Determinants of Asset Pricing in Retail Real Estate – The Case of Investor Risk Perception

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1 Introduction

1.1 Motivation and Background

Arguably, no other sector within commercial real estate has endured as much disruption in recent years as retail – even before the COVID-19 pandemic. Over the last two decades, the retail industry has been tremendously impacted by various developments. Fundamentally, online shopping has evolved into a major challenge for traditional brick-and-mortar retailers. Internet and other technologies enable consumers to interact remotely with retailers without the need for physical store visits, in turn affecting critical elements of demand and market structure in the retail real estate industry (e.g., Burt & Sparks, 2003; Baen, 2000; Hendershott *et al*., 2000). In 2000, e-commerce accounted for less than 1% of total retail sales in the US. By 2022, this share had risen to 14.3%, equaling about $250 billion in sales.[1,2] Within stationary retailing, a fast-growing discount competition, such as supercenters, dollar and discount stores, has been upsetting long-established retailing patterns (e.g., Hortaçsu & Syverson, 2015; Jia, 2008). At the same time, consumer behavior and preferences have changed, with shoppers seeking a higher level of entertainment, customization and real time information about their products (e.g., Bawa *et al*., 2019; Donnley & Scaff, 2013). Finally, the recent COVID-19 pandemic merely accelerated e-commerce and related trends, while simultaneously introducing new disruptions from, amongst others, stay-at-home orders, mask mandates, capacity restrictions or mandated store closures. Overall, the retail industry has undergone a fundamental transformation, directly affecting retail properties and thus, increasing uncertainties for retail real estate investors in the twenty-first century.

Recent events on the US American retail market[3] reveal an inherent imbalance that appears to emerge from this evolving industry. For example, while former e-retailers such as Amazon, Warby Parker and Everlane are venturing into brick-and-mortar stores as part of their omni-channel retail strategy, major traditional department store retailers like Sears, Kmart or Macy's drastically close stores across the country. This

[1] Although re-settled, this percentage includes a spike induced by the worldwide COVID-19 pandemic. In Q4 2019 (pre-pandemic), the share of online sales had already risen to 11.4%, followed by a record high of 15.7% with the rise of the pandemic in Q2 2020.

[2] All data is obtained from the Monthly Retail Trade from the US Census Bureau, available at: https://www.census.gov/retail/index.html#ecommerce.

[3] Due to data availability as well as the comparably progressive nature of the retail and retail real estate market, this dissertation focuses exclusively on the US market. Conclusions for other markets, including Germany, can nevertheless be drawn from the findings.

dynamism in the retail sector, with certain retailer categories performing well and other tenant groups struggling or disappearing, mirrors the pressing uncertainty that retail real estate investors face, particularly with regard to general-purpose shopping centers.[4]

General-purpose shopping centers are explicitly vulnerable to the changing retail landscape due to their historically grown oversupply of retail space[5], as well as threats from e-commerce and accompanying trends for major anchor tenant categories of these types of centers, including apparel, electronics, and department stores. Such dynamics contributed significantly to the historically highest number of store closures across the US in 2019 (Coresight Research, 2020), as well as a pandemic-spurred wave of closures in 2020, most of which occurred in shopping centers (BDO, 2020). Although anchor tenants typically pay below-market rent (e.g., Liu & Liu, 2013; Gould *et al*., 2005), they are crucial for the overall drawing power of the shopping center, and consequently impact the sales of non-anchor tenants that pay market rate rent and thus, rental income of retail landlords (e.g., Liu & Liu, 2013). Furthermore, smaller retailers may have co-tenancy clauses that allow them to terminate or renegotiate their leases if an anchor leaves, which leads to an increased vacancy and lower appeal of a mall to consumers that arise from economies of agglomeration. In this context, losing an anchor tenant in a shopping center can result into an approximate 25% decline in the overall rental rate (Gatzlaff *et al*., 1994), posing a tangible risk to investors.[6]

More specifically, continuing e-commerce growth along with rising discount competition and existing shifts in consumer preference increase uncertainty for traditional retail real estate investors with regard to tenant default risk, store closures, and ultimately, overall investment performance. In addition, in the wake of containing the COVID-19 pandemic, government-mandated restrictions on physical retailing and society in general led to yet another form of risk for investors in an already strained market environment. Previous studies investigating the commercial real estate market find a particularly strong impact of the pandemic on the retail property type (Hoesli & Malle, 2021; Ling *et al*., 2020; Milcheva, 2021; van Dijk *et al*., 2020), emphasizing the risk

[4] As the name suggests, a general range of goods and fashion (as opposed to a much-selected assortment) dominates general-purpose shopping centers.

[5] The US has the largest amount of retail space per capita in the world, mostly driven by shopping center space. In 2018, it recorded 23 square feet of gross leasable area per person (Cushman & Wakefield, 2019). In comparison, in 2018, Germany has had 2.3 square feet retail space per capita.

[6] Subsequent struggles and implications for investors can be illustrated by the example of 60 acre Bangor Mall in Bangor, Maine. With its anchor tenants struggling and eventually failing (department stores Macy's and Sears vacated the center in 2017 and 2018 respectively), the owner at the time, Simon Property Group, eventually defaulted on an $80 million loan. Consequently, the general-purpose shopping center was sold at auction in early 2019 for $12.6 million, less than half of its assessed value (Valigra, 2019).

associated with the COVID-19 pandemic and its impact on determinants in pricing retail assets.

Despite its relevance, the impact of changes in the retail sector on underlying real estate from an investor's perspective has not received considerable attention in the scholarly literature overall.[7] Against the backdrop of this research gap and an ever-changing retail landscape, this dissertation takes the perspective of a risk-assessing investor and aims to provide insights into the implications of retail industry disruptions for the risk perception of retail real estate investors. It contributes to practice and literature by investigating investor risk perception as captured by

- returns (*Paper 1, Chapter 2*),
- asset prices (*Paper 2, Chapter 3*),
- and cap rates (*Paper 3, Chapter 4*).

The empirical analyses focuses on general-purpose shopping centers. General-purpose shopping centers provide an appropriate laboratory to analyze investor risk perception and retail asset pricing for a number of reasons. First, the business of traditional anchor tenants in these shopping centers has been particularly disrupted. Second, these shopping centers represent a relatively homogeneous sample with regard to tenant mix, architectural features and other characteristics, while the subcategories allow for in-depth analyses based on differences in center concept. Third, over the period under investigation, general-purpose shopping center types accounted for about 70-80% of the industry's gross leasable area (ICSC, CoStar). And lastly, they are relevant for a broad investor pool: REITs, private and cross-border investors, while representing an important institutional-grade asset type. This focus also is in line with previous studies investigating the pricing of retail assets (e.g., Hardin & Carr, 2006; Des Rosiers *et al*., 2005; Mejia & Benjamin, 2002; Hardin *et al*., 2002; Hardin & Wolverton, 2001; Sirmans & Guidry, 1993).

Overall, the objective of this dissertation is to arrive at a rather holistic understanding of the extent to which the risks arising from a changing retail landscape have an impact on investor risk perception and consequently on the pricing of retail real estate assets. With that, this thesis seeks to contribute to the scholarly literature, and to provide retail real estate investors with information relevant to their investment decision-making.

[7] At the same time, however, the economic literature has thoroughly examined the rise of e-commerce and its impact on different retail markets; for a review, see Lieber & Syverson, 2012.

1.2 Course of Analysis

While the main chapters of this dissertation represent self-contained research papers investigating the topic of investor risk perception within asset pricing of retail real estate, they highlight distinct aspects of the area under investigation.

Considering how e-commerce and related trends affect major anchor tenant categories, very fundamentally, the question arises as to whether e-commerce is priced as an investment risk by retail investors. In a first step, the purpose of ***Paper 1*** (Chapter 2) is to provide more insights into the relationship of e-commerce and retail real estate asset pricing by analyzing the informative value of e-commerce sales for retail real estate returns.

After providing first evidence that e-commerce indeed is a risk priced by investors, ***Paper 2*** (Chapter 3) investigates a possible explanation for the findings in *Paper 1*. Based on the consideration that recent shifts in the retail market have increased uncertainty about tenant default and store closure risks, the question arises as to whether investors rely on alternative sources of information to help assess future tenant quality and to price assets accordingly. Against this background, *Paper 2* investigates the informative value of the stock market performance of department stores as a proxy for tenant quality for general-purpose shopping center prices. Since department stores traditionally represent a major anchor tenant group in these centers, they have a large impact on the risk faced by retail real estate investors.

While the COVID-19 pandemic has reinforced the need for the issues raised beforehand, it has also introduced government-imposed restrictions as a new form of risk for retail real estate investors. Throughout the US, state governors have implemented disruptive measures in response to the pandemic, directly and indirectly affecting the underlying real estate assets. Considering the pandemic-induced increase in cash flow uncertainties, ***Paper 3*** (Chapter 4) investigates the impact of government risk, as restrictions imposed by local political decision-makers, on the risk perception of retail real estate investors. In particular, the paper analyzes the informative value of the political affiliation of state governors, proxying for length and severity of COVID-19 restrictions, for going-in cap rates of general-purpose shopping centers.

1.3 Research Layout

The following section provides an overview of the research questions addressed in each individual article. This is complemented by information on authors, journal submission, publication status, and conference presentation.

Paper 1 | Chapter 2

Is E-Commerce an Investment Risk Priced by Retail Real Estate Investors? An Investigation

Research Questions

(1) Do retail real estate investors price e-commerce as an investment risk? Hence, do e-commerce sales have informative value for the total, capital and income return of institutional-grade retail real estate?

(2) If so, is the impact of e-commerce on shopping center performance differing by shopping center type (center-specific risks)?

(3) Do recent developments, such as integrating online and physical retailing and enhanced experiential retailing strategies, have any further impact on retail real estate performance?

(4) Thus, does this indicate whether e-commerce generally has to be considered a threat or rather a chance for retail real estate investors in today's retailing environment?

Submission Details and Conference Presentation

Authors	Carina Kaiser, Julia Freybote
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Conference Presentation	27th Annual Conference of the European Real Estate Society (ERES) in Kaiserslautern, Germany (2021; held digitally)

Paper 2 | Chapter 3

Tenant Stock Market Performance and Retail Real Estate Prices

Research Questions

(1) Is tenant quality, proxied by the stock market performance of department stores, predictive of retail real estate investor sentiment and returns?

(2) Accordingly, does the stock market performance of department stores have informative value for transaction prices of shopping centers?

(3) Thus, do retail real estate investors use the stock market performance of tenants as a source of information in making pricing decisions?

(4) Considering different risk associations, do these relations differ respectively by department store segments (tenant-specific risks), property quality, and property location (center-specific risks)?

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Authors	Carina Kaiser, Julia Freybote
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Paper 3 | Chapter 4

Government Risk and Real Estate Investor Risk Perception

Research Questions

(1) Is the risk perception of retail real estate investors impacted by government risk? More specifically, does the short-term (long-term) risk perception shift as a result of governmental restrictions in response to the COVID-19 pandemic?

(2) Hence, does the political affiliation of the state governor, proxying for length and severity of restrictions, have informative value for going-in cap rates (pre-tax yield, IRR) of retail real estate?

(3) In view of divergent sensitivities, does the impact on investor risk perception differ by shopping center type (center-specific risks)?

(4) Next to government risk, what impact does the political attitude in an MSA have on investor risk perception?

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2 Is E-Commerce an Investment Risk Priced by Retail Real Estate Investors? An Investigation

2.1 Abstract

Over the last 20 years, online shopping has evolved into a major threat to the physical retail store. We investigate whether retail real estate investors price e-commerce as an investment risk. In particular, we analyze whether e-commerce sales have informative value for retail real estate returns. Focusing on institutional-grade shopping centers over the period of 2000 to 2018, we find that e-commerce sales predict total returns in the next quarter. This effect is driven by capital returns, which suggests that e-commerce is indeed priced as an investment risk. While consistent across mall types, this effect is stronger for regional and super-regional malls than neighborhood and community shopping centers. Explanations for this difference include the types of retail tenants in these different mall categories and the varying impact of e-commerce on their business.

Keywords: Commercial Real Estate, Asset Pricing, Retail, E-Commerce, Institutional Investors

2.2 Background

Over the last two decades, online shopping has been a major disruptor to the retail industry. Between 2000 and 2019, online spending in the US rose from $27 billion to $602 billion.[8] COVID-19 has further accelerated this trend: Compared to 2019, annual e-commerce grew 32.4% in 2020, and online sales represented 14% of the total retail sales compared to 11% in 2019.[9] Traditional anchor tenants of shopping centers such as department stores, apparel and electronics retailers have been particularly threatened by the internet competition contributing to store closures and bankruptcies. While anchor tenants pay no or below market rent, their store closures negatively impact the appeal of a mall to shoppers and traffic to rent-paying tenants. Additionally, rent-paying tenants may have co-tenancy clauses in their leases which allow them, for example, to lower their rent or even break a lease prematurely if specific tenants leave.

[8] US Census Bureau; https://www.census.gov/retail/index.html#ecommerce

[9] ICSC; https://www.icsc.com/uploads/t7-subpage/Q4_Quarterly_E-Commerce_Industry_Sector_Series.pdf

Considering how e-commerce affects major anchor tenant categories, the question arises as to whether e-commerce is priced as an investment risk by retail investors. Investor pessimism about the future income potential of shopping centers with anchor tenants negatively affected by the online competition is expected to translate into higher cap rates and lower valuations. Consequently, if e-commerce is priced as a risk by retail real estate investors, we expect e-commerce sales to predict capital returns in the next quarter. In this study, we focus on the short-term effects of e-commerce sales on capital returns considering that retail real estate investors rely on the most recent information, i.e., the current or previous quarter's e-commerce sales, in their pricing and investment decision-making.

In our empirical analysis, we focus on general-purpose shopping centers[10] in line with previous studies investigating the pricing of retail assets (Sirmans & Guidry, 1993; Mejia & Benjamin, 2002; Des Rosiers *et al.*, 2005; Hardin *et al.*, 2002; Hardin & Wolverton, 2001). General-purpose shopping centers provide an ideal laboratory to analyze the impact of e-commerce sales on retail asset pricing for a number of reasons. First, the business of traditional anchor tenants in these shopping centers such as department stores or apparel retailers has been particularly disrupted by e-commerce.[11] Second, these shopping centers represent a relatively homogeneous sample with regard to tenant mix, architectural features, and other characteristics. Third, these shopping centers represent institutional-grade assets owned by National Council of Real Estate Investment Fiduciaries (NCREIF) members, which allows us to obtain mall type-specific return data.

Over the period of 2000 to 2018, we find that e-commerce sales have a negative relation with total returns of general-purpose shopping centers in the next quarter. As expected, this effect is driven by capital returns, providing evidence that e-commerce as an investment risk is indeed priced by retail real estate investors. Our results are robust to different measures of e-commerce sales and across different categories of shopping centers. We find the negative relation of e-commerce sales and capital returns to be larger for regional and super-regional shopping centers than neighborhood and community shopping centers. One explanation for this finding is the type of tenants in these malls. Anchor tenants in regional and super-regional shopping centers include full-line department and apparel stores, whose business has been particularly negatively impacted by online and/or lower price competition. Community and neighborhood

[10] For more information on ICSC shopping center categories, please visit: https://www.icsc.com/uploads/research/general/US_CENTER_CLASSIFICATION.pdf

[11] https://business.gmu.edu/blog/realestate/2018/06/06/impact-e-commerce-retail-real-estate/

centers have anchor tenants such as discount department stores, specialty discount, or grocery stores, which have been impacted by online competition to a lesser degree. Compared to the first decade of the twenty-first century, technological innovations such as smart phones and mobile internet resulted in a small positive effect of e-commerce sales on capital returns for regional and super-regional shopping centers in the second decade. Explanations for this effect include omni- and multi-channel retailing strategies[12], which we refer to as multiple-channel retailing in the remainder of this study, and a stronger focus on experiential shopping, which in turn benefited physical stores in these mall types. We find no relation of e-commerce sales and income returns in the next quarter. This lack of a short-term impact of online sales on income returns can be explained with how retail leases are structured.

Our study contributes to the literature on retail real estate in general (e.g., Zhang *et al.*, 2020; Hui *et al.*, 2007; Des Rosiers *et al.*, 2005; Mejia & Benjamin, 2002; Gatzlaff *et al.*, 1994; Sirmans & Guidry, 1993) and retail asset pricing in particular (e.g., Freybote *et al.*, 2016; Nase *et al.*, 2013; Eppli *et al.*, 1998). To our knowledge, this is the first study to empirically investigate e-commerce as an investment risk. Our findings have implications for retail real estate investors. First, they provide evidence that e-commerce indeed represents a risk to investors that affects asset pricing. Our results for the smart phone period and regional and super-regional shopping centers further suggest that new retailing strategies integrating online shopping and the physical store environment reduce the risk for retail real estate investors.

The remainder of this paper proceeds as follows. Next, we review the relevant literature to provide a theoretical framework. The following section discusses our variables, data, and methodology, which is followed by a presentation of our empirical results. Concluding remarks and areas for future research are provided in the final section.

[12] Both omni- and multi-channel retailing involve selling across multiple physical and digital channels (e.g., online, mobile, and social media channels). Whereas in the case of multi-channel retailing, channels remain unrelated to each other distributing their goods, in omni-channel retailing, all channels partially interact with each other and are connected (Verhoef *et al.*, 2015).

