An Analysis of the Determinants of Retail Capitalization Rates[*]

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Abstract

Despite an abundant literature on micro- and macroeconomic factors that influence capitalization rates, little is known about tenant and location-specific risk pricing, especially for smaller, single-tenant commercial properties. This study examines the variation in cap rates for single tenant net lease (STNL) properties. We use a unique dataset of more than 8,200 single-tenant retail property transactions from 2005 to 2019 in the United States. We focus on quantifying the pricing of risk associated with tenant characteristics, including the listing status of the parent company, ownership structure, default risk, and industry type. Our results show that these tenant characteristics play an important role in explaining cap rate variations after controlling for a comprehensive list of macro-and micro-level determinants that have been previously documented in the extant literature.

JEL Classifications:
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1 Introduction

The capitalization rate (cap rate) plays a crucial role in commercial real estate (CRE) valuation since it is the primary method by which investors convert income into value. Defined as net operating income (NOI) divided by transaction price, the cap rate can provide important information on both efficient market pricing and potential changes in rental growth rates (see Chichernea et al. (2008)). The cap rate is essentially a property's price/earnings (P/E) ratio and, as Sivitanides et al. (2003) point out, the price/earnings ratio is the primary indicator of how the market views an asset in the securities markets. A high P/E ratio reflects a more positive outlook for the asset while a lower P/E indicates the opposite. Being the reciprocal of the P/E ratio, the cap rate is the rate at which the market is capitalizing a property's net operating income. As with the P/E ratio, the cap rate should reflect current market conditions and the expected future direction. For example, Peng (2018) finds that the cap rate predicts a property's non-systematic risk and future volatility.

Despite the abundant literature on the determinants of cap rates (e.g., Ambrose and Nourse (1993), Chervachidze et al. (2009), Chervachidze and Wheaton (2013), Hendershott and MacGregor (2005), Chaney and Hoesli (2015)), little is known about the pricing of risk (and therefore cap rates) for individual commercial property tenants, primarily due to a lack of data.[1] To fill this void, our study quantifies the contribution of tenant characteristics in explaining the variation in cap rates for single tenant net lease (STNL) properties. Adding tenant specific characteristics to previous documented factors such as lease and property attributes, local demand and employment, along with macroeconomic variables, we explore the most complete set of cap rate determinants to date that drives the pricing of smaller commercial properties.

[1] Traditionally, commercial real estate transactions have been predominantly multi-tenant properties, which act in a similar manner to an investment portfolio by diversifying risk across a variety of tenants. Because of this and a lack of data for smaller individual properties, very little research has focused on smaller commercial properties.

A good understanding of the determinants of cap rates, particularly at the property level, has direct implications for CRE investments. As Peng (2013) notes, research on individual property cap rates is important because real estate properties' heterogeneous pricing, due to individual property characteristics and local market conditions, has very definite implications for an investor's portfolio performance.[2] While prices in highly liquid public securities markets adjust quickly to changes in market fundamentals, observed cap rates in private CRE markets may adjust more gradually to the arrival of new information. As Clayton et al. (2009) show, this is due primarily to market inefficiencies, such as high transaction costs, lengthy decision-making processes and due-diligence periods, and informational inefficiencies. Therefore, understanding the components of the cap rate is imperative to ensure that a CRE investment is correctly priced. Misstatement of the cap rate can possibly result in substantial valuation error.

In this study, we identify how various factors and characteristics contribute to cap rate composition. We utilize a unique dataset of more than 8,000 single-tenant retail property transactions.[3] Single-tenant properties function as single-security holdings, causing their risk and return to be dependent upon pre-existing tenants and conditional on observed property and locational characteristics. We focus on retail properties to capture the large variation in tenant industries (e.g., traditional retail trade, services, administration, and entertainment) and tenant ownership structure (e.g., corporate or franchise). We also observe tenant credit-worthiness attributes such as the public listing status of the parent company and default rate. To optimize the set of explanatory variables to explain cap rate variation and identify the most significant determinants of cap rates, we utilize a machine learning technique, Least Absolute Shrinkage and Selection Operator (LASSO). Our results show that listing status, ownership, credit rating, and tenant line of business significantly explain cap rates both statistically and economically. Given the long time period and nationwide geographic dispersion of our sample, we are able to observe cap rate variations through several local and national economic cycles.

The cap rate literature can generally be divided into two main strands, looking at either

[2]To some extent by its nature, the cap rate implies constant-quality market measures, such as similar properties in similar locations with similar leasing terms (see Hendershott and MacGregor (2005)). Valuing individual properties is problematic because of different property and lease characteristics.

[3]Data was obtained from Verum Properties, LLC, a leading real estate data company that focuses on single tenant net lease properties and transactions. See Section 3 for detailed discussion.

the macro- or micro-level determinants of cap rates. Cap rates are shown to vary greatly at the aggregate level (e.g., national or MSA) depending on macro-level indicators such as inflation, GDP growth, and stock market performance (e.g., Chichernea et al. (2008), Clayton et al. (2009)). Research focusing on micro-level factors, especially using smaller, single-tenant properties as the unit of observation, is much scarcer due to data limitations. Existing micro-level studies focus mainly on property characteristics and local market conditions (e.g., McDonald and Dermisi (2009), Gunnelin et al. (2004)). Combining tenant characteristics with previous research that has analyzed cap rate variation at both the macro- and micro-level, we assess risk factors associated with tenant characteristics such as industry type, ownership structure, and creditworthiness of the tenant. Our findings contribute significantly to the literature by quantifying the difficulty in diversifying tenant risk in a single-tenant asset. Our study is the first to explicitly examine the role of tenant credit in explaining cap rate variations in retail properties.

A number of studies such as Miller (2021) investigate tenant resilience along with imbalances in retail supply and demand. As suggested by Zhou and Clapp (2016), and Clapp et al. (2020), this is largely driven by over-retailing. However, given this unique dataset of individual STNL properties, our research provides an enhanced perception of these phenomena.

As of 2017, CoStar data showed 166 million square feet (about 0.6 SF per capita) of vacant U.S. retail space. However, the COVID-19 pandemic has caused increased uncertainty in retail sector performance. With the possibility of massive store closings and bankruptcies of large retail chains, future vacancy rates could increase dramatically. If this were to happen, investment values would suffer, and state and local jurisdictions could see declining property tax revenue. This would only serve to highlight the advantage and stability of STNL properties.

The popularity of STNL properties comes primarily from the hands-off nature and relative security of the investments. As suggested by Seaward and Larson (2020), the increased uncertainty in retail sector performance will likely allow STNL properties to outperform other investments, due to their more predictable and stable cash flows. Also, since the credit rating of the tenant can affect the risk of the investment, our findings may provide meaningful implications on how to fill vacant retail spaces and can be useful in helping practitioners, researchers, and policymakers to better understand the risk and return associated with tenant characteristics.

2 Prior Literature

As this section shows, studies examining income real estate capitalization rates have generally fallen into two camps: studies examining cap rate effects of microeconomic variables, such as project size, age, location, vacancy, class, tenant diversification, etc. and studies measuring cap rate effects of macroeconomic variables such as credit spreads, inflation, market interest rates, unemployment, and investor sentiment. Although the existing literature is quite extensive, a missing component is analysis of cap rates for STNL properties. Historically, data for these properties have been limited since they tend to be held privately and, as such, public disclosure of NOI or other micro-level variables is not required. Access to a unique dataset allows us to explore cap rates for these properties. The following discussion of existing studies provides a backdrop for our study's contribution to the cap rate literature.

2.1 Micro-Variable Effects on Capitalization Rates

An early study by Handy (1993) finds that distance to routine destinations, such as grocery stores, eating places and banks, is important in determining local accessibility. Local accessibility translates to convenience for consumers and can be extremely important for net lease tenants such as convenience stores, fast food restaurants, dry cleaners, etc. since consumers typically make their purchasing decisions based on retail tenants' proximity to their current path of travel. In a later related study, Pivo and Fisher (2011) find that investors are willing to pay price premiums for properties that are given a high Walkscore. The authors find that walkability is associated with lower capitalization rates and higher incomes and that the benefits of greater walkability are capitalized into higher ofce, retail, and apartment values but not industrial property values. A logical conclusion is that properties located in urban and suburban centers with high population density and within favorable proximity (walkability) should experience lower cap rates relative to properties located in sparsely populated tertiary markets.

Another early study by Saderion et al. (1994) finds that apartment cap rates appear to vary systemically with project size, age, and location. The authors argue that the market approach is likely not sufficient in valuation because of the lack of data explaining subtle differences in complex quality and that the income approach is likely not adequate because of the failure to account for major differences in cap rates across alternative property types. The authors present a model that treats these data limitations problems by including NOI and characteristic variables.

A couple of studies have focused on micro-variable effects on office market cap rates. Sivitanidou and Sivitanides (1999) perform a two-part analysis, first examining the importance of cap rate local-fixed effects and time-variant components and then examining the importance of local versus national markets. Their results show that office cap rates incorporate both a local-fixed component and a time-variant component and are affected by local market traits (such as location heterogeneity, the diversity of the local office employment base, and tenant mix) and time-variant features (such as the level of office space absorption, normalized vacancy rates, office employment-growth stability, and past rates of rental-income growth). A later study of office market cap rates by McDonald and Dermisi (2009) expand the traditional capital asset pricing model to include variables affecting office markets. They show that a lower cap rate is associated with a smaller risk-free rate, a lower borrowing rate, class A buildings, newer buildings, buildings that had been renovated, a reduction in the vacancy rate, and an increase in employment in the financial sector of the metropolitan area. Other results show that the cap rate is associated with building characteristics (class and age) and market forces (changes in the downtown office vacancy rate and changes in financial sector employment).

Corgel et al. (2015) examine hotel valuation and test two hedonic pricing models: the traditional residential model and a model that incorporates city-specific net operating incomes and discount rates (thereby recognizing property, city, and capital market determinants contributions). They argue that variation in hotel prices is best explained by systematic economic factors in the city and nation, along with property specific attributes that relate to generation of cash flow. They conclude that their empirical analysis does not support the inclusion of variables measuring city and national market effects.

Using data on retail properties, Rosiers et al. (2016) examine whether store rent levels are affected by chain affiliation within regional and super-regional shopping centers. Their results show that, even when accounting for cyclical and micro-market influences, chain-affiliated stores specializing in high-end and standard-quality goods experience a rent premium. No rent premium is observed for independent or local chain affiliated stores selling high-end goods. The authors show that, regardless of the chain affiliation, no significant rent discount is obtained for stores selling low-quality goods.

Several studies focus on the variation in cap rates either across properties or across appraisal-based versus transaction-based cap rates. Hendershott and MacGregor (2005) examine cap rate disparities across income property sectors. They find lower apartment cap rates relative to cap rates of other income properties. Office cap rates are found to be lower than retail. Their results also show that below-market financing is fully capitalized in apartment prices and that location is important. Netzell (2009) regresses cap rates on property characteristics, the property's market rent, and variables to capture time series variation in cap rates. His results show that, for the most part, appraisals do not deviate from the expected pattern and do not exhibit irrationality. Chaney and Hoesli (2015) compare the driving factors of appraisal-based cap rates versus those of transaction-based cap rates. Their results identify several variables and categories of variables that explain cap rates. These include property-specific risks (such as land leverage, ownership leverage, refurbishment risk, and illiquidity risk), construction quality, building condition, and micro-level risk categories such as tenant diversification, tenant risk, regulatory risk, and the degree to which the transaction is arms-length.

In examining REITs, Fisher et al. (2020) show that location density affects cap rates. They find that REITs with property holdings in high-density locations experience higher NOI growth, earn higher risk-adjusted returns, and carry higher systematic risk than their otherwise comparable peers in low-density locations. These high-density REITs are also shown to have lower leverage, better access to public bond markets, and lower implied cap rates. The authors conclude that location density is a significant driver of real estate investment risk and return.

Several studies examine the relationship between cap rates and commercial property risk-adjusted discount rates. Gunnelin et al. (2004) examine the variation in discount rates, expected NOI growth rates, and exit cap rates and find that exit cap rates are highly correlated with discount rates but are not related to expected NOI growth rates. However, expected NOI growth is highly correlated with differences in both actual and market rents and long-run vacancy rates. Ghysels et al. (2007) examine the connection between cap rates and future real estate returns and find that a large part of cap rate predictability is unrelated to fundamentals. The authors conclude that property and local economic factors account for only a small part of the variation in cap rates. Cho and Shilling (2007), examining valuation of retail shopping centers under uncertainty, develop a shopping center lease contract default model. They find, to compensate for externality effects, a slightly higher discount rate is needed for valuation and ignoring this can result in valuations that are too high and cap rates that are too low.

