

---

# The Impact of Tenant Diversification on Spreads and Default Rates for Mortgages on Retail Properties

Brent Ambrose

*The Smeal College of Business The Pennsylvania State University  
University Park, USA*

Michael Shafer<sup>1</sup>

*School of Business Providence College, USA*

Yıldıray Yıldırım

*Whitman School of Management Syracuse University, Syracuse, NY, USA*

## Abstract

We use an empirical model of commercial mortgage spreads to examine how tenant diversification impacts credit spreads for mortgages on retail properties. We find that mortgages on properties with a highly diversified tenant base have spreads that are up to 8.5 basis points higher than spreads on mortgages for single-tenant properties, but that mortgages on properties with moderate levels of tenant diversification have spreads that are up to 5.5 basis points lower than mortgages on single-tenant properties. The spread discount for mortgages on properties with moderate levels of tenant diversification disappears when the lease of the property's largest tenant expires before the loan matures. Despite the spread discount that is given to properties with moderate levels of tenant diversification, we find that the likelihood with which a mortgage goes into default increases as tenant diversification increases.

**Keywords:** Commercial mortgages, mortgage spreads, tenant diversification

## 1. Introduction

Traditional portfolio theory dictates that a greater degree of diversification leads to a greater amount of safety for investors. Considering that a commercial property's value is effectively reliant on cash flows that are generated by a portfolio of tenants, it is natural to assume that commercial properties with greater diversification in their tenant mix (i.e., a large rent roll) should have more stable cash flows than properties that are less diversified. If this is indeed the case, then mortgage lenders should recognize the benefits of tenant diversification by offering lower mortgage spreads to properties whose tenant base is more diverse than similar, less diverse properties. However, given the fixed physical size of commercial properties, there may also be benefits to limiting the degree of tenant diversification. For instance, tenants that lease

---

<sup>1</sup> Corresponding author: Telephone 401-865-1928. We thank JPMorgan Chase for providing access to data from the Trepp Data Feed and for providing valuable feedback on the paper. We thank Sergey Tsyplakov, Richard Green, John Clapp, and Andy Naranjo, and seminar participants at the 2015 AREUEA-ASSA meetings in Boston, The Homer Hoyt Institute, and Providence College for their helpful comments. All errors and omissions are our own.

larger amounts of space are likely to be more creditworthy and to provide property owners with rental payments that are stable and predictable.

In this paper, we empirically investigate how the structure of a property's rent roll influences the credit spreads charged by commercial mortgage lenders. Our analysis suggests a U-shape pattern indicating that lenders value moderate levels of tenant diversification, but that properties with the highest levels of tenant diversification have spreads that are higher than spreads on mortgages for single-tenant properties. However, these results are sensitive to the relation between the expiration date on the lease of the property's largest tenant and the maturity date of the mortgage. We find that the U-shaped interest rate spread pattern disappears when the largest tenant's lease expires before the mortgage matures. Our findings confirm the importance of tenant diversification and lease rollover risk in mortgage underwriting.

In addition to our analysis of commercial mortgage spreads, we examine how a property's rent roll influences mortgage default rates. We find that the likelihood with which a mortgage defaults increases as the level of tenant diversification on the property increases. Thus, increasing levels of tenant diversification are associated with increasing levels of default risk. We also find that lease rollover risk increases default risk regardless of how diversified a property's rent roll is. Overall, our analysis confirms that a property's tenant portfolio and lease structure is important in assessing the riskiness of commercial mortgages.

There is an extensive literature documenting the importance of tenant characteristics and the structure of tenant portfolios. For example, Colwell and Munneke (1998) note that a landlord adds value to a portfolio of leases by bringing together a diverse group of tenants. Ciochetti et al. (2003) acknowledge that the credit quality of tenants influences default risk. When modeling default risk, they attempt to capture the impact of tenant credit quality by controlling for property types, as property types are assumed to be heterogeneous with respect to tenant credit riskiness. Grovenstein et al. (2005) point out that lenders consider current tenants and lease structure as part of the risk in commercial mortgage lending. Titman, Tompaidis and Tsyplakov (2005) view property size as a potential proxy for diversification and expect larger properties to have lower spreads at least in part due to this diversification.

In addition to providing diversification benefits to a property owner's cash flow stream, having multiple tenants in a given property may provide firms with positive business externalities. For example, Wheaton (2000) points out that research has recognized that stores within shopping centers or business districts generate sales or business traffic externalities amongst themselves. A number of researchers have incorporated these types of positive externalities into theoretical models. For instance, Brueckner (1993) builds a model in which developers consider sales externalities when allocating space in a shopping center. Colwell and Munneke (1998) explore value created through percentage leases in regional malls and discuss sales externalities as a reason for price discrimination in leases. Cho and Shilling (2007) incorporate the effect of sales externalities into a model for valuing retail lease contracts.

While business traffic externalities may exist amongst highly diversified properties, large anchor tenants may generate larger externalities than a number of smaller

tenants are able to generate amongst themselves. Research indicates that large tenants get favorable lease terms due to the positive externalities they provide. For example, Pashigian and Gould (1998) find that large anchor properties receive rent subsidies and smaller, lesser known stores pay rent premiums due to these externalities. Gould, Pashigian and Prendergast (2005) note that, on average, anchor stores occupy over 58% of the total leasable space in a mall, but that they only pay 10% of the total rent collected by the developer. They claim that this can only be explained by the externalities created by large anchor stores. This research suggests business traffic externalities will be larger for a property with a large tenant than they will be for a property that only has number of small tenants. Thus, lenders may prefer properties that are not highly diversified, as properties with high levels of diversification may not get the full benefit of sales externalities generated by an anchor tenant.

In addition to the literature on the impact that a property's rent roll on has on property values, there is a large literature that investigates the determination of commercial mortgage credit spreads. For example, Maris and Segal (2002) examine the determinants of credit spreads on commercial mortgage backed security (CMBS) tranches. Their model of credit spreads includes the dollar value of the CMBS issue, the dollar value of the tranche, and macroeconomic terms such as the difference in the AAA corporate bond rate and the 10-year Treasury bond rate, the volatility of the 10-year Treasury bond yield, and the NBER's Experimental Recession Index. Similarly, Nothaft and Freund (2003) estimate a model of credit spreads for multifamily loans with macroeconomic covariates, such as the A-AAA spread and the volatility of the 10-year Treasury bond yield, as well as loan characteristics such as LTV ratios and term to maturity. Titman, Tompaidis and Tsyplakov (2005) estimate a cross-sectional spread model that incorporates a number of loan and property specific characteristics, time dummy variables, and a dummy variable indicating whether or not the originator of the loan is a large investment bank. They find that a number of loan and property characteristics are significantly related to commercial mortgage spreads.

Research clearly indicates that tenant characteristics and space allocation amongst tenants are important for commercial lenders and property owners. However, to our knowledge, none of the existing literature provides a direct empirical examination into the impact of tenant diversification on commercial mortgage spreads or default rates. In this paper, we seek to bridge this gap in the literature.

To examine how tenant diversification influences commercial mortgage spreads, we use an empirical model that is similar to the model of Titman, Tompaidis and Tsyplakov (2005). Our model incorporates a number of the same variables to explain commercial mortgage spreads, but we also include measures for tenant diversification and lease rollover risk. In the main specification of our spread model, we use the percent of square footage occupied by a property's largest lessee as a proxy for the degree of tenant diversification on that property. Using this proxy, we break properties into categories of tenant diversification. We find that mortgage spreads on properties with moderate levels of tenant diversification are up to 5.12 basis points lower than mortgage spreads on single-tenant properties. However, while spreads are lower for properties with moderate levels of diversification, mortgage spreads on properties with the highest

levels of tenant diversification are higher than spreads on single-tenant properties by up to 6.96 basis points. These results are consistent with moderate degrees of tenant diversification providing greater cash flow stability and thus lowering the risk to making loans on buildings with moderate levels of rent roll diversification.

We also find that when the largest tenant's lease expires before the mortgage matures, the discount that borrowers receive for having moderate levels of rent roll diversification vanishes. This reflects the increased risk associated with the large tenant's decision to roll over its lease. If the tenant does not renew its lease, then the property owner will lose what is likely the largest source of cash flow on the property, and the remaining tenants will lose the positive externality that is generated by a large tenant. Interestingly, we find that this rollover risk is not priced for properties with the highest or lowest levels of tenant diversification. For highly diversified properties, the failure of the largest tenant to roll over its lease will not have a major impact on the cash flows that the property owner receives from its tenants. Thus, diversification reduces the rollover risk associated with the property's largest tenant. However, for properties with lower levels of tenant diversification, losing a large tenant could significantly impact the landlord's cash flow stream. Despite this, the largest lessee in an undiversified property is unlikely to vacate a property due to the costs of relocating. Thus, rollover risk in properties with low levels of diversification will not have a significant impact on spreads for mortgages on these properties.

To test the robustness of our results, we compute the Herfindahl-Hirschman Index (HHI) for each property as an alternate proxy for tenant diversification. To calculate a property's HHI, we use the percent of square footage occupied by its three largest lessees. The results using HHI to measure diversification are consistent with our findings that use the percent of square footage occupied by the property's largest tenant as a proxy for tenant diversification. Additionally, we employ a two-stage least squares procedure to adjust for the endogeneity of mortgage spreads and LTVs. The results we obtain in our two-stage procedure are also consistent with our primary results. Thus, our findings about the impact of tenant diversification on mortgage spreads are robust to using different measures of diversification and to adjusting for the simultaneous decision of spreads and LTVs.

In addition to examining how tenant diversification influences commercial mortgage spreads, we examine the impact of tenant diversification on commercial mortgage default rates. We find that the default risk of commercial mortgages increases monotonically as the level of tenant diversification increases. Thus, while lenders give a spread discount on mortgages for properties with low and moderate levels of tenant diversification, any level of diversification adds to the default risk of a loan.