2.3 Literature Review

Previous studies investigate retail real estate from a variety of perspectives. Most relevant to shopping center managers and developers, several studies investigate aspects such as selecting the ideal retail tenant mix (e.g., Gerbich, 1998), the impact of anchors on pedestrian traffic (e.g., Konishi & Sandfort, 2003), or optimal retail lease contracts (e.g., Lee, 1995). Others take on a corporate real estate management perspective regarding the effects of real estate ownership on retailers' stock market performance (Yu & Liow, 2009) or, relevant to lenders, the impact of tenant diversification on credit spreads for mortgages on retail properties (Ambrose *et al.*, 2018).

Most relevant to our study are previous studies taking the perspective of investors and focusing on rental rates, returns, and prices. One stream of literature focuses on determinants of retail rental rates (Zhang *et al.*, 2020; Nase *et al.*, 2013; Hui *et al.*, 2007; Des Rosiers *et al.*, 2005; Mejia & Benjamin, 2002; Gatzlaff *et al.*, 1994; Sirmans & Guidry, 1993). Benjamin, Boyle and Sirmans (1992) show that shopping center landlords use tenant characteristics, such as default probability and customer traffic-generating potential, to determine rental rates. Benjamin and Chinloy (2004) provide further evidence that shopping center landlords differentiate between tenants while showing that tenants also distinguish between landlords. The study also identifies determinants of percentage rent clauses used by landlords, such as capital expenditures. Gatzlaff *et al.* (1994) estimate the impact of losing an anchor tenant on the rent of remaining shopping center tenants. They find an approximate 25% decline in rental rates due to the loss of an anchor tenant. Another set of determinants relates to architectural features, physical and location characteristics (Adebayo *et al.*, 2019; Hui *et al.*, 2007; Hardin & Carr, 2006; Hardin *et al.*, 2002; O'Roarty & McGreal, 1997; Sirmans & Guidry, 1993). Wheaton (2000) focuses on percentage rents in retail leasing and argues that this feature of retail leases can help align landlord and tenant interests.

A second stream of literature identifies determinants of retail real estate asset prices and returns. Eppli, Shilling and Vandell (1998) focus on the impact of macro-economic factors, such as commercial mortgage rates, retail sales, stock-market returns, retail construction starts, inflation, and stock-market volatility on retail real estate returns at a metropolitan level in the US. They find hardly any evidence that these macro-economic variables explain retail return fluctuations. Nase, Berry and Adair (2013) focus on urban design quality and values of high street retail properties for Belfast city center (UK). They find that quality design characteristics such as frontage continuity and variety, material quality and connectivity add to retail property values. Several studies focus on lease clauses, particularly percentage rents, and provide evidence for the impact of lease clauses on shopping center values and retail real estate returns (Cho & Shilling, 2007; Hendershott & Ward, 2003; Colwell & Munneke, 1998).

A variety of studies investigate the impact of e-commerce on retail real estate markets. However, these studies were predominantly conducted in the early days of e-commerce at the start of the twenty-first century and have yielded contradicting conclusions. For the US, Roulac (1994) anticipates that new non-store shopping forms will significantly change the shape of retailing to come, as well as reduce the aggregate demand for retail space. While some studies expect e-commerce to negatively affect the demand for retail space, whether overall or for different segments, store types or regions (Dixon & Marston, 2002a; Damesick, 2001; Baen, 2000), others consider e-commerce to have negligible impact on physical stores (Weltevreden & van Rietbergen, 2007; Muhanna & Wolf, 2002; Dixon & Marston, 2002b; Currah, 2002; Worzala *et al.*, 2002; Hendershott *et al.*, 2000). Some earlier studies also emphasize the importance of focusing on experience-oriented shopping (DeKare-Silver, 2001; Damesick, 2001; Worzala *et al.*, 2002) and omni-channel retailing (Hendershott *et al.*, 2000; Currah, 2002).

A few studies investigate e-commerce in the context of retail real estate outside the US and provide ambiguous findings. Using case studies, McClatchey, Cattell and Michell (2007) find no evidence that online grocery shopping has an impact on brick-and-mortar stores in South Africa. Razali *et al.* (2014) conclude that online shopping and the application of e-commerce only had minor impacts on Malaysian retail real estate. Zhang, Zhu and Ye (2016) investigate the impact of e-commerce on retail real estate in China and find supermarkets to be less affected and department stores to be more vulnerable. For the UK market, Livingstone and Jones (2015) demonstrate that the largest retailers are benefitting from the growth of online sales and multi-channel retailing, and thus, properties with these tenants are expected to suffer less from e-commerce growth. Jones (2010) on the other hand finds that the share of UK high street retail in investment portfolios has halved since the mid-1990s, partly because of the threat of e-commerce.

However, none of these previous studies on e-commerce and retail real estate investigate e-commerce in the context of retail asset pricing. If e-commerce represents a significant investment risk for retail real estate investors due to its impact on tenants and future cash flows, we expect e-commerce to be priced by investors. Therefore, we hypothesize e-commerce sales to negatively predict future capital returns of general-purpose shopping centers.

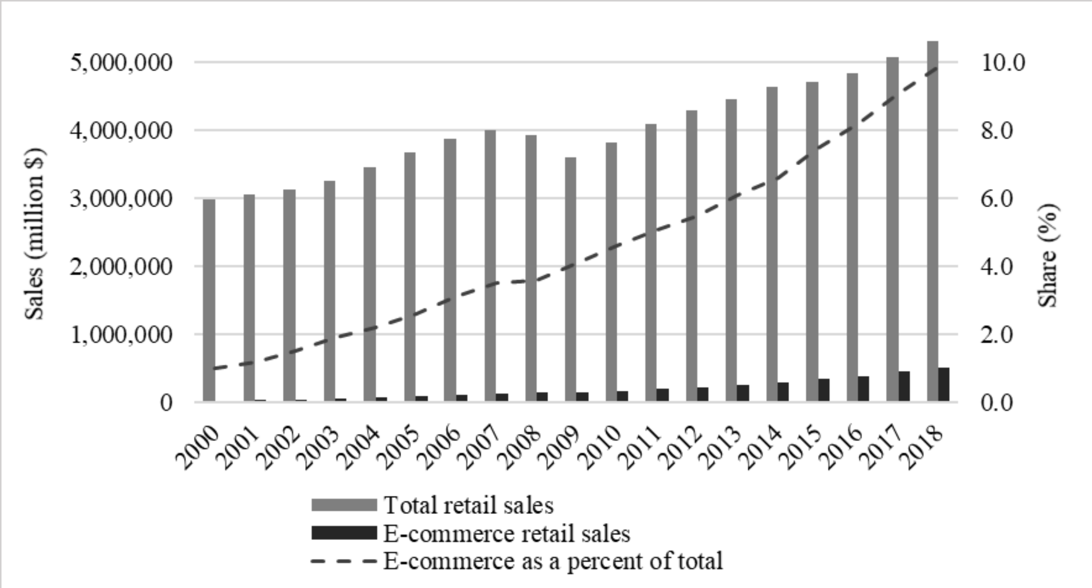
2.4 Data and Methodology

Our independent variable of interest is e-commerce sales. To assess the robustness of our results, we create two e-commerce sales variables. First, we define e-commerce as the quarterly change in US retail e-commerce sales (*ECOM1*). Second, we put e-commerce in relation to all retail sales and define e-commerce sales as the quarterly change of US e-commerce as a percentage of total sales (*ECOM2*). We obtain our e-commerce and total retail sales data from the Monthly Retail Trade Survey available through the US Census Bureau for the period of Q1/2000 to Q4/2018. We start with the first quarter of 2000 because 1) this is the first year for which the Census Bureau reports historical data on e-commerce, and 2) mainstream e-commerce emerged at the start of the twenty-first century.

The Monthly Retail Trade Survey dataset classifies a transaction as e-commerce sales, if the buyer has placed an order for goods and services over the internet, mobile device, extranet, electronic mail, or other comparable online systems. Financial brokers and dealers, online travel services, and ticket offices are not included in the retail sales estimates. Further, the payment does not have to be made online. We use e-commerce and total sales that are seasonally adjusted to account for seasonal variations in retail sales, for example, due to different holidays.

Figure 2-1 presents an overview of absolute total and e-commerce retail sales in the US, and their relation over our sample period (2000 to 2018). It becomes apparent that e-commerce has not just grown in total revenue, but also continued to make up a larger share of total retail sales. Not only have online sales continued to grow steadily; their growth has exceeded the relative rise in total sales over time. While e-commerce sales accounted for only 1% of total sales in 2000, this share reached almost 10% at the end of 2018, which equals an absolute spending of about $510 billion. With that, online spending increased almost twentyfold from 2000 to 2018, or to put it differently, e-commerce sales increased by 1,770% within that 18-year period.

Figure 2-1: US Total and E-Commerce Sales over Time



Note: This figure presents total retail sales, e-commerce retail sales and e-commerce sales as a percentage of total retail sales over the period of 2000 to 2018 based on data from the Census Bureau.

In our empirical investigation, we focus on general-purpose shopping centers (neighborhood, regional, super-regional, and community centers). Compared to other forms of retail real estate, these shopping centers represent a relatively homogeneous sample and are institutional investment-grade assets, which is relevant considering that we use NCREIF returns as dependent variables. We obtain the quarterly total, income, and capital return on the NCREIF property index (NPI) for these shopping center types for the period of the first quarter of 2000 to the fourth quarter of 2018. The resulting sample comprises of 76 property type-quarter observations.

We control for a number of variables that affect retail real estate returns. First, we control for retail space market conditions by including quarterly property type-specific occupancy rates (*OCCR*) from NCREIF. Second, we control for debt capital market conditions, which affect the cost of debt capital and funding opportunities for retail real estate investors. In particular, we follow the literature (e.g., Ghosh & Petrova, 2017; An *et al.*, 2016; Ling & Naranjo, 2015; Ling *et al.*, 2014; Chervachidze & Wheaton, 2013; Fisher *et al.*, 2009) and define the credit spread (*CSPREAD*) as the difference in yields between Moody's seasoned Aaa corporate bonds and 10-year Treasury bonds, and term structure (*TERM*) as the difference in yields between 10-year Treasury bonds and 3-months Treasury bills. Furthermore, we control for the long-term interest rate (*TRYLD*), representing the 10-year Treasury constant maturity yield. All three variables are obtained from the Federal Reserve Bank of St. Louis (Fed St. Louis). With regard to its impact on interest rates, cap rates, and returns, we furthermore control for inflation by including the quarterly US consumer price index for urban consumers (*CPI*) from the Bureau of Labor Statistics (Fed St. Louis).

In addition to debt capital market conditions, we control for stock market conditions. Previous studies such as Ling and Naranjo (2015) or Li, Mooradian and Yang (2009) show that equity REIT returns respond more quickly to information than private market returns. Thus, REITs serve as a fundamental source of information to private market returns when asset-pricing variables are omitted. Hoesli and Oikarinen (2012) also find that REIT market performance is related to the direct real estate market, even closer than to the general stock market. Therefore, we include the quarterly property type-specific ZIMAN index (*ZIMAN*) to control for retail REIT market conditions. The information is obtained from CRSP.

In line with previous studies (Li *et al.*, 2009; Fisher *et al.*, 2009; Fisher *et al.*, 2004), we control for the general macro-economic condition of the market by including the quarterly unemployment rate for the US (*UNEMP*) and the quarterly growth rate of the gross domestic product (*GDP*), both obtained from the Bureau of Labor Statistics. To control for the impact of the Great Financial Crisis (*GFC*) on retail real estate, we follow previous studies (Ghosh & Petrova, 2017; Devaney *et al.*, 2017) and create a binary variable equal to one for quarters over the period 2007 to 2009.

Table 2-1 presents our descriptive statistics. The mean quarterly change in e-commerce sales (*ECOM1*) over the period of 2000 to 2018 is 4.33%, with a range of -8.96% to 14.76%. Similarly, the mean quarterly change of e-commerce sales as a percentage of total retail sales (*ECOM2*) is 3.49%, with a range of -0.06% to 13.77%. The mean quarterly total NPI return aggregated for all mall types is 2.49%, with a range of -6.34% to 8.10%. Income returns average 1.61% while capital returns are about 0.9%, on average. Figure 2-2 depicts the quarterly NPI returns averaged across the different mall types. The mean total NPI return appears to be primarily driven by the mean capital return while the mean income return shows hardly any volatility over the years.

Table 2-1: Descriptive Statistics

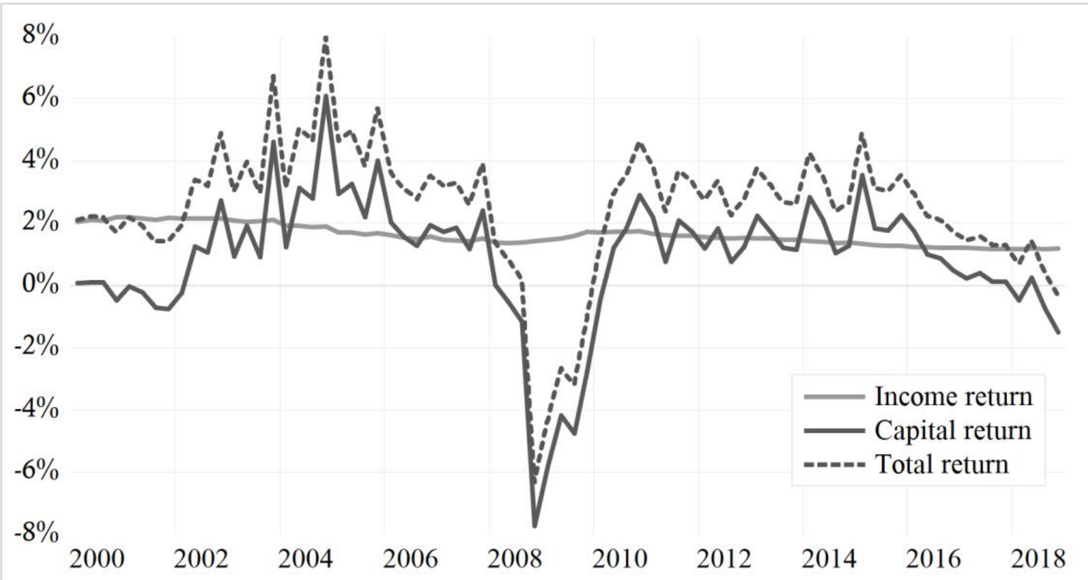
	Mean	Median	Max	Min	Std. Dev.
TOTR	0.0249	0.0263	0.0810	-0.0634	0.0235
INCR	0.0161	0.0155	0.0228	0.0115	0.0033
CAPR	0.0088	0.0096	0.0621	-0.0777	0.0229
ECOM1	0.0433	0.0374	0.1476	-0.0896	0.0299
ECOM2	0.0349	0.0310	0.1377	-0.0006	0.0244
CPI	0.0053	0.0054	0.0220	-0.0283	0.0071
CSPREAD	0.0158	0.0163	0.0253	0.0064	0.0045
GDP	0.0203	0.0220	0.0750	-0.0840	0.0235
TERM	0.0188	0.0194	0.0369	-0.0055	0.0114

Table 2-1: Descriptive Statistics *(continued)*

TRYLD	0.0348	0.0356	0.0605	0.0150	0.0121
UNRATE	6.0231	5.5000	9.9333	3.8000	1.7751
ZIMAN	0.0099	0.0187	0.1155	-0.1822	0.0418
Δ OCCR	-0.0000	0.0002	0.0381	-0.0527	0.0089

Note: This table presents the descriptive statistics for a sample of NCREIF shopping center categories over the period of Q1/2000 to Q4/2018 (N=300 property type-quarters), where TOTR, INCR and CAPR represent the quarterly total, income and capital return on the NCREIF property index (NPI) for the respective property type. ECOM1 and ECOM2 are %-change from prior quarter based on absolute e-commerce sales and e-commerce as a percentage of total sales respectively, CPI is the consumer price index, CSPREAD is the difference in yields between Moody's seasoned Aaa corporate bonds and 10-year Treasury bonds, GDP is the quarterly growth rate of the Gross Domestic Product, TERM is the difference in yields between 10-year Treasury bonds and 3-months Treasury bills, TRYLD is the 10-year Treasury constant maturity yield, UNRATE is the civilian unemployment rate, ZIMAN is the retail property-type specific ZIMAN index, and ΔOCCR is the first difference of shopping center occupancy rate.

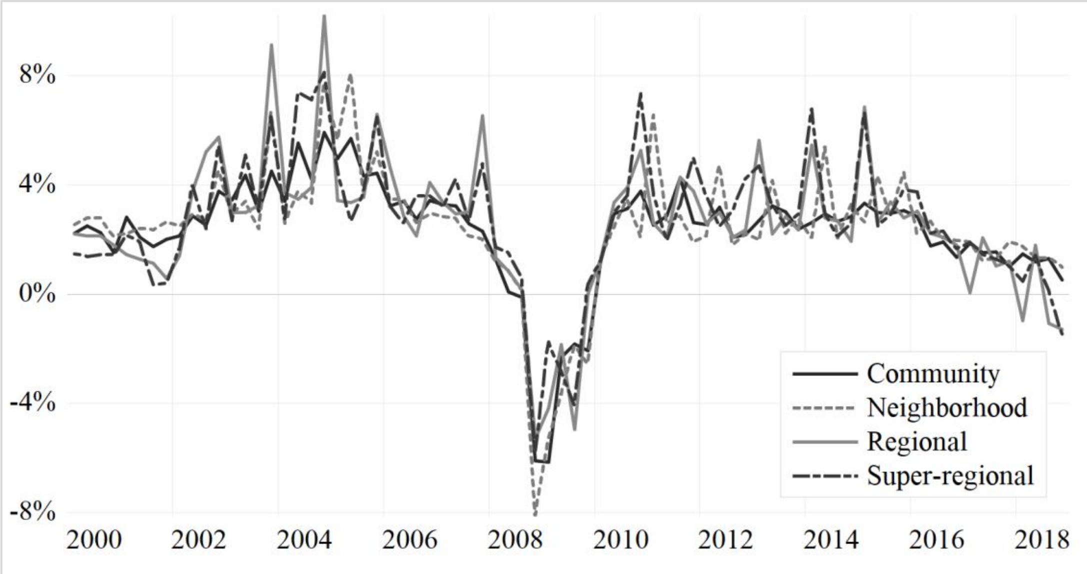
Figure 2-2: Return Series over Time



Note: This figure presents total, income and capital return on the NPI aggregated for four shopping center types (regional, super-regional, neighborhood, and community) over the period of 2000 to 2018.

