*0.116*

Note: These are results from OLS estimation vacancy rates at the property level. Large Property is a binary variable set to 1 if property size is greater that the sample's median property size. The figures in parentheses are robust White standard errors with *, ** or *** indicating statistical significance at 10%, 5% or 1%, respectively.

remaining rent and default control variables behave largely as previously reported.

Finally, we explore the effect of regulations on vacancy rates because building occupancy may also be affected by landlord rent setting and tenant screening decisions. Using the RentBureau data, we compute monthly property vacancy rates by comparing the total number of leases outstanding each month to the property size and then derive average property and MSA vacancy rates used in the vacancy model in Table 9. We lag explanatory variables relative to vacancy. Table 9 shows that, on average, larger properties do not experience higher vacancy rates, despite charging higher rents (column (1) in Table 8). We speculate that this result is probably due to higher demand for that type of property, which would also lead to lower defaults (column (2) in Table 8).

Table 9 also documents a positive relation between regulations and vacancy rates for larger properties. As stricter landlord regulations cause tighter tenant screening by large landlords, which results in the negative relation between regulations and defaults, vacancy should normally rise. Table 9 documents this effect, which supports the argument advanced by Downs (1996) that smaller landlords in general prefer to avoid vacancies. The remaining control variables in the vacancy model show as expected that vacancy decreases with rental demand and increases with supply. The surprising negative effect of property rent on vacancies may be due to stronger demand for properties offering higher amenities.

Conclusion

Using lease-level performance data, we present new evidence on the impact on landlord behavior and ultimately equilibrium market outcomes of policies that limit the rights of property owners. We confirm that market rents reflect regulatory costs. However and more importantly, we show that as regulations impinge on landlords' operational flexibility, landlords increase investment in tenant screening to lower incidental costs. Unfortunately, tenant screening leads to a form of credit rationing and thus reduces the supply of rental housing. As a result, our findings suggest that landlord regulations that presumably were designed to benefit vulnerable lower income tenants may ultimately limit access to rental housing for this segment of the population. Thus, in the long term, low-income households may be more likely to benefit from policies aimed at increasing the supply elasticity of rental housing rather than from stricter landlord regulations.

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Appendix A

Table A1 ■ OLS rent and 2SLS default estimations at the property level.

	(1) Log Avg. Rent OLS	*(2) Three-Month Default 2SLS*	*(3) Six-Month Default 2SLS*
High Regulations	0.0739^{***}	-0.0414^{***}	-0.0622^{***}
	(0.0029)	(0.0082)	(0.0086)
MSA Lease Default (12-Month Forecast)	-1.8455^{***}		
	(0.0879)		
FMR MSA (log)	0.7106^{***}	-0.0105^{***}	-0.0077^{***}
	(0.0061)	(0.0020)	(0.0019)
Median Income State (log)	0.5115^{***}	-0.0755^{***}	-0.1024^{***}
	(0.0137)	(0.0088)	(0.0090)
Vacancy Rate	-2.2494^{***}	0.0125^{***}	0.0089^{***}
	(0.0446)	(0.0023)	(0.0023)
Renter Population (State)	0.0143	0.8955^{***}	1.3343^{***}
	(0.0951)	(0.1540)	(0.1597)
House Price Index (MSA)	−0.0000	-0.0001^{***}	-0.0002^{***}
	(0.0000)	(0.0000)	(0.0000)
Affordable Housing Supply State (log)	0.0181^{***}	-0.0078^{***}	-0.0130^{***}
	(0.0018)	(0.0014)	(0.0014)
Rental Supply State (log)	0.0210^{***}	0.0099^{***}	0.0163^{***}
	(0.0019)	(0.0021)	(0.0022)
HOI (MSA)		0.0004^{***}	0.0005^{***}
		(0.0000)	(0.0001)
Lease -Year FE	Yes	Yes	Yes
line *Observations*	*107,654*	*79,592*	*79,592*
Adjusted R-squared/Chi-squared	*0.442*	*1,180.83*	*1,225.14*

Note: These are results from OLS estimation of rent and 2SLS estimation of three-month and six-month defaults at the property level. The dependent variable in column (1) is log of average monthly rent, computed for each property on leases outstanding every month. The default variables in columns (2) and (3) are average three-month and six-month default rates at the property level. The figures in parentheses are robust White standard errors, with *, ** or *** indicating statistical significance at 10%, 5% or 1%, respectively.

Table A2 ■ Rent and default estimations restricted to 2000–2004 MSAs.

	(1) *Log Rent* *OLS*	(2) *Three-Month Default* *2SLS*	(3) Six-Month Default *2SLS*
High Regulations	0.0876***	−0.0935***	−0.2209***
	(0.0203)	(0.0329)	(0.0746)
MSA Lease Default (12-Month Forecast)	−1.6656***		
	(0.5537)		
FMR MSA (log)	0.6666***	−0.0199**	−0.0364*
	(0.0394)	(0.0095)	(0.0196)
Median Income State (log)	0.8188***	−0.2182***	−0.4914***
	(0.0929)	(0.0640)	(0.1435)
Vacancy Rate	−1.7790***	0.0259***	0.0238
	(0.2359)	(0.0099)	(0.0194)
Renter Population (State)	−0.6256	2.0242***	4.7057***
	(0.7046)	(0.7087)	(1.6139)
House Price Index (MSA)	0.0004**	−0.0003**	−0.0007**
	(0.0002)	(0.0001)	(0.0003)
Affordable Housing Supply State (log)	0.0318***	−0.0119***	−0.0320***
	(0.0095)	(0.0039)	(0.0086)
Rental Supply State (log)	0.0059	0.0220***	0.0563***
	(0.0106)	(0.0079)	(0.0180)
HOI (MSA)		0.0007***	0.0014***
		(0.0002)	(0.0004)
Lease-Year FE	Yes	Yes	Yes
SE Clustering	Properties	Properties	Properties
Observations	*1,510,871*	*1,150,159*	*1,150,159*
Adjusted R-squared/Chi-squared	*0.438*	*201.78*	*244.79*

Note: This table presents OLS rent estimation and 2SLS default estimation results when we restrict our sample to the 89 MSAs represented in our sample from 2000 to 2004. The figures in parentheses are property-clustered standard errors with *, ** or *** indicating statistical significance at 10%, 5% or 1%, respectively.

Table A3 ■ First stage of 2SLS estimation of lease defaults.

	(1) *High Regulations*
Estate Tax	-0.1045^{***}
	(0.0364)
FMR MSA (log)	-0.0119
	(0.0680)
Median Income State (log)	-1.2806^{***}
	(0.1813)
Renter Population (State)	13.5386^{***}
	(2.1436)
Vacancy Rate (Property)	-0.1396^{***}
	(0.0478)
House Price Index (MSA)	-0.0046^{***}
	(0.0004)
HOI (MSA)	0.0030^{***}
	(0.0011)
Affordable Housing Supply State (log)	-0.1537^{***}
	(0.0202)
Rental Supply State (log)	0.2823^{***}
	(0.0291)
Lease-Year FE	Yes
SE Clustering	Properties
Observations	*1,207,712*
Adjusted R-squared	*0.628*

Note: These are the results of the first-stage of the 2SLS estimation of lease defaults reported in Table 7. The dependent variable is our high-regulation dummy. Our instrument for regulations is state estate tax. The standard errors in parentheses are clustered at the property level with *, ** or *** indicating statistical significance at 10%, 5% or 1%, respectively.