Our finding that tenant diversification increases default risk is somewhat analogous to the string of literature that finds that banks do not gain benefits from diversified loan portfolios, and that banks with diversified portfolios may actually perform worse and have higher levels of risk. For instance, Acharya, Hasan and Saunders (2006) find that loan portfolio diversification is not guaranteed to produce superior performance or greater safety for Italian banks. They conclude that diversification deteriorates monitoring effectiveness. Mercieca, Schaeck and Wolfe (2007) find that higher loan

concentration reduces the risk of insolvency and that loan concentration enables small banks to monitor borrowers more effectively. When examining a set of Chinese banks, Berger, Hasan and Zhou (2010) find that diversification increases monitoring costs and reduces profits. Tabak, Fazio and Cajueiro (2011) find that loan portfolio concentration for Brazilian banks increases bank returns and reduces default risk, leading them to hypothesize that loan concentration increases monitoring efficiency.

If we view a commercial property as a portfolio of tenants, the property owner and/or the mortgage lender have a distinct interest in ensuring that the property's tenants are performing well. However, as tenant diversification increases, it becomes increasingly costly to monitor tenants, and monitoring may become less effective. Thus, the reduction in monitoring effectiveness may be at least partially responsible for the increased default risk that results from increased tenant diversification.

Our paper adds to the literature on commercial mortgage spreads and default rates by explicitly incorporating the degree of tenant diversification into empirical models of commercial mortgage spreads and default risk. Understanding the influence of tenant diversification is important from both the borrower's and the lender's perspective, as borrowers need to understand how lenders perceive tenant structure when determining commercial mortgage interest rates, and lenders need to understand how tenant structure influences commercial mortgage default risk.

The remainder of this paper is organized as follows. In Section 2, we describe our empirical model of commercial mortgage spread and present the results of our main results. We also examine the robustness of our results to an alternate specification of tenant diversification and to adjusting for the endogeneity of the decision of mortgage spreads and LTVs. In Section 3, we examine how tenant diversification influences the default risk on a commercial mortgage. In the last section, we summarize our main findings and discuss potential directions for future research.

## **2. Data and empirical model for commercial mortgage spreads**

### **2.1 Data**

Our dataset consists of commercial loans originated between January 1998 and March 2012. The data come from the Trepp Data Feed loan file. Trepp provides loan-level data about the individual loans that compose commercial mortgage-backed securities. The loan file contains a series of tape dates corresponding to the bond payment dates that provide updated information about mortgage, property, and tenant characteristics. In addition, the loan file provides data about the loan both at the time of origination and at the time of securitization. While we seek to isolate loan, tenant, and property characteristics at the time the loan is originated, data at origination are somewhat sparse. Thus, when data at origination are unavailable, we use data at the time the loan is securitized. If data are not available at either the time of origination or the time of securitization, we use data from the earliest tape date that occurs within 18 months of the loan's origination.

We restrict our sample to retail properties, as we seek to examine mortgages on properties for which tenant diversification is most likely to vary across properties and to be of significant importance to lenders. Our final dataset consists of 18,815 loans with originations that span from January 1998 to March 2012. The majority of the originations occur between 1998 and 2007, as there was an immense drop in the amount of commercial lending during the time of the recent financial crisis. The mortgage, property, and lessee characteristics that we use in our spread model are discussed below.

### 2.1.1 Mortgage and property characteristics

For each mortgage, we have information about the interest rate, the loan-to-value ratio (LTV), the balloon balance, the original loan balance, and the time until the mortgage matures. We compute the mortgage spread as the difference between the mortgage's interest rate and the interest rate on a maturity matched Treasury security. Following Titman et al. (2005), we compute the amortization rate as

$$1 - \frac{\text{balloon balance}}{\text{original loan balance}}.$$

For each property, we collect data on net operating income (NOI) and the property's appraised value and compute the ratio of NOI to property value. We also collect data on the year the property was built to determine the age of the property at the time of origination. Finally, we collect data on the occupancy rate and the property type.

### 2.1.2 Tenant characteristics

We collect information on the percent of square footage occupied by the largest lessee of a property (L1%) to measure the degree of tenant diversification for a given property. We use this as a proxy for diversification because, as the space occupied by a property's largest tenant increases, the amount of space available for other tenants decreases. Thus, the more space that is occupied by the largest tenant, the more a property owner is reliant on a single source of cash flow.

In addition to collecting data on the percent of square footage occupied by the property's largest tenant, we collect data on the expiration date of the largest tenant's lease. If the largest tenant's lease expires and the tenant vacates the property, the borrower will lose what is likely the largest source of cash flow from that property. If the lease expiration date occurs before mortgage maturity, the borrower may have difficulty paying the mortgage, indicating that there is lease rollover risk associated with that loan. Therefore, using the mortgage maturity date and the largest tenant's lease expiration date, we are able to determine if the lender faces the risk that the property's largest tenant will not roll over its lease (L1 rollover).

### 2.1.3 Summary statistics

Table 1 presents the summary statistics for the properties in our sample.<sup>2</sup> Properties are broken into 6 tenant diversification categories based on the percent of square footage occupied by the each property's largest lessee (L1%). The L1 categories are formed using

---

<sup>2</sup> We winsorize all continuous variables at the 1% and 99% levels to control for extreme outlying observations.

20 percentage point increments for L1%. Table 1 defines the L1% range for each L1 category and reports summary statistics for each category.

**Table 1:** Summary statistics by category of percent square footage occupied by the property's largest lessee (L1%)

Average values for mortgage, property, and tenant characteristics are shown for categories of the percent of square footage occupied by the property's largest tenant (L1%).

L1 Category	Range of L1%	N	% Sample	Spread (%)	L1%	Fraction L1 Rollover	Property Value (mil)	LTV	NOI/Property Value	Amort. Rate	Occ. Rate (%)	Property Age	Years to Loan Maturity
1	$0 \leq L1\% < 20$	3,878	20.61	1.5631	14.46	0.83	28.59	0.68	0.0761	0.16	93.83	18.47	9.90
2	$20 \leq L1\% < 40$	6,426	34.15	1.5644	28.87	0.75	16.94	0.69	0.0762	0.15	95.71	19.72	9.93
3	$40 \leq L1\% < 60$	3,180	16.90	1.5695	49.04	0.58	11.83	0.70	0.0765	0.16	97.08	19.21	9.98
4	$60 \leq L1\% < 80$	1,581	8.40	1.5549	68.32	0.41	9.57	0.70	0.0759	0.16	97.78	16.25	10.02
5	$80 \leq L1\% < 100$	374	1.99	1.6131	87.37	0.33	9.56	0.69	0.0759	0.18	98.94	17.17	10.11
6	$L1\% = 100$	3,376	17.94	1.5174	100.00	0.23	6.31	0.67	0.0720	0.20	99.97	11.96	10.36
All	$0 \leq L1\% \leq 100$	18,815	100.00	1.5567	46.55	0.61	15.80	0.69	0.0754	0.16	96.56	17.64	10.02

As the L1 category increases, the percent of space occupied by the largest tenant of the properties in that category increases, meaning that the level of tenant diversification in that category decreases. Thus, properties in L1 category 1 are the most diversified properties in the sample, as the largest tenant of properties in this category take up the smallest percentage of space. Properties in L1 category 6 consist of properties whose largest tenant takes up 100 percent of the property's square footage, indicating that these are completely undiversified, single-tenant properties.

About 18 percent of the properties in our sample are single-tenant properties, while only 2 percent of the properties fall into L1 category 5. Thus, there are very few multi-tenant properties whose largest tenant occupies 80-percent or more of the property's available space. Properties in L1 category 4 make up 8.4 percent of the sample, and properties in L1 categories 2 and 3 make up 34.15 and 16.90 percent of the sample, respectively. Properties with the highest degree of tenant diversification, which fall into L1 category 1, make up 20.61 percent of the properties in our sample.

Not surprisingly, the most diversified properties tend to have the highest property values, while completely undiversified properties have the lowest property values. Relative to properties in other tenant diversification categories, single-tenant properties have the lowest average spread. Single-tenant properties are also younger than properties in other L1 categories and tend to have the lowest ratio of NOI to property value, the lowest LTV, the highest amortization rate, and the longest time to loan maturity. Properties with the highest level of tenant diversification have the lowest occupancy rates, and their loans tend to mature more quickly.

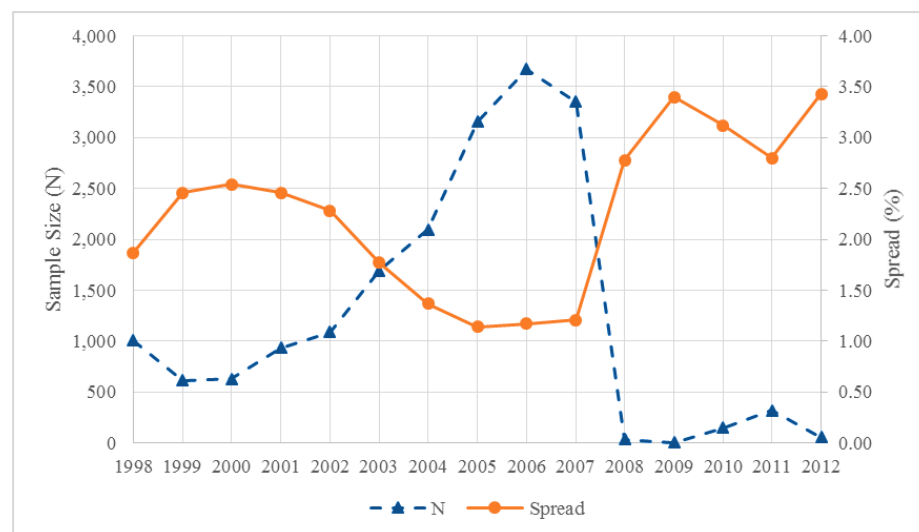
Table 1 also reports the fraction of L1 rollover for each L1 category. The fraction of properties whose largest tenant's lease expires before the mortgage matures decreases as the size of the largest tenant increases. For 83 percent of properties in L1 category 1, the largest tenant's lease expires before the mortgage matures. This fraction decreases monotonically as the L1 category increases, and only 23 percent of single-tenant

properties must roll over the largest tenant's lease before mortgage maturity. These statistics indicate that, as tenant diversification decreases, property owners try to protect themselves by locking tenants into longer term leases.