The total NPI returns for individual mall types over time are presented in Figure 2-3. It shows that total returns for different mall types exhibit similar patterns. After increases from 2002 to 2006, shopping center returns in general show a downward trend until 2010. Regional and super-regional mall returns experienced a short spike shortly before the GFC. In the years following the GFC, retail returns appear to plateau. Since 2015, total returns for all mall types show a noticeable downward trend. It is noteworthy that for the full period the total returns for community centers appear to be less volatile than the returns of other mall types, and over the period of 2015 to 2018 the returns for regional and super-regional malls have decreased more than for other mall types.

Figure 2-3: Total Return by Mall Type over Time



Note: This figure presents total returns on the NPI for different shopping center types over the period of 2000 to 2018.

We employ a mall type-fixed effects regression to estimate our model shown in Equation 2-1. As our panel dataset exhibits autocorrelation and heteroscedasticity, we use White robust standard errors. We use the Augmented Dickey Fuller (ADF) test to assess the stationarity of our variables. All variables are stationary at the 10% level or lower.[13] To assess the threat of multicollinearity, we examine the variance inflation factors (VIFs) of our independent variables. The mean VIF is 1.78 and the highest VIF is 2.33, which is below the value of 2.50 and suggests that multicollinearity is not a concern for the validity of our results.

$$Return_{it} = \alpha_i + \beta_1 X_{it} + \beta_2 Z_{it} + \varepsilon_{it} \qquad \text{2-1}$$

where $Return_{it}$ is the NPI return for mall type i in quarter t, X_{it} represents our e-commerce variables and their first lags (*ECOM1* and *ECOM2*), Z_{it} is a vector of control variables and ε_{it} is the idiosyncratic error.

[13] We had to detrend income return and obtain the first difference of the property-specific occupancy rate (*OCCR*) to achieve stationarity for these two variables (based on the ADF).

2.5 Results

Table 2-2 presents our results for total NPI return. Please note, the e-commerce variables are the percentage change from the prior quarter based on absolute e-commerce sales (*ECOM1*) and e-commerce as a percentage of total sales (*ECOM2*) respectively. Irrespective of which e-commerce measure we use, the first lag of *ECOM* has a significantly negative relation with total returns. Thus, the higher e-commerce sales are in a quarter, the lower are total returns for general-purpose shopping centers in the next quarter. More specifically, our findings indicate that, ceteris paribus, a one unit increase in the quarterly change in e-commerce sales (*ECOM1*) and e-commerce sales as a percentage of total sales (*ECOM2*) leads to an average decrease in total return of about 0.095% and 0.082% respectively in the following quarter. This is in line with our expectation that e-commerce represents a risk that is priced by investors. On the other hand, e-commerce sales have no impact on total return in the same quarter. This suggests that investors rely on e-commerce sales in the previous quarter to make pricing decisions in the current.

Coefficients on our control variables are in line with expectations. *CPI* coefficients are highly significant in both models and have the expected positive sign. Further, for *ECOM1*, we find a highly statistically significant negative effect of the change of unemployment rate (*UNRATE*) on total returns. This is intuitive, since unemployment serves as an indicator for the spending by consumers. In terms of the overall market conditions, we find a positive effect of *GDP* on total return for *ECOM2*. Turning to capital market conditions, our results show that the total return has a significant relation with the 10-year Treasury constant maturity yield (*TRYLD*). This is intuitive as by definition, a higher risk-free rate adds to higher return. In addition, if *ECOM2* is used, higher credit spreads (*CSPREAD*) have a negative relation with total returns. We also find that total returns during the great financial crisis (*GFC*) were significantly lower than in other quarters, which is in line with expectations.

Table 2-2: Results for Total Return

	Model (1) – *ECOM1*		**Model (2) – *ECOM2***	
	Coef.	*SE*	*Coef.*	*SE*
ECOM	0.072	0.047	0.034	0.061
lagECOM	**-0.095*** **	**0.022**	**-0.082*** **	**0.031**
CPI	**0.418*** **	**0.139**	**0.548*** **	**0.155**
CSPREAD	0.201	0.373	**-0.843** **	**0.341**
GDP	0.095	0.067	**0.182*** **	**0.069**
GFC	**-0.011** **	**0.005**	**-0.027*** **	**0.004**
Δ OCCR	0.142	0.121	0.199	0.128
TRYLD	**0.527*** **	**0.113**	**0.248** **	**0.126**

Table 2-2: Results for Total Return *(continued)*

TERM	0.003	0.107	-0.025	0.111
UNRATE	**-0.037***	**0.005**	0.001	0.001
ZIMAN	0.026	0.030	0.046	0.035
Property fixed effects (FE)	*Yes*		*Yes*	
Obs.	*300*		*300*	
R-squared	*0.492*		*0.425*	
Adj. R-squared (R2)	*0.467*		*0.397*	

Note: This table reports the regression statistics for the total return based on the model specified by Eq. (2-1) for all four mall types and including property fixed effects. The used e-commerce variables in Models 1 and 2 are %-change from prior quarter based on absolute e-commerce sales and e-commerce as a percentage of total sales respectively. All variables are as defined in Table 2-1. Standard errors are White-corrected.

, **, and * denote statistical significance at the 10, 5, and 1 % level respectively.*

Capital returns are the component of total returns that reflect investor risk perceptions, sentiment, and valuations. Therefore, we investigate the relation of e-commerce sales and future capital returns in more detail. To ensure that the relation of e-commerce sales and future total returns is driven by capital returns and not income returns, we also analyze the relation of e-commerce sales and income return.

We estimate our model in Equation 2-1 separately for income returns (*INCR*) and capital returns (*CAPR*) and report our results in Table 2-3. As displayed, e-commerce sales have a significantly negative relation with capital returns. Irrespective of which e-commerce measure is used, the lag of *ECOM* has a significantly negative relation with capital returns. Thus, the higher e-commerce sales are, the lower are capital returns in the subsequent quarter. On the other hand, e-commerce sales have no relation with income returns. One explanation for our findings is that we only focus on the short-term (one quarter) impact of online sales on returns. Due to the structure of shopping center leases, e-commerce sales may not have an immediate effect on income returns. Even in the event of a sharp drop in sales in a shopping center, the base rent proportion would keep the overall income for investors at a constant level to some extent. Our descriptive statistics in Table 2-1 and Figure 2-3 provide additional evidence of the stability in income returns. Future investigations may investigate the impact of e-commerce on the income return of shopping centers in the mid- to long-term. Overall, our results in Table 2-3 suggest that our findings for the total return in Table 2-2 are driven by capital return. This provides further evidence that investors account for e-commerce as a risk when valuing properties and making pricing decisions.

Table 2-3: Results for Income and Capital Return

	Model (1) – *ECOM1*				Model (2) – *ECOM2*			
	INCR		*CAPR*		*INCR*		*CAPR*	
	Coef.	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
ECOM	-0.001	0.003	0.063	0.046	-0.006	0.004	0.025	0.060
lagECOM	0.001	0.002	**-0.090*****	**0.021**	0.002	0.002	**-0.073****	**0.030**
CPI	-0.017	0.010	**0.430*****	**0.135**	**-0.018***	**0.011**	**0.552*****	**0.150**
CSPREAD	**0.146*****	**0.024**	-0.178	0.364	**0.131*****	**0.020**	**-1.200*****	**0.333**
GDP	**0.012*****	**0.004**	0.074	0.066	**0.014*****	**0.004**	**0.156****	**0.067**
GFC	**-0.002*****	**0.000**	**-0.009****	**0.005**	**-0.002*****	**0.000**	**-0.025*****	**0.004**
Δ OCCR	0.002	0.006	0.142	0.117	0.001	0.006	0.200	0.124
TRYLD	**0.013***	**0.007**	**0.282****	**0.110**	**0.021****	**0.008**	-0.032	0.122
TERM	**0.032*****	**0.007**	-0.035	0.105	**0.019*****	**0.006**	-0.004	0.109
UNRATE	0.000	0.000	**-0.037*****	**0.005**	**0.000***	**0.000**	0.000	0.001
ZIMAN	**0.003****	**0.001**	0.020	0.030	**0.003***	**0.001**	0.042	0.034
Property FE	*Yes*		*Yes*		*Yes*		*Yes*	
Obs.	*300*		*300*		*300*		*300*	
R-squared	*0.662*		*0.495*		*0.674*		*0.495*	
Adj. R2	*0.645*		*0.470*		*0.658*		*0.398*	

Note: This table reports the regression statistics for the income and capital return based on the model specified by Eq. (2-1) for all four mall types and including property fixed effects. The used e-commerce variables in Models 1 and 2 are %-change from prior quarter based on absolute e-commerce sales and e-commerce as a percentage of total sales respectively. All variables are as defined in Table 2-1. Standard errors are White-corrected.

, **, and * denote statistical significance at the 10, 5, and 1 % level respectively.*

Our sample of shopping centers includes four types of general-purpose shopping centers: regional, super-regional, community, and neighborhood centers. Regional and super-regional malls focus on non-essential goods and have anchor tenants, such as full-line department and apparel stores[14], whose business has been particularly challenged by e-commerce[15]. On the other hand, community and neighborhood centers have anchor tenants such as discount department stores or grocery stores, whose business has been threatened by online competition to a lesser degree. This is in line with previous studies that conclude that e-commerce represents a limited threat to certain retailer segments such as grocery stores (Zhang *et al.*, 2016; McClatchey *et al.*, 2007).

To investigate whether the impact of e-commerce sales on the pricing of retail real estate assets varies across these different mall categories, we separate our sample in 1) regional and super-regional shopping centers, and 2) neighborhood and community shopping centers. Next, we estimate our model in Equation 2-1 for each of these sub-samples and report the results in Table 2-4. Considering that the results in Table 2-2 and 2-3 are robust to the measure of e-commerce sales, we only report the results for *ECOM1* in Table 2-4 for brevity reasons.

[14] For more information, please see the ICSC shopping center classifications: https://www.icsc.com/uploads/research/general/US_CENTER_CLASSIFICATION.pdf

[15] https://business.gmu.edu/blog/realestate/2018/06/06/impact-e-commerce-retail-real-estate/

Table 2-4: Results for Total and Capital Return Separated by Mall Type

	Regional & Super-Regional				Neighborhood & Community			
	TOTR		*CAPR*		*TOTR*		*CAPR*	
	Coef.	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
ECOM	0.064	0.076	0.058	0.072	0.081	0.053	0.069	0.053
lagECOM	**-0.109*****	**0.037**	**-0.103*****	**0.034**	**-0.081*****	**0.023**	**-0.078*****	**0.022**
CPI	0.151	0.224	0.193	0.218	**0.692*****	**0.161**	**0.676*****	**0.156**
CSPREAD	0.543	0.624	0.165	0.605	-0.150	0.408	-0.529	0.402
GDP	**0.178***	**0.105**	0.155	0.104	0.008	0.081	-0.011	0.079
GFC	-0.004	0.008	-0.003	0.008	**-0.018*****	**0.004**	**-0.16*****	**0.004**
Δ OCCR	0.155	0.152	0.155	0.146	0.172	0.183	0.176	0.179
TRYLD	**0.554*****	**0.186**	0.234	0.181	**0.498*****	**0.121**	**0.027****	**0.120**
TERM	0.027	0.179	-0.019	0.176	-0.021	0.122	-0.050	0.120
UNRATE	**-0.042*****	**0.009**	**-0.041*****	**0.009**	**-0.033*****	**0.006**	**-0.032*****	**0.006**
ZIMAN	0.007	0.051	0.001	0.050	0.045	0.032	0.041	0.031
Property FE	*Yes*		*Yes*		*Yes*		*Yes*	
Obs.	*150*		*150*		*150*		*150*	
R-squared	*0.380*		*0.386*		*0.667*		*0.662*	
Adj. R2	*0.325*		*0.332*		*0.637*		*0.633*	

Note: This table reports the regression statistics for the total and capital return based on the model specified by Eq. (2-1) separated by mall type and including property fixed effects. The used e-commerce variable is ECOM1. All variables are as defined in Table 2-1. Standard errors are White-corrected.

, **, and * denote statistical significance at the 10, 5, and 1 % level respectively.*

For both categories of malls, *lagECOM* has a significantly negative coefficient for total and capital return. This is in line with our previous results in Table 2-2 and 2-3 and suggests that e-commerce sales have informative value for future returns of shopping centers with different types of tenants and trade areas. However, the coefficient on *lagECOM* is larger for regional and super-regional centers than neighborhood and community centers suggesting that e-commerce sales may represent a greater investment risk for investors in malls focused on non-essential goods as opposed to malls focused on convenience-oriented goods. This result is consistent with expectations.

E-commerce developed in different phases over the last 20 years, aided by innovations in devices, internet mobility and payment options. Prior to the introduction of smart phones and mobile internet, consumers shopping online required access to a computer/laptop and stationary internet access (e.g., cable). The introduction of mobile internet and devices contributed to an accelerated e-commerce growth and allowed further technological innovations such as Google's online wallet payment app (2011), Facebook online adds (2012), Apple Pay (2014) and Instagram's shoppable tags (2017). In 2019, Cyber Monday sales reached $9.4 billion spent online with smartphone sales accounting for about 32%, or $3.0 billion, of these sales. This represented a 46% year-over-year growth (Adobe Analytics). These innovations in technology are likely to have increased online shopping by consumers.

On the other hand, faced with the loss in sales due to online competition, retailers have developed new retailing strategies that integrate online experiences with the physical store. In fact, Livingston and Jones (2015) find that larger retailers employing multi-channel retailing strategies have benefited, which in turn results in a lower impact of e-commerce on retail properties with these retailers as tenants. Furthermore, shopping centers and retailers have focused on experience-oriented shopping and multiple-channel retailing to a larger degree.[16]

To assess whether the introduction of smart phones, mobile internet, and mobile payment options, which coincided with a larger focus on multiple-channel and experiential retailing strategies, has changed the relation of e-commerce and capital returns over time, we distinguish the period of 2000 to 2018 into a pre-smart phone period (2000 to 2009) and smart phone period (2010 to 2018). In particular, we include a binary variable coded 1 for quarters in the smart phone period (*SPP*) and the interaction term of this variable with the percent change of e-commerce sales of the prior period (one-quarter lag) in our model in Equation 2-1. Considering the fact that the unlagged e-commerce variable (*ECOM*) has no impact on total and capital returns (Table 2-2 to 2-4), we eliminate this variable from the model and only focus on the first lag of *ECOM1*.

As shown in Table 2-5, the significantly negative coefficient on *lagECOM* is robust to different types of mall categories and return definitions. Additionally, compared to the 2000 to 2009 period, capital and total returns over the period of 2010 to 2018 (*SPP*) are significantly lower. Interestingly, not only the coefficient on *lagECOM* is smaller for neighborhood and community shopping centers, but also the one on *SPP*. The interaction effect of *lagECOM* and *SPP* is significantly positive, albeit only at the 10% level, for regional and super-regional malls, but insignificant for neighborhood and community malls. This suggests that, while e-commerce sales have a negative relation with future returns for all mall types (main effect), in the smart phone period, e-commerce sales also predict higher total and capital returns in the next quarter for regional and super-regional malls (interaction effect). One explanation for this finding is the use of multiple-channel and experiential retailing strategies by tenants in regional and super-regional malls aimed at attracting shoppers to physical stores. Our finding suggests that investors and appraisers account for these innovative retailing strategies and their impact on in-store performance to some degree.

[16] https://www.icsc.com/shopping-for-the-truth

Table 2-5: Results for Income and Capital Return Separated by Mall Type and pre/post-Smart Phone Period

	Regional & Super-Regional				Neighborhood & Community			
	TOTR		*CAPR*		*TOTR*		*CAPR*	
	Coef.	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
lagECOM	**-0.093*****	**0.032**	**-0.088*****	**0.031**	**-0.063****	**0.025**	**-0.062****	**0.025**
SPP	**-0.048*****	**0.011**	**-0.044*****	**0.011**	**-0.025*****	**0.007**	**-0.022*****	**0.008**
lagECOMxSPP	**0.500***	**0.298**	**0.482***	**0.291**	0.139	0.171	0.137	0.172
CPI	0.180	0.241	0.218	0.233	**0.756*****	**0.179**	**0.730*****	**0.171**
CSPREAD	0.434	0.553	0.064	0.540	-0.185	0.386	-0.563	0.384
GDP	0.123	0.103	0.104	0.101	-0.013	0.076	-0.030	0.07
GFC	-0.012	0.008	-0.011	0.008	**-0.025*****	**0.005**	**-0.022*****	**0.005**
Δ OCCR	0.151	0.138	0.150	0.134	0.207	0.181	0.208	0.177
TRYLD	-0.336	0.245	**-0.517****	**0.239**	-0.083	0.190	**-0.248**	**0.189**
TERM	0.027	0.166	-0.020	0.163	-0.033	0.117	-0.060	0.116
UNRATE	**-0.054*****	**0.008**	**-0.052*****	**0.008**	**-0.040*****	**0.006**	**-0.039*****	**0.006**
ZIMAN	-0.005	0.055	-0.011	0.054	0.045	0.033	0.041	0.032
Property FE	*Yes*		*Yes*		*Yes*		*Yes*	
Obs.	*150*		*150*		*150*		*150*	
R-squared	*0.380*		*0.386*		*0.667*		*0.662*	
Adj. R2	*0.325*		*0.332*		*0.637*		*0.633*	

Note: This table reports the regression statistics for the total and capital return based on the model specified by Eq. (2-1) separated by mall type and including property fixed effects. The used e-commerce variable is ECOM1. SPP is a binary variable coded 1 for the period of Q1/2010 to Q4/2018; 0 otherwise. All variables are as defined in Table 2-1. Standard errors are White-corrected.