McDonald and Dermisi (2009) examine the relationship between cap rates and risk-adjusted discount rates. Their results show a low (although statistically significant) beta and a risk-free rate with a positive effect on the cap rate. Other results show that the cap rate is correlated with building characteristics (class, age, and whether the building had been renovated) and market forces (changes in the downtown office vacancy rate and changes in financial sector employment). Finally, Fisher et al. (2009) examine the effects of short- and long-run dynamics in institutional capital flows on private real estate market returns. At the national level, the authors find that lagged institutional flows significantly influence subsequent returns. However, when the national data are disaggregated by property type, capital flows predict subsequent returns for the apartment and office sectors but not for the retail and industrial markets. There is also no evidence that returns are predictive of future institutional capital flows. The authors conclude that institutional investors do not appear to systematically chase either returns or capital flows of other institutional investors.

Together, the above studies indicate that location and other micro-variables of a property affect its market value and therefore its cap rate. We extend this research by examining determinants of cap rates for single-tenant net lease retail properties. This study overcomes the historical lack-of-date problem by quantifying a set of location, property specific, and other variables to measure their effects on property values and cap rates.

2.2 Macroeconomic Factor Effects on Capitalization Rates

Capitalization rates for income producing real estate can be affected by the overall economic environment and macroeconomic factors such as interest rates, inflation, availability capital, house price movements, etc. Several studies have examined the integration of real estate and capital markets and the effect of the macroeconomic environment and factors on cap rates.

Jud and Winkler (1995) develop a model of income property cap rates by property type that draws on the weighted average cost of capital and the capital asset pricing model. Using a two-step procedure for a one-way fixed effects model, the authors find a positive relationship between cap rates and the cost of debt and equity and that cap rates are determined by debt and equity spreads. However, the authors find there are significant adjustment lags and significant variation in market relationships across locations, leading to less than complete integration of the real estate market with the national capital market. Chen et al. (2004) also examine the interaction between the capital markets and income property market fundamentals. Arguing that cap rates alone do not indicate over or underpricing, the authors examine cap rates, asset over or under-pricing, interaction between capital markets, and property market fundamentals. They find that prices for most property types are set fairly relative to capital market factors. Peyton (2009) argues that commercial real estate investors are cognizant of the risk-adjusted returns from other asset types. The author shows that the transactions cap rate spread is predictable over short time periods using macroeconomic/financial market conditions and income property market fundamentals. Employing macroeconomic and interest rate factors, credit pricing factors, and commercial property performance factors, the author argues that the integration of income real estate into the larger capital markets is validated through the significance of corporate bond spreads.

Sivitanides et al. (2001) and Sivitanides et al. (2003), using panel-based NCREIF data, find that movements in market-specific cap rates have strong predictable components. The authors show the differences that cap rates exhibit across markets are mainly due to variations in fixed market characteristics. They also find that movements in market-specific cap rates are affected by both local market behavior and macroeconomic factors such as interest rate levels and general price inflation. In a later related study, Chichernea et al. (2008) explain the effect of supply constraints, liquidity, risk, and flow/availability of capital on the geographical variation in cap rates. Examining variation in cap rates across MSAs, the authors find a strong relationship between cap rates and supply constraints and a weaker relationship between cap rates and expected growth rates, liquidity, and other risk factors. The authors conclude that MSAs with more restrictive supply constraints and more liquid markets will exhibit lower cap rates.

Plazzi et al. (2008) examine cross-sectional dispersion of returns and rent growth for apartments, offices, industrial, and retail properties. The cross-sectional dispersions are shown to be time varying and explained by macroeconomic variables such as the term and credit spreads, inflation, and the short rate of interest. The authors also show the cross-sectional dispersions to be counter-cyclical, increasing in recessions and decreasing in expansions, and that they vary inversely with the credit spread. Cross-sectional dispersions are also shown to respond asymmetrically to economic shocks, increasing more in response to negative shocks than positive shocks.

Several studies have examined specific macroeconomic variable effects on cap rates. Conner and Liang (2005), examining the interaction between interest rates and cap rates, argue that low interest rates lead to a decline in cap rates by allowing investors to pay price premiums using financial leverage. Using a duration model, the authors find a positive relationship between cap rates and interest rates, with cap rates increasing by about 50 to 75 bps for every 100 to 150 bps increase in interest rates. Hendershott and MacGregor (2005) find a mean or trend reversion behavior in both property rents and dividends and that dividends above trend make the property more attractive and cause the property cap rate to decline. Clayton et al. (2009)), specifying cap rates as a function of real estate space and capital market fundamentals, find that fundamentals (expected rental growth, equity risk premiums, T-bond yields, and lagged adjustments from long run equilibrium) are the primary drivers of cap rates, with sentiment also playing role. Chervachidze et al. (2009), Chervachidze and Wheaton (2013) examine the determinants of income property cap rates using treasury rates, local market fundamentals, a market-observed corporate risk premium, and the growth rate of debt relative to GDP (general market liquidity). Their results show that much of the decline and subsequent rise in cap rates in the 2000s are attributable more to macroeconomic factors and less to movements in market fundamentals. The authors find that local rent fundamentals are a relatively small part of the explanation of cap rates and that three macroeconomic variables (real Treasury rate, bond risk premium, and expansion of debt) are extremely important.

Peng (2013) analyzes the effect of macroeconomic factors, local market conditions, and property attributes on cap rates and cap rate uncertainty. His results show that location fixed effects and macroeconomic conditions such as credit availability, past returns in real estate, movements in house price indices, and nonresidential construction spending are significant in explaining cap rates. He finds that the Treasury-yield, Term Spread, Credit Spread, and availability of CMBS within an MSA are significant in explaining cap rate risk premiums of income properties. The author finds that property characteristics and location specific factors have a limited effect on property cap rates across sectors. In a more recent study, Beracha et al. (2019) examine ex ante real estate return premiums and show that realized cap rates have limited predictive power for expected returns for all property types. They find that both fundamental and non-fundamental factors are significant predictors of ex ante risk premiums. These factors include debt capital market conditions, unemployment, NAREIT and NCREIF returns, stock market volatility, and investor sentiment. Their results also show that sources of fundamental and non-fundamental information vary across states and may be driven by differences in investor risk perception or information availability.

As these studies show, macroeconomic factors can affect commercial property cap rates. Interestingly, some of these studies (Peng (2013), for example) also show that property attributes and location specific factors have a limited effect on cap rates across sectors. Our paper contrasts this view and shows that, among single-tenant net lease retail properties, a significant portion of a property's cap rate risk premium lies in the location of that property within a given market.

2.3 Tenant Credit and Lease Term's Effects on Real Estate

The importance of tenant characteristics and/or lease terms on CRE valuation is not well documented in the literature. Closest to our study is the work of Mooney et al. (1998) who examine a sample of 26 net lease properties with publicly traded tenants. The authors find that the characteristics of the tenant's leases (i.e., lease term, number of options, number of step-ups) and the market's assessment of the riskiness of the tenant's return (measured by the tenant's stock beta) are significant in explaining cap rates.[4] Recently, Liu et al. (2019a) use credit quality of multi-tenant assets to assess implications for REIT values. They show that REITs with higher asset values (proxied by tenant quality) tend to borrow more debt.[5] These results suggest that the credit of the tenant is deemed important to the variance of the cap rate of STNL properties.

3 Sample Construction

We obtain a sample of 8,242 transactions of single-tenant retail properties in 2000-2019 from Verum Properties, LLC, a real estate data company that focuses on single tenant net lease properties and transactions. The properties are dispersed across the United States. Figure 1 provides an overview of the geographic distribution of the transactions. While the number of locations could introduce a lower level of control, the widespread variability of location permits location-specific characteristics to be averaged across markets. The data for Tenant/Guarantor/Ownership information was collected by Verum Properties, LLC from Koyfin, Mergent, SEC, and Tenant Investor Relations. Verum Properties, LLC reports that sample construction included surveying appraisers, brokers, investors, and developers. This led to the compilation of a database with 104 variables that were deemed to influence cap rates. Any variable selected as important by at least two industry professionals was included in the initial model. The large number of variables allows us to make a significant contribution to the literature on the variance of cap rates among single-tenant retail properties. Other data that we utilize include lease data, collected from actual leases and verified Offering Memorandums; sales data, collected from County Records; and property data, collected from county records and/or landlords.

[4] The authors first use simple regressions by regressing one of the covariates against cap rates. They find that the beta of the tenant's stock and the total lease term plus options appear to best explain the cap rate. Next, they use a multiple regression to test these variables jointly. Their model produces an Adjusted R2 of 0.884, indicating that 88.4% in the variance in these properties' cap rates is explained by these variables. This study, therefore, appears to substantially explain the variation in cap rates. However, an adjusted R2 over 0.80 can also be a strong indicator of the presence of multicollinearity within the model. The authors provide no details regarding the collinearity of the variables in the model. Also, with a sample size of 26, the ability of the models to provide an accurate explanation of cap rate variance may be limited.

[5] In a related study, Liu and Liu (2013) exam how tenant bankruptcy announcements impact the performance of its landlord REIT company.

4 Methodology

We first specify a baseline regression model and incrementally operationalize our core theoretical concepts which include macro-level indicators, property characteristics, location characteristics, deal-level controls, lease terms, and tenant characteristics, with more refined variables. For the baseline regression, we apply ordinary least squares (OLS) regression to comprehensively analyze the determinants of our dependent variable, *Cap Rate*. The basic structure of our baseline regression model is as follows:

$$\begin{aligned} CapRate_{i,j,l,t} = \alpha + \boldsymbol{\beta} Tenant_{i,t-1} + \boldsymbol{\lambda} Lease\&Deal_{i,j,l,t-1} + \boldsymbol{\gamma} Property_{j,t-1} \\ + \boldsymbol{\delta} Location_{l,t-1} + \boldsymbol{\delta} 5mileDemand_{l,t-1} + \boldsymbol{\delta} CBP_{l,t-1} \\ + \boldsymbol{\delta} NCREIF_{l,t-1} + \boldsymbol{\theta} Macro_{t-1} + \psi_{MSA} + \phi_t + \zeta_l + \epsilon_{i,j,l,t} \end{aligned} \tag{1}$$

Table 1 provides an overview of the variable blocks. Our outcome variable, $CapRate_{i,j,l,t}$, is the cap rate for property j sold with tenant i in location l at time t. The main explanatory variables in the tenant characteristics block ($Tenant_{i,t-1}$) are listing status (i.e., public versus private), ownership type (i.e., corporate versus franchisee), industry classifications based on NAICS code (e.g., retail trade, information, finance/insurance/real estate), default rate and credit rating, measured at $t-1$.

$Lease\&Deal_{i,j,l,t-1}$ include years left on lease and lease type (gross, net, or triple-net lease), deal type (i.e., fee simple, ground lease, and leasehold), and rent to market rent ratio. The property characteristics block, $Property_{j,t-1}$, includes building size, land area, and property age. $Location_{l,t-1}$ includes a comprehensive list of variable for locational characteristics, including distance to downtown, distance to the nearest regional or super-regional center. We include the squared terms to account for nonlinearity.

$5mileDemand$ are proxies for local demand within a 5-mile radius. We include demand density (as a proxy for potential revenue) and growth in demand density. In unreported results we also use alternative trade areas such as 1-mile and 3-mile radius and find similar results. The CBP variable block includes county-level total employment, share of employment in the tenant industry, and employment concentration measured by Herfindahl-Hirschman Index (HHI). The $NCREIF$ variable block controls for private retail market transaction volume, return and price level.

The macro indicator variable block, $Macro_{t-1}$, includes risk-free rate, risk premium, debt availability, CPI, term spread, S&P return and volatility, REIT index, mortgage rate, and change in financial employment. We classify MSAs into three tiers in ψ_{MSA}, including gateway, secondary, and tertiary markets. We also test models by replacing macro indicators with year fixed effects, ϕ_t, and by replacing ψ_{MSA} with MSA fixed effects (ζ_l). We use robust standard errors that are clustered by MSA level in all regressions.

With many highly correlated regressors, OLS estimation might lead to large coefficient estimates of opposite signs for highly correlated regressors that are difficult to interpret. In addition, our results might be influenced by the functional form and model specification. To mitigate these concerns, we use a machine learning technique, Least Absolute Shrinkage and Selection Operator (LASSO), to optimize the set of explanatory variables ("predictors") for cap rate variation.[6] LASSO estimation modifies OLS by adding a penalty term on the sum of absolute coefficients and lets the model to select the most important variables by assigning zero coefficients to many potential explanatory variables. The LASSO method will allow us to both assess variable selection and perform coefficient estimation (Tibshirani, 1996).[7]

The linear LASSO solves the following absolute value function

$$\hat{\boldsymbol{\beta}} = \underset{\beta}{\operatorname{argmin}}\{1/n\sum_{i=1}^{n}(y_i - \boldsymbol{X_i}\boldsymbol{\beta}')^2 + \lambda\sum_{j=1}^{p} w_j|\beta_j|\} \tag{2}$$

where $\hat{\boldsymbol{\beta}}$ are the linear lasso point estimates. y_i is the outcome variable which is cap rate in our study. n is the sample size. X_i contains the p potential covariates. $\lambda > 0$ is the

[6] One could also use Ridge for regularization. The common form of both LASSO and Ridge is to add a penalty term that shrinks the β toward zero. There are also various hybrid methods and modifications, including elastic nets, which combine penalty terms from LASSO and ridge. We use LASSO because it's easier to interpret when it generates solutions with regression coefficients exactly equal to zero, a sparse solution. In contrast, Ridge leads to estimated regression coefficients generally differ from zero. We use STATA LASSO Package (StataCorp. (2021)) to perform the analysis.