Figure 1 shows the sample size and average spread for loans in each year of our sample. The sample size increases continuously from 1999 through 2006 before dropping off slightly in 2007. However, of all the years in our sample, 2007 has the second highest number of loan originations. During the crisis years of 2008 and 2009, the sample size drops significantly and never fully recovers to the sample sizes in any of the years prior to the crisis. Additionally, the average spread has an inverse relationship with the number of loans.<sup>3</sup> As our sample size increases through the early to mid-2000s, spreads drop continuously. The increasing number of loans with lower credit spreads indicates the ease with which borrowers could obtain commercial mortgage loans during the pre-crisis period. Once the crisis hits and mortgage lending drops, average spreads increase to their highest levels in our sample and sustain these high levels through March 2012 when our sample ends.

**Figure 1:** Sample size and average spreads over time

The figure displays the sample size and average spread of commercial mortgage loans on retail properties. The data consists of loans originated between January 1998 and March 2012.



## 2.2 Regression model for commercial mortgage spreads

Following Titman, Tompaidis and Tsyplakov (2005), we estimate a model for commercial mortgage spreads that includes a variety of property and mortgage characteristics. We also include a proxy for the degree of tenant diversification and fixed effects for each month. We specify our regression model as follows:

<sup>3</sup> The correlation coefficient between the number of loans in each year and the average spread in each year is -0.93.



$$\begin{aligned}
 \text{Spread} = & \text{Intercept} + \sum_i l_i \times \text{lessee characteristic}_i \\
 & + \sum_i c_i \times \text{property characteristic}_i \\
 & + \sum_i m_i \times \text{mortgage characteristic}_i \\
 & + \sum_i t_i \times \text{time dummy variable}_i + \varepsilon.
 \end{aligned}
 \tag{1}$$

We summarize all of the variables used in our model in Table 2, and each variable is discussed below.

**Table 2: Variables used to Model Commercial Mortgage Spreads**

The variables used to explain commercial mortgage spreads are explained in the table below.

Variable	Meaning
Spread (%)	The difference between the interest rate on the mortgage and the rate on a maturity matched Treasury bond, expressed as a percentage.
D(L1 Category 1)	Indicator that the largest lessee of the property occupies 0% to less than 20% of the property's square footage.
D(L1 Category 2)	Indicator that the largest lessee occupies 20% to less than 40% of the property's square footage.
D(L1 Category 3)	Indicator that the largest lessee occupies 40% to less than 60% of the property's square footage.
D(L1 Category 4)	Indicator that the largest lessee occupies 60% to less than 80% of the property's square footage.
D(L1 Category 5)	Indicator that the largest lessee occupies 80% to less than 100% of the property's square footage.
D(L1 Category 6)	Indicator that the largest lessee occupies 100% of the property's square footage, meaning that the property is a single-tenant, completely undiversified property.
D(L1 Rollover)	Lease rollover dummy: An indicator that the property's largest tenant has a lease that expires before the mortgage on the property matures.
Log(Property Value)	The natural log of the property's appraised value.
LTV	Ratio of the value of the loan to the value of the property.
D(LTV $\geq$ 0.70)	A dummy variable indicating an LTV greater than or equal to 0.70.
NOI/Prop Value	The property's NOI relative to its appraised value.
Amortization Rate	$1 - \frac{\text{balloon balance}}{\text{original loan balance}}$
Occupancy Rate	The property's occupancy rate expressed as a percentage.
Log(Property Age)	The natural log of the property's age in years.
Years to Maturity	The number of years from loan origination to loan maturity.

In our primary model specification, we use a series of dummy variables representing the L1 categories to investigate the impact of tenant diversification on mortgage spreads. The dummy variable specification for L1% allows us to control for a potential nonlinear relationship between tenant diversification and mortgage spreads. Because we expect more diversified properties to be less risky, we expect the spread to decrease as the degree of tenant diversification increases. However, it is also possible that larger tenants are more creditworthy than smaller tenants and that the larger tenants provide

a more stable source of cash flow for property owners. If this is the case, then the benefits of diversification will dissipate as diversification increases due to the absence of a large, stable tenant. Thus, our model allows us to examine if borrowers on diversified properties benefit by receiving lower spreads than borrowers with a less diversified tenant base, and if so, if there are limits to which the degree of tenant diversification benefits borrowers.

In the second specification of our spread model, we incorporate the structure of the largest tenant's lease. Specifically, we create a dummy variable that equals 1 if the largest tenant's lease expires before the mortgage matures and 0 otherwise. This dummy variable, which we refer to as the lease rollover dummy, is intended to capture the risk that the largest tenant may not renew its lease, causing the property to lose a large source of cash flow before the mortgage matures. We expect lease rollovers to cause higher spreads to reflect this risk. The second model specification includes the largest tenant relative size dummies and interaction terms between these dummies and the lease rollover dummy. We use interaction terms because we expect lease rollover risk to be higher for properties with lower levels of tenant diversification, as properties that are not diversified are more reliant on the cash flows generated by the property's largest tenant.

Each specification of our model includes the LTV ratio and a dummy variable indicating whether or not the loan has an LTV greater than or equal to 0.70. We use this specification because, as is pointed out by Titman et al. (2005), LTV is determined endogenously through negotiations between the borrower and the lender. *Ceteris paribus*, a higher LTV results in a riskier loan and a higher spread. However, riskier borrowers are typically forced to make higher down payments, which reduces the LTV on risky loans. Thus, riskier borrowers may end up with loans that have lower LTVs than safe borrowers would obtain. The specification that we use is intended to control for the endogeneity associated with a loan's LTV.

Our model includes a number of other property and mortgage characteristics as control variables.<sup>4</sup> To control for property characteristics, we include the natural log of the property's value, the ratio of net operating income to property value, the occupancy rate, and the natural log of the property's age. To control for characteristics of the mortgage, we use the mortgage's amortization rate, time to maturity, and the LTV ratio as was discussed previously. To control for changes in the lending environment over time, all regressions include month fixed effects, and coefficient standard errors are clustered by month.<sup>5</sup>

### 2.3 Regression Results

The estimation results for each specification of our spread model are displayed in **Table 3**. In our first specification, we use L1 category 6, which consists of single-tenant properties, as the base case for tenant diversification. Because the properties in L1

---

<sup>4</sup> See Titman, Tompaidis and Tsyplakov (2005) for a detailed explanation about the expected impact of these variables on mortgage spreads.

<sup>5</sup> Petersen (2009) and Thompson (2011) discuss the importance of clustering standard errors in panel datasets.

category 6 are completely undiversified, the tenant diversification dummies allow us to examine the incremental effect of different levels of tenant diversification.

**Table 3:** Spread regressions with largest lessee percent square footage dummies

*The dependent variable in the regression model is the spread between the mortgage interest rate and the rate on a maturity matched Treasury security. In the first model, the spread is regressed on dummy variables representing the percent of square footage occupied by the property's largest tenant (L1%) and a number of control variables. In the second model, the L1% dummy variables are interacted with a dummy variable that equals 1 if the largest tenant's lease expires before the loan matures and 0 otherwise. The data span from January 1998 to March 2012. The models include month fixed effects, and coefficient standard errors are clustered by month.*

Variable	Dependent Variable = Commercial Mortgage Spread (%)			
	L1 Specification 1		L1 Specification 2	
	Coefficient Estimate	t-stat	Coefficient Estimate	t-stat
D(L1 Category 1)	0.0528	(3.7314)	0.0696	(2.5736)
D(L1 Category 1) × D(L1 Rollover)			-0.0174	(-0.7428)
D(L1 Category 2)	0.0204	(1.6000)	0.0125	(0.8358)
D(L1 Category 2) × D(L1 Rollover)			0.0146	(1.1825)
D(L1 Category 3)	-0.0235	(-1.6195)	-0.0502	(-2.9385)
D(L1 Category 3) × D(L1 Rollover)			0.0515	(4.0470)
D(L1 Category 4)	-0.0407	(-2.7959)	-0.0512	(-3.0332)
D(L1 Category 4) × D(L1 Rollover)			0.0334	(1.8672)
D(L1 Category 5)	-0.0260	(-1.2289)	-0.0341	(-1.3673)
D(L1 Category 5) × D(L1 Rollover)			0.0347	(0.8789)
D(L1 Category 6) × D(L1 Rollover)			0.0190	(0.8041)
Log(Property Value)	-0.1275	(-22.9484)	-0.1253	(-21.9703)
LTV	0.3514	(4.2022)	0.3596	(4.2463)
D(LTV ≥ 0.70)	-0.0102	(-0.8296)	-0.0102	(-0.8345)
NOI / Prop Value	3.0022	(5.0011)	2.9956	(5.0139)
Amortization Rate	-0.2759	(-5.6805)	-0.2775	(-5.7047)
Occupancy Rate	-0.0010	(-1.6614)	-0.0011	(-1.8391)
Log(Property Age)	0.0250	(7.1040)	0.0234	(6.5860)
Years to Maturity	-0.0308	(-7.0338)	-0.0313	(-7.1371)
Month FE	Yes		Yes	
N	18,815		18,815	
R-squared	0.1629		0.1638	

In the first specification, the coefficient on the L1 category 5 dummy variable indicates that these properties receive mortgages spreads that are 2.60 basis points lower than those on single-tenant, completely undiversified properties. However, this result is not statistically significant. Mortgages on properties in L1 category 4 get a 4.07 basis point spread discount relative to single-tenant properties, and the discount is significant at the 1% level. Thus, having a moderate degree of tenant diversification is viewed favorably by lenders. Mortgages for properties in L1 categories 2 and 3 have spreads that are not significantly different from spreads of mortgages on undiversified properties. Thus, once properties begin to reach higher levels of tenant diversification,

borrowers on these properties do not gain any benefit relative to borrowers on completely undiversified properties. Finally, mortgage spreads on properties in L1 category 1, which have the highest level of diversification, are 5.28 basis points higher than spreads on single-tenant properties. Thus, properties with the highest levels of tenant diversification have the highest mortgage spreads.