, **, and * denote statistical significance at the 10, 5, and 1 % level respectively.*

2.6 Conclusion

The emergence of e-commerce has substantially disrupted the business of retailers operating physical stores. Our study is the first to empirically investigate e-commerce as a risk to retail real estate investors. If e-commerce is a risk priced by investors, we expect e-commerce sales to have informative value for capital returns. Focusing on the period of 2000 to 2018 and institutional-grade general-purpose shopping centers, our empirical analysis provides evidence that e-commerce sales have a significantly negative relation with total returns in the next quarter. In particular, we find that the informative value of e-commerce sales for total returns is driven by capital returns. Thus, higher e-commerce sales result in lower capital returns for shopping centers in the subsequent quarter. This suggests that retail real estate investors indeed price e-commerce as an investment risk. We find no relation exists between e-commerce sales and income return, which can be explained with the characteristics of retail real estate leases and our short-term (one quarter) focus.

While we find a consistent negative relation of e-commerce sales and capital returns in the next quarter, our results indicate that it varies across shopping center types. In particular, the negative relation appears stronger for regional and super-regional malls than neighborhood and community shopping centers suggesting that e-commerce sales have a larger impact on asset pricing of malls focused on non-essential goods as opposed to convenience-oriented goods. With that, our findings indicate that investors account for e-commerce not only as a general risk but consider center-specific risks when valuing properties and making pricing decisions.

Last, we provide evidence that in the period from 2010 to 2018, which saw the rise of smart phones and mobile shopping as well as multiple-channel and experiential retailing strategies, e-commerce sales have a small additional positive effect on capital returns in the next quarter for regional and super-regional shopping centers. One explanation for this finding is that multiple-channel and experiential retailing strategies benefit brick-and-mortar stores in shopping centers. Retailers may use their physical stores as fulfillment centers or locations for shoppers to pick up online orders. Furthermore, they may use physical stores to create an experience that cannot be recreated in an online environment. Thus, our findings suggest that retail real estate investors account for the impact of new retailing strategies on physical stores in their risk assessment.

We consider our study as a starting point for future investigations into the impact of e-commerce and innovative retailing strategies on the performance of retail real estate assets. Future studies may investigate the impact of multiple-channel and experiential retailing strategies on rental rates and asset prices of different mall types. In the context of multiple-channel retailing, future investigations could focus in particular on the role of physical stores as fulfillment centers. Others may investigate different types of tenants and their impact on rental rates and asset prices. For example, over the last years, a number of formerly online retailers such as Amazon or Warby Parker have started to open physical stores as part of their retailing strategies. As a result of traditional anchor tenants such as department stores closing stores in regional and super-regional malls, grocery retailers have emerged as a new tenant group for these types of malls. Other malls have started to integrate office (e.g., co-working) or medical service providers into their tenant mix. Future studies may investigate the impact of these new tenant mixes on asset pricing. Other investigations could focus on how a larger emphasis on multiple-channel retailing and experiential learning affect the risk perception of shopping center investors, particularly with regards to different types of malls such as lifestyle shopping centers and regional malls.

Furthermore, future investigations may also investigate the impact of COVID-19 and resulting changes of shopping behaviors, for example with regard to groceries, on rental rates and pricing of certain types of shopping centers. Traditionally, consumers were less likely to shop for groceries online. However, the COVID-19 crisis changed this. With grocery retailers such as Whole Foods, which is owned by Amazon, increasingly offering online shopping as an option, shoppers have become more comfortable with shopping for groceries online. The share of shoppers is likely to continue to be high or may even increase once the COVID-19 crisis is over. On the other hand, grocery retailers may use their existing stores as fulfillment centers for online orders, which is likely to reduce the impact of a larger share of e-commerce for community and neighborhood shopping centers.

Future studies may also investigate the e-commerce and return relation in the pre-COVID, COVID, and post-COVID period to assess how the pandemic has changed the effect of e-commerce sales on capital returns. Last, our study focuses on the short-term effects of e-commerce sales on retail real estate returns. While an investigation into the long-term relation of these variables is beyond the scope of our study, future investigations could take our results as a starting point and further investigate this relation.

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3 Tenant Stock Market Performance and Retail Real Estate Prices

3.1 Abstract

We investigate the informative value of tenant stock market performance, as a proxy for tenant quality, for retail real estate transaction prices. In our empirical investigation, we focus on discount and non-discount department stores, which represent important anchor tenant groups in general-purpose shopping centers. To validate our tenant quality measure, we first show that the stock market performance of non-discount department stores, but not discount department stores, predicts retail real estate investor sentiment and total returns in the next quarter. Explanations for our findings include the struggles of non-discount department stores with changing consumer preferences, e-commerce, and discount competition, which affect their credit, bankruptcy, and store closure risk. Using a sample of 5,507 general-purpose shopping center transactions, we then provide evidence that the stock market performance of non-discount department stores in the previous quarter has a positive relation with transaction prices for shopping centers in lower quality locations (suburban) and of lower property quality. The previous stock market performance of discount department stores only has informative value for transaction prices of malls with the highest risk to investors. Our results suggest that commercial real estate investors use the stock market performance of tenants as a source of information to make pricing decisions for shopping centers for which it is more difficult to replace anchor tenants.

Keywords: Commercial Real Estate, Tenant Quality, Transaction Prices, Stock Market, Mixed Effects Regression

3.2 Background

The ability of tenants to make rental payments over the life of their leases is an important consideration in the pricing decisions of commercial real estate investors. While rent roll and credit ratings provide past and current information on tenant quality in terms of credit risk, information to assess the future credit and bankruptcy risk of tenants is more difficult to find. To understand industry- and firm-specific factors that impact tenants in the future, investors can use sources such as industry-specific research reports from consulting firms, industry analyses from stock market analysts, or articles in the financial press. Another source of information is the stock market performance of tenants as it reflects the expectations of stock market investors about future cash flows based on their assessment of industry and firm-specific fundamentals. In fact, Chen, Harrison and Khoshnoud (2018) find that the stock market performance can serve as a signal about the future credit risk of the respective firms. As a result, the question arises as to whether commercial real estate investors rely on the stock market performance of tenants as a source of information in their pricing decisions.

The purpose of this study is to investigate the informative value of tenant stock market performance, as a proxy for tenant quality, for commercial real estate prices. We use general-purpose shopping centers as a laboratory and focus on department stores as a tenant group. This focus has several advantages for our investigation. First, department stores represent an easy to identify industry based on standard industrial classification (SIC) code. Second, most department store retailers are publicly listed and traded companies. Third, department stores traditionally represent a major anchor tenant group in general-purpose shopping centers, and therefore have a large impact on the risk faced by investors. Hereby, we define general-purpose shopping centers in line with the International Council of Shopping Centers (ICSC) as regional malls and neighborhood shopping centers.[17]

In our analysis, we distinguish between non-discount and discount department stores. Non-discount department stores (e.g., Neiman Marcus, JC Penney, Macy's) have been negatively affected by, amongst others, e-commerce, discount competition and changing consumer preferences[18] while discount department stores (e.g., Burlington, Value City) have not faced these challenges due to their lower price points (RERC *et al.*, 2021). Compared to discount department stores, the struggles of non-discount department stores in a changing retail environment increase their credit and store closure risk for shopping center investors.

However, Liu and Liu (2013) show that the impact of retail tenant bankruptcy on landlords varies by location. The easier it is to replace an anchor tenant, due to the desirability of a location for other retailers, the lower is the negative impact of an anchor tenant vacating a store. Consequently, we hypothesize that the informative value of tenant stock market performance for transaction prices is the highest for 1) tenants with

[17] https://www.icsc.com/uploads/t07-subpage/US-Shopping-Center-Definition-Standard.pdf

[18] https://www.vox.com/recode/21717536/department-store-middle-class-amazon-online-shopping-covid-19; https://www.washingtonpost.com/business/2021/04/16/half-countrys-remaining-mall-based-department-stores-are-expected-shutter-by-2025/

a higher credit and store closure risk (i.e., non-discount department stores) and 2) properties whose location and quality increase the difficulty to replace an anchor tenant.

In our empirical analysis, we first assess the robustness of our tenant quality measure by investigating its relation with retail real estate investor sentiment and returns. We find that the industry-level stock market performance of non-discount department stores in the previous quarter predicts investor sentiment and total returns for general-purpose malls. The stock market performance of discount department stores on the other hand has no relation with future sentiment and returns.

Then, using a sample of 5,507 transactions of general-purpose shopping centers in California over the period of 2000 to 2020, we show that the industry-level stock market performance of non-discount stores has informative value for transaction prices. In particular, we find that the better the stock market performance of non-discount department stores was in the previous quarter, the higher are transaction prices. However, this positive relation is driven by more risky locations (suburban) and properties with a lower quality in terms of CoStar rating, which captures property characteristics such as tenant mix, architectural, and site features. The stock market performance of discount department stores only has informative value for properties that represent the highest risk to investors – lower quality malls in suburban locations. Overall, our results suggest that retail real estate investors rely on the stock market performance of tenants with a higher credit, bankruptcy, and store closure risk (non-discount department stores) in their pricing decisions for properties with a higher risk in terms of the ability to replace anchor tenants.

Our investigation differs from previous studies that investigate tenant quality by focusing on landlord-level outcomes with publicly traded equity REITs being the landlords (e.g., Chen *et al*., 2018; Liu *et al*. 2019; Lu-Andrews, 2017; Liu & Liu, 2013). Our study is the first to investigate the informative value of tenant stock market performance as proxy for tenant quality for commercial real estate prices. We hereby complement Chen, Harrison and Khoshnoud (2018), who find that the stock market performance of major tenants predicts future returns of publicly listed landlords (REITs).

We also contribute to a wider literature on asset pricing in the context of commercial real estate markets (e.g., Beracha *et al*., 2018; Freybote *et al*., 2016; Corgel *et al*., 2015; Wiley *et al*., 2010; Dermisi & McDonald, 2010) by introducing industry-level stock market performance as a tenant-specific factor in a hedonic pricing model and showing that commercial real estate investors rely on tenant-specific stock market information in their pricing decisions. Furthermore, we contribute to the commercial real estate sentiment literature (e.g., Freybote & Seagraves, 2018, 2017; Ling *et al*., 2014;

Clayton *et al*., 2009) by providing evidence that the stock market performance of a major tenant group affects the sentiment of commercial real estate investors.

Our study is structured as follows. Next, we review the relevant literature and develop our hypotheses. Then we discuss our data, variables, and methodology, followed by the presentation of our results and a conclusion.

3.3 Literature Review

An extensive literature investigates retail real estate with a focus on, for example, tenants (e.g., Guven *et al*., 2022; Nase *et al*., 2013; Hui *et al*., 2007; Des Rosiers *et al*., 2005; Konishi & Sandfort, 2003; Mejia & Benjamin, 2002; Gerbich, 1998; Gatzlaff *et al*., 1994; Sirmans & Guidry, 1993), lease contracts (Cho & Shilling, 2007; Benjamin & Chinloy, 2004; Chun *et al*., 2003; Hendershott & Ward, 2003; Lee, 1995), location (e.g., Koller & Pennington-Cross, 2019; DiPasquale & Wheaton, 1996; Eppli & Shilling, 1996; Ownbey *et al*., 1994), development (e.g., Tsolacos, 1999; Benjamin *et al*., 1998a, 1998b; Eppli & Laposa, 1997), retail REITs (Neil & Webb, 1994), retail sales (Lee & Pace, 2005; Okoruwa *et al*., 1994), e-commerce (e.g., Kaiser & Freybote, 2022; Schlauch & Laposa, 2001) as well as rents and transaction prices (e.g., Freybote *et al*., 2016; Nase *et al*., 2013; Hardin & Carr, 2006; Hardin *et al*., 2002; Hardin & Wolverten, 2001; Chun *et al*., 2001; Wheaton, 2000; Eppli *et al*., 1998).

Most important to our investigation are studies investigating tenant quality. Several studies analyze the impact of tenant quality on landlord-level variables such as profitability, cost of debt, stock market returns, and financing decisions for commercial real estate investors in property types with long-term leases (e.g., Chacon, 2021; Ambrose *et al*., 2018; Liu *et al*., 2019; Chen *et al*., 2018; Lu-Andrews, 2017; Liu & Liu, 2013). Ambrose, Shafer and Yildirim (2018) show that tenant diversification in retail properties impacts mortgage spreads and the default risk of landlords. Chacon (2021) investigates the impact of tenant concentration, i.e., a few tenants generating a large share of rental revenues, on the property portfolio performance and risk for REITs. The author finds that REITs with a higher tenant concentration in their portfolios have a higher profitability driven by operational efficiency. However, they also have a higher idiosyncratic risk. The author furthermore provides evidence for the importance of tenant quality when investigating tenant concentration effects. While high quality tenants yield positive effects, lower quality tenants yield negative ones.

Chen, Harrison and Khoshnoud (2018) investigate whether the future returns of publicly traded REITs are affected by the financial performance of their tenants. The authors provide evidence that the stock market performance of tenants predicts future returns of their landlords. Furthermore, a REIT investment strategy based on tenant performance can yield abnormal returns. Lu-Andrews (2017) focuses on tenant quality in terms of credit and bankruptcy risk and the liquidity management of REITs. The author concludes that tenant quality negatively impacts the liquidity of landlords (i.e., cash and unused credit lines). Liu, Liu and Zhang (2019) show the importance of tenant quality as a proxy of asset quality/liquidation value for financing decisions of landlords (i.e., publicly traded REITs).

Previous studies emphasize the importance of anchor tenants and choosing the optimal tenant mix (e.g., Zhang *et al.*, 2020; Des Rosiers *et al.*, 2009; Cho & Shilling, 2007; Gatzlaff *et al.*, 1994; Benjamin *et al.*, 1992). In this context, losing an anchor tenant in a shopping center can result in an approximate 25% decline in the overall rental rate (Gatzlaff *et al.*, 1994). While department stores as anchor tenants commonly pay less to no rent (Liu & Liu, 2013; Gould *et al.*, 2005), they have an impact on the appeal of a shopping center to shoppers and consequently impact the sales of non-anchor tenants that pay market rate rent. Furthermore, department store closures in shopping centers may trigger co-tenancy clauses in the leases of other tenants, which leads to an increased vacancy and lower appeal of the mall to shoppers.

Liu and Liu (2013) focus on the bankruptcy of retail tenants and show that it impacts the stock market returns of the respective landlords (publicly traded REITs), albeit differently across geographic markets. The authors find that in geographical markets that are 1) well-performing and 2) have a highly diversified economic base, the bankruptcy of a retail tenant positively impacts the landlord's stock market return considering the opportunity to replace the failed tenant with a new, higher quality tenant. Focusing on anchor tenants in particular, the authors find that anchor tenant bankruptcy leads to a larger negative stock market response, unless the affected properties are in well-performing geographical markets. In the latter case, the bankruptcy of an anchor tenant positively affects the stock market returns of the landlord as the locations are desirable to other large retailers and vacated stores can be easily released.

Considering these previous studies (e.g., Chen *et al.*, 2018; Liu & Liu, 2013), we hypothesize that the stock market performance of department stores as a proxy for tenant quality has a positive relation with future commercial real estate prices. A higher optimism of stock market investors based on their expectations for future industry and firm-level fundamentals of department stores is expected to lead to a better stock market performance of these tenants. Retail real estate investors in turn are expected to use this information from the more informationally efficient stock market as a source of information in their asset pricing decisions, which then leads to a positive relation of tenant stock market performance and transaction prices.

However, we expect this positive relation between tenant stock market performance and asset prices to vary across different department store segments and property characteristics. First, we hypothesize this relation to be stronger for department stores that have a higher credit, bankruptcy, and store closure risk. Non-discount department stores have been impacted to a larger extent by changes in the retail industry (e.g., shifting consumer preferences, e-commerce) than discount department stores[19], which in turn makes them a riskier tenant category for investors. Thus, we expect retail investors to rely more on stock market information for non-discount department stores than discount ones as a source of information in their asset pricing. Second, considering the findings of Liu and Liu (2013), we hypothesize that the informative value of tenant stock market performance for retail asset prices is higher for properties for which it is more difficult to replace anchor tenants, either due to location or property quality.

3.4 Data and Variables

3.4.1 Stock Market Indices

We derive our measure of tenant quality based on the stock market performance of publicly listed department stores. In particular, we obtain the monthly closing prices for all publicly listed firms with the standard industrial classification (SIC) code of 5311 (Department Stores) for the period of January 2000 to December 2020 from CRSP. We include active and defunct department stores in our sample to eliminate a potential survivorship bias, which results in a sample of 15 firms.[20] Then, we create a price index (*DEPSTI*) for all department stores and each month with January 2000 being the base month. Over the twenty-year period, *DEPSTI* averages 1.36 with a median of 1.29 and standard deviation of 0.38.