[7] The method has been previously used to address scenarios with a plethora of available variables, as in Liu et al. (2019b).

lasso penalty parameter. w_j are parameter-level weights known as penalty loadings. β_j is the jth elements of $\boldsymbol{\beta}$. λ and w_j are called the lasso tuning parameters, which specify the weight applied to the penalty term. When $\lambda = 0$, the linear lasso reduces to the OLS estimator. As λ grows, the coefficient estimate shrinks towards zero. There exists a λ_{max} which makes all the estimated coefficients exactly zero. Therefore, we must choose the tuning parameters λ, $\lambda \in (0, \lambda_{max})$, and w_j before using the lasso for model selection, as the value of these tuning parameters determines which covariate will be included and which will be excluded.

To select the tuning parameters, we use cross-validation (CV), adaptive lasso, and plug-in methods, which are the most frequently used methods. The CV method selects the value that minimizes the out-of-sample mean squared error (MSE) of the predictions. We first divide our sample into (1) a training subsample and (2) a validation subsample. We then estimate the parameters using the training sample and the out-of-sample MSE of the predictions using the validation sample. The best predictors are the set of estimators that produces the smallest out-of-sample MSE. The plug-in method finds the value of the λ that is large enough to dominate the estimation noise. The adaptive lasso is a multi-step version of CV.

5 Results

5.1 Data Description

We combine the lease data set with the variables described in Table 1 to form our final sample of 7,912 transaction observations. A summary of the variables is provided in Table 2. The mean (median) Cap Rate in our sample is 6.63% (6.44%). Nearly three quarters of the lessees are publicly traded firms. The average lease term at the time of sale is 11.8 years, and only 11.6% of the leases are gross leases. The vast majority of the net leases are triple net leases. The average (median) property size is 11,322 (6,727) square feet. The average (median) property age is 13 (9) years. Approximately 14% of the properties leased are located in each Gateway and Secondary MSAs, and 63% in Tertiary MSAs, with the remainder of the properties located in non-metropolitan areas.

The sample contains 968 distinct tenants. The industry classifications show that there is variation in the types of tenants represented. Appendix A.1 lists the top ten tenants occurring in the sample, with the top 5 being Walgreens (9.6% of the sample) , Dollar General (9.3%), CVS (5.5%), Family Dollar (3.8%) and Burger King (2.8%). Figure 2 (a) provides a plot of the correlation between cap rates and determinants of cap rate, using the abbreviated short name from Table 1. Figure 2 (b) provides a graph shaded depiction of the correlation matrix. Figure 2 (a) shows that the variables with the highest absolute value correlations with cap rate are lease term variables (e.g., DC1-4) and the lending market environment variables (e.g., MA12-14). However, there are many other variable blocks, such as county business pattern controls, showing high correlations.

5.2 Regression Results

We estimate *Equation 1* with OLS and report the results in Table 3. We start with a model specification with only tenant characteristics in column 1, and we gradually add property, deal and lease, location characteristics, local demand proxies, county business pattern controls, and macro indicators through columns 2-8. To access the importance of our tenant variables, we plot Figure 3 showing the incremental contribution of each block of variables in Table 3. The observed variables often mentioned - property characteristics, lease terms, and macroeconomic indicators are important, yet tenant characteristics provide the largest contribution in explaining cap rates.

Figure 4 illustrates the contribution of tenant characteristics to determining cap rates when included simultaneously with other explanatory variables. Specifically, we plot comparisons by adding tenant characteristics to a model in which we include only a particular set of determinants (e.g., property characteristics, location characteristics etc.). The blue bar shows the R-squared from the model with that particular set of determinants only. The red bar shows how much addition explanatory power we can add by including tenant characteristics. In all the models, tenant characteristics contribution far more than the other groups alone. We discuss each of the variable blocks below.

5.2.1 Tenant Characteristics

The tenant characteristics included in our study are indicator variables for whether the tenant is a publicly traded company or a subsidiary of a publicly traded company, credit worthiness, and industry classification. The credit of the tenant was quantified using the corporate credit rating according to Standard & Poor's (S&P), Moody's, or Fitch. The provided ratings were then used to determine the probability of default over the next 5 years, reflected in a percentage rate. Private companies and franchisee operators were given a credit rating based on financial statements in the year of sale, according to the following four factors: the ratio of current assets to current liabilities comparable to industry average, and ratios of net sales to working capital, fixed charges to available earnings and total debt to net worth. Consistent with the findings in Mooney et al. (1998) and Liu et al. (2019a), we find that properties with tenants that are corporate owned (as opposed to franchise), tenants with direct or subsidiary publicly traded ownership, and tenants with lower default probabilities are trade at significantly lower cap rates. The economic significance is quite large. Using our most conservative estimates in column (8), compared with properties with tenants operating as a franchise, properties with corporate-owned tenants are traded at a lower cap rate by 34 basis points. We also observe a 31 basis point difference between transactions with publicly traded tenants and those with private tenants. A one-standard-deviation change in $\%Default$ is associated with a 21 basis point change of cap rates (=0.015*13.8).

Importantly, the differential effect estimates for these tenant characteristics are relatively stable as additional controls are added. For example, the coefficient estimate for $Ownership$ reduces from -0.487 (in column (1) with only tenant variables) to -0.337 (in column (8) with our full set of controls). We use Oster (2019)'s rule of thumb for a maximum R-squared of 1.3 times the R-squared for the unrestricted model and find an Oster statistic of 2.25 suggesting that the effects of unobservables would have to be more than twice as important than the observables to eliminate the estimated relationship, consistent with a robust positive relationship between our tenant variables and cap rate. The results for $\%Default$ and $Listed$ are even more robust: unobservables could erode the effects of default probability (listed status) if they were almost ten (one and a half) times more influential and that influence was in the *opposite* direction. Results adding MSA and year fixed effects in Table 4 are qualitatively similar.

There is substantial variation in the industries represented in our sample. Smith (2010) mention that retail property is used by as many as ninety different industries. We find that Wholesale, Transportation, Educational and Non-Services trade at higher cap rates, while FIRE, Hospitality and Other Services have traded at significantly lower cap rates. In terms of economic magnitude, we find sizable effects on Wholesale. Information, FIRE and hospitality have similar effects.

Location specific factors could have a large impact on cap rates, depending on tenant quality.[8] For investment grade tenants, the impact of location attributes on pricing can range substantially. However, for assets without investment grade tenants, location attributes almost always matter. To investigate this issue, we follow the model specification in Column (8) of Table 3 and interact the *Gateway* dummy with our three main tenant variables, *Listed*, $\%Default$, and $Ownership$. In unreported results, we find that the coefficient estimates of the three tenant variables as well as the gateway dummy are still highly significant and of a similar magnitude. However, only the interaction between $\%Default$ and *Gateway* is statistically significant: the coefficient estimate equals -0.005 with a standard error of 0.001. This finding suggests a trade-off between location and tenant quality as either fear of default lessens in gateway markets or the possibility of re-leasing is viewed as a lesser risk.

5.2.2 Other Determinants

Property Characteristics The property characteristics available in our sample are Building size, Land Area and Property Age. Land Area has a negative relationship with cap rates. We find that Property Age has a positive relationship with cap rates due to the added risk of building maintenance for older assets. While Property Age and Land Area are both statistically significant, the economic significance of property attributes is relatively small. For example, a one-standard-deviation increase in Land Area from its mean is associated with less than one basis point reduction in cap rates.

[8]We thank Andrew McCulloch for this valuable suggestion.

Deal and Lease Characteristics Our deal characteristics include type of transaction, *Deal*, with the vast majority of deals are fee simple, *Years Left on Lease*, an indicator variable for *Gross Lease*, with the vast majority of leases being net leases, and *Rent to Market Rent Ratio. Years Left on Lease* has a negative and slightly significant (in both economic and statistical terms) coefficient. *Rent to Market Rent Ratio* has a negative and significant coefficient in Table 3, which does not persist when MSA and Year Fixed effects are included in Table 4. The initial finding is not surprising, given that the average term left on the lease in our sample is 11.8 years. Having a below market lease prevents a new buyer from capturing market rents for a long period of time.

Local Characteristics Next we take a look at location characteristics, local demand proxies and county level controls. Among location characteristics, *Distance to CBD* has a positive and significant coefficient, implying that assets located further from CBD demand a premium in yield for the less desirable location. *Distance to Mall* has a negative and significant coefficient which could be explained by the lack of competition for shoppers in the immediate target area. Local area *Demand Density*, *Demand Density Growth* and county employment patterns, all proxies for the economic health of the local area, have a negative and highly statistically significant relationship with cap rates. Pivo and Fisher (2011) find that walkability is associated with lower capitalization rates, especially for properties located in urban and suburban centers with high population density. We are able to collect walkability scores for a subsample, and we re-run our results by adding walkability scores. Results in Table A.2 are highly consistent with those in Tables 3 and 4.

Macro Indicators To account for the overall macro market conditions, we consider NCREIF retail returns, interest rate, unemployment, stock market, and commercial real estate loan supply indicators. Table 3 shows that *Term Spread*, *GDP Growth*, *Δ in Debt to GDP Ratio*, and Market Vacancy Rate have positive and highly statistically significant relationship with cap rates. At the same time, *Inflation* and *Stock Volatility Index* have a negative relationship with cap rates, consistent with the explanation that real estate provides an inflation hedge to other investment opportunities. *NCREIF Index & Returns* has a negative and significant coefficient, yet the significance does not persist when MSA and year fixed effects are included in Table 4.

5.3 Using LASSO for Model Selection

We next use LASSO to identify the most significant determinants of cap rates. The advantage of LASSO is that it does not depend on the functional form and model specification. If the importance of tenant characteristics we document are simply driven by other observed determinants that have already been included in the model, those tenant variables would be dropped by LASSO. As described in the Methodology section, the tuning parameters must be selected before using the lasso for model selection. We first use cross-validation (CV) that uses split samples to find the best out-of-sample predictors. As a starting point, we split our sample into a training subsample with 75% of the observations and a validation subsample with 25% of the observations. Results are qualitatively similar when we use alternative splits such as 80-20, 60-40, or 50-50.[9]

We provide LASSO the full set of 50 potential variables. As shown in Figure 5, the CV function is minimized by including 33 covariates when $\lambda = 0.0098$. Table 5 shows the lasso knot table which summarizes when a covariate is added or subtracted to the set of covariates with nonzero values at a certain value of λ. One λ is a knot if a new variable is added or removed from the model. Each knot (shown in column (2) with the corresponding value of λ) marks the entry or removal of some variable(s) from the current active set (i.e., its coefficient becomes nonzero or zero). For example, when $\lambda = 0.16$, 8 variables are selected. Note that some variables, including $\triangle$ Charge Off rate on CRE Loans, Total CRE Loans, and Deal (Fee Simple) are first added to the variable set but then removed before the CV function reaches its minimum.

As shown in Table 5, LASSO selects most of tenant characteristics variables, including $Listed$, $\%Default$, and $Ownership$. These variables are chosen when λ is large, indicating a relative high order of importance, and are never removed from the active set. In Table 6, we compare LASSO selection using alternative turning parameter selection methods including CV without sample split, the plugin method, and the adaptive lasso with three steps. The plugin lasso include the least number of covariates (i.e., 20) while the CV and adaptive lasso generate similar results (30 versus 27). Importantly, tenant characteristics, especially ownership status, default

[9]There is no standard rule for split ratio. The most common choice in practice is to use 75% to 80% of the total sample for training and the remaining samples for validation. With more training data, the parameter estimates have a low variance Li and Lin (2021).

probability, and listed, are selected by all three methods. These results provide support for the importance of tenant characteristics in explaining cap rate variations.

5.4 Market Industry

Next we focus on particular market demand for a certain type of retail. The rationale is that if a given tenant business type is common in that market (say children's store near World Disney), then it would be easy to replace the tenant with minimum vacancy downtime. To address this potential explanation, we add an indicator variable if a tenant's business classification falls in the top three or top five employment industries in their market. Table A.3 reports the results. Top 3 (establishment) equals one if the tenant's industry (2-digit NAICS code) ranks among top-3 industries in terms of number of establishments in the county where the property is located, and zero otherwise. Similarly, top 3 (employment) equals one if the tenant's industry (2-digit NAICS code) ranks among top-3 industries in terms of employment in the county where the property is located, and zero otherwise. Consistent with intuition, we see that tenants whose line of business falls into the dominant industries in that market trade at significantly lower cap rates. Importantly, the results of tenant characteristics are robust to adding these "top-industry" effects: the coefficients of $Ownership$, $Listed$, and $\%Default$ are of similar statistical significance levels and magnitudes.