Our regression results indicate that there is a non-linear relationship between tenant diversification and commercial mortgage spreads. Attaining a moderate degree of diversification results in lower spreads, but high levels of diversification cause the spread discount to disappear. Thus, a moderate degree of diversification carries the benefit of providing a diverse source of cash flow, building in a cushion in the circumstance that some of the property's tenants are unable to meet their promised payments. Additionally, the results support the notion that a large anchor tenant generates positive externalities for other tenants that are viewed favorably by lenders.

Our second specification incorporates the lease structure of a property's largest tenant. If the largest tenant of a property has a lease that expires before the mortgage matures, borrowers run the risk of losing a large source of cash flow. The impact of losing the property's largest tenant should be greater for properties that are not highly diversified. Thus, we add interaction terms of a lease rollover dummy and each of the L1 category dummies to examine the impact of lease rollover risk. The base case for the specification that uses this set of dummy variables is a single-tenant property without a lease rollover for that tenant. The regression results for this specification are displayed in Table.

The regression results indicate that lease rollover risk has no significant impact on the spread for single-tenant properties. Similarly, there is no significant impact of lease rollover risk on spreads for properties in L1 category 5. This is likely the case because tenants that occupy all or most of a property's square footage are unlikely to leave that property, yielding very little rollover risk for these properties despite the fact that the large tenant has the option to vacate the property before the mortgage matures.

Mortgage spreads on properties in L1 category 4 without a lease rollover are 5.12 basis points lower than mortgage spreads on single-tenant properties without a lease rollover. This spread reduction is significant at the 1% level. The rollover and L1 category 4 interaction term indicates that the spread discount is reduced by 3.34 basis points when the largest tenant's lease expires before the mortgage matures. The coefficient on the interaction term is significant at the 10% level, and a test of the null hypothesis that the sum of the coefficients on L1 category dummy and the rollover interaction term equals zero cannot be rejected.<sup>6</sup>

Mortgage spreads on properties in L1 category 3 without a lease rollover are 5.02 basis points lower than spreads on single-tenant properties without a lease rollover. This result is statistically significant at the 1% level. The interaction term between the L1 category 3 dummy and the rollover dummy indicates that the spread discount for properties in this category decreases by a statistically significant 5.15 basis points if the largest tenant's lease expires before the loan matures. In addition, a test of the null

---

<sup>6</sup> Tests that the sum of the coefficients on the tenant diversification dummies and the lease rollover term for this model and other models that appear later in the paper are reported in Appendix 1.

hypothesis that the sum of the coefficients on the L1 category 3 dummy and the rollover interaction term equals zero cannot be rejected. Therefore, the spread discount for moderate tenant diversification disappears when the property has lease rollover risk associated with its largest tenant.

The results for L1 categories 3 and 4 provide further support that lenders give lower spreads to mortgages on moderately diversified properties, as these properties get obtain benefits from diversification and from having an anchor tenant. The results also indicate that the spread discount for mortgages on properties with moderate levels of diversification disappears if the largest tenant is not locked into its lease until the mortgage matures. Thus, lenders consider lease rollover risk and charge higher spreads for bearing this risk when properties are not highly diversified.

Mortgage spreads on properties in L1 category 2 without lease rollover risk are not significantly different from spreads on single-tenant properties, and lease rollovers for properties in category 2 do not have a significant influence on spreads. Spreads on properties in L1 category 1 without a lease rollover are almost 7 basis points higher than spreads on single-tenant properties without a rollover. However, like properties in L1 category 2, lease rollovers for properties in category 1 do not result in significantly higher spreads. The results for properties in L1 categories 1 and 2 indicate that there is a limit to the degree with which lenders value tenant diversification, as high levels of diversification result in the loss of the benefits of having a large, stable tenant. However, lenders do seem to value diversification as protection against lease rollover risk, as diversified properties do not face higher mortgage spreads when their largest tenant's lease expires before the mortgage matures.

## 2.4 Robustness checks

### 2.4.1 Measuring tenant diversification using the Herfindahl-Hirschman Index

While the percent of square footage occupied by a property's largest tenant is a reasonable proxy for tenant diversification, it does not incorporate information about diversification that can be attained with the property's remaining space. Thus, we create a proxy for tenant diversification that incorporates the percent of square footage occupied by the property's largest 3 tenants. We compute the Herfindahl-Hirschman Index (HHI) for tenant diversification as follows:

$$(2) \quad HHI = \frac{L1\%^2 + L2\%^2 + L3\%^2}{10,000} \times 100,$$

where L1% is the percent of square footage occupied by the largest tenant, L2% is the percent of square footage occupied by the second largest tenant, and L3% is the percent of square footage occupied by the third largest tenant. Thus, HHI is computed to be on a scale that ranges from 0 to 100, with lower values indicating a higher degree of tenant diversification.

#### 2.4.1.1 Summary statistics by HHI quantile

Similar to our previous analysis, we break properties into 6 quantiles based on their level of tenant diversification. Quantile 6, the highest quantile, consists of all properties

with an HHI equal to 100, indicating that these are single-tenant properties. The remaining properties are divided into 5 equally sized HHI quantiles. We report summary statistics for each quantile in Table 4. The summary statistics have a similar pattern to those that were computed for the largest tenant percent square footage categories. The quantile with single-tenant properties has the lowest average property value, LTV, and property age. This quantile also has the smallest fraction of properties whose largest tenant's lease expires before the mortgage matures. The lowest HHI quantile has highest fraction of properties facing a lease rollover for their largest tenant.

**Table 4:** Summary statistics by Herfindahl-Hirschman Index quantile

Average values for mortgage, property, and tenant characteristics are shown by quantile of the Herfindahl-Hirschman Index (HHI). HHI is computed as follows:

$$HHI = \frac{L1\%^2 + L2\%^2 + L3\%^2}{10,000} \times 100,$$

where L1% is the percent of square footage occupied by the largest tenant, L2% is the percent of square footage occupied by the 2<sup>nd</sup> largest tenant, and L3% is the percent of square footage occupied by the 3<sup>rd</sup> largest tenant. Properties are broken into 6 quantiles based on their HHI. The highest quantile consists of all properties with an HHI equal to 100. The remaining properties are divided into 5 equally sized HHI quantiles.

HHI Quantile	HHI	N	% Sample	Spread (%)	Property Value (mil)	LTV	NOI/ Property Value	Amort. Rate	Occ. Rate (%)	Property Age	Years to Loan Maturity	Top Lessee % Sq. Ft.	Fraction Top Lessee Rollover
1	3.72	2,803	16.12	1.5008	33.45	0.68	0.0745	0.15	93.21	18.61	9.82	13.62	0.82
2	8.55	2,803	16.12	1.5201	21.26	0.70	0.0757	0.15	94.75	19.16	9.94	22.20	0.80
3	14.43	2,803	16.12	1.5282	16.04	0.70	0.0750	0.14	95.87	19.29	9.89	30.40	0.74
4	24.52	2,803	16.12	1.5261	12.43	0.70	0.0755	0.15	96.82	19.40	9.95	42.25	0.64
5	48.89	2,802	16.11	1.5134	10.05	0.70	0.0745	0.16	98.30	17.56	9.98	64.37	0.47
6	100.00	3,376	19.41	1.5174	6.31	0.67	0.0720	0.20	99.97	11.96	10.36	100.00	0.23
Total	35.55	17,390	100.00	1.5177	16.25	0.69	0.0744	0.16	96.60	17.47	10.00	47.27	0.60

Table 4 also shows that, as the HHI quantile increases, the percent of square footage occupied by the property's largest tenant increases. This indicates that the HHI measure of diversification is similar to the largest tenant percent square footage measure that was used to measure diversification in our earlier analysis.

#### 2.4.1.2 Regression Results

We estimate two regression specifications for mortgage spreads that are analogous to those that were estimated previously. The only difference is that we use a dummy variable for each HHI quantile instead of a dummy variable for each L1 category. The results for each specification are presented in Table 5

**Table 5:** Spread regressions with Herfindahl-Hirschman Index (HHI) quantile dummies

The dependent variable in the regression model is the spread between the mortgage interest rate and the rate on a maturity matched Treasury security. In the first model, the spread is regressed on dummy variables representing the quantile of the Herfindahl-Hirschman Index (HHI) that a property is in and a number of control variables. In the second model, the HHI dummy variables are interacted with a dummy variable that equals 1 if the largest tenant's lease expires before the loan matures and 0 otherwise. The data span from January 1998 to March 2012. The models include month fixed effects, and coefficient standard errors are clustered by month.