Our approach differs from Chen, Harrison and Khoshnoud (2018), who obtain information for three or more publicly traded tenants of each REIT in their sample to

[19] https://www.vox.com/recode/21717536/department-store-middle-class-amazon-online-shopping-covid-19

[20] The firms are Saks Inc, May Department Stores Co, Dillards Co, Macys Co, Neiman Marcus Group Inc, Penney JC Co Inc, Gottschalks Inc, Stein Mart Inc, Kohls Inc, Burlington Stores Inc, Value City Department Stores Inc, Retail Ventures Inc, Federated Department Stores Inc, Sears Roebuck & Co, Nordstrom Inc.

derive a stock market performance measure. For our analysis, we create an industry-level stock market index for a tenant group (department stores). The motivation for our approach is that the CoStar data used in our main analysis does not include sufficient information on individual tenants in transacted properties to use their stock market performance in our analysis. However, we only focus on a shopping center type that commonly has department stores as anchor tenants (general-purpose shopping centers) to increase the probability that shopping centers in our sample had a department store as tenant at the time of sale.

Trends in the retail industry such as changing consumer preference, e-commerce, and discount competition have had a varying effect on different department stores. Non-discount department stores have been more negatively affected by these trends than discount department stores.[21] As a consequence, we separate our sample into non-discount department stores (e.g., Neiman Marcus Group Inc, Dillards Inc, Penney JC Co Inc) and discount department stores (e.g., Burlington Stores Inc, Value City Department Stores Inc, Retail Ventures Inc) and create two separate monthly stock market indices for 1) non-discount ($DEPSTI_{nondisc}$), and 2) discount department stores ($DEPSTI_{disc}$). $DEPSTI_{nondisc}$ ($DEPSTI_{disc}$) averages 1.19 (1.96) with a median of 1.41 (1.70) and a standard deviation of 0.31 (1.23).

To assess whether our stock market indices contain information relevant to retail real estate investors, we analyze their relations with investor sentiment and real estate returns. In particular, we measure investor sentiment based on the quarterly investment conditions reported in the Situs RERC survey in line with previous sentiment studies (Freybote & Seagraves, 2018; Ling *et al*., 2014; Clayton *et al*., 2009). Returns are defined as the quarterly total return on the NCREIF property index (NPI). We use the Situs RERC sentiment measure (*SENT*) and NPI total return (*TOTR*) for general-purpose shopping centers over the period of Q1/2000 to Q4/2018. Considering that investor sentiment and total returns are quarterly time series, we convert our monthly stock market indices to quarterly time series. As commercial real estate investors are likely to rely on the most recent stock market information in their current investment decision-making, we use the lagged stock market indices in our analysis ($L.DEPSTI$, $L.DEPSTI_{nondisc}$ *and* $L.DEPSTI_{disc}$).

Panel A of Table 3-1 presents the pairwise correlations between *TOTR* and *SENT* with the overall and separated stock market indices ($L.DEPSTI$, $L.DEPSTI_{nondisc}$ *and* $L.DEPSTI_{disc}$) respectively. All correlation coefficients are significant at the 1% level,

[21] https://www.vox.com/recode/21717536/department-store-middle-class-amazon-online-shopping-covid-19; https://www.washingtonpost.com/business/2021/04/16/half-countrys-remaining-mall-based-department-stores-are-expected-shutter-by-2025/

except for the discount department store index ($L.DEPSTI_{disc}$) and total NPI returns ($TOTR$), which is significant at the 10% level. Thus, our stock market indices are correlated with retail investor sentiment and total returns in the next quarter.

To further assess the relation of our indices across different commercial real estate market cycle phases, as proxied by investor sentiment and NPI returns, we employ a non-linear Markov-Switching regression for the time series data. For both dependent variables, we specify two states, i.e., hot and cold market cycle phases based on $TOTR$ and optimistic and pessimistic investors based on $SENT$. All our variables, except $L.DEPSTI$ and $L.DEPSTI_{disc}$, are stationary at the 5% level or lower based on the Augmented Dickey Fuller test. We employ the Christiano-Fitzgerald filter to separate the time series for $L.DEPSTI$ and $L.DEPSTI_{disc}$ into trend and cyclical components and retain the cyclical component, which is stationary, for the model as shown in Equation 3-1.

$$y_t = \alpha_{S_t} + L.DEPSTI_t\beta_{S_t} + \phi_p y_{t-p} + \varepsilon_{S_t} \tag{3-1}$$

$$\alpha_{S_t} = S_t\alpha_1 + (1 - S_t)\alpha_2 \tag{3-2}$$

where y_t is the total NPI return ($TOTR$) or investor sentiment ($SENT$). α_{S_t} is the state-dependent intercept, S_t is the unobserved state and β_{S_t} is the state-dependent coefficient for the respective lag of stock market index (i.e., $L.DEPSTI$, $L.DEPSTI_{nondisc}$ *or* $L.DEPSTI_{disc}$). ε_{S_t} is the i.i.d. normal error with zero-mean and state-dependent variance. ϕ_p is an autoregressive coefficient. The autoregressive term was selected based on minimizing the AIC, HQIC and SBIC.

We present the results of the Markov-Switching regressions for total return ($TOTR$) in Panel B of Table 3-1. The lag of the overall price index (full sample column) as well as non-discount department store index (non-discount column) have a highly significant positive relation with total returns for general-purpose shopping centers, irrespective of state. On the other hand, the stock market index for discount department stores (discount column) has no relation with future total NPI returns. Thus, the results for the full sample are driven by non-discount department stores. They suggest that the better the stock market performance of non-discount department stores, the higher are total returns for general-purpose shopping centers in the next quarter.

The results for investor sentiment are presented in Panel C in Table 3-1. Similar to the NPI results, the lag of the stock market index predicts the sentiment of investors in general-purpose shopping centers for non-discount department stores, but not for the discount segment. In particular, the better the stock market performance of non-discount department stores, the more optimistic are retail investors in the next quarter, irrespective of the state they are in. However, it is noteworthy that the coefficient on *L.DEPSTI* is larger in the pessimistic than optimistic state.

Overall, our results in Table 3-1 suggest that our measure of tenant quality based on the industry-level stock market performance of non-discount department stores predicts retail real estate investor sentiment and returns in the next quarter. On the other hand, the stock market performance of discount department stores has no relation with future returns and investor sentiment. One explanation for this finding is that discount department stores are considered less risky by investors in terms of bankruptcy and credit risk.

Table 3-1: Validation of Stock Market Indices

Panel A: Pairwise Correlations				
		L.DEPSTI	*L.DEPSTI$_{nondisc}$*	*L.DEPSTI$_{disc}$*
	TOTR	**0.34*** **	**0.42*** **	**0.23***
	SENT	**0.50*** **	**0.57*** **	**0.44*** **
Panel B: Markov-Switching Results for NPI Total Return				
TOTR		**Full sample**	**Non-Discount**	**Discount**
	ϕ_p	**0.77 (0.06)*** **	**0.73 (0.05)*** **	**0.77 (0.06)*** **
Low Return State	Constant	**0.02 (0.004)*** **	-0.01 (0.01)	**0.02 (0.01)** **
	L.DEPSTI	**0.006 (0.003)** **	**0.01 (0.003)*** **	-0.002 (0.002)
	Duration	*3.28*	*4.72*	*7.08*
	P11	*0.70*	*0.79*	*0.86*
	Sigma	*0.003*	*0.02*	*0.01*
High Return State	Constant	**0.02 (0.01)*** **	0.002 (0.01)	**0.02 (0.01)** **
	L.DEPSTI	**0.02 (0.01)*** **	**0.005 (0.001)*** **	0.001 (0.004)
	Duration	*4.33*	*3.32*	*6.49*
	P22	*0.76*	*0.70*	*0.85*
	Sigma	*0.02*	*0.003*	*0.02*
Panel C: Markov-Switching Results for RERC Sentiment				
SENT		**Full sample**	**Non-Discount**	**Discount**
	ϕ_p	**0.91 (0.05)*** **	**0.85 (0.05)*** **	**0.92 (0.05)*** **
Pessimistic State	Constant	**5.14 (0.43)*** **	**3.74 (0.46)*** **	**4.89 (0.43)*** **
	L.DEPSTI	**0.41 (0.14)*** **	**0.39 (0.12)*** **	0.41 (0.15)
	Duration	*1.71*	*3.91*	*1.68*
	P11	*0.41*	*0.74*	*0.40*
	Sigma	*0.33*	*0.35*	*0.31*
Optimistic State	Constant	**5.52 (0.40)*** **	**5.12 (0.32)*** **	**5.49 (0.41)*** **
	L.DEPSTI	0.12 (0.13)	**0.17 (0.06)*** **	0.03 (0.07)
	Duration	*2.86*	*4.30*	*6.09*
	P22	*0.65*	*0.77*	*0.84*
	Sigma	*0.35*	*0.16*	*0.29*

*Note: This table presents the results for the Markov-Switching regression for NPI total return and RERC sentiment respectively with the department store stock market index (DEPSTI) and its components, as well as their correlations for the period 2000 to 2018. DEPSTI is the index for the overall stock market performance of department stores in a quarter, with DEPSTI$_{nondisc}$ and DEPSTI$_{disc}$ representing the index for non-discount as well as discount department stores respectively. L. denotes the quarterly lag of the respective variable. SENT represents the quarterly sentiment for all investors in the retail market, based on the RERC/Situs RERC survey. TOTR represents the quarterly NPI total return measure from NCREIF. ϕ_p captures the autoregressive components for SENT and TOTR. For both, an AR(1) regressive term is used based on AIC, HQIC and SBIC (N=74). '***', '**' and '*' denote significance at the 1%, 5% and 10% level respectively.*

The relations between lagged stock market indices and investor sentiment and returns respectively in Table 3-1 indicate that retail real estate investors use stock market information about a major tenant category as a source of information. Future studies can use our findings as a starting point to further investigate information channels to understand why and how commercial real estate investors use stock market information for their decision-making. These studies could also investigate to which extent stock market investor sentiment, as opposed to firm and industry fundamentals reflected in stock prices, affects commercial real estate investors in terms of asset pricing, risk assessment, and investment decisions.

3.4.2 Commercial Real Estate Transaction Data

For our main analysis, we collect cross-sectional data of arm-length transactions of general-purpose shopping centers from California over the period of January 2000 to December 2020. We eliminate transactions without sales price, submarket, and zip code information. Transaction and property-level data is obtained from CoStar. Our final sample compromises 5,507 shopping center transactions. For each transaction, we add the quarterly lag of the stock market index for all department stores (*L.DEPSTI*), non-discount department stores ($L.DEPSTI_{nondisc}$) and discount department stores ($L.DEPSTI_{dis}$) based on the month of transaction. Our dependent variable is the log of sales price (*logSP*).

We control for several shopping center characteristics such as the age of a center (*AGE*), defined as the difference between the years it was sold and built, and its quadratic term (AGE_{sq}). We also control for the overall quality of a property using the five-star CoStar's Building Rating System℠ (*STAR).* This rating is property-type specific and for retail real estate considers, amongst others, tenants, site access and design, location, architecture, or certifications.[22] The higher the CoStar rating is, the higher is the quality of a shopping center. For example, a five-star property has a prime location with high purchasing power and a high concentration of retail tenants. The tenants are leading national or international retailers or high-end local retailers with a high drawing power. Architecture, landscaping, site access and design are of superior quality, and the mall might have green building certifications. On the other hand, a two-star property has a low concentration of retail tenants in close proximity and relies mostly on local and regional retailers. Architecture, landscaping, access, and site design are of lower quality.

[22] https://www.costar.com/docs/default-source/brs-lib/costar_buildingratingsystem-definition.pdf?sfvrsn=12a507a4_2

In addition, we control for a property's building class (*CLASS*) and size, defined as log of square footage (*logSF*). We account for a property's location and create a binary variable coded 1 for transactions in urban locations and 0 for suburban locations (*URBAN*) based on the respective Costar categorization. To control for transaction-specific characteristics, we include a binary variable coded 1 if a shopping center classifies as repeated sale, i.e., has been sold more than once (*REPS*), and a binary variable coded 1 if a transaction was part of a multi-property sale (*MPROPS*). Furthermore, we account for whether the transaction was for investment purposes by including a binary variable coded 1 for investment transactions, 0 for all other type of transactions (e.g., owner-occupied). Last, we create binary variables for each year, except 2000 as the reference year, to account for temporal effects on transaction prices.

The descriptive statistics are reported in Table 3-2. On average, shopping centers in our sample have a sale price of $6,766,805 (*not reported*), and a star rating of 2.78 (median: 3). 21% of transactions in our sample are located in urban locations. Most transactions are for investment purposes (96%) and part of multi-property sales (72%). The average overall building quality is Class B (61%) while only 4% are classified as Class A. 39% of properties in our sample represent shopping centers sold more than once over our sample period.

Table 3-2: Descriptive Statistics

	Mean	**Median**	**Std. Dev.**	**Max**	**Min**
logSP	14.98	14.96	1.23	19.56	9.33
AGE	24.42	23	16.06	120	0
STAR	2.78	3	0.58	5	1
logSF	9.69	9.63	1.20	13.99	4.61
REPS	0.39	0	0.49	1	0
URBAN	0.21	0	0.41	1	0
INVESTM	0.96	1	0.21	1	0
MPROPS	0.72	1	0.45	1	0
CLASS	2.31	2	0.55	3	1
$CLASS_A$	0.04	0	0.20	1	0
$CLASS_B$	0.61	1	0.49	1	0
$CLASS_C$	0.35	0	0.48	1	0

Note: This table presents the descriptive statistics for a dataset of shopping center transactions for California over the period of 2000 to 2020. logSP is the log of sales price. DEPSTI is the index for the overall stock market performance of department stores. AGE is the difference between year sold and built. STAR is a center's overall quality based on criteria like tenants, site access and design, location, architecture, or certifications, with 5 being the highest and 1 being the lowest ranking. logSF is the log of a shopping center's square footage. REPS is coded 1 if a shopping center has been sold more than once. URBAN is coded 1 if a shopping center is located in an urban area; 0 for a suburban location. INVESTM is coded 1 if sale type qualifies as an investment; 0 for owner transaction. MPROPS is coded 1 if a transaction was part of a multi-property sale. CLASS classifies the center's general condition as either Class A, B or C.

3.5 Methodology

Spatial effects at submarket and/or zip code level can threaten the independence of observations in our sample. In particular, our sample contains transactions across 749 zip code groups (q_2) and 267 submarkets (q_3). Because the zip codes are nested within submarkets, we fit a three-level mixed effects model with random intercepts at both the submarket and the zip codes-within-submarket levels as shown in Equation 3-1. Multi-level mixed effects regressions have been employed in the context of real estate markets to account for spatial effects (e.g., DeFranco, 2022; Chasco & Le Gallo, 2013; Riley, 2012; Shin *et al*., 2011; Djurdjevic *et al*., 2008; Isakson, 2004). We also cluster standard errors at submarket level.

$$logSP_{jk} = X_{jk}\beta + Z_{jk}^{(3)}u_k^{(3)} + Z_{jk}^{(2)}u_{jk}^{(2)} + \epsilon_{jk} \tag{3-3}$$

where center-specific observations (first level) are nested within $j = 1, \dots, M_k$ zip codes (second level), which are nested within $k = 1, \dots, M$ submarkets (third level). Group j, k consists of n_{jk} observations. Thus, $logSP_{jk}$, X_{jk} and ϵ_{jk} each have row dimension n_{jk} with $X_{jk}\beta$ representing the fixed portion to be estimated. $Z_{jk}^{(3)}$ is the $n_{jk}\ x\ q_3$ design matrix for the submarket random effects $u_k^{(3)}$ (q_3 = 267), and $Z_{jk}^{(2)}$ is the $n_{jk}\ x\ q_2$ design matrix for the zip codes random effects $u_{jk}^{(2)}$ (q_2 = 749). Furthermore, we assume that

$$u_k^{(3)} \sim N(0, \Sigma_3)\ ;\ \ u_{jk}^{(2)} \sim N(0, \Sigma_2);\ \ \epsilon_{jk} \sim N(0, \sigma_\epsilon^2 \mathrm{I}) \tag{3-4}$$

and that $u_k^{(3)}$, $u_{jk}^{(2)}$, and ϵ_{jk} are independent.

3.6 Results

Table 3-3 presents the results of our multi-level mixed effects regression based on Equation 3-3 for the aggregated stock market index *L.DEPSTI* (Model 1) and disaggregated indices *L.DEPSTI$_{nondisc}$* (Model 2) and *L.DEPSTI$_{disc}$* (Model 3). For the aggregated index, we find a significant positive relation between the stock market performance of retailers in the previous quarter and transaction prices. This is driven by non-discount department stores while the stock market index for discount stores has no relation with transaction prices. Thus, the higher (lower) the stock market performance of non-discount department stores was in the previous quarter, the higher (lower) are sales prices for shopping centers.

The findings in Table 3-3 are in line with our previous findings that the stock market performance of non-discount department stores, but not discount department stores, affects retail real estate returns and investor sentiment in the future (Table 3-2). They also provide support for our hypothesis that commercial real estate investors obtain information about higher risk tenants (non-discount department stores) from the more informationally efficient stock market. Or put differently, our results in Table 3-2 provide evidence that retail investors use the stock market performance of tenants as a source of information and account for tenant-specific risk based on industry-level stock market performance in their pricing decisions.

Our results for control variables across the different models are in line with expectations. Age shows the expected quadratic relation with sales price (*AGE*, AGE_{sq}). Furthermore, the higher the quality (*STAR*) and size of a shopping center (*logSF*), the higher its sales price. Our findings for size are in line with Benjamin, Bolye and Sirmans (1992), who find that tenants of larger shopping centers typically pay higher rents. Further, we find a discount on sales prices if a transaction was part of a multi-property sale (*MPROPS*) as well as a premium if a center is located in an urban area (*URBAN*) or was bought for investment purposes (*INVESTM*).