5.5 Access Tenant Characteristics Using Decomposition

While we sofar conclude that the tenant characteristics are important determinants of cap rates, the differences in for example, listing status or ownership structure, might be explained away by other determinants (e.g., property and locational characteristics) that have been documented in the literature. To investigate this issue, we focus on the three main tenant variables, $Listed$, $\%Default$, and $Ownership$, and use the Blinder-Oaxaca decomposition method (Blinder (1973), Oaxaca (1973)) to study (1) cap rate differences between the subsample with publicly listed tenant and the subsample with non-listed tenants, (2) differences between tenants with corporate ownership and those with franchise ownership, and (3) differences between tenants with probability of default higher than the sample median and those with probability of default lower than the sample median. The decomposition divides the cap rate differential between two groups (that differ in one dimension of the tenant characteristics) into a part that is explained by other covariates, and a residual part that cannot be explained by differences in cap rate determinants. The objective is to access how much of the mean outcome differences could be explained by other covariates.

In Table 7, the mean of cap rates is lower for public, corporate owned, and credit tenants (i.e., the "Low Group"). Importantly, the explained portions are all negative, suggesting that the overall difference would even be larger without accounting for tenant characteristics. Since the explained part is negative, the cap rate differences between high- and low-quality tenants are largely unexplained by all the other groups of covariates, supporting the importance of tenant characteristics that we have documented.

For ease of interpretation, we group the variables into main categories (e.g., property characteristics, deal & lease characteristics) following the previous tables. Delving deep into each group of covariates, the negative contribution comes from local demand, county business pattern controls, and macro factors. First, local demand has a negative effect on cap rates and properties occupied by low-quality tenants are located, on average, in areas with higher demand than high-quality tenants. For example, the mean of 5-mile Demand Density Growth is 3.3% for tenants owned by private firms and 2.9% for tenants owned by public firms. Second, properties with high-quality tenants tend to trade during down market periods and therefore are associated with poorer macro indicators, which is consistent with the flight-to-safety explanation (Boudry et al. (2022)). In addition, transactions with tenants owned by public firms are associated with higher unemployment rates, lower GDP growth, and higher vacancy rate. These findings suggest a potential upward (downward) bias on demand-side factors in a model explaining cap rate (valuation) differentials, if tenant characteristics are omitted.

6 Conclusion

Our study extends prior literature on cap rates by exploring the significance and pricing of the yield premiums associated with tenant characteristics. Our analysis is made possible by a unique data set of single tenant retail acquisitions which allow us to include the most complete set of cap rate determinants in the literature to date. Our findings show that tenant credit worthiness indicators, such as the listing status of the parent company, ownership structure, and default risk are some of the primary drivers of cap rates, along with local economic indicators previously documented in literature. Our results are robust to various model specifications and the use of the LASSO technique to parcel through a plethora of explanatory variables. We also complete a separate analysis on the important of both the tenant industry and the predominance of that industry in the surrounding market. We find that both have a significant relationship with cap rates, providing further evidence that the risk of re-leasing the property in the event the tenant vacates is explicitly priced in the acquisition cap rate.

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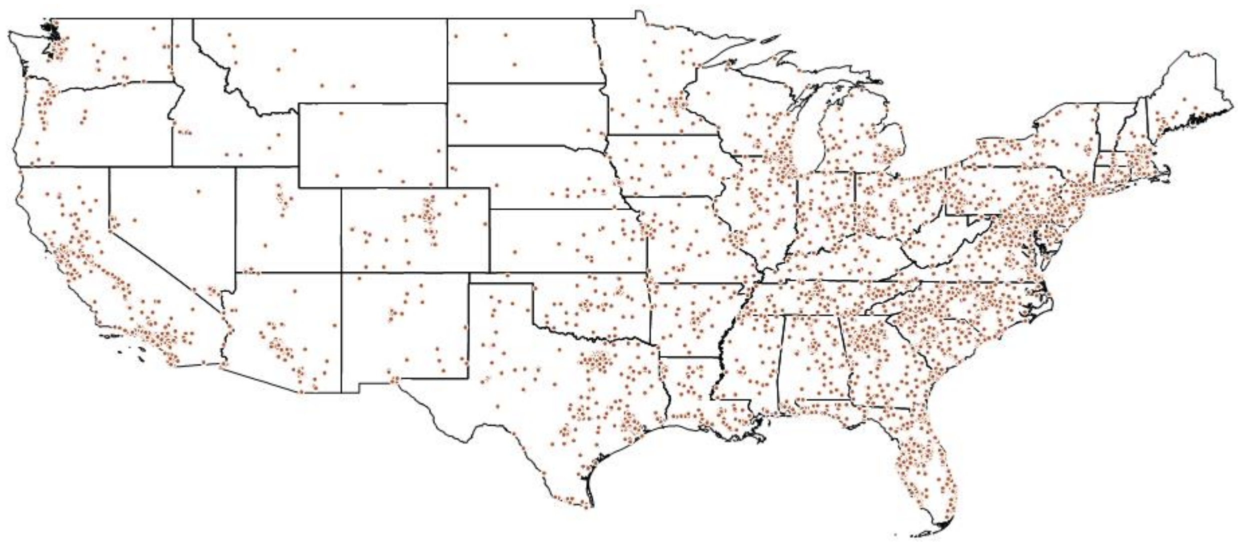
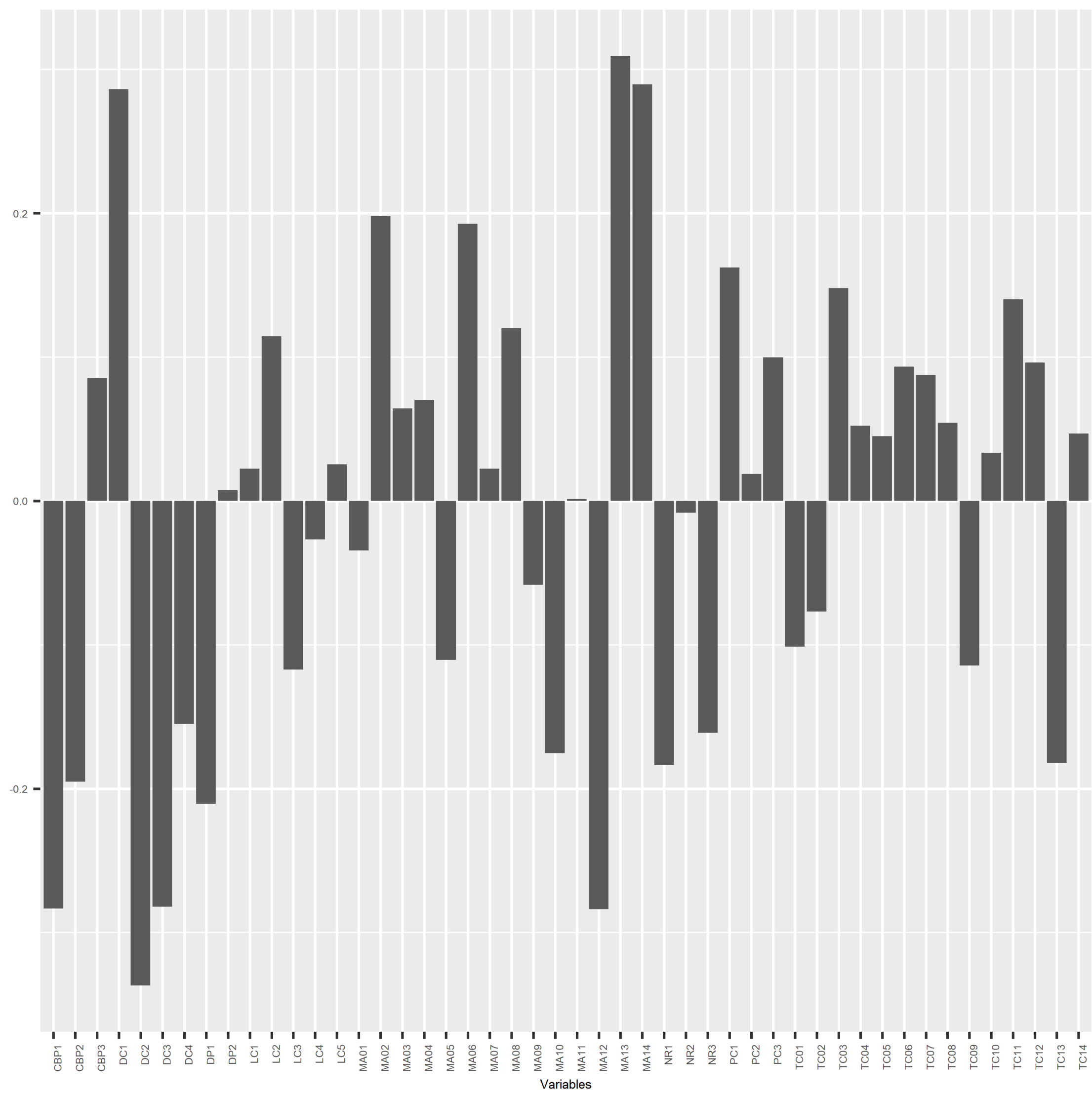
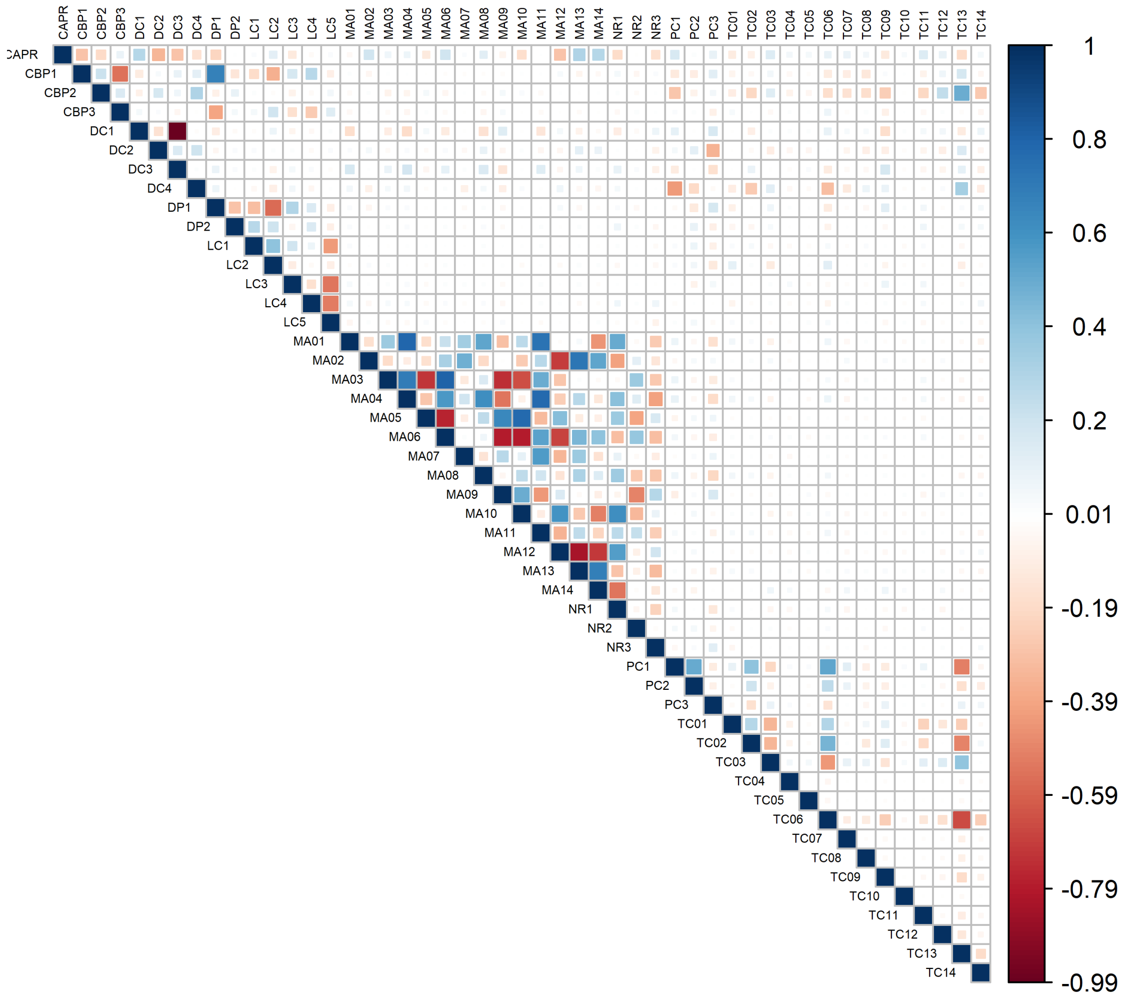


In this figure, we plot geographic distribution of our sample of 8,242 single-tenant retail properties.