Dependent Variable = Commercial Mortgage Spread (%)				
Variable	HHI Specification 1		HHI Specification 2	
	Coefficient Estimate	t-stat	Coefficient Estimate	t-stat
D(HHI quantile=1)	0.0539	(3.5903)	0.0728	(2.4510)
D(HHI quantile=1) × D(L1 Rollover)			-0.0209	(-0.7874)
D(HHI quantile=2)	0.0197	(1.4101)	0.0171	(0.7750)
D(HHI quantile=2) × D(L1 Rollover)			0.0066	(0.3647)
D(HHI quantile=3)	0.0211	(1.4510)	0.0199	(1.0869)
D(HHI quantile=3) × D(L1 Rollover)			0.0057	(0.3623)
D(HHI quantile=4)	-0.0149	(-1.0624)	-0.0416	(-2.2010)
D(HHI quantile=4) × D(L1 Rollover)			0.0471	(3.1357)
D(HHI quantile=5)	-0.0287	(-1.9726)	-0.0473	(-2.9526)
D(HHI quantile=5) × D(L1 Rollover)			0.0468	(3.8112)
D(HHI quantile=6) × D(L1 Rollover)			0.0201	(0.8456)
Log(Property Value)	-0.1241	(-21.8508)	-0.1217	(-20.7315)
LTV	0.3672	(4.3408)	0.3757	(4.3853)
D(LTV ≥ 0.70)	-0.0042	(-0.3730)	-0.0041	(-0.3638)
NOI / Prop Value	2.4457	(4.0799)	2.4505	(4.1062)
Amortization Rate	-0.2452	(-4.8481)	-0.2474	(-4.8676)
Occupancy Rate	-0.0010	(-1.5793)	-0.0011	(-1.7611)
Log(Property Age)	0.0243	(6.7645)	0.0226	(6.1245)
Years to Maturity	-0.0319	(-7.4222)	-0.0325	(-7.5690)
Month FE		Yes		Yes
N		17,390		17,390
R-squared		0.1581		0.1593

The first specification indicates that properties in HHI quantile 5 get a spread discount of about 2.9 basis points. Spreads for properties in HHI quantiles 2 through 4 are not significantly different from spreads on single-tenant properties. However, spreads for properties in quantile 1 are a significantly positive 5.39 basis points higher than spreads on single-tenant properties.

The second specification shows that properties in quantiles 4 and 5 get a spread discount of 4.16 and 4.73 basis points, respectively, if the largest tenant's lease does not expire before the lease matures. These results indicate that properties with a moderate level of tenant diversification get a spread discount. However, the lease rollover interaction term for each of these quantiles is significantly positive. In addition, for each of these quantiles, tests of the null hypothesis that the sum of the coefficients on the quantile dummy variable and its lease rollover interaction term equal zero cannot be rejected. Thus, the spread discount for properties moderate levels of tenant diversification disappears if the largest tenant is not locked into its lease beyond the mortgage's maturity.

The coefficients for the HHI quantile dummy variables are insignificant for quantiles 2 and 3. However, the coefficient for HHI quantile 1 dummy variable is significantly positive and indicates that mortgages on properties in quantile 1 have spreads that are 7.28 basis points higher than spreads on single-tenant properties. Additionally, lease rollovers for a property's largest tenant do not have a significant impact on spreads, indicating that tenant diversification helps protect borrowers from the risk that the largest tenant on the property will not roll its lease over before the mortgage matures.

The results using the property's HHI to measure diversification are similar to those that are obtained when using the percent of square footage occupied by the property's largest tenant to measure diversification. The results indicate that lenders provide a spread discount for properties with a moderate degree of tenant diversification, but that this discount disappears if the largest tenant's lease expires before the mortgage matures. Also, borrowers on properties with the highest levels of diversification pay spreads that are significantly higher than spreads for single-tenant properties.

#### 2.4.2 Addressing the endogeneity of spreads and LTV

Lenders consider mortgage spreads and LTVs simultaneously. To adjust for the risk associated with a particular mortgage, lenders may require a higher spread or a lower LTV. If lenders adjust spreads and LTVs to account for tenant diversification and lease rollover risk, then the coefficient estimates in the regression models that were estimated previously may be biased.

To address the issue of endogeneity, we implement a two-stage least squares procedure in which a model for LTV is estimated in the first stage and a model for mortgage spreads is estimated in the second stage. For each loan, we compute the average LTV of all other loans from the same originator. This is used as an instrument in our second stage regressions because evidence indicates that some originators prefer to make low LTV loans, while other lenders are willing to make loans with high LTVs.<sup>7</sup> Thus, for a given loan from a particular originator, the average LTV of other loans from the same originator will be predictive of the LTV on that loan. However, the average LTV of all other loans from the same originator should not have a direct influence on the spread on that loan, as lenders consider the characteristics of a given loan when determining the spread.

To implement the two-stage least squares (2SLS) procedure, we eliminate mortgages for which the originator is unknown and mortgages whose originator issued less than 5 loans in our sample. We also drop the dummy variable indicating that a loan's LTV is greater than 0.70 from our model, as it was included in the model to address the endogeneity of mortgage spreads and LTVs. Finally, we estimate the models that include the lease rollover interaction terms.

The results for the first and second stage regressions are reported in **Table**. The first stage LTV regressions shown in Panel A indicate that, for a given loan, the average LTV

<sup>7</sup> Ambrose, Benjamin and Chinloy (2003) note that nonbank lenders tend to make low LTV loans while bank lenders are more willing to accept a loan package with a higher LTV. Titman, Tompaidis and Tsyplakov (2005) also document a clientele effect, as they find that some originators attract mortgages with higher LTVs.



of other loans made from the same originator is a strong predictor of that loan's LTV. In the two model specifications, the coefficient on the average LTV is positive and highly significant, with t-statistics of 19.58 and 19.22 in specifications 1 and 2, respectively.

**Table 6:** Two-stage least squares spread regressions

This table shows the results of a two-stage least squares procedure that is used to address the endogeneity between loan-to-value (LTV) and mortgage spreads. For a given loan, the average of the LTV of all other loans from the same originator is computed. This is used as an instrument for LTV. Panel A reports the results of the first stage LTV regressions. Panel B reports results from the second stage spread regressions that use the predicted LTV. The models include month fixed effects, and standard errors are clustered by month.

*Panel A: First stage LTV regressions*

Dependent Variable = LTV				
Variable	2SLS Spec. 1		2SLS Spec. 2	
	Coeff.Est.	t-stat	Coeff.Est.	t-stat
Average LTV of Other Loans from Same Originator	0.7417	(19.5777)	0.7485	(19.2228)
D(L1 Category 1)	-0.0137	(-2.8095)		
D(L1 Category 1) × D(L1 Rollover)	0.0031	(0.6667)		
D(L1 Category 2)	0.0066	(1.7276)		
D(L1 Category 2) × D(L1 Rollover)	-0.0122	(-3.8027)		
D(L1 Category 3)	0.0178	(4.6877)		
D(L1 Category 3) × D(L1 Rollover)	-0.0180	(-5.4963)		
D(L1 Category 4)	0.0170	(4.1234)		
D(L1 Category 4) × D(L1 Rollover)	-0.0121	(-3.1552)		
D(L1 Category 5)	0.0121	(1.2934)		
D(L1 Category 5) × D(L1 Rollover)	-0.0183	(-1.8074)		
D(L1 Category 6) × D(L1 Rollover)	-0.0113	(-1.9858)		
D(HHI quantile=1)			-0.0174	(-3.3688)
D(HHI quantile=1) × D(L1 Rollover)			0.0044	(0.8646)
D(HHI quantile=2)			0.0049	(1.0366)
D(HHI quantile=2) × D(L1 Rollover)			-0.0103	(-2.3324)
D(HHI quantile=3)			0.0049	(1.0020)
D(HHI quantile=3) × D(L1 Rollover)			-0.0059	(-1.4448)
D(HHI quantile=4)			0.0152	(3.6858)
D(HHI quantile=4) × D(L1 Rollover)			-0.0212	(-5.5762)
D(HHI quantile=5)			0.0156	(3.7631)
D(HHI quantile=5) × D(L1 Rollover)			-0.0140	(-4.5604)
D(HHI quantile=6) × D(L1 Rollover)			-0.0123	(-2.1700)
Log(Property Value)	0.0039	(3.6504)	0.0043	(3.7774)
NOI / Prop Value	4.0757	(24.1488)	4.2327	(23.2112)
Amortization Rate	-0.2139	(-23.3947)	-0.2065	(-21.8578)
Occupancy Rate	0.0002	(1.6280)	0.0001	(0.8673)
Log(Property Age)	-0.0108	(-13.3442)	-0.0107	(-12.8867)
Years to Maturity	0.0126	(18.8955)	0.0121	(17.6057)
Month FE		Yes		Yes
Observations		18,739		17,324
R-squared		0.2586		0.2580

*Panel B: Second stage spread regressions using fitted values for LTV*

Variable	Dependent Variable = Spread (%)			
	2SLS Spec. 1		2SLS Spec. 2	
	Coeff. Est.	t-stat	Coeff. Est.	t-stat
D(L1 Category 1)	0.0757	(2.7696)		
D(L1 Category 1) × D(L1 Rollover)	-0.0197	(-0.8398)		
D(L1 Category 2)	0.0108	(0.7129)		
D(L1 Category 2) × D(L1 Rollover)	0.0176	(1.3115)		
D(L1 Category 3)	-0.0575	(-3.1653)		
D(L1 Category 3) × D(L1 Rollover)	0.0587	(3.9674)		
D(L1 Category 4)	-0.0560	(-3.2688)		
D(L1 Category 4) × D(L1 Rollover)	0.0356	(2.0774)		
D(L1 Category 5)	-0.0418	(-1.5414)		
D(L1 Category 5) × D(L1 Rollover)	0.0457	(1.1084)		
D(L1 Category 6) × D(L1 Rollover)	0.0234	(0.9529)		
D(HHI quantile=1)			0.0847	(2.8149)
D(HHI quantile=1) × D(L1 Rollover)			-0.0259	(-0.9772)
D(HHI quantile=2)			0.0130	(0.5999)
D(HHI quantile=2) × D(L1 Rollover)			0.0132	(0.7349)
D(HHI quantile=3)			0.0207	(1.1297)
D(HHI quantile=3) × D(L1 Rollover)			0.0058	(0.3629)
D(HHI quantile=4)			-0.0474	(-2.3394)
D(HHI quantile=4) × D(L1 Rollover)			0.0561	(3.2014)
D(HHI quantile=5)			-0.0545	(-3.2034)
D(HHI quantile=5) × D(L1 Rollover)			0.0534	(4.1810)
D(HHI quantile=6) × D(L1 Rollover)			0.0242	(0.9602)
Log(Property Value)	-0.1275	(-22.6860)	-0.1246	(-21.9810)
LTV	0.6765	(1.8181)	0.8104	(2.0028)
NOI / Prop Value	1.5058	(1.0893)	0.4640	(0.3002)
Amortization Rate	-0.1930	(-1.9886)	-0.1431	(-1.4620)
Occupancy Rate	-0.0011	(-1.8807)	-0.0012	(-1.7240)
Log(Property Age)	0.0275	(5.6321)	0.0279	(5.5919)
Years to Maturity	-0.0360	(-5.1267)	-0.0382	(-5.4262)
Month FE		Yes		Yes
Observations		18,739		17,324
R-squared		0.1579		0.1490