Table 3-3: Results for Sales Price

	Model (1)		**Model (2)**		**Model (3)**	
	Coef.	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
L.DEPSTI	**0.09****	**0.05**				
$L.DEPSTI_{nondisc}$			**0.09****	**0.04**		
$L.DEPSTI_{disc}$					0.008	0.02
AGE	**-0.02*****	**0.002**	**-0.02*****	**0.002**	**-0.02*****	**0.003**
AGE_{sq}	**0.0001*****	**<0.0001**	**0.0001*****	**<0.0001**	**0.0002*****	**<0.0001**
STAR	**0.11*****	**0.02**	**0.15*****	**0.02**	**0.11*****	**0.03**
logSF	**0.78*****	**0.01**	**0.78*****	**0.01**	**0.79*****	**0.01**
REPS	0.04	0.03	0.04	0.04	**0.07****	**0.03**
MPROPS	**-0.22*****	**0.03**	**-0.26*****	**0.04**	**-0.27*****	**0.03**
URBAN	**0.36*****	**0.06**	**0.31*****	**0.07**	**0.31*****	**0.06**
INVESTM	**1.15*****	**0.36**	**1.20*****	**0.43**	**0.91***	**0.53**
$CLASS_B$	-0.07	0.05	-0.06	0.06	-0.10	0.07
$CLASS_C$	-0.01	0.06	-0.11	0.07	-0.12	0.08
Fixed eff.	*Year*		*Year*		*Year*	
Obs.	*5,507*		*5,507*		*5,507*	
Group variable	*No. of groups*	*Avg. obs./group*	*No. of groups*	*Avg. obs./group*	*No. of groups*	*Avg. obs./group*
Submarket	*267*	*20.6*	*267*	*20.6*	*242*	*13.7*
Zipcode	*749*	*7.4*	*749*	*7.4*	*644*	*5.2*
Log pseudo-likelihood	*-4,722.11*		*-4,721.70*		*-2,700.97*	
Wald χ^2	*12,345.20****		*12,333.47****		*7,991.79****	
Random eff. parameters	*Est.*	*SE*	*Est.*	*SE*	*Est.*	*SE*
Submarket	*0.18*	*0.03*	*0.18*	*0.03*	*0.12*	*0.03*
Zipcode	*0.11*	*0.01*	*0.11*	*0.01*	*0.11*	*0.02*

Table 3-3: Results for Sales Price *(continued)*

Residuals	*0.26*	*0.01*	*0.26*	*0.01*	*0.22*	*0.01*

Note: This table reports the multilevel mixed effect regression statistics for shopping center transactions for California over the period from 2000 to 2020 based on the model specified by Eq.(3-3). DEPSTI is the index for the overall stock market performance of department stores in a quarter, with $DEPSTI_{nondisc}$ and $DEPSTI_{disc}$ representing the index for non-discount as well as discount department stores respectively L. denotes the quarterly lag of the respective variable. All other variables are as defined in Table 3-1. Standard errors are clustered at submarket level.

*'***', '**' and '*' denote significance at the 1%, 5% and 10% level respectively.*

Liu and Liu (2013) show that the impact of retail tenant bankruptcy on landlords varies across location. In better locations, landlords can replace a failed tenant more easily with a new tenant. Furthermore, department stores focused on optimizing their store portfolios are less likely to vacate well-performing stores in better locations. Consequently, store closure risk is less likely a concern for investors with assets in more affluent and economically diversified locations.

To investigate our second hypothesis that property location has an impact on the relation of stock market performance and asset prices, we separate our sample into sub-samples of transactions in urban and suburban locations based on *URBAN*. Hereby urban locations proxy for more desirable locations for retailers and retail real estate investors for a number of reasons. First, over the first two decades of the twenty-first century, urban areas were able to attract more prime working age adults (25 to 44) and more educated residents than suburban areas (Fry *et al*., 2020; Parker *et al*., 2018). Furthermore, income, employment rates, and home prices grew more in urban areas than in suburban ones (Fry *et al*., 2020; Parker *et al*., 2018). On the other hand, poverty rates increased by 51% in suburban counties, which is higher than for urban or rural counties (Parker *et al*., 2018). Second, suburban locations suffer from an excess supply of retail space (Parlette & Cowen, 2011). As a result, technological innovation and changing consumer preferences particularly impact suburban retail (Bliss, 2018).

Table 3-4 presents our results separated by location. Considering the results in Table 3-3, we only report the results for the stock market indices disaggregated by department store type ($L.DEPSTI_{nondisc}$ and $L.DEPSTI_{disc}$). The previous quarter's stock market performance of non-discount department stores has a positive relation with transaction prices in suburban locations, while it has no relation for urban location. This is in line with the expectation that retail investors in more risky locations (suburban) rely on the tenant stock market performance as a source of information when making pricing decisions. On the other hand, the lag of stock market performance of discount department stores continues to have no relation with transaction prices, irrespective of location. Overall, our results in Table 3-4 suggest that stock market performance as a measure of tenant quality has informative value for tenants with a higher risk (non-discount department stores) in higher risk locations (suburban).

Table 3-4: Results for Sales Price Separated by Location Type

	Model (1)			
	Urban		Suburban	
	Coef.	*SE*	*Coef.*	*SE*
$L.DEPSTI_{nondisc}$	0.07	0.07	0.11**	0.05
AGE	-0.01***	0.005	-0.02***	0.002
AGE_{sq}	0.0001*	<0.0001	0.0001***	<0.0001
STAR	0.14***	0.04	0.09***	0.02
logSF	0.82***	0.02	0.78***	0.01
REPS	0.13***	0.05	0.02	0.03
MPROPS	-0.14**	0.06	-0.24***	0.03
INVESTM	2.32***	0.14	0.86**	0.40
$CLASS_B$	-0.07	0.11	-0.05	0.05
$CLASS_C$	-0.11	0.14	-0.07	0.06
Fixed eff.	*Year*		*Year*	
Obs.	*1,179*		*4,328*	
Group variable	*No. of groups*	*Avg. obs./group*	*No. of groups*	*Avg. obs./group*
Submarket	*87*	*13.6*	*188*	*23.0*
Zipcode	*221*	*5.3*	*533*	*8.1*
Log pseudo-likelihood	*-961.02*		*-3,721.49*	
Wald χ^2	*1,330,000****		*11,996.89****	
Random eff. parameters	*Est.*	*SE*	*Est.*	*SE*
Submarket	*0.07*	*0.03*	*0.16*	*0.04*
Zipcode	*0.17*	*0.04*	*0.09*	*0.01*
Residuals	*0.22*	*0.03*	*0.26*	*0.02*
	Model (2)			
	Urban		**Suburban**	
	Coef.	*SE*	*Coef.*	*SE*
$L.DEPSTI_{disc}$	0.04	0.04	0.006	0.02
AGE	-0.01**	0.007	-0.02***	0.003
AGE_{sq}	0.0001	< 0.0001	0.0002***	< 0.0001
STAR	0.16***	0.04	0.09***	0.03
logSF	0.82***	0.02	0.78***	0.01
REPS	0.16**	0.07	0.06*	0.03
MPROPS	-0.26***	0.07	-0.29***	0.04
INVESTM	2.39***	0.14	0.25**	0.12
$CLASS_B$	-0.10	0.10	-0.08	0.09
$CLASS_C$	-0.10	0.12	-0.09	0.10
Fixed eff.	*Year*		*Year*	
Obs.	*766*		*2,551*	
Group variable	*No. of groups*	*Avg. obs./group*	*No. of groups*	*Avg. obs./group*
Submarket	*77*	*9.9*	*172*	*14.8*
Zipcode	*182*	*4.2*	*467*	*5.5*
Log pseudo-likelihood	*-596.01*		*-2,075.80*	
Wald χ^2	*486,426.42****		*7,529.88****	
Random eff. parameters	*Est.*	*SE*	*Est.*	*SE*
Submarket	*0.07*	*0.03*	*0.15*	*0.04*

Table 3-4: Results for Sales Price Separated by Location Type *(continued)*

Zipcode	*0.17*	*0.04*	*0.09*	*0.02*
Residuals	*0.19*	*0.02*	*0.23*	*0.01*

Note: This table reports the multilevel mixed effect regression statistics for shopping center transactions for California over the period from 2000 to 2020, separated by location type and based on the model specified by Eq.(3-3). Location information for properties is based on CoStar classifications. $DEPSTI_{nondisc}$ and $DEPSTI_{disc}$ are the indices for the department store stock market performance for non-discount as well as discount department stores respectively. L. denotes the quarterly lag of the respective variable. All other variables are as defined in Table 3-1. URBAN is omitted in the model due to collinearity. Standard errors are clustered at submarket level.

*'***', '**' and '*' denote significance at the 1%, 5% and 10% level respectively.*

In addition to location, the quality of a shopping center in terms of tenant mix, design, landscaping, or site access is expected to also have an impact on whether investors rely on stock market information to assess tenant quality. Tenant quality is less of a concern to investors in higher quality shopping centers, which are more desirable to retailers and increase the ease with which a landlord can replace a failed tenant.

To assess the impact of mall quality on the relation of tenant stock market performance and transaction prices, we separate our sample into malls with a 1) CoStar rating of 3 or higher (High Quality sample) and 2) 2 or 1 (Low Quality sample). Our motivation to separate our overall sample in this manner is that retail properties with a 3-star rating represent the average in terms of tenant concentration, mix of regional and local retailers as well as architecture and site quality. Properties with a 1 or 2-star rating are below average and represent a higher risk to investors.

Our results for the sub-samples based on property quality are presented in Table 3-5. The coefficient on the lag of the stock market index for non-discount department stores ($L.DEPSTI_{nondisc}$) is significantly positive, irrespective of quality. However, the coefficient is larger for lower quality shopping centers than higher quality ones. The lag of stock market index for discount department stores ($L.DEPSTI_{disc}$) has no informative value for transaction prices of higher quality malls. However, it has a significantly positive relation with transaction prices of lower quality properties. Lower quality malls have a lower tenant concentration and tenants, especially anchor tenants, are more difficult to replace. The importance of discount department stores to these malls explains why retail investors also rely on the stock market performance of this department store segment in their pricing decisions for these types of malls. Overall, our results in Table 3-5 suggest that the quality of a general-purpose shopping center has an impact on the informative value of tenant stock market performance for transaction prices.

Table 3-5: Results for Sales Price Separated by Star Rating

	Model (1)			
	High		Low	
	Coef.	*SE*	*Coef.*	*SE*
L.DEPSTI$_{nondisc}$	**0.10****	**0.05**	**0.12****	**0.06**
AGE	**-0.02*****	**0.002**	**-0.02*****	**0.003**
AGE$_{sq}$	**0.0001*****	**<0.0001**	**0.0001*****	**<0.0001**
STAR	**0.81*****	**0.01**	**0.72*****	**0.02**
logSF	0.03	0.03	**0.11****	**0.04**
REPS	**-0.22*****	**0.03**	**-0.22*****	**0.07**
MPROPS	**0.38*****	**0.06**	**0.35*****	**0.09**
INVESTM	**1.75*****	**0.31**	0.27	0.18
CLASS$_B$	**-0.13*****	**0.05**	**-0.68*****	**0.11**
CLASS$_C$	**-0.16*****	**0.06**	**-0.76*****	**0.11**
Fixed eff.	*Year*		*Year*	
Obs.	*4,293*		*1,215*	
Group variable	*No. of groups*	*Avg. obs./group*	*No. of groups*	*Avg. obs./group*
Submarket	*258*	*16.6*	*187*	*6.5*
Zipcode	*702*	*6.1*	*404*	*3.0*
Log pseudo-likelihood	*-3,739.73*		*-1,037.95*	
Wald χ^2	*8,643,67****		*1,370,000****	
Random eff. parameters	*Est.*	*SE*	*Est.*	*SE*
Submarket	*0.16*	*0.03*	*0.17*	*0.05*
Zipcode	*0.11*	*0.01*	*0.14*	*0.02*
Residuals	*0.26*	*0.01*	*0.20*	*0.02*
	Model (2)			
	High		**Low**	
	Coef.	*SE*	*Coef.*	*SE*
L.DEPSTI$_{disc}$	-0.004	0.02	**0.09*****	**0.03**
AGE	**-0.02*****	**0.003**	**-0.02*****	**0.005**
AGE$_{sq}$	**0.0002*****	**0.0001**	**0.0001****	**< 0.0001**
STAR	**0.81*****	**0.01**	**0.70*****	**0.04**
logSF	**0.08*****	**0.03**	0.09	0.06
REPS	**-0.29*****	**0.04**	**-0.31*****	**0.10**
MPROPS	**0.32*****	**0.06**	**0.20****	**0.10**
INVESTM	**2.30*****	**0.09**	-0.16	0.24
CLASS$_B$	**-0.18*****	**0.06**		
CLASS$_C$	**-0.20*****	**0.08**	-0.05	0.08
Fixed eff.	*Year*		*Year*	
Obs.	*2,582*		*736*	
Group variable	*No. of groups*	*Avg. obs./group*	*No. of groups*	*Avg. obs./group*
Submarket	*235*	*11.0*	*153*	*4.8*
Zipcode	*596*	*4.3*	*300*	*2.5*
Log pseudo-likelihood	*-2,144.04*		*-585.20*	
Wald χ^2	*927,659.61****		*1,519.94****	
Random eff. parameters	*Est.*	*SE*	*Est.*	*SE*
Submarket	*0.11*	*0.03*	*0.12*	*0.04*
Zipcode	*0.12*	*0.02*	*0.13*	*0.03*
Residuals	*0.23*	*0.01*	*0.17*	*0.02*

Table 3-5: Results for Sales Price Separated by Star Rating *(continued)*

Note: This table reports the multilevel mixed effect regression statistics for shopping center transactions for California over the period from 2000 to 2020, separated by star rating and based on the model specified by Eq.(3-3). Low is defined as having a CoStar rating of 1 or 2-stars while high is defined as 3-stars or more. $DEPSTI_{nondisc}$ and $DEPSTI_{disc}$ are the indices for the department store stock market performance for non-discount as well as discount department stores respectively. L. denotes the quarterly lag of the respective variable. All other variables are as defined in Table 3-1. STAR is omitted in the model due to collinearity. Standard errors are clustered at submarket level.

*'***', '**' and '*' denote significance at the 1%, 5% and 10% level respectively.*

Last, we investigate the joint effect of location and property quality, as a proxy for the ease with which a landlord can replace a failed tenant, on the relation of stock market performance and transaction prices. In particular, we separate our dataset in four sub-samples based on 1) location (urban vs. suburban) and 2) property quality (3-star or higher vs. 1 and 2-star). We estimate our model in Equation 3-3 and present the results in Table 3-6.

For non-discount department stores, the previous quarter's stock market performance has no explanatory power for transaction prices of malls in urban locations in the next month, irrespective of quality. On the other hand, for properties in suburban locations, the stock market performance has informative value for transaction prices of properties of any quality in the next month. However, the coefficient for higher quality properties is lower than the one for lower quality properties and only significant at the 10% level. Our results for $L.DEPSTI_{nondisc}$ in Table 3-6 suggest that the positive coefficient in Table 3-5 was driven by higher quality malls in suburban locations. They also suggest that location is most important for whether investors rely on the stock market performance of non-discount department stores as a source of information in their decision-making or not.

For discount department stores, the lag of stock market index only has explanatory power for transaction prices of lower quality properties in suburban locations. Thus, our results for $L.DEPSTI_{disc}$ in Table 3-5 were driven by properties in these locations. Overall, our results in Table 3-6 suggest that location and then property quality are most important for the informative value of tenant stock market performance for transaction prices.