Figure 1: Geographic Distribution



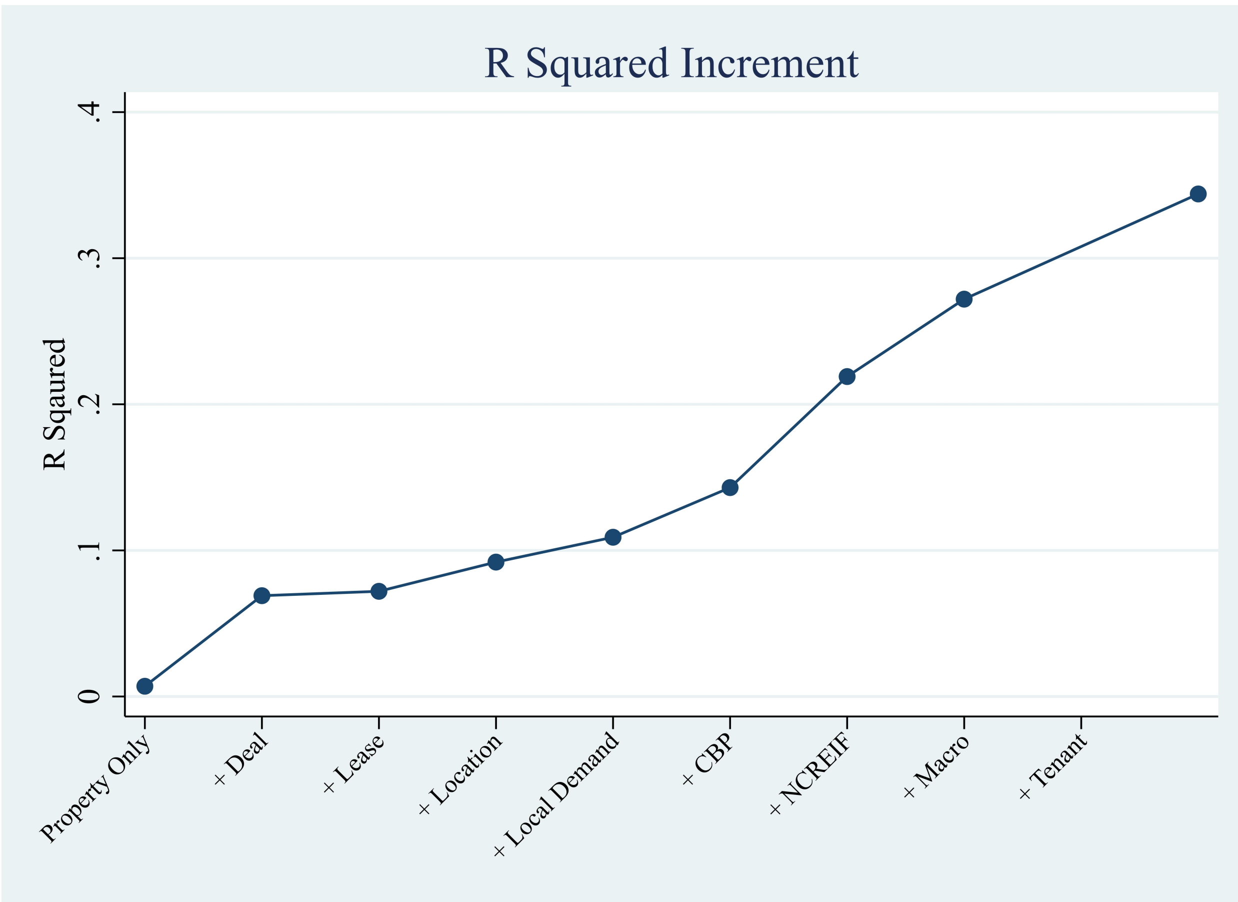
(a) Correlation between cap rates and the determinants of cap rates



(b) Correlations among all variables

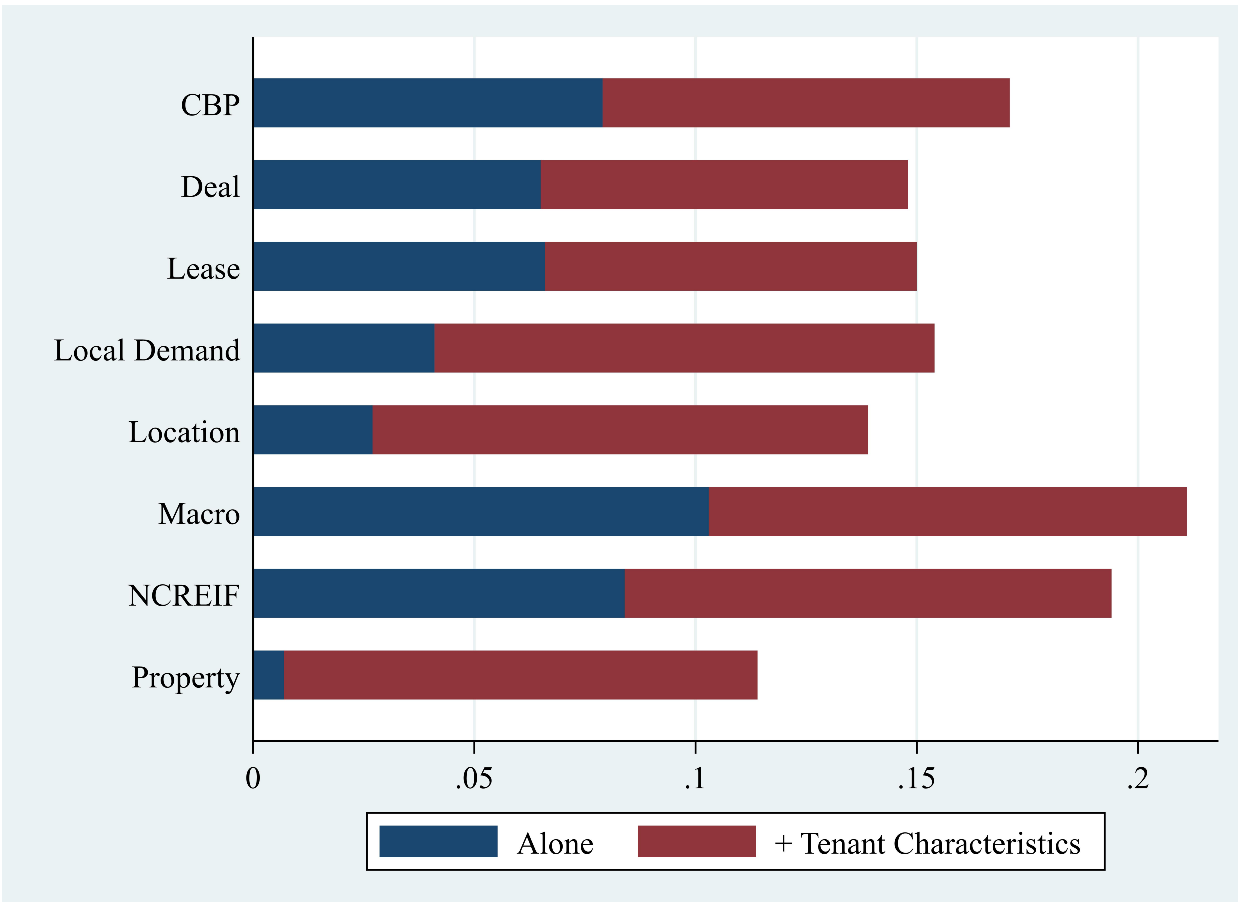
In this figure, we plot correlation matrix. Panel 2a plots the correlations between cap rate and its determinants. The horizontal axis is the determinants of cap rates listed (in short names) in Table 1. The vertical axis shows the correlation between cap rate and each determinant. Panel 2b plots the correlations among all variables (in short names) in Table 1.

Figure 2: Correlation Matrix



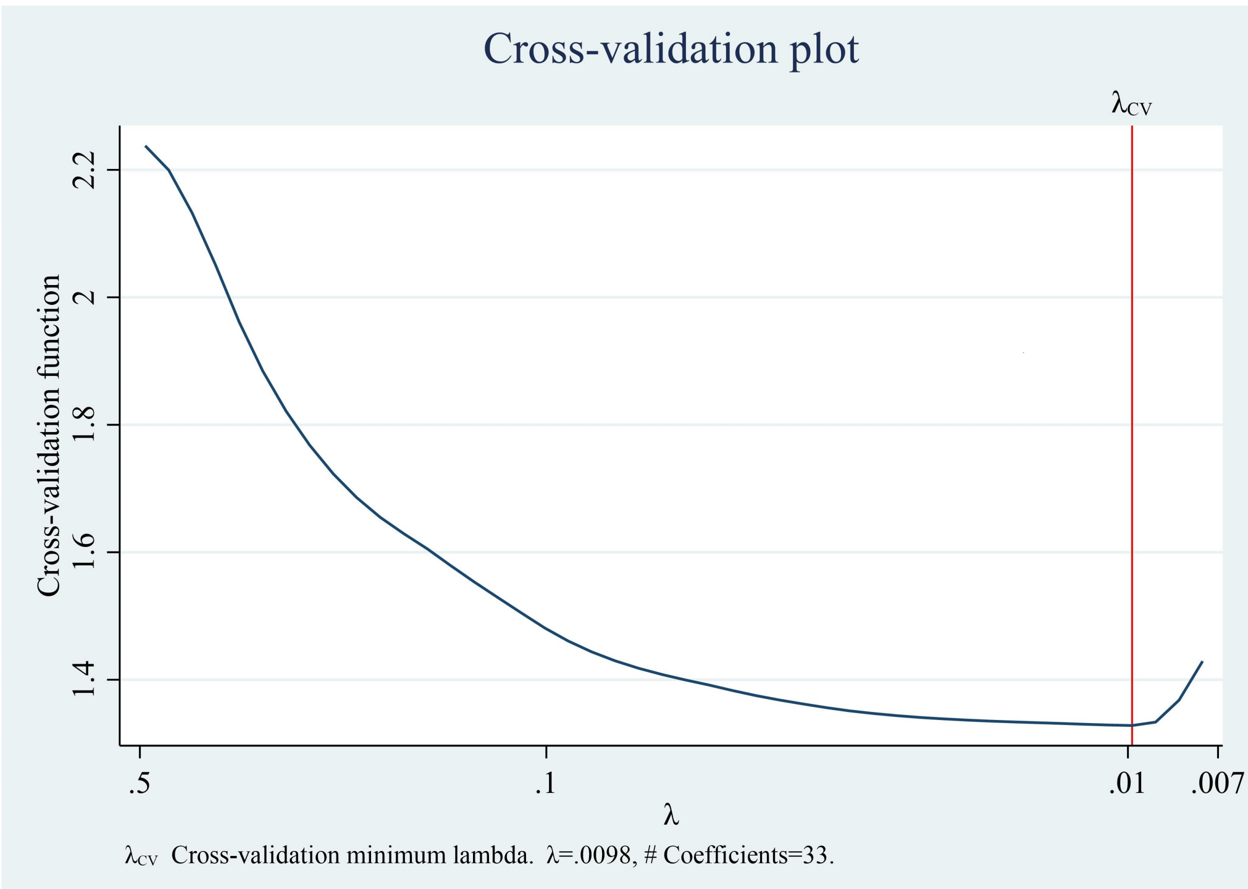
In this figure, we plot the increment in R Squared in Table 3.

Figure 3: R Squared Increment



In this figure, we plot comparisons by adding tenant characteristics to a model in which we include only a particular set of determinants (e.g., property characteristics, location characteristics etc). The blue bar show the R-squared from the model with that particular set of determinants only. The red bar shows how much addition explanatory power we can add by including tenant characteristics. The purpose is to show that, in all the models, tenant characteristics contribution far more than the other groups alone.

Figure 4: Model Comparisons



In this figure, we plot cross-valuation (CV) function with respect to λ. The vertical line, λ_{CV}, denotes the CV minimum lambda.