The first stage regressions also indicate that tenant diversification plays a role in the lender's LTV decision. Specification 1 shows that mortgages on properties in L1 categories 3 and 4 without a lease rollover have LTVs that are 1.78 and 1.70 percentage points higher than those on single-tenant properties without a lease rollover. Additionally, LTVs for mortgages in largest tenant category 2 are 0.66 percentage points lower than LTVs for single-tenant properties. However, this impact is only marginally significant. The lease rollover interaction terms for mortgages in categories 2 through 4 indicate that lease rollover risk has a significantly negative impact on LTVs that counteracts the higher LTVs associated with mortgages on properties in these categories. Additionally, properties in largest tenant category 1, which are the least diversified, have significantly lower LTVs than single-tenant properties.

The results for model specification 2 are similar to those that are obtained from specification 1. Properties in HHI quantiles 4 and 5 that do not have a largest tenant lease rollover have significantly higher LTVs than single-tenant properties without a lease rollover. However, properties in the HHI quantiles 2 and 3 without a lease rollover do not have LTVs that are significantly different from LTVs on single-tenant properties without a lease rollover, and the LTVs on properties in HHI quantile 1 without a lease rollover have significantly lower LTVs than single-tenant properties without a lease rollover. This indicates that LTVs on mortgages for properties without a largest tenant lease rollover are higher for moderate levels of tenant diversification, but they are reduced when properties have very high levels of tenant diversification. The rollover interaction terms again indicate that lease rollover risk reduces LTVs on mortgages for properties that are not very diversified.

The LTV regressions indicate that lenders consider properties with a moderate degree of diversification to be desirable, as mortgages on these properties have higher LTVs. However, mortgages on highly diversified properties must have lower LTVs. Additionally, the lease rollover interaction terms indicate that the higher LTVs on properties with moderate levels of tenant diversification are not permitted if there is a risk that the largest tenant will vacate the property before the mortgage matures.

In the second stage regressions shown in Panel B, we use fitted values of from the LTV regressions to estimate a model of mortgage spreads. The coefficients for LTV in each of the two 2SLS regressions are much larger than the coefficients in the standard one-stage regression estimates shown in Table and. This indicates that adjusting for endogeneity with the two-stage procedure enables us to better capture the economic impact of LTVs on spreads.

The results for 2SLS specification 1 show that mortgages on properties in largest tenant categories 3 and 4 without a lease rollover have spreads that are 5.8 and 5.6 basis points lower than spreads on mortgages for single-tenant properties without a lease rollover. However, tests that the sum of the L1 category dummy and the rollover interaction term show that borrowers lose this discount if the largest tenant's lease expires before the mortgage matures. Thus, lease rollover risk is incorporated into spreads when properties are not highly diversified. The results also show that mortgages on properties in tenant size category 1 have higher spreads than mortgages single-tenant properties.

The 2SLS results when using HHI to measure tenant diversification are similar to those that are obtained when using the percent of square footage occupied by a property's largest tenant as a proxy for diversification. Properties in HHI quantiles 4 and 5 have mortgages with lower spreads, but they do not get this discount if the largest tenant's lease expires before the mortgage matures. Additionally, properties in HHI quantile 1 have spreads that are 8.47 basis points higher than spreads on single-tenant properties without rollover risk.

The 2SLS results indicate that properties get lower spreads as they achieve moderate levels of diversification, but that they lose the discount if the lease of the largest tenant of the property expires before the mortgage matures. Mortgages on properties with higher levels of diversification have spreads that are significantly higher

than spreads for mortgages on single-tenant properties, but these properties do not face a penalty for lease rollover risk. These results are consistent with those that are presented earlier in this paper. Thus, we conclude that our results are robust to adjusting for the joint determination of LTVs and spreads.

### 3. Tenant diversification and the likelihood of mortgage default

In this section, we examine if tenant diversification at mortgage origination impacts the likelihood that the loan eventually goes into default. The Trepp loan file reports the delinquency status of each loan on every tape date. For each loan, we examine the loan's delinquency status over its lifetime. If the loan enters a period of 90 or more days delinquent during its lifetime, we consider it to be loan a loan that eventually defaults.

#### 3.1 Modeling the likelihood of mortgage default

To model default likelihood, we use a logistic model in which the dependent variable is a dummy variable that equals 1 if the loan eventually becomes 90 or more days delinquent and 0 otherwise. We use a number of the same variables that were used in the spread analysis as explanatory variables in our default model, since variables that influence spreads are likely to reflect the default risk of the loan. In addition, many of these variables are in line with the existing literature that examines the likelihood of commercial mortgage default.<sup>8</sup>

The loan-specific characteristics that we include in the model are the spread, the loan-to-value ratio (LTV) expressed as a percentage, the amortization rate, the debt service coverage ratio (DSCR), and the number of years until the mortgage matures. The property-specific characteristics that we include in the default model are the natural log of the property's value, the ratio of net operating income (NOI) to property value, the occupancy rate, and the property's age in years. We also include U.S. census division dummies to control for the property's location and the maturity matched Treasury bond rate to capture general market conditions and the risk associated with the loan's term structure. Finally, we use various specifications of the percent of square footage occupied by the largest tenant, the tenant diversification HHI, and the largest tenant lease rollover dummies to examine how tenant diversification and lease structure influences default rates.

Summary statistics for several of the variables used in our model can be found in Table .<sup>9</sup> Panel A presents summary statistics for variables included in regressions that use the percent of square footage occupied by the largest tenant as a proxy for diversification, and panel B presents statistics for the regressions that use HHI to measure tenant diversification. In each sample, a little over 11 percent of the loans eventually default. On average, the percent of square footage occupied by the largest tenant and the tenant HHI values are smaller for mortgages that default, indicating that mortgages on more diversified properties are more likely to default.

---

<sup>8</sup> See Archer et al. (2002), Ciocchetti et al. (2002), Ambrose and Sanders (2003), Ciocchetti et al. (2003), Christopoulos, Jarrow and Yildirim (2008), Yildirim (2008), and Titman and Tsyplakov (2010).

<sup>9</sup> The sample size in our default analysis is smaller than the sample size in our spread model because we drop loans that are missing data on the DSCR or the property's U.S. Census division.

**Table 7: Summary statistics for loans by Default Group**

The tables break loans into groups of loans that do not eventually default and groups of loans that do eventually default. Average values for mortgage, property, and tenant characteristics are shown for each group. Panel A shows statistics for variables used in default regressions that use the percent of square footage occupied by the property's largest tenant. Panel B shows statistics for variables used in default regressions that use the property's HHI, which is computed as follows:

$$HHI = \frac{L1\%^2 + L2\%^2 + L3\%^2}{10,000} \times 100,$$

where L1% is the percent of square footage occupied by the largest tenant, L2% is the percent of square footage occupied by the 2<sup>nd</sup> largest tenant, and L3% is the percent of square footage occupied by the 3<sup>rd</sup> largest tenant.

*Panel A: Summary statistics by default group for largest lessee % Sq. footage sample*

Eventual 90+ Day Delinquency	N	% Sample	Fraction 90+Days Delinquent	Top Lessee % Sq. Ft.	Fraction Top Lessee Rollover	Spread (%)	Property Value (mil)	LTV (%)	NOI/Property Value	Occ. Rate (%)	Amort. Rate	Property Age	Years to Loan Maturity	DSCR
0	14,678	88.80	0.00	48.27	0.59	1.4787	15.42	68.60	0.0745	96.73	0.1604	17.74	10.02	1.62
1	1,851	11.20	1.00	37.02	0.76	1.4123	14.28	72.86	0.0729	95.41	0.1308	14.70	9.94	1.49
Total	16,529	100.00	0.11	47.01	0.61	1.4712	15.29	69.08	0.0743	96.58	0.1571	17.40	10.01	1.61

*Panel B: Summary statistics by default group for HHI Sample*

Eventual 90+ Day Delinquency	N	% Sample	Fraction 90+Days Delinquent	HHI	Fraction Top Lessee Rollover	Spread (%)	Property Value (mil)	LTV (%)	NOI/Property Value	Occ. Rate (%)	Amort. Rate	Property Age	Years to Loan Maturity	DSCR
0	14,003	88.53	0.00	37.23	0.58	1.4498	15.59	68.61	0.0740	96.78	0.1591	17.63	10.00	1.63
1	1,814	11.47	1.00	23.87	0.76	1.3982	14.40	72.88	0.0727	95.43	0.1305	14.57	9.93	1.49
Total	15,817	100.00	0.11	35.70	0.60	1.4439	15.46	69.10	0.0738	96.63	0.1558	17.28	10.00	1.61

### 3.2 Default model regression results

The results for logistic regressions modeling eventual default are shown in Table 8, Panel A displays the results for 3 different specifications that use the percent of square footage occupied by the largest tenant (L1%) as a proxy for tenant diversification. The first specification includes L1% as a continuous variable. The coefficient estimate on L1% is negative and significant, indicating that as tenant diversification increases, the likelihood of mortgage default increases. The results in the second specification are similar. The coefficient estimates on the dummy variables for L1 categories 1 through 4 are positive and significant, indicating that diversified properties are more likely to default than single-tenant properties. Additionally, the coefficient estimates on the L1 dummy variables increase monotonically as the L1 category decreases, indicating that the likelihood of mortgage default increases as tenant diversification increases. The third specification includes lease rollover interaction terms with the L1 category dummy variables. The coefficients on the dummy variables are positive and significant for L1 categories 1 through 4, meaning that loans on properties in these categories without a lease rollover are more likely to go into default than loans on single-tenant properties without lease rollovers. The lease rollover interaction term is also significantly positive for each of these categories, indicating that there is increased default risk for mortgages

on properties in each of those L1 categories when the largest tenant of the property has a lease expires before mortgage maturity.