Table 3-6: Results for Sales Price Separated by Location Type and Star Rating

	Model (1)			
	Urban		**Suburban**	
	High	**Low**	**High**	**Low**
L.DEPSTI$_{nondisc}$	0.10	0.05	**0.09***	**0.18*****
	(0.08)	(0.16)	**(0.05)**	**(0.06)**
AGE	**-0.01*****	**-0.02*****	**-0.02*****	**-0.01*****
	(0.005)	**(0.002)**	**(0.003)**	**(0.003)**
AGE$_{sq}$	0.0001	**0.0001*****	**0.0001*****	**0.0001*****
	(<0.0001)	**(<0.0001)**	**(<0.0001)**	**(<0.0001)**
logSF	**0.86*****	**0.79*****	**0.78*****	**0.80*****
	(0.02)	**(0.01)**	**(0.02)**	**(0.02)**
REPS	**0.14****	0.02	0.01	**0.14*****
	(0.07)	(0.03)	(0.04)	**(0.04)**
MPROPS	**-0.14***	**-0.24*****	**-0.31*****	**-0.16*****
	(0.07)	**(0.03)**	**(0.05)**	**(0.09)**
INVESTM	**2.42*****	**0.91*****	**1.37*****	**1.25****
	(0.18)	**(0.32)**	**(0.06)**	**(0.59)**
CLASS$_B$	-0.15	**-0.12****	**-0.15****	**-0.23****
	(0.11)	**(0.05)**	**(0.06)**	**(0.11)**
CLASS$_C$	**-0.24***	**-0.19*****	**-0.17****	**-0.35*****
	(0.14)	**(0.05)**	**(0.08)**	**(0.12)**
Fixed eff.	*Year*	*Year*	*Year*	*Year*
Obs.	*958*	*4,550*	*3,335*	*2,173*
Group variable				
Submarket	*87 (11.0)*	*235 (19.4)*	*179 (18.6)*	*220 (9.9)*
Zipcode	*214 (4.5)*	*623 (7.3)*	*492 (6.8)*	*531 (4.1)*
Log pseudolikelihood	*-799.57*	*-3,943.78*	*-2,929.32*	*-1,854.06*
Wald χ^2	*1,270,000****	*11,685****	*5,580,000****	*5,730****
Random eff. parameters				
Submarket	*0.07 (0.02)*	*0.25 (0.04)*	*0.12 (0.04)*	*0.19 (0.05)*
Zipcode	*0.13 (0.03)*	*0.10 (0.01)*	*0.10 (0.01)*	*0.15 (0.02)*
Residuals	*0.22 (0.03)*	*0.27 (0.01)*	*0.27 (0.2)*	*0.22 (0.02)*

	Model (2)			
	Urban		**Suburban**	
	High	**Low**	**High**	**Low**
L.DEPSTI$_{disc}$	0.04	-0.02	-0.02	**0.09*****
	(0.04)	(0.03)	(0.02)	**(0.03)**
AGE	**-0.01****	**-0.02*****	**-0.02*****	**-0.02*****
	(0.007)	**(0.007)**	**(0.004)**	**(0.004)**
AGE$_{sq}$	0.0001	**0.0002*****	**0.0002*****	**0.0001****
	(<0.0001)	**(<0.0001)**	**(0.0001)**	**(<0.0001)**
logSF	**0.84*****	**0.79*****	**0.80*****	**0.80*****
	(0.02)	**(0.01)**	**(0.02)**	**(0.02)**
REPS	**0.16****	**0.06****	**0.08****	**0.13****
	(0.07)	**(0.03)**	**(0.04)**	**(0.05)**
MPROPS	**-0.24*****	**-0.29*****	**-0.31*****	**-0.21*****
	(0.08)	**(0.04)**	**(0.05)**	**(0.06)**
INVESTM	**2.39*****	**-0.34*****	**0.51*****	**-1.21***
	(0.15)	**(0.08)**	**(0.10)**	**(0.61)**
CLASS$_B$	**-0.23*****	**-0.15***	**-0.15***	**-0.33*****
	(0.14)	**(0.08)**	**(0.08)**	**(0.10)**
CLASS$_C$	**-0.23****	**-0.21****	**-0.18***	**-0.41*****
	(0.11)	**(0.09)**	**(0.10)**	**(0.11)**
Fixed eff.	*Year*	*Year*	*Year*	*Year*
Obs.	*621*	*2,697*	*1,961*	*1,357*

Table 3-6: Results for Sales Price Separated by Location Type and Star Rating *(continued)*

Group variable				
Submarket	*77 (8.1)*	*208 (13.0)*	*164 (12.0)*	*188 (7.2)*
Zipcode	*172 (3.6)*	*534 (5.1)*	*427 (4.6)*	*413 (3.3)*
Log pseudolikelihood	*-496.43*	*-2,212.63*	*-1,628.07*	*-1,110.40*
Wald χ^2	*278,638****	*8,481****	*4,606****	*4,009****
Random eff. parameters				
Submarket	*0.05 (0.03)*	*0.18 (0.04)*	*0.14 (0.04)*	*0.12 (0.03)*
Zipcode	*0.13 (0.04)*	*0.09 (0.02)*	*0.11 (0.02)*	*0.15 (0.03)*
Residuals	*0.21 (0.03)*	*0.23 (0.01)*	*0.23 (0.01)*	*0.20 (0.02)*

Note: This table reports the multilevel mixed effect regression statistics for shopping center transactions for California over the period from 2000 to 2020, separated by star rating as well as location type and based on the model specified by Eq.(3-3). $DEPSTI_{nondisc}$ and $DEPSTI_{disc}$ are the indices for the department store stock market performance for non-discount as well as discount department stores respectively. L. denotes the quarterly lag of the respective variable. All other variables are as defined in Table 3-1. STAR and URBAN are omitted in the model due to collinearity. For group variables, the number of observations is presented and the average observations per group are given in parenthesis. Standard errors are clustered at submarket level and presented in parenthesis.

*'***', '**' and '*' denote significance at the 1%, 5% and 10% level respectively.*

3.7 Conclusion

Tenant quality has been found to have an impact on the profitability, cost of debt, stock market returns, and financing decisions of commercial real estate investors (e.g., Chacon, 2021; Ambrose *et al*., 2018; Liu *et al*., 2019; Chen *et al*., 2018; Lu-Andrews, 2017; Liu & Liu, 2013). We contribute to the literature by investigating the impact of tenant quality on transaction prices. We proxy for tenant quality by using the industry-level stock market performance of major anchor tenant groups, namely non-discount and discount department stores, in general-purpose shopping centers. This stock market performance measure is based on the expectations of investors in the more informationally efficient stock market and can be understood as a signal of future tenant credit risk (Chen *et al*., 2018). We hypothesize that tenant stock market performance in the past quarter has a positive relation with transaction prices of general-purpose shopping centers for 1) department stores with a higher credit, bankruptcy, and store closure risk (i.e., non-discount department stores) and 2) properties for which it is more difficult to replace failed tenants due to location or property quality.

In our empirical analysis, we first assess the validity of our tenant quality measure by investigating its relation with the investor sentiment and total returns for general-purpose shopping centers in the next quarter. We find that the stock market performance of non-discount department stores, but not discount department stores, positively predicts future investor sentiment and returns. In our main analysis, we use a sample of 5,507 shopping center transactions over the period of 2000 to 2020 in California and show that the stock market performance of non-discount department stores in the previous quarter positively predicts the transaction prices of properties in lower quality locations (i.e., suburban locations) and lower overall quality in terms of CoStar rating. Our results are in line with our expectations that the informative value of tenant stock market performance for transaction prices is the highest for higher risk tenants and properties with a higher difficulty to replace anchor tenants. Our results suggest that commercial real estate investors rely on stock market information in their pricing decisions for certain types of tenants and properties.

We consider our approach generalizable to other property types with long-term leases such as office or industrial. Investors and appraisers may use the stock market performance of individual tenants or tenant groups such as logistics firms or tech firms to assess investment risk and make pricing decisions for warehouse or office properties respectively. Furthermore, our findings have implications for commercial real estate investors considering that we show the stock market performance of a major tenant group to contain information that predicts asset prices and thus, can be used in the investment decision-making process.

Future investigations can use our study as a starting point. They could identify alternative forward-looking measures of tenant quality such as the deviations of analyst consensus earnings per share (EPS) forecast and actual EPS of tenant firms. Other investigations could focus on alternative measures of tenant quality, for example, based on a textual analysis of social media posts or press articles. Furthermore, future studies could also focus on how different types of retail real estate investors (e.g., institutional vs. non-institutional, local vs. national) use different tenant information in their decision-making. More sophisticated investors with access to more data and information might use tenant stock market information differently than less sophisticated investors.

Considering the changing retail landscape, future investigations can focus on how the importance of anchor tenants for shopping centers are changing. Future studies can also focus on other property types or other retail tenant groups (e.g., grocery stores) to further analyze the impact of tenant quality on commercial real estate transaction prices and rents. These studies could also account for the ease to replace tenants in their analysis and/or the exposure of a particular tenant or landlord to a particular geographical market. Future investigations could also focus on the interplay of housing and retail by investigating the impact of housing market fundamentals on asset pricing for different types of shopping centers and retailers.

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4 Government Risk and Real Estate Investor Risk Perception

4.1 Abstract

We investigate the impact of restrictions imposed by local political decision-makers (government risk) on the short-term risk perception of commercial real estate investors. We focus on retail real estate investors and proxy for their risk perception using a survey-based going-in cap rate. We use the COVID-19 pandemic as a natural quasi-experiment and proxy for the length and severity of COVID-19 restrictions with the political affiliation of state governors. Focusing on MSA-level going-in cap rates over the period of 2018/2019 (pre-COVID) and 2020/21 (COVID), we show that the pandemic increased investor risk perception for neighborhood and regional shopping centers. However, for states with Republican governors, which proxy for shorter and fewer COVID-19 restrictions, investors in regional malls required a lower going-in cap rate in the pandemic period than for states with Democratic governors. This suggests that the risk perception shifted as a result of governmental restrictions in response to the pandemic. This effect does not exist for neighborhood shopping centers, whose tenants were not as affected by COVID-19 restrictions. Robustness checks suggest that our findings can be explained with mask mandates as one type of governmental restrictions, and that restrictions do not impact the long-term risk perception of retail real estate investors as captured by the pre-tax yield (IRR) over the entire holding period. Last, we also find that political attitudes in an MSA impact investor risk perception. One explanation is that they signal information about future space and asset market conditions.

Keywords: Commercial Real Estate Investment, Risk Perception, Government Risk, COVID, Political Attitudes

4.2 Background

Characteristics of geographical commercial real estate markets, such as economic growth (Feng & Wu, 2021) or location density (Fisher *et al.*, 2022), impact the investment risk for investors. Local political decision-making represents another important risk factor. Political uncertainty has been found to impact residential property values (Monfared & Pavlov, 2019) and construction activity (Luo *et al.*, 2021). Governmental policies targeting multifamily, such as rent control or inclusionary zoning, have been found to impact investor behavior in terms of development, tenant screening, or divestment from the affected market (Ambrose & Diop, 2021; Asquith, 2019; Diamond *et al.*, 2019a, 2019b; Schuetz *et al.*, 2011; Suzuki & Asami, 2020).

Previous studies on the impact of political decision-making on real estate markets have focused on the single- and multifamily housing market and ignore other commercial property types. The purpose of this study is to investigate the impact of government risk on the risk perception of commercial real estate investors. Hereby, we define investor risk perception as the beliefs about the possibility of loss, and government risk as risks resulting from governmental regulations, restrictions, and other actions.

One challenge of investigating government risk in the context of commercial real estate markets is the difficulty of capturing political regulations, restrictions, and attitudes at the local level. Fortunately, the COVID-19 pandemic represents a unique opportunity for our empirical investigation. As coronavirus cases increased across US states, Republicans and Democrats increasingly viewed the outbreak from very different angles, ranging from personal health risks posed by the virus to the conveniences of everyday life (Pew Research Center, 2021). As the federal government did not take the lead in proposing nationwide policies, responses to the pandemic such as social distancing, mask mandates, or stay at home orders were left to state governments. The result was a clear distinction along party lines on actions taken with Democratic-led states imposing stricter and longer public health measures than Republican-led states. The political polarization also resulted in a partisan split in the risk perception of the disease (Benton *et al.*, 2021).

In our analysis, we measure local governmental restrictions, i.e., the level of government risk, with the political affiliation of each state's governor. Hereby, Democratic governors proxy for more severe and longer COVID-19 restrictions than Republican governors. This is consistent with recent studies showing that governor partisanship is the most important explanation for differences in social distancing policies and mask mandates across states during the pandemic (Adolph *et al.*, 2021; Adolph *et al.*, 2022).

We employ a quasi-experimental design to analyze the effects of governmental restrictions, proxied by the political affiliation of governors, on the risk perception of real estate investors in the pre-COVID (2018/2019) and COVID (2020/2021) period. We proxy for the risk perceived by investors using the survey-based Situs RERC going-in cap rate, which captures a short-term ex-ante risk premium. While local governmental restrictions during the COVID-19 crisis had an impact on several commercial property types, such as office (e.g., stay at home) and multifamily (e.g., eviction moratoriums), we focus on retail real estate, particularly neighborhood and regional shopping centers. Previous studies find a particularly strong impact of the pandemic on this property type (Hoesli & Malle, 2021; Ling *et al*., 2020; Milcheva, 2021; van Dijk *et al*., 2020). However, the strength of this impact varied across segments. While regional shopping centers with tenants focused on leisure shopping, food, and non-essential goods were impacted by regulations such as mask mandates, social distancing, and limits on store occupancy, which resulted in consumers shifting to online shopping, neighborhood shopping centers with tenants focused on essential goods such as groceries were less affected by governmental restrictions.

We hypothesize that increased government risk stemming from stricter and longer governmental restrictions imposed by Democratic governors during the pandemic led to a higher short-term risk perception of retail real estate investors and thus, higher required going-in cap rates for retail real estate assets in Democratic states compared to Republican states. We also expect this effect to be stronger for regional malls than neighborhood shopping centers.

Using a sample of 40 metropolitan statistical areas (MSAs) across 27 states, we find that the COVID-19 pandemic, unsurprisingly, increased the risk perception of retail investors. However, during this period, the political affiliation of the state governor, proxying for the length and severity of restrictions, significantly impacts the investor risk perception for regional malls. In particular, compared to Democratic-led states, retail real estate investors required a lower going-in cap rate for regional malls in MSAs located in Republican-led states. This effect does not exist for neighborhood shopping centers. Thus, our findings suggest that governmental restrictions as a form of government risk have an impact on investor risk perception for the shopping center category that was most impacted by them. In a robustness check, we show that mask mandates as one type of governmental restrictions represent one explanation for our results. Furthermore, we find no impact of governmental restrictions on the long-term risk perception of retail investors, proxied by the required pre-tax yield (IRR). This suggests that the shift in risk perception is short-term due to the COVID-19 restrictions being temporary. We also show that the political attitudes of an MSA's population have an impact on investor risk perception. Compared to Democratic-leaning MSAs, investors require a higher going-in cap rate for Republican-leaning MSAs, irrespective of mall type. One explanation is that the political attitudes of an MSA proxy for factors such as population growth, income, or diversity that impact future space and asset market conditions.

To our knowledge, this is the first study to investigate the impact of government risk on the risk perception of commercial real estate investors. In the context of real estate, risk perception has been primarily studied in housing markets and residential mortgage markets, particularly in the context of environmental risks (Duanmu *et al.*, 2022; Liao *et al.*, 2022; Pollack & Kaufmann, 2022; Xu & Xu, 2020; Yi & Choi, 2020). The risk perception of commercial real estate investors has been neglected in the real estate literature, with the exception of Beracha, Freybote and Lin (2019) who investigate the determinants of the ex-ante risk premium required by commercial real estate investors. We contribute to the literature on the impact of governmental regulations and political risks on real estate market participants (Ambrose & Diop, 2021; Asquith, 2019; Diamond *et al.*, 2019a, 2019b; Luo *et al.*, 2021; Monfared & Pavlov, 2019; Suzuki & Asami, 2020) by 1) focusing on a non-housing property type and 2) focusing on investor risk perception. We furthermore contribute to an emerging stream of literature investigating the impact of the COVID-19 pandemic on commercial real estate markets (Hoesli & Malle, 2021; Ling *et al.*, 2020; Milcheva, 2021; van Dijk *et al.*, 2020).

The remainder of this paper is structured as follows. Next, we review the relevant literature, which is followed by a discussion of our data and methodology. Then, we present our results and a conclusion.

4.3 Literature Review

Previous studies in the finance and real estate literature provide evidence for the impact of political uncertainty and governmental regulations on corporate and real estate investments. Political uncertainty has been found to impact corporate investments (Azzimonti, 2018; Çolak *et al.*, 2017; Gulen & Ion, 2015; Jens, 2017; Julio & Yook, 2012; Nguyen & Phan, 2017). In particular, M&A activities and corporate investments have a negative relation with political uncertainty. Studies focused on corporate financing activities find that an increase in political uncertainty is associated with higher debt financing costs (Francis *et al.*, 2014; Waisman *et al.*, 2015) and declining equity financing (Chan *et al.*, 2021; Çolak *et al.*, 2017).

A number of studies investigate political uncertainty in the context of housing markets. Bahmani-Oskooee and Ghodsi (2017) and Choudhry (2020) examine the impact of economic policy uncertainty on house prices in the US and England. Both studies find predominantly negative effects. Another set of studies supports that homeowners tend to vote in favor of safeguarding or increasing real estate values (Brunner *et al.*, 2001; Brunner & Sonstelie, 2003; Dehring *et al.*, 2008; Zahirovic-Herbert

& Turnbull, 2009). Luo, Tidwell and Clements (2021) find that building permits on US state-level are negatively associated with aggregate political uncertainty. Monfared and Pavlov (2019) study the impact of the Brexit referendum on residential real estate prices in areas of London and find that areas with a higher concentration of EU passport holders or highly-educated residents experienced a disproportionately large price decline following the vote.

Another stream of literature focuses on governmental policies in the context of single-family housing markets such as property taxes (Hoyt *et al*., 2011), conservation districts (Diaz *et al*., 2008), anti-discrimination (Bostic & Martin, 2005), loan-to-value restrictions (Armstrong *et al*., 2019) or land use regulations (Lima & Silveira Neto, 2019; Takeda *et al*., 2019).

While political uncertainty and governmental regulations have received considerable attention in the housing literature, they have received less attention in the commercial real estate literature. Previous studies primarily focus on the multifamily market and governmental regulations such as inclusionary zoning (Schuetz *et al*., 2011), rent control (Asquith, 2019; Diamond *et al*., 2019a, 2019b), evictions (Suzuki & Asami, 2020), and other regulations (Ambrose & Diop, 2021). Overall, these previous studies suggest that multifamily investors respond to governmental restrictions by, amongst others, shifting their investment strategies, changing their supply of space, or increasing their tenant screening.

In addition to governmental regulations and political uncertainty, the political attitudes of managers have been found to impact corporate decision-making. Hutton, Jiang and Kumar (2014) find that the political leaning of corporate executives impacts investment, financing, and other corporate decisions. Subrahmanyam, Singh and Pennathur (2020) show that CEO characteristics such as interests impact political donations. Hereby, firms have a preference to donate to local politicians in the state a company is headquartered, emphasizing the importance of local politics to firms. Focusing on the COVID-19 pandemic, Benton, Cobb and Werner (2021) find that the political leaning of a firm's management impacts the voluntary disclosure of COVID-19 risks and political donations. One explanation for these findings is that Democratic-leaning managers perceived the disease's risks to be higher than Republican-leaning.