Figure 5: Cross-validation (CV) Plot

Table 1: Information Strategies

Variable Name	Short Name	Variable Description
Dependent Variable		
Cap Rate	CAPR	The ratio of net operating income to transaction price.
Tenant Characteristics		
Listed	T01	Dummy variable = 1 if the tenant is a public company; = 0 if private
Ownership (Corporate)	T02	Dummy variable = 1 if the tenant's ownership is corporate; = 0 if franchise
% Default	T03	Percentage chance of default over 5 years
NAICS = Retail Trade	T04	Dummy variable for tenant business in Retail Trade.
NAICS = Transportation	T05	Dummy variable for tenant business in Transportation or Warehousing
NAICS = Wholesale	T06	Dummy variable for tenant business in Wholesale
NAICS = Information	T07	Dummy variable for tenant business in Information
NAICS = FIRE	T08	Dummy variable for tenant business in Finance, Insurance, and Real Estate
NAICS = Professional	T09	Dummy variable for tenant business in Professional, Management, or Administration
NAICS = Educational	T10	Dummy variable for tenant business in Education
NAICS = Healthcare	T11	Dummy variable for tenant business in Healthcare
NAICS = Hospitality	T12	Dummy variable for tenant business in Hospitality and Entertainment
NAICS = (Other) non-service	T13	Dummy variable for tenant business in other non-service industries, including Manufacturing, Agriculture, Construction and Mining.
NAICS = (Other) service	T14	Dummy variable for tenant business in other services not specified above
Property Characteristics		
Building SF	PC1	Square footage of the property
Land Area	PC2	Square footage of land
Property Age	PC3	Property age
Deal & Lease Characteristics		
Deal (Fee Simple)	DC1	Dummy variable that equals 1 if the deal is fee simple
Years Left on Lease	DC2	Number of years left on lease upon sale
Gross Lease	DC3	Dummy variable for gross lease
Rent to Market Rent Ratio	DC4	Rent to market rent ratio

Continued on next page

Location Characteristics		
Distance to CBD	LC1	Distance (in mile) to the nearest CBD retail based on the geographic coordinates in Hollian (2019).
Distance to CBD Squared		The squared term of Distance to CBD
Distance to Mall	LC2	Distance (in mile) to the nearest regional or super regional mall. The definition of regional or super regional mall follows ICSC or CoStar. The geographic coordinates of malls are collected using Google Map.
Distance to Mall Squared		The squared term of Distance to Mall
Gateway MSA	LC3	Dummy variable for Gateway MSAs based on the definition used by the S&P Global Market Intelligence, CoStar and National Association of Real Estate Investment Trusts (NAREIT). The gateway MSAs include Atlanta, Boston, Chicago, Los Angeles, New York, San Francisco, and Washington DC.
Secondary MSA	LC4	Dummy variable for Secondary MSAs based the definition used by the S&P Global Market Intelligence, CoStar and National Association of Real Estate Investment Trusts (NAREIT). The secondary MSAs include Austin, Dallas, Denver, Houston, Nashville, Phoenix, San Jose, Seattle, and Tampa.
Tertiary MSA	LC5	Dummy variable for Tertiary MSAs based the definition used by the S&P Global Market Intelligence, CoStar and National Association of Real Estate Investment Trusts (NAREIT). The tertiary MSAs include the remaining MSAs.
Walk Score	LC6	A walkability measures on a scale from 0 - 100 based on walking routes to destinations such as grocery stores, schools, parks, restaurants, and retail. Data are collected from https://www.walkscore.com
Local Demand Proxies (5-mile radius)		
Demand Density	DP1	Log of per square mile median household income multiplied by number of households, within 5-mile radius of the property, measured using the 2000 Census
Demand Density Growth	DP2	Demand density growth from 1990 to 2000
County Business Pattern Controls		
Total Employment	CBP1	Log of total employment in the county, measured in the year prior to the transaction
Industry Employment Share	CBP2	Share of employment in the tenant's industry in the county, measured in the year prior to the transaction
Industry HHI	CBP3	Herfindahl-Hirschman Index (HHI) calculated based on employment in the county, measured in the year prior to the transaction

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NCREIF Index & Returns, Retail (Region)		
NCREIF Retail Return	NR1	NCREIF total return for retail properties in the region that the property is located, measured in the year prior to the transaction
NCREIF Retail Transaction Volume	NR2	NCREIF transaction volume for retail properties in the region that the property is located, measured in the year prior to the transaction
NCREIF Retail Property Index	NR3	NCREIF property index for retail properties in the region that the property is located, measured in the year prior to the transaction
Macro Indicators (Nationwide)		
Term Spread	MA01	Term spread between 2- and 10-year treasury rate
Inflation	MA02	Consumer Price Index (CPI)
Risk Premium	MA03	Spread between Moody's AAA Corporate Bond and 10-year Treasury
Unemployment Rate	MA04	Unemployment rate
GDP Growth	MA05	Nominal Gross Domestic Product (GDP)
in Debt to GDP Ratio	MA06	Changes in debt to GDP ratio
S&P 500 Growth	MA07	Growth in the S&P 500 Index
Stock Volatility Index	MA08	Russell 2000 Volatility Index
Market Vacancy Rate	MA09	Market vacancy rate
CRE Price Index	MA10	Growth in the Commercial Real Estate Price Index
Demand for CRE Loans	MA11	Changes in net Percentage of Domestic Respondents Reporting Stronger Demand for Commercial Real Estate Loans
Total CRE Loans	MA12	Total volume of CRE loans
$\triangle$ Charge Off Rate on CRE Loans	MA13	Parentage change in charge off rate on CRE loans
$\triangle$ Delinquency Rate on CRE Loans	MA14	Parentage change in delinquency rate on CRE loans

This table shows detailed descriptions of the data-gathering process and calculation methods for all variables.

Table 2: Summary Statistics

Variable	# Obs.	Mean	Std. Dev.	P25	Median	P75
Dependent Variable						
Cap Rate	7,912	6.630	1.505	5.650	6.440	7.390
Tenant Characteristics						
Ownership (Corporate)	7,912	0.714	0.452	0.000	1.000	1.000
% Default	7,912	15.844	13.812	2.000	9.000	31.000
Listed	7,912	0.744	0.436	0.000	1.000	1.000
NAICS = Retail Trade	7,912	0.462	0.499	0.000	0.000	1.000
NAICS = Transportation	7,912	0.002	0.048	0.000	0.000	0.000
NAICS = Wholesale	7,912	0.002	0.041	0.000	0.000	0.000
NAICS = Information	7,912	0.010	0.100	0.000	0.000	0.000
NAICS = FIRE	7,912	0.012	0.109	0.000	0.000	0.000
NAICS = Professional	7,912	0.065	0.246	0.000	0.000	0.000
NAICS = Educational	7,912	0.001	0.034	0.000	0.000	0.000
NAICS = Healthcare	7,912	0.018	0.134	0.000	0.000	0.000
NAICS = Hospitality	7,912	0.032	0.177	0.000	0.000	0.000
NAICS = Other services	7,912	0.065	0.247	0.000	0.000	0.000
NAICS = Other non-service	7,912	0.330	0.470	0.000	0.000	1.000
Deal & Lease Characteristics						
Deal (Fee Simple)	7,912	0.885	0.319	1.000	1.000	1.000
Years Left on Lease	7,912	11.800	39.435	8.154	12.085	16.000
Gross Lease	7,912	0.116	0.320	0.000	0.000	0.000
Rent to Market Rent Ratio	7,912	2.068	2.554	0.974	1.630	2.592
Property Characteristics						
Building SF	7,912	11322	23045	3398	6727	11524
Land Area	7,912	4.550	258.096	0.660	1.050	1.650
Property Age	7,912	13.089	14.496	2.000	9.000	18.000
Location Characteristics						
Distance to CBD	7,912	28	26	10	22	39
Distance to CBD Squared	7,912	1512	4130	100	469	1524
Distance to Mall	7,912	9	42	2	4	9
Distance to Mall Squared	7,912	1808	90139	5	20	73
Gateway MSA	7,912	0.144	0.351	0.000	0.000	0.000
Secondary MSA	7,912	0.138	0.345	0.000	0.000	0.000
Tertiary MSA	7,912	0.626	0.484	0.000	1.000	1.000

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Variable	# Obs.	Mean	Std. Dev.	P25	Median	P75
Local Demand Proxies (5-mile radius)						
5-mile Demand Density	7,912	16.861	1.300	16.102	17.078	17.796
5-mile Demand Density Growth	7,912	0.031	0.036	0.008	0.022	0.043
County Business Pattern Controls (County)						
Total Employment	7,912	9.344	1.602	8.293	9.460	10.448
Industry Employment Share	7,912	0.088	0.046	0.050	0.087	0.114
Industry HHI	7,912	0.090	0.023	0.076	0.084	0.098
NCREIF Index & Returns, Retail (Region)						
NCREIF Retail Return	7,912	12.299	0.177	12.229	12.375	12.394
NCREIF Retail Transaction Volume	7,912	14.629	6.943	15.057	17.775	19.280
NCREIF Retail Property Index	7,912	2627.088	997.271	1963.270	2415.930	3302.000
Macro Indicators (Nationwide)						
Term Spread	7,912	1.618	0.691	1.240	1.730	1.840
Inflation	7,912	1.456	0.998	0.119	1.622	2.130
Risk Premium	7,912	1.660	0.304	1.570	1.810	1.820
Unemployment Rate	7,912	6.143	1.587	4.800	5.700	7.800
GDP Growth	7,912	0.040	0.014	0.032	0.038	0.053
△ in Debt to GDP Ratio	7,912	1.855	3.260	-1.137	1.686	3.797
S&P 500 Growth	7,912	0.123	0.122	0.113	0.138	0.226
Stock Market Volatility	7,912	22.165	9.631	17.670	19.740	21.680
Market Vacancy Rate	7,912	9.247	4.286	7.480	7.559	7.807
△ CRE Price Index	7,912	0.069	0.087	0.040	0.069	0.139
△ Demand for CRE Loans	7,912	4.356	11.567	0.000	0.000	7.600
Total CRE Loans	7,912	6.263	4.966	4.196	8.706	10.330
△ Charge Off Rate on CRE Loans (%)	7,912	-18.905	30.160	-35.734	-32.306	-13.422
△ Delinquency Rate on CRE Loans (%)	7,912	-32.468	86.545	-70.906	-62.647	-52.103

This table gives the descriptive statistics (mean, standard deviation, min, and max). See Table 1 for variable descriptions.

Table 3: Multivariate Analysis of Cap Rates with Macro Indicators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tenant Characteristics								
Ownership (Corporate)	-0.487***	-0.458***	-0.375***	-0.370***	-0.344***	-0.345***	-0.341***	-0.337***
	(0.045)	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
% default	0.014***	0.014***	0.014***	0.015***	0.016***	0.016***	0.016***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Listed	-0.217***	-0.219***	-0.230***	-0.239***	-0.261***	-0.237***	-0.267***	-0.314***
	(0.041)	(0.042)	(0.039)	(0.040)	(0.039)	(0.038)	(0.037)	(0.037)
NAICS = Wholesale	1.701**	1.722**	1.936**	1.859**	1.902**	1.770**	1.780**	2.046**
	(0.726)	(0.716)	(0.874)	(0.855)	(0.830)	(0.803)	(0.816)	(0.799)
NAICS = Transportation	0.879***	0.913***	0.831***	0.817***	0.760***	0.392*	0.270	0.280
	(0.211)	(0.231)	(0.233)	(0.233)	(0.227)	(0.236)	(0.235)	(0.226)
NAICS = Information	-0.155	-0.129	-0.126	-0.176	-0.176	-0.659***	-0.737***	-0.658***
	(0.162)	(0.156)	(0.152)	(0.145)	(0.145)	(0.164)	(0.149)	(0.139)
NAICS = FIRE	-0.767***	-0.814***	-0.540***	-0.472***	-0.405***	-0.567***	-0.637***	-0.638***
	(0.085)	(0.080)	(0.086)	(0.090)	(0.087)	(0.089)	(0.085)	(0.083)
NAICS = Professional	0.465	0.489	0.455	0.536	0.583	0.597	0.297	0.323
	(0.370)	(0.364)	(0.363)	(0.361)	(0.377)	(0.373)	(0.405)	(0.396)
NAICS = Educational	0.496***	0.509***	0.499***	0.617***	0.724***	0.369***	0.347***	0.261**
	(0.137)	(0.134)	(0.130)	(0.132)	(0.129)	(0.140)	(0.133)	(0.129)
NAICS = Healthcare	0.180	0.178	0.146	0.125	0.129	0.499***	0.430***	0.402***
	(0.119)	(0.119)	(0.117)	(0.115)	(0.114)	(0.110)	(0.109)	(0.102)
NAICS = Hospitality	-1.006***	-1.013***	-0.865***	-0.868***	-0.844***	-0.678***	-0.709***	-0.685***
	(0.066)	(0.068)	(0.064)	(0.059)	(0.057)	(0.060)	(0.060)	(0.058)
NAICS = Other services	-0.173**	-0.199***	-0.232***	-0.187***	-0.140**	-0.310***	-0.289***	-0.231***
	(0.073)	(0.074)	(0.070)	(0.067)	(0.065)	(0.070)	(0.069)	(0.068)
NAICS = Other non-service	0.741**	0.724*	0.723**	0.854**	0.827*	0.429	0.166	0.205
	(0.362)	(0.374)	(0.361)	(0.418)	(0.444)	(0.376)	(0.296)	(0.293)
Property Characteristics								
Building SF		-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land Area		-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Property Age		0.006	0.002	0.004	0.006**	0.006**	0.007***	0.011***
		(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Deal and Lease Characteristics								
Deal (Fee Simple)			0.375	0.246	0.073	-0.023	-0.044	0.255
			(0.653)	(0.646)	(0.620)	(0.612)	(0.636)	(0.613)
Years Left on Lease			-0.001	-0.001	-0.001	-0.001	-0.001*	-0.001*
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gross Lease			-0.555	-0.612	-0.739	-0.809	-0.811	-0.670
			(0.641)	(0.633)	(0.608)	(0.603)	(0.624)	(0.608)
Rent to Market Rent Ratio			-0.023***	-0.020**	-0.016**	-0.012*	-0.009	-0.011*
			(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Location Characteristics								
Distance to CBD				0.002	-0.002	-0.002	-0.003	-0.002
				(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Distance to CBD Squared				-0.000	0.000	0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to Mall				0.005	-0.002	-0.002	-0.003	-0.002
				(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Distance to Mall Squared				-0.000	0.000	0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gateway MSA				-0.853***	-0.465*	-0.336*	-0.384**	-0.389**
				(0.273)	(0.251)	(0.190)	(0.150)	(0.171)
Secondary MSA				-0.547***	-0.248*	-0.014	0.012	0.043
				(0.115)	(0.130)	(0.145)	(0.189)	(0.132)
Tertiary MSA				-0.405***	-0.256***	-0.119	-0.179**	-0.130
				(0.119)	(0.095)	(0.095)	(0.088)	(0.086)
Local Demand								
5-mile Demand Density					-0.219***	-0.107***	-0.112***	-0.127***
					(0.034)	(0.031)	(0.030)	(0.027)
5-mile Demand Density Growth					-1.916**	-1.295*	-1.284*	-0.832
					(0.851)	(0.719)	(0.702)	(0.648)
County Business Pattern Controls								
County Log of Total Employment						-0.167***	-0.149***	-0.124***
						(0.043)	(0.034)	(0.032)
County Industry Employment Share						-2.864***	-2.911***	-2.751***
						(0.733)	(0.737)	(0.683)
County Industry HHI						-1.865	-1.401	-0.444
						(1.179)	(1.156)	(1.224)
NCREIF Index & Returns								
NCREIF Return							-1.795***	-5.131***
							(0.119)	(0.851)
NCREIF Transaction Volume							0.006***	-0.006**
							(0.002)	(0.003)
NCREIF Price Index							-0.000***	-0.000***
							(0.000)	(0.000)