**Table 8:** Logistic regressions for likelihood of eventual 90+ day loan delinquency

This table displays results from logistic regressions that model the likelihood with which a commercial mortgage loan eventually becomes 90+ days delinquent. Standard errors for the coefficients are clustered by quarter.

*Panel A: Diversification measured using percent square footage of occupied by the Property's Largest Tenant*

Variable	Specification 1			Specification 2			Specification 3		
	Coefficient Estimate	Odds Ratio	Z-stat	Coefficient Estimate	Odds Ratio	Z-stat	Coefficient Estimate	Odds Ratio	Z-stat
L1%	-0.0140	0.9861	(-7.2585)						
D(L1 Category 1)				1.2958	3.6538	(6.7327)	0.9100	2.4843	(3.4838)
D(L1 Category 1) × D(L1 Rollover)							0.6427	1.9016	(3.9355)
D(L1 Category 2)				1.1670	3.2122	(7.2318)	1.0789	2.9414	(4.7976)
D(L1 Category 2) × D(L1 Rollover)							0.3521	1.4220	(3.0761)
D(L1 Category 3)				1.0902	2.9748	(7.2751)	1.0710	2.9184	(4.3827)
D(L1 Category 3) × D(L1 Rollover)							0.3476	1.4157	(2.3916)
D(L1 Category 4)				0.7453	2.1071	(4.4641)	0.4835	1.6217	(2.3234)
D(L1 Category 4) × D(L1 Rollover)							0.9404	2.5611	(5.3828)
D(L1 Category 5)				0.0028	1.0028	(0.0093)	0.1685	1.1835	(0.5343)
D(L1 Category 5) × D(L1 Rollover)							0.0558	1.0574	(0.0917)
D(L1 Category 6) × D(L1 Rollover)							0.8898	2.4346	(3.7391)
Spread	0.9561	2.6014	(9.4255)	0.9794	2.6628	(10.0422)	0.9851	2.6781	(9.9476)
Log(Property Value)	0.0006	1.0006	(0.0207)	0.0043	1.0043	(0.1405)	0.0796	1.0828	(2.4183)
LTV (%)	0.0515	1.0528	(10.2455)	0.0510	1.0523	(9.9542)	0.0522	1.0536	(10.4244)
NOI / Prop Value	-4.2772	0.0139	(-1.0145)	-5.5024	0.0041	(-1.3506)	-6.5348	0.0015	(-1.6276)
Occupancy Rate	-0.0150	0.9851	(-2.4225)	-0.0162	0.9839	(-2.7196)	-0.0169	0.9832	(-2.8092)
Amortization Rate	0.2651	1.3036	(0.8213)	0.3081	1.3608	(0.9632)	0.3519	1.4218	(1.1101)
Log(Property Age)	-0.1879	0.8287	(-7.1142)	-0.1960	0.8220	(-7.5175)	-0.2315	0.7933	(-9.8817)
Years to Maturity	-0.0412	0.9597	(-1.8088)	-0.0426	0.9583	(-1.8790)	-0.0644	0.9376	(-2.8703)
DSCR	-0.2067	0.8132	(-1.4926)	-0.1842	0.8317	(-1.3575)	-0.1666	0.8465	(-1.2252)
Maturity Matched Treasury Rate	0.7527	2.1227	(4.3837)	0.7686	2.1568	(4.4306)	0.7834	2.1888	(4.5443)
Census Region Dummies	Yes			Yes			Yes		
Quarter Dummies	Yes			Yes			Yes		
N	16,529			16,529			16,529		
Pseudo R-Square	0.11			0.11			0.12		

*Panel B: Diversification measured using the Property's HHI*

Variable	Specification 1			Specification 2			Specification 3		
	Coefficient Estimate	Odds Ratio	Z-stat	Coefficient Estimate	Odds Ratio	Z-stat	Coefficient Estimate	Odds Ratio	Z-stat
HHI	-0.0137	0.9864	(-7.5065)						
D(HHI quantile=1)				1.3941	4.0315	(6.8687)	1.1194	3.0629	(4.2185)
D(HHI quantile=1) × D(L1 Rollover)							0.4932	1.6376	(2.7679)
D(HHI quantile=2)				1.2731	3.5720	(7.0501)	0.9893	2.6894	(4.0633)
D(HHI quantile=2) × D(L1 Rollover)							0.5385	1.7135	(4.1562)
D(HHI quantile=3)				1.2302	3.4218	(7.0790)	1.2320	3.4279	(4.4987)
D(HHI quantile=3) × D(L1 Rollover)							0.2294	1.2579	(1.5455)
D(HHI quantile=4)				0.9612	2.6149	(6.4726)	0.8270	2.2865	(3.3552)
D(HHI quantile=4) × D(L1 Rollover)							0.4661	1.5937	(2.9709)
D(HHI quantile=5)				0.9082	2.4797	(5.9350)	0.7366	2.0889	(3.8507)
D(HHI quantile=5) × D(L1 Rollover)							0.6791	1.9721	(6.1120)
D(HHI quantile=6) × D(L1 Rollover)							0.8736	2.3955	(3.6536)
Spread	0.9967	2.7095	(10.1139)	0.9961	2.7078	(10.3603)	0.9987	2.7149	(10.1804)
Log(Property Value)	-0.0167	0.9835	(-0.5728)	-0.0176	0.9825	(-0.5798)	0.0634	1.0655	(1.9103)
LTV (%)	0.0516	1.0529	(9.9995)	0.0514	1.0527	(9.9464)	0.0528	1.0542	(10.4740)
NOI / Prop Value	-4.7195	0.0089	(-1.1235)	-4.7918	0.0083	(-1.1472)	-5.3176	0.0049	(-1.2896)
Occupancy Rate	-0.0136	0.9865	(-2.0879)	-0.0142	0.9859	(-2.3154)	-0.0155	0.9846	(-2.5022)
Amortization Rate	0.3646	1.4400	(1.0846)	0.3593	1.4323	(1.0724)	0.3914	1.4791	(1.1780)
Log(Property Age)	-0.2053	0.8144	(-7.4675)	-0.2032	0.8161	(-7.4890)	-0.2393	0.7872	(-9.3625)
Years to Maturity	-0.0545	0.9470	(-2.6093)	-0.0539	0.9475	(-2.5519)	-0.0745	0.9282	(-3.6031)
DSCR	-0.1623	0.8502	(-1.2560)	-0.1611	0.8512	(-1.2440)	-0.1481	0.8623	(-1.1433)
Maturity Matched Treasury Rate	0.8090	2.2456	(4.7088)	0.8009	2.2275	(4.6311)	0.8093	2.2463	(4.6986)
Census Region Dummies	Yes			Yes			Yes		
Quarter Dummies	Yes			Yes			Yes		
N	15,817			15,817			15,817		
Pseudo R-Square	0.11			0.11			0.12		

Panel B of Table shows logistic regression results when using tenant HHI as a proxy for tenant diversification. Specification 1 includes HHI as a continuous variable. The coefficient estimate on HHI is negative and significant, meaning that as diversification increases, default risk increases. In the second specification, coefficients for all HHI quantiles are positive and significant, and the coefficients increase monotonically as tenant diversification in each category increases. Thus, diversified properties have higher default risk than single-tenant properties, and this risk increases with the level of diversification. Specification 3 also shows that diversified properties have higher default risk than single-tenant properties. In addition, default risk increases for all HHI

quantiles when the lease of the property's largest tenant expires before the lease matures. This risk is largest for the least diversified properties, as the coefficient estimates on the rollover dummy interaction term is highest for HHI quantiles 5 and 6. This indicates that diversification provides some protection against lease rollover risk, but that it does not eliminate rollover risk entirely.

The default results provide a strong indication that, holding all else constant, as the level of tenant diversification increases, the likelihood of mortgage default increases. Thus, while lenders and developers may prefer properties with some tenant diversification, increasing the level of tenant diversification leads to increased default risk. While this does not reflect what one would typically expect from diversification, there are reasons that retail properties may benefit from having a single tenant that occupies a substantial proportion, if not all, of the property's space. One of the benefits of having a large tenant is that the tenant is likely to have better, more stable credit than a number of smaller tenants that could occupy the same amount of space. Thus, a large tenant may provide less risky cash flows than a number of small tenants splitting that space. Additionally, for properties with multiple tenants, a large tenant may generate significant externalities by increasing business for smaller tenants. This means that a property with some small tenants is likely to be less risky if that property has a large anchor to draw customers for all of the property's tenants. The results also indicate that default risk increases when the lease of the property's largest tenant expires before the mortgage matures. This underscores the importance of locking large tenants into long term leases.