Several studies provide evidence that the political orientation of CEOs affects corporate social responsibility (CSR). Chin, Hambrick and Treviño (2013) provide evidence that the liberalism or conservatism of CEOs impact CSR engagement. Di Giuli and Kostovetsky (2014) find that the political leaning of founders, CEOs, directors as well as the headquarters' state determine CSR engagement. Jeong and Kim (2020) show that

CEO liberalism positively predicts CSR, albeit results vary depending on the political affiliation of the US president. Gupta, Fung and Murphy (2021) find that the political leaning of CEOs impacts the adoption of CSR executives. Focusing on REITs, Deng *et al*. (2021) show that the political leaning of CEOs of REITs affect business decisions. In particular, Democratic-leaning CEOs are willing to take on more risks, e.g., in terms of financing decisions, and adopt more (environmental) ESG strategies than Republican-leaning CEOs.

Early studies analyzing the effects of the COVID-19 pandemic on commercial real estate markets show that retail real estate markets were the most affected, which motivates the focus of our study on this property type. Van Dijk, Thompson and Geltner (2020) use the liquidity impact at the beginning of the pandemic to forecast future price changes in commercial real estate markets. They project that retail real estate markets will be the most affected, with price declines in the range of 14-19 %. Focusing mostly on European real estate markets, Hoesli and Malle (2021) analyze effects of COVID-19 on prices of commercial real estate. They find property prices in the retail and hospitality sectors to be affected to the highest degree. Ling, Wang and Zhou (2020) examine US REIT returns in the context of the geographical exposure of REIT portfolios to COVID-19. They find a negative reaction of returns to increasing case numbers. The most negative response across all REIT property is found for firms focused on retail and residential real estate, while those focused on healthcare are positively correlated with COVID-19 growth. Milcheva (2021) shows that the effect of COVID-19 is associated with steep declines in international real estate security returns and an increase in risk. Retail real estate is found to have the highest sensitivity to COVID-19, whereas healthcare has the lowest sensitivity. Generally, in line with Ling, Wang and Zhou (2020), she finds that US REITs perform significantly worse the higher their exposure is to COVID-19.

We assume that longer and stricter governmental restrictions in response to the COVID-19 pandemic increase the cash flow uncertainty for investors and thus, their perceived investment risk in short-term. As a result, investors are expected to require a risk premium for retail assets in Democratic-led states during the pandemic. This is consistent with recent studies showing that governor partisanship is the most important explanation for differences in social distancing policies and mask mandates across states during the pandemic (Adolph *et al*., 2021; Adolph *et al*., 2022). However, considering that neighborhood shopping centers were less affected by restrictions due to the essential nature of their tenants, we expect the impact of governmental restrictions to be lower for this type of shopping center compared to regional malls with their tenant mix aimed at dining out, entertainment, and leisure shopping.

4.4 Data and Methodology

To measure the short-term risk perception of retail real estate investors in regional malls and neighborhood centers, we obtain the going-in cap rate (*GICAPR*) for the respective mall types from Situs RERC. This cap rate represents an ex-ante return required by investors responding to the Situs RERC survey based on current risk perception and market information. We hereby follow the approach of Beracha, Freybote and Lin (2019), who use the Situs RERC data as basis for their ex-ante return measure. Please note that one limitation of our study is that we do not have information on the political orientation of market participants responding to the Situs RERC survey. The political attitudes of individual investors likely impact their risk perception, particularly with regard to the COVID-19 pandemic. Future studies with the appropriate datasets may further investigate the impact of political attitudes of real estate investors and risk perception.

While Situs RERC survey data is not derived from transactions and relies on the voluntary participation of real estate investors, we assume that the data reflects unbiased estimates of investors' expectations. Clayton, Ling and Naranjo (2009) compare Situs RERC capitalization rates with those derived from real estate transactions (RCA and NCREIF). The authors find that all three cap rate series are in near perfect agreement, providing reasonable assurance that the RERC survey data is reflective of market behavior. Situs RERC going-in cap rates are available for 40 MSAs across 27 states. We obtain the data from Situs RERC for the period of the first quarter of 2018 to the fourth quarter of 2021. The years 2018/19 indicate the pre-pandemic control (base) period and 2020/2021 represent the COVID-period.

To assess the impact of government restrictions in response to COVID-19, we take advantage of the sharp partisan differences in pandemic-related measures between the Democratic and Republican party. Depending on political leaning, the US population has been divided on many pandemic-related issues. Some of these directly affect retail real estate. For example, Republicans were far more comfortable than Democrats going to hair salons (72% vs. 37%), restaurants (65% vs. 28%), or indoor events (40% vs. 11%) (Pew Research Center, 2020).

Our independent variable of interest is a state governor's party affiliation for the respective MSA in our sample, coded 1 for a Republican governor and 0 for a Democratic one (*REPUBGOV*). This proxy is suitable, as governors are responsible for implementing state laws and monitoring the work of the state executive branch. With that, they promote and track new and amended policies and programs through a variety of tools (e.g., executive orders, executive budgets, and legislative proposals and vetoes), and thus, were responsible for pandemic-related provisions.[23] Recent studies show that governor partisanship, rather than health or economic conditions, is the most important explanation for differences in social distancing policies and mask mandates across states (Adolph *et al*., 2021; Adolph *et al*., 2022). We create a binary variable for the COVID-19 pandemic (*COVID*) which equals to 1 for 2020/21 and 0 for 2018/19. Then, we create interaction effects with REPUBGOV to capture the pandemic-specific impact of governmental restrictions on investor risk perception.

We control for a number of variables that affect going-in cap rates of retail real estate investors. At MSA-level, we first obtain the population (*POPUL*) as well as the annual population growth rate ($POPUL_{Growth}$) from the US Census Bureau (Federal Reserve Economic Data). We also include the quarterly unemployment rate (*UNEMPL*) for each MSA, obtained from the US Bureau of Labor Statistics, and the per capita income (*PCI*) of an MSA from the US Bureau of Economic Analysis. Frey (2021) shows that, based on the 2020 census, the majority of the largest MSAs grew faster than in the past and became more racially diverse. Thus, diversity of an MSA proxies for future population growth, which is an important demand driver for retail real estate. Furthermore, research has shown that diversity plays an important role in reducing poverty, expanding opportunity, and promoting economic mobility (Chetty *et al*., 2014; Chetty & Hendren; Cortright, 2018; Zhang & Logan, 2016). Based on Frey (2021), we create a dummy variable indicating if an MSA classifies as race-ethnically diverse (*DIVERSE*). *DIVERSE* is coded 1 if the percentage of the white population is below the average of all MSAs in the sample (54.21%) and 0 if it exceeds the average.

We also capture retail real estate market conditions by including quarterly property type-specific information obtained from the Situs RERC survey. In particular, we include leasing assumptions with regard to the renewal probability of tenants in percent (*RENPROB*), the marketing time in months (*MARKT*), and the assessment of investment conditions (*INVCOND*) on a scale of one (poor) to ten (excellent).

Summary statistics are presented in Table 4-1. The party affiliation of state governors is balanced between Democratic and Republican (50% each). The average MSA size is just over 4.1 million people. However, the standard deviation is comparably large, indicating wide gaps between populations. On average, the number of people living in an MSA increased by 0.71% per year during the sample period. About 47% of MSAs in

[23] For a comprehensive overview into the rights and responsibilities of state governors, please see National Governors Association (NGA): https://www.nga.org/governors/powers-and-authority/.

our sample can be considered diverse, considering the percentage of the white population accounts for less than 54.21%.

Going-in cap rates are slightly higher for regional malls than for neighborhood centers reflecting the higher risk of this shopping center type to investors due to, e.g., a higher e-commerce and discount competition (Kaiser & Freybote, 2022). Other property market variables provide further evidence for the lower risk of neighborhood centers compared to regional malls. Investment conditions and tenant renewal probability were higher, on average, for neighborhood centers (5.45 and about 67%) than for regional malls (3.25 and about 62%). While marketing time for regional malls was estimated at 9.45 months on average, it was just under 7 months for neighborhood centers.

Table 4-1: Descriptive Statistics

	Mean	**Median**	**Std. Dev.**	**Max**	**Min**
REPUBGOV	0.50	0.00	0.50	1.00	0.00
DIVERSE	0.47	0.00	0.49	1.00	0.00
POPUL	4129.48	2805.80	3498.43	20096.41	1204.75
POPULGrowth	0.71	0.69	1.02	4.49	-2.45
UNEMPL	4.89	4.10	2.52	18.50	1.20
PCI	63445.52	60911.18	14743.18	129889.1	38418
Regional Mall					
GICAPR	7.01	7.00	0.52	8.60	6.00
RENPROB	62.02	61.80	1.61	65.80	59.70
MARKT	9.45	10.00	1.27	11.10	7.40
INVCOND	3.25	3.00	0.83	4.70	2.20
Neighborhood Center					
GICAPR	6.80	6.80	0.45	8.20	5.80
RENPROB	67.38	67.05	1.97	71.40	64.50
MARKT	6.95	7.22	0.78	8.40	6.00
INVCOND	5.45	5.31	0.54	6.10	4.30

Note: This table presents the descriptive statistics aggregated by MSAs (N=40) and where applicable, disaggregated at property type level. The sample period spans Q1/2018 to Q4/2020. REPUBGOV is the state governor's political party and is coded 1 for republican; 0 for democratic. DIVERSE is based on the race-ethnic composition of an MSA and coded 1 if the percentage of the white population is below the average of all MSAs in the sample; 0 if it exceeds the average. POPUL is the resident population estimate in thousands of persons, POPULGrowth its percent change from a year ago. UNEMPL is the civilian unemployment rate. D1.PCI is the first difference of the per capita income level. Based on the Situs RERC survey, GICAPR is the going in cap rate, RENPROB is the renewal probability, MARKT is the marketing time in month, and INVCOND is investment conditions rated on a scale of 1 = poor to 10 = excellent.

We assess the stationarity of variables using the Im-Pesaran-Shin test for MSA-specific variables (*GICAPR, POPUL,* $POPUL_{Growth}$, *UNEMPL, PCI*) as this test assumes panel-specific autoregressive parameters and heterogeneous variances across panels. For variables that do not vary across panels, i.e., have the same autoregressive parameter (*RENPROB, MARKT, INVCOND*), the Breitung test was applied. After integrating *PCI* at first order, the results for all variables suggest that the null hypothesis of (all) panels containing unit roots can be rejected.

We conduct a number of diagnostic tests to assess heteroskedasticity, serial and contemporaneous correlation. First, we conduct the Pesaran and Friedman cross-sectional dependence tests to assess whether residuals are cross-sectionally correlated (Hoechle, 2007; Hoyos & Sarafidis, 2006). Both tests suggest the presence of contemporaneous correlation in our dataset. Next, we conduct the Wooldridge test for serial correlation in panel data, which indicates serial correlation. Last, the Wald test suggests the presence of heteroskedasticity in our panels.

To control for heteroskedasticity, contemporaneous and serial correlation, we estimate the model in Equation (4-1) using Prais-Winsten regression with correlated panel-corrected standard errors (PCSE). The autocorrelation within panels is AR(1) and panel-specific. Errors are set to be panel-level heteroskedastic and correlated across panels. Prais-Winsten regression with PCSE is preferable to a GLS model controlling for auto- and cross-sectional correlation, as the latter is inappropriate for the present data set given that the number of groups (N) is larger than the time periods (T) (Hoechle, 2007). The model can be written as

$$Y_{it} = \beta_1 X_{it} + \beta_2 Z_{it} + \alpha_i + \varepsilon_{it} \qquad \text{4-1}$$

where Y_{it} is the mall type-specific going-in cap rate (*GICAP*) for MSA i in quarter t, X_{it} represents our independent variables of interest (*REPUBGOV, COVID,* and the interaction term), and Z_{it} is a vector of our control variables (*POPUL, POPULGrowth, UNEMPL, RENPROB, MARKT, INVCOND* and *D1.PCI*). α_i represents MSA-specific effects, and ε_{it} is the idiosyncratic error.

4.5 Results

Table 4-2 presents the results for the going-in cap rate (*GICAPR*) based on Equation 4-1 with Model 1 showing the results for regional malls and Model 2 for neighborhood centers. The coefficients on COVID are highly significant and positive for both shopping center types, indicating the increase in investor risk perception due to the higher pandemic-induced cash flow uncertainty. Compared to the pre-COVID period, retail real estate investors require an additional risk premium to going-in cap rates in the COVID period.

The positively significant coefficients on *REPUBGOV* for both mall types indicate that the party affiliation of a state's governor affects going-in cap rates. In particular, compared to Democratic-led states, going-in cap rates for both mall types are significantly higher in Republican-led states. We will further investigate this finding in the remainder of this study.

The interaction effect of *REPUBGOV* and *COVID* is significantly negative for regional malls. Thus, compared to Democratic-led states, investors require a lower going-in cap rate, i.e., have a lower risk perception, for regional malls in Republican-led states. This suggests that the political affiliation of a governor, proxying for the lengths and severity of COVID-19 restrictions, impacts investor risk perception in terms of going-in cap rates. On the other hand, the results for Model 2 indicate no impact of governmental restrictions on the risk perception of investors in the COVID period for neighborhood centers. The essential nature of their tenants protected them from imposed temporary store closures during the pandemic, and at the same time customers continue to visit stores such as grocery stores, despite health risks or the inconvenience of lines or mask mandates. The results for the interaction effect of *REPUBGOV* and *COVID* for regional and neighborhood shopping centers are in line with our expectations.

It is also worth noting that *DIVERSE* has a highly significant negative relation with going-in cap rates in both models, suggesting that an ethnical-diverse population composition in an MSA presents a lower risk to retail real estate investors. This is consistent with economic research, which shows that diversity can have an impact on, among others, economic mobility and thus, economic potential (Chetty *et al.*, 2014; Chetty & Hendren; Cortright, 2018; Zhang & Logan, 2016).

Table 4-2: Results for Going-In Cap Rate and State Governor

	Model (1) Regional Mall		Model (2) Neighborhood Center	
	Coef.	*SE*	*Coef.*	*SE*
COVID	0.36***	0.07	0.24***	0.06
REPUBGOV	0.07**	0.03	0.08**	0.04
REPUBGOV#COVID	-0.07***	0.03	0.03	0.03
UNEMPL	-0.01**	0.006	-0.01**	0.005
RENPROB	-0.02*	0.01	-0.01**	0.006
MARKT	0.01	0.02	0.03	0.03
INVCOND	0.06*	0.03	0.07**	0.03
DIVERSE	-0.13***	0.04	-0.21***	0.03
POPUL	<0.0001	<0.0001	0.00001**	<0.0001
POPULGrowth	-0.02***	0.01	-0.01	0.01
D1.PCI	-0.00001**	<0.0001	<0.0001	<0.0001
Constant	7.79***	0.75	6.95***	0.44
Obs.	*600*		*600*	
No. of groups	*40*		*40*	
Avg. obs./group	*15*		*15*	
Wald χ^2	*79.95****		*110.43****	

Table 4-2: Results for Going-In Cap Rate and State Governor *(continued)*

*Note: This table presents the results for the Prais-Winsten regression (panel-specific AR, autocorrelation is calculated based on the autocorrelation of residuals, heteroskedastic panels) for GICAPR. All variables are as defined in Table 3-1. *, **, and *** denote statistical significance at the 10, 5, and 1 % level respectively.*

To assess whether our findings in Table 4-2 are indeed driven by COVID-19 related restrictions, we next examine the relation between mask mandates and going-in cap rates. We focus on mask mandates as a type of governmental restrictions for several reasons. First, the respective data on mask mandates is available on a monthly basis for the sample period and all MSAs. Second, mask mandates in particular have influenced public opinion and serve as a suitable proxy for other regulations such as social distancing and limits to shoppers in store. Adolph *et al.* (2022) find the presence of a Republican governor to be the most important predictor for the delay of indoor mask mandates.

Using data from the Centers for Disease Control and Prevention, we create a dummy (*MASKM*) equaling 1 if a public mask mandate was in place on the majority of days in a quarter and 0 if it was not. As the name implies, a public mask mandate requires facemasks to be worn in public. More specifically, individuals operating in a private capacity are required to wear a mask anywhere outside their homes, including retail businesses and restaurants. We estimate a modified model with MASKM as our independent variable of interest (Model A) and *MASKM* and its lag to capture whether mask mandates continued from the previous quarter (Model B).

The results are presented in Table 4-3. For regional malls, the coefficient on *MASKM* in Model A is significantly positive, albeit only at the 10% level. If we include the lag of *MASKM* (*L.MASKM*; Model B), the coefficient on *MASKM* becomes insignificant, however, the coefficient on *L.MASKM* is significantly positive at the 5% level. These results suggest that mask mandates lead to a cap rate premium for this mall type, independent from the *COVID* premium. On the other hand, mask mandates have no impact on going-in cap rates for neighborhood centers.

One explanation for this finding are shopper attitudes with regard to masks. While shoppers might be willing to shop for a shorter time with a mask for essential goods in grocery stores or other retailers anchoring neighborhood malls, they are less willing to spend an extended time leisurely shopping or dining out with masks, which negatively impacts the tenants of regional malls. Overall, our results in Table 4-3 indicate that our previous findings for state governor (Table 4-2) can be explained by COVID-19 related restrictions such as mask mandates.

Table 4-3: Robustness Check: Mask Mandate

	Model (1) Regional Mall			
	Model A		Model B	
	Coef.	*SE*	*Coef.*	*SE*
COVID	**0.33*** **	**0.06**	**0.32*** **	**0.06**
MASKM	**0.05***	**0.03**	0.04	0.03
L.MASKM			**0.07*** **	**0.03**
UNEMPL	**-0.02*** **	**0.01**	**-0.01*** **	**0.006**
RENPROB	**-0.02***	**0.01**	**-0.02*** **	**