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Macro Indicators								
Term spread								18.938***
								(4.180)
Inflation								-12.601***
								(2.834)
Risk Premium								-32.854***
								(7.211)
Unemployment Rate								-3.058***
								(0.822)
GDP Growth								1556.104***
								(347.022)
△ in Debt to GDP Ratio								11.205***
								(2.522)
S&P 500 Growth								-92.675***
								(20.466)
Stock Volatility Index								-1.969***
								(0.436)
Market Vacancy Rate								3.541***
								(0.794)
△ CRE Price Index								31.314***
								(7.588)
△ Demand for CRE Loans								-0.346***
								(0.075)
Total CRE Loans								-2.508***
								(0.581)
△ Charge Off Rate on CRE Loans								-2.776***
								(0.629)
△ Delinquency Rate on CRE Loans								0.932***
								(0.210)
Constant	7.287***	7.213***	6.925***	7.381***	11.169***	11.141***	33.967***	67.698***
	(0.099)	(0.092)	(0.673)	(0.649)	(0.778)	(0.739)	(1.756)	(10.209)
R-squared	0.111	0.114	0.151	0.175	0.194	0.216	0.292	0.344
Observations	7,912	7,912	7,912	7,912	7,912	7,912	7,912	7,912

In this table, we apply OLS regressions to analyze cap rate determinants. The dependent variable, Cap Rates, is the ratio of net operating income to transaction price. The sample includes 7,912 transactions of single-tenant retail properties (see Table 1 for variable definitions and Table 2 for summary statistics). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the MSA level.

Table 4: Multivariate Analysis of Cap Rates with MSA and Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tenant Characteristics								
Ownership (Corporate)	-0.467***	-0.399***	-0.313***	-0.303***	-0.301***	-0.309***	-0.309***	-0.293***
	(0.046)	(0.044)	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)	(0.052)
% default	0.015***	0.015***	0.015***	0.015***	0.016***	0.016***	0.015***	0.014***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Listed	-0.287***	-0.293***	-0.306***	-0.312***	-0.317***	-0.301***	-0.305***	-0.294***
	(0.038)	(0.040)	(0.038)	(0.038)	(0.038)	(0.037)	(0.037)	(0.052)
NAICS = Wholesale	1.697**	1.732**	1.934**	1.989**	1.993**	1.850**	1.837**	1.183
	(0.765)	(0.723)	(0.859)	(0.847)	(0.840)	(0.830)	(0.831)	(1.046)
NAICS = Transportation	0.607***	0.646***	0.587**	0.594**	0.568**	0.316	0.304	0.152
	(0.210)	(0.238)	(0.241)	(0.240)	(0.237)	(0.242)	(0.241)	(0.295)
NAICS = Information	-0.361***	-0.314**	-0.301**	-0.311**	-0.305**	-0.610***	-0.612***	-0.727***
	(0.137)	(0.130)	(0.128)	(0.125)	(0.126)	(0.142)	(0.142)	(0.181)
NAICS = FIRE	-0.593***	-0.693***	-0.438***	-0.417***	-0.408***	-0.543***	-0.550***	-0.483***
	(0.074)	(0.075)	(0.069)	(0.070)	(0.070)	(0.078)	(0.077)	(0.107)
NAICS = Professional	0.308	0.382	0.339	0.407	0.411	0.408	0.422	0.504
	(0.431)	(0.434)	(0.447)	(0.436)	(0.430)	(0.404)	(0.405)	(0.460)
NAICS = Educational	0.586***	0.607***	0.556***	0.564***	0.601***	0.364***	0.354***	0.506***
	(0.127)	(0.122)	(0.120)	(0.122)	(0.123)	(0.134)	(0.133)	(0.159)
NAICS = Healthcare	0.012	0.021	0.001	0.009	0.013	0.307***	0.308***	0.309**
	(0.112)	(0.110)	(0.106)	(0.105)	(0.105)	(0.100)	(0.101)	(0.123)
NAICS = Hospitality	-1.006***	-1.015***	-0.854***	-0.845***	-0.840***	-0.715***	-0.717***	-0.660***
	(0.071)	(0.073)	(0.068)	(0.067)	(0.066)	(0.067)	(0.067)	(0.091)
NAICS = Other services	-0.060	-0.107	-0.127*	-0.123*	-0.108	-0.238***	-0.240***	-0.187**
	(0.077)	(0.078)	(0.075)	(0.074)	(0.072)	(0.076)	(0.076)	(0.093)
NAICS = Other non-service	0.526	0.465	0.441	0.498	0.491	0.219	0.214	0.292
	(0.360)	(0.365)	(0.340)	(0.356)	(0.354)	(0.360)	(0.356)	(0.432)
Property Characteristics								
Building SF		-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land Area		-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Property Age		0.014***	0.012***	0.013***	0.013***	0.013***	0.013***	0.013***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Deal and Lease Characteristics								
Deal (Fee Simple)			0.320	0.293	0.289	0.249	0.247	0.493
			(0.621)	(0.625)	(0.627)	(0.616)	(0.616)	(0.850)
Years Left on Lease			-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gross Lease			-0.640	-0.661	-0.661	-0.678	-0.678	-0.383
			(0.617)	(0.621)	(0.622)	(0.612)	(0.612)	(0.841)
Rent to Market Rent Ratio			-0.017**	-0.016**	-0.015*	-0.011	-0.011	-0.004
			(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Location Characteristics								
Distance to CBD				0.007***	0.005***	0.003**	0.003**	0.004**
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Distance to CBD Squared				-0.000**	-0.000	-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to Mall				-0.001	-0.013*	-0.015**	-0.015**	-0.016*
				(0.006)	(0.007)	(0.007)	(0.007)	(0.009)
Distance to Mall Squared				0.000	0.000	0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local Demand								
5-mile Demand Density					-0.115***	-0.096**	-0.095**	-0.086*
					(0.038)	(0.038)	(0.038)	(0.052)
5-mile Demand Density Growth					-1.819**	-1.642**	-1.619**	-1.970**
					(0.704)	(0.694)	(0.698)	(0.888)
County Business Pattern Controls								
County Log of Total Employment						-0.076***	-0.078***	-0.069**
						(0.025)	(0.025)	(0.033)
County Industry Employment Share						-2.854***	-2.817***	-2.779***
						(0.591)	(0.595)	(0.733)
County Industry HHI						-2.043*	-2.047*	-1.485
						(1.225)	(1.217)	(1.642)
NCREIF Index & Returns								
NNCREIF Return							-1.534**	0.317
							(0.654)	(3.199)
NCREIF Transaction Volume							-0.006*	-0.004
							(0.003)	(0.019)
NCREIF Price Index							-0.000	0.000
							(0.000)	(0.000)
Constant	7.333***	7.221***	7.171***	6.608***	8.605***	9.324***	28.867***	4.345
	(0.409)	(0.398)	(0.694)	(0.775)	(1.156)	(1.106)	(8.493)	(39.342)
R-squared	0.385	0.399	0.434	0.439	0.442	0.448	0.449	0.620
Observations	7,912	7,912	7,912	7,912	7,912	7,912	7,912	7,912
MSA FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
MSA-Year FEs	No	No	No	No	No	No	No	Yes

In this table, we apply OLS regressions to analyze cap rate determinants. The dependent variable, Cap Rates, is the ratio of net operating income to transaction price. The sample includes 7,912 transactions of single-tenant retail properties (see Table 1 for variable definitions and Table 2 for summary statistics). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the MSA level.

Table 5: Determinants of Cap Rates - the Least Absolute Shrinkage and Selection Operator ("LASSO") with tuning parameter selection using CV

# of Coeff.	Lambda	CV mean predicted error	Variable(s) Added	Variable(s) Dropped
1	0.446	2.200	Years Left on Lease	
2	0.406	2.132	Delinquency Rate on CRE Loans	
3	0.370	2.050	Total Employment	
4	0.337	1.961	Deal (Fee Simple)	
5	0.255	1.768	Total CRE Loans	
6	0.233	1.723	Gross Lease	
8	0.160	1.606	**Listed**	
			NCREIF Regional Retail Property Index	
11	0.146	1.579	**NAICS = FIRE**	
			Inflation	
			5-mile Demand Density	
12	0.133	1.554	**NAICS = Educational**	
14	0.121	1.529	Gateway MSA	
			NAICS = Hospitality	
15	0.110	1.505	**% Default**	
16	0.101	1.481	**Ownership (Corporate)**	
19	0.063	1.408	Unemployement Rate	
			NAICS = Wholesale	
			% change in charge off rate on CRE Loans	
19	0.058	1.400	Industry Employment Share	
19	0.058	1.400		△ Charge Off rate on CRE Loans
21	0.052	1.392	5-mile Demand Density Growth	
			NCREIF Regional Retail Return	
22	0.048	1.383	**NAICS = Retail Trade**	
23	0.044	1.375	**NAICS = Information**	
25	0.040	1.368	Age	
			NAICS = Healthcare	
27	0.036	1.362	Term Spread	
			NAICS = Transportation	
27	0.030	1.351	GDP Growth	
27	0.030	1.351		Total CRE Loans
26	0.027	1.347		Deal (Fee Simple)
27	0.023	1.341	NCREIF Regional Retail Transaction Volume	
28	0.021	1.339	△ Charge Off rate on CRE Loans	
29	0.017	1.335	Industry HHI	
31	0.014	1.333	**NAICS = Professional**	
			△ Demand for CRE Loans	
32	0.012	1.330	Distance to CBD	
32	0.011	1.329	Risk Premium	
32	0.011	1.329		△ Charge Off rate on CRE Loans
33*	0.010	1.328	Tertiary MSA	
35	0.008	1.368	Land Area	
			Building SF	

In this table, we apply the Least Absolute Shrinkage and Selection Operator ("LASSO) to analyze cap rate determinants, where the dependent variable, Cap Rate, is the ratio of net operating income to transaction price. The sample includes 7,912 transactions of single-tenant retail properties (see Table 1 for variable definitions and Table 2 for summary statistics). Variables in bold are tenant characteristics. * denote lambda selected by cross-validation.

Table 6: Comparing LASSO Selection Using Alternative Turning Parameter Selection Methods

Variable	CV	Plugin	Adaptive
Tenant Characteristics			
Ownership (Corporate)	Y	Y	Y
% Default	Y	Y	Y
Listed	Y	Y	Y
NAICS = Retail Trade	Y	Y	Y
NAICS = Transportation	Y	N	Y
NAICS = Wholesale	Y	N	Y
NAICS = Information	Y	N	Y
NAICS = FIRE	Y	Y	Y
NAICS = Professional	Y	N	N
NAICS = Educational	Y	Y	Y
NAICS = Healthcare	Y	Y	Y
NAICS = Hospitality	Y	Y	Y
NAICS = Other services	N	N	N
NAICS = Other non-service	N	N	N
Deal & Lease Characteristics			
Deal (Fee Simple)	Y	Y	N
Years Left on Lease	Y	Y	Y
Gross Lease	Y	Y	Y
Rent to Market Rent Ratio	Y	N	Y
Property Characteristics			
Building SF	N	N	N
Land Area	N	N	N
Property Age	Y	Y	Y
Location Characteristics			
Distance to CBD	N	N	N
Distance to CBD Squared	N	N	N
Distance to Mall	N	N	N
Distance to Mall Squared	N	N	N
Gateway MSA	Y	Y	Y
Secondary MSA	Y	N	Y
Tertiary MSA	Y	N	N

Continued on next page

Variable	CV	Plugin	Adaptive
Tenant Characteristics			
Local Demand Proxies (5-mile radius)			
5-mile Demand Density	Y	Y	Y
5-mile Demand Density Growth	Y	N	Y
County Business Pattern Controls (County)			
Total Employment	Y	Y	Y
Industry Employment Share	Y	Y	Y
Industry HHI	N	N	N
NCREIF Index & Returns, Retail (Region)			
NCREIF Retail Return	N	N	N
NCREIF Retail Transaction Volume	N	N	N
NCREIF Retail Property Index	Y	Y	Y
Macro Indicators (Nationwide)			
Term Spread	Y	N	N
Inflation	Y	Y	Y
Risk Premium	N	N	N
Unemployment Rate	N	N	N
GDP Growth	Y	N	Y
$\triangle$ in Debt to GDP Ratio	N	N	N
S&P 500 Growth	N	N	N
Stock Market Volatility	N	N	N
Market Vacancy Rate	N	N	N
$\triangle$ CRE Price Index	N	N	N
$\triangle$ Demand for CRE Loans	N	N	N
Total CRE Loans	N	Y	N
$\triangle$ Charge Off Rate on CRE Loans (%)	N	Y	N
$\triangle$ Delinquency Rate on CRE Loans (%)	Y	Y	Y
Number of variables selected	30	20	27

This table compares LASSO selection of the determinants for cap rate using cross-validation (CV), a plugin iterative formula, and an adaptive lasso with three steps. "Y" ("N") indicates the variable is (not) selected by the corresponding methods. See Table 1 for variable descriptions.

Table 7: Decomposition of Tenant Characteristics

	(1) Ownership (Corporate)	(2) Listed	(3) % Default
Overall			
High Group	6.807***	6.881***	6.735***
	(0.032)	(0.035)	(0.024)
Low Group	6.559***	6.544***	6.501***
	(0.020)	(0.019)	(0.023)
Difference	0.247***	0.338***	0.234***
	(0.037)	(0.040)	(0.033)
Explained	-0.037	-0.136***	-0.133***
	(0.023)	(0.021)	(0.021)
Unexplained	0.284***	0.474***	0.367***
	(0.036)	(0.035)	(0.031)
Explained			
Property Characteristics	0.030***	0.016***	0.031***
	(0.008)	(0.005)	(0.005)
Deal & Lease Characteristics	0.054***	-0.002	-0.014
	(0.012)	(0.010)	(0.011)
Location Characteristics	0.004	0.010**	0.002
	(0.004)	(0.005)	(0.004)
Local Demand Proxies	-0.008**	-0.035***	-0.035***
	(0.003)	(0.006)	(0.007)
County Business Pattern Controls	-0.076***	-0.059***	-0.123***
	(0.011)	(0.008)	(0.011)
NCREIF Index & Returns	0.015	0.005	0.034*
	(0.022)	(0.022)	(0.020)
Macro Indicators	-0.056***	-0.071***	-0.028*
	(0.018)	(0.019)	(0.017)
Unexplained			
Property Characteristics	-0.104**	-0.110**	-0.034
	(0.046)	(0.048)	(0.040)
Deal & Lease Characteristics	-2.253*	-0.937	4.532***
	(1.204)	(1.156)	(1.086)
Location Characteristics	0.125	0.525***	0.157
	(0.166)	(0.180)	(0.179)
Local Demand Proxies	1.393**	0.162	1.717**
	(0.706)	(0.821)	(0.706)
County Business Pattern Controls	0.165	0.081	-0.280
	(0.364)	(0.410)	(0.339)
NCREIF Index & Returns	-2.352	15.826	-4.303
	(11.869)	(12.224)	(10.452)
Macro Indicators	6.681	-0.486	1.978
	(4.555)	(4.746)	(3.127)
Constant	-3.371	-14.588	-3.401
	(11.596)	(11.890)	(10.146)

This table summaries decomposition results for mean cap rate differences between "High Group" and "Low Group." "Low Group" ("High Group") includes tenants with corporate (franchise) ownership in column (1), tenants that (does not) belong to a publicly traded company or a subsidiary of a publicly traded company in column (2), and tenants with lower-than-median (higher-than-median) default probability in column (3). See Table 1 for variable descriptions.

Table A.1: Top 10 Tenants (by Frequency)

Tenant Name	Average Cap Rate	Number of Obs.
Walgreens	6.414	760
Dollar General	7.360	740
CVS	6.303	434
Family Dollar	7.546	298
Burger King	6.441	222
7-Eleven	5.550	221
Advance Auto Parts	7.116	176
Rite Aid	7.519	158
Wendy's	6.025	149
Starbucks	5.633	148

Table A.2: Multivariate Analysis of Cap Rates, Adding Walk Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Adding Walk Score to Models (5)-(8) in Table 3				*Adding Walk Score to Models (5)-(8) in Table 4*			
Tenant Characteristics								
Ownership (Corporate)	-0.394***	-0.388***	-0.384***	-0.375***	-0.346***	-0.347***	-0.347***	-0.314***
	(0.050)	(0.048)	(0.047)	(0.045)	(0.050)	(0.050)	(0.050)	(0.060)
% default	0.016***	0.016***	0.016***	0.015***	0.015***	0.015***	0.015***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Listed	-0.218***	-0.194***	-0.242***	-0.291***	-0.319***	-0.305***	-0.308***	-0.289***
	(0.048)	(0.047)	(0.043)	(0.042)	(0.044)	(0.043)	(0.043)	(0.058)
NAICS = Wholesale	3.192**	2.947**	3.070***	3.151***	3.138**	2.938**	2.930**	2.329
	(1.253)	(1.199)	(1.151)	(1.122)	(1.268)	(1.224)	(1.226)	(1.612)
NAICS = Transportation	0.580	0.065	0.132	0.161	0.639**	0.361	0.365	0.145
	(0.393)	(0.387)	(0.360)	(0.321)	(0.320)	(0.333)	(0.334)	(0.412)
NAICS = Information	-0.184	-0.653***	-0.774***	-0.678***	-0.349***	-0.605***	-0.607***	-0.597***
	(0.151)	(0.167)	(0.152)	(0.147)	(0.134)	(0.157)	(0.157)	(0.195)
NAICS = FIRE	-0.394***	-0.572***	-0.602***	-0.603***	-0.384***	-0.514***	-0.521***	-0.477***
	(0.086)	(0.087)	(0.084)	(0.080)	(0.076)	(0.080)	(0.080)	(0.106)
NAICS = Professional	-0.826***	-0.990***	-0.779***	-0.683***	-1.223***	-1.243***	-1.094***	0.003
	(0.103)	(0.096)	(0.095)	(0.098)	(0.105)	(0.105)	(0.136)	(0.314)
NAICS = Educational	0.539***	0.220	0.264*	0.268**	0.556***	0.367***	0.362***	0.523***
	(0.144)	(0.159)	(0.140)	(0.136)	(0.130)	(0.140)	(0.138)	(0.175)
NAICS = Healthcare	0.130	0.448***	0.442***	0.407***	0.111	0.353**	0.358**	0.496***
	(0.155)	(0.144)	(0.146)	(0.137)	(0.149)	(0.139)	(0.140)	(0.155)
NAICS = Hospitality	-0.798***	-0.669***	-0.698***	-0.680***	-0.792***	-0.700***	-0.703***	-0.641***
	(0.062)	(0.068)	(0.068)	(0.067)	(0.075)	(0.079)	(0.079)	(0.112)
NAICS = Other services	-0.097	-0.274***	-0.238***	-0.200***	-0.064	-0.183**	-0.185**	-0.095
	(0.069)	(0.073)	(0.070)	(0.068)	(0.077)	(0.081)	(0.081)	(0.098)
NAICS = Other non-service	1.223	0.795	0.893	0.955	1.254	1.020	1.008	1.196
	(0.789)	(0.749)	(0.761)	(0.757)	(0.815)	(0.818)	(0.811)	(0.910)
Walk Score								
Walk Score	-0.008***	-0.008***	-0.007***	-0.007***	-0.006***	-0.005***	-0.005***	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.221	0.241	0.332	0.383	0.495	0.499	0.500	0.646
Observations	5789	5789	5789	5789	5789	5789	5789	5789
Other Controls in Table 3 or 4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FEs	No	No	No	No	Yes	Yes	Yes	No
Year FEs	No	No	No	No	Yes	Yes	Yes	No
MSA-Year FEs	No	No	No	No	No	No	No	Yes

In this table, we show additional results by adding walk score in Tables 3 and 4. The sample includes 5,789 transactions of single-tenant retail properties with non-mssing walk scare. See Table 1 for variable definitions and Table 2 for summary statistics.

Table A.3: Tenants in Top Industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tenant Characteristics								
Top 3 (establishment)	-0.107**	-0.157***						
	(0.048)	(0.060)						
Top 5 (establishment)			-0.189***	-0.231***				
			(0.042)	(0.058)				
Top 3 (Employment)					-0.109*	-0.029		
					(0.056)	(0.074)		
Top 5 (Employment)							-0.162***	-0.151*
							(0.062)	(0.079)
Ownership (Corporate)	-0.336***	-0.291***	-0.340***	-0.291***	-0.337***	-0.293***	-0.339***	-0.294***
	(0.043)	(0.052)	(0.043)	(0.052)	(0.043)	(0.053)	(0.043)	(0.052)
% default	0.015***	0.014***	0.015***	0.014***	0.015***	0.014***	0.015***	0.014***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Listed	-0.316***	-0.297***	-0.320***	-0.302***	-0.315***	-0.295***	-0.314***	-0.295***
	(0.037)	(0.052)	(0.038)	(0.053)	(0.037)	(0.052)	(0.037)	(0.052)
NAICS = Wholesale	2.028**	1.178	1.981**	1.130	2.026**	1.175	1.993**	1.151
	(0.797)	(1.042)	(0.794)	(1.031)	(0.800)	(1.050)	(0.798)	(1.048)
NAICS = Transportation	0.275	0.158	0.260	0.159	0.293	0.157	0.267	0.153
	(0.225)	(0.293)	(0.223)	(0.290)	(0.225)	(0.293)	(0.225)	(0.293)
NAICS = Information	-0.667***	-0.735***	-0.691***	-0.731***	-0.650***	-0.726***	-0.695***	-0.750***
	(0.139)	(0.182)	(0.135)	(0.177)	(0.138)	(0.180)	(0.138)	(0.180)
NAICS = FIRE	-0.666***	-0.522***	-0.711***	-0.567***	-0.651***	-0.487***	-0.680***	-0.514***
	(0.082)	(0.109)	(0.080)	(0.106)	(0.083)	(0.106)	(0.086)	(0.112)
NAICS = Professional	0.338	0.564	0.348	0.533	0.306	0.504	0.327	0.525
	(0.389)	(0.447)	(0.393)	(0.449)	(0.398)	(0.461)	(0.380)	(0.441)
NAICS = Educational	0.248*	0.491***	0.208*	0.459***	0.267**	0.508***	0.223*	0.483***
	(0.129)	(0.158)	(0.126)	(0.158)	(0.129)	(0.159)	(0.131)	(0.161)
NAICS = Healthcare	0.401***	0.321**	0.374***	0.270**	0.408***	0.313**	0.376***	0.289**
	(0.101)	(0.125)	(0.100)	(0.122)	(0.100)	(0.124)	(0.101)	(0.126)
NAICS = Hospitality	-0.730***	-0.725***	-0.725***	-0.724***	-0.665***	-0.653***	-0.673***	-0.650***
	(0.064)	(0.099)	(0.059)	(0.094)	(0.058)	(0.093)	(0.057)	(0.091)
NAICS = Other services	-0.223***	-0.179*	-0.150**	-0.083	-0.243***	-0.190**	-0.294***	-0.241**
	(0.068)	(0.092)	(0.074)	(0.103)	(0.067)	(0.093)	(0.069)	(0.097)
NAICS = Other non-service	0.199	0.299	0.170	0.271	0.207	0.294	0.181	0.290
R-squared	0.345	0.621	0.347	0.622	0.345	0.620	0.345	0.621
Observations	7912	7912	7912	7912	7912	7912	7912	7912
Other Controls in Table 3 or 4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year FEs	No	Yes	No	Yes	No	Yes	No	Yes

In this table, we show additional results by adding a dummy variable for tenants in top industries to our baseline model specifications in Tables 3 and 4. Top 3 (establishment) equals one if the tenant's industry (2-digit NAICS code) ranks among top-3 industries in terms of number of establishments in the county where the property is located, and zero otherwise. Top 5 (establishment) equals one if the tenant's industry (2-digit NAICS code) ranks among top-5 industries in terms of number of establishments in the county where the property is located, and zero otherwise. Top 3 (employment) equals one if the tenant's industry (2-digit NAICS code) ranks among top-3 industries in terms of employment in the county where the property is located, and zero otherwise. Top 5 (employment) equals one if the tenant's industry (2-digit NAICS code) ranks among top-5 industries in terms of employment in the county where the property is located, and zero otherwise. See Table 1 for variable definitions and Table 2 for summary statistics.