#### 4. Conclusion

Existing research on commercial mortgages clearly indicates that tenant characteristics are important in assessing the risk of a commercial mortgage. Additionally, research has found that the structure of tenants within a commercial property is important. In this paper, we use the percent of square footage occupied by a property's largest tenants to generate proxies for tenant diversification, and we investigate the degree to which tenant diversification influences spreads and defaults rates on mortgages for retail properties.

We find that properties with moderate levels of tenant diversification receive lower mortgage spreads than single-tenant properties, but that spreads of mortgages on properties with high levels of diversification are higher than spreads of mortgages on single-tenant properties. The spread discount that exists for mortgages on properties with moderate levels of diversification only exists for properties in which the largest tenant's lease does not expire before the mortgage matures. These results highlight the importance that lenders place on anchor tenants. Large tenants are important because they are able to generate significant sales externalities for smaller tenants on the property, and highly diversified properties are likely to lack an anchor tenant and therefore lose the benefit of these externalities. Large tenants may also likely to be important to lenders because these tenants are likely to be more credit-worthy than smaller tenants, meaning that cash flows from a large tenant are considered to be less risky than those generated by a number of smaller tenants despite the increased



diversification that is attained from having a larger number of tenants. While large tenants are important, the results indicate that lenders are concerned about the lease structure of these tenants, as the spread discount for properties with moderate levels of tenant diversification disappears if the lease of the property's largest tenant expires before the mortgage matures. Spreads for highly diversified properties that face this same rollover risk are not different from spreads for highly diversified properties without this risk, so tenant diversification may be seen as protection against the risk that the largest tenant may vacate the property.

While mortgages on properties with moderate levels of tenant diversification have lower spreads, we find that default risk increases as tenant diversification increases. Thus, tenant diversification does not result in lower default risk. Instead, properties with larger tenants and lower levels of diversification are less risky. Additionally, regardless of how diversified a property is, default risk on the property's mortgage increases if the lease of the property's largest tenant expires before the mortgage matures. The default results provide further evidence about the importance of large tenants, as properties with lower levels of diversification are less likely to default. They also indicate that lenders may overvalue externalities provided by anchor tenants in moderately diversified properties, as these properties have lower mortgage spreads but higher default rates.

One of the drawbacks of our study is that we do not have data about the credit quality of a property's tenants. Our default analysis indicates that diversification increases default risk, but large tenants in properties with low levels of diversification may be high quality, creditworthy tenants. For these properties, lenders should easily be able to identify the quality of the largest tenants, so they may only extend loans to undiversified properties if the tenants are safe and stable. Similarly, the credit quality of tenants is likely to be an important factor in determining credit spreads on commercial mortgages. Moderately diversified properties with 1 or 2 large tenants may get lower spreads than single-tenant properties because of the credit quality of the large tenants and the externalities the large tenants provide for the property's smaller tenants. Because we do not have access to data on the credit quality of tenants in a property, we are unable to control for tenant credit risk in this paper. This is a potentially fruitful avenue for further research.

## References

- Acharya, Viral V, I Hasan, and A Saunders 2006. Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios. *The Journal of Business* 79:1355-1412.
- Ambrose, BW, JD Benjamin, and P Chinloy 2003. Bank and Nonbank Lenders and the Commercial Mortgage Market. *Journal of Real Estate Finance & Economics* 26:81.
- Ambrose, BW, and AB Sanders 2003. Commercial Mortgage-Backed Securities: Prepayment and Default. *Journal of Real Estate Finance & Economics* 26:179.
- Archer, WR, PJ Elmer, DM Harrison, and DC Ling 2002. Determinants of Multifamily Mortgage Default. *Real Estate Economics* 30:445-473.
- Bebczuk, R, and A Galindo 2008. Financial crisis and sectoral diversification of Argentine banks, 1999-2004. *Applied Financial Economics* 18:199-211.
- Berger, AN, I Hasan, and M Zhou 2010. The effects of focus versus diversification on bank performance: Evidence from Chinese banks. *Journal of Banking & Finance* 34:1417-1435.

- Brueckner, JK 1993. Inter-Store Externalities and Space Allocation in Shopping Centers. *Journal of Real Estate Finance & Economics* 7:5-16.
- Cho, H, and JD Shilling 2007. Valuing Retail Shopping Center Lease Contracts. *Real Estate Economics* 35:623-649.
- Christopoulos, AD, RA Jarrow, and Y Yildirim 2008. Commercial Mortgage-Backed Securities (CMBS) and Market Efficiency with Respect to Costly Information. *Real Estate Economics* 36:441-498.
- Ciochetti, BA, D Yongheng, G Lee, JD Shilling, and Y Rui 2003. A Proportional Hazards Model of Commercial Mortgage Default with Originator Bias. *Journal of Real Estate Finance & Economics* 27:5.
- Ciochetti, BA, D Young, G Bin, and Y Rui 2002. The Termination of Commercial Mortgage Contracts through Prepayment and Default: A Proportional Hazard Approach with Competing Risks. *Real Estate Economics* 30:595-633.
- Colwell, PF, and HJ Munneke 1998. Percentage Leases and the Advantages of Regional Malls. *Journal of Real Estate Research* 15:239.
- Gould, ED, BP Pashigian, and CJ Prendergast 2005. Contracts, Externalities, and Incentives in Shopping Malls. *The Review of Economics and Statistics* 87:411-422.
- Grovenstein, RA, JP Harding, CF Sirmans, S Thebpanya, and GK Turnbull 2005. Commercial mortgage underwriting: How well do lenders manage the risks? *Journal of Housing Economics* 14:355-383.
- Maris, BA, and W Segal 2002. Analysis of Yield Spreads on Commercial Mortgage-Backed Securities. *Journal of Real Estate Research* 23:235.
- Mercieca, S, K Schaeck, and S Wolfe 2007. Small European banks: Benefits from diversification? *Journal of Banking & Finance* 31:1975-1998.
- Nothaft, FE, and JL Freund 2003. The Evolution of Securitization in Multifamily Mortgage Markets and Its Effect on Lending Rates. *Journal of Real Estate Research* 25:91.
- Pashigian, BP, and Eric D Gould 1998. Internalizing Externalities: The Pricing of Space in Shopping Malls. *Journal of Law and Economics* 41:115-142.
- Petersen, MA 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies* 22:435-480.
- Tabak, BM, DM Fazio, and DO Cajueiro 2011. The effects of loan portfolio concentration on Brazilian banks' return and risk. *Journal of Banking & Finance* 35:3065-3076.
- Thompson, SB 2011. Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics* 99:1-10.
- Titman, S, S Tompaidis, and S Tsyplakov 2005. Determinants of Credit Spreads in Commercial Mortgages. *Real Estate Economics* 33:711-738.
- Titman, S, and S Tsyplakov 2010. Originator Performance, CMBS Structures, and the Risk of Commercial Mortgages. *Review of Financial Studies*.
- Wheaton, WC 2000. Percentage Rent in Retail Leasing: The Alignment of Landlord-Tenant Interests. *Real Estate Economics* 28:185-204.
- Yildirim, Y 2008. Estimating Default Probabilities of CMBS Loans with Clustering and Heavy Censoring. *The Journal of Real Estate Finance and Economics* 37:93-111.

### Appendix 1: Linear Restriction Tests

Tests with L1% Dummies:

$$\text{coeff}[D(0 \leq L1\% < 20)] + \text{coeff}[D(0 \leq L1\% < 20) \times D(L1 \text{ Rollover})] = 0$$

$$\text{coeff}[D(20 \leq L1\% < 40)] + \text{coeff}[D(20 \leq L1\% < 40) \times D(L1 \text{ Rollover})] = 0$$

$$\text{coeff}[D(40 \leq L1\% < 60)] + \text{coeff}[D(40 \leq L1\% < 60) \times D(L1 \text{ Rollover})] = 0$$

$$\text{coeff}[D(60 \leq L1\% < 80)] + \text{coeff}[D(60 \leq L1\% < 80) \times D(L1 \text{ Rollover})] = 0$$

$$\text{coeff}[D(80 \leq L1\% < 100)] + \text{coeff}[D(80 \leq L1\% < 100) \times D(L1 \text{ Rollover})] = 0$$

Tests with HHI Dummies:

$$\text{coeff}[D(\text{HHI quantile}=1)] + \text{coeff}[D(\text{HHI quantile}=1) \times D(\text{L1 Rollover})] = 0$$

$$\text{coeff}[D(\text{HHI quantile}=2)] + \text{coeff}[D(\text{HHI quantile}=2) \times D(\text{L1 Rollover})] = 0$$

$$\text{coeff}[D(\text{HHI quantile}=3)] + \text{coeff}[D(\text{HHI quantile}=3) \times D(\text{L1 Rollover})] = 0$$

$$\text{coeff}[D(\text{HHI quantile}=4)] + \text{coeff}[D(\text{HHI quantile}=4) \times D(\text{L1 Rollover})] = 0$$

$$\text{coeff}[D(\text{HHI quantile}=5)] + \text{coeff}[D(\text{HHI quantile}=5) \times D(\text{L1 Rollover})] = 0$$

Tests for Table and

Restriction	L1% Dummies		HHI Dummies	
	chi <sup>2</sup>	p-val	chi <sup>2</sup>	p-val
1	12.38	0.0006	10.95	0.0012
2	3.41	0.0669	2.43	0.1214
3	0.01	0.9344	2.28	0.1335
4	1.09	0.2974	0.15	0.7038
5	0.00	0.9860	0.00	0.9734

Tests for Panel B of Table

Restriction	L1% Dummies		HHI Dummies	
	chi <sup>2</sup>	p-val	chi <sup>2</sup>	p-val
1	12.95	0.0003	12.41	0.0004
2	3.48	0.0622	2.81	0.0938
3	0.01	0.9404	2.38	0.1232
4	1.41	0.2355	0.36	0.5493
5	0.01	0.9187	0.00	0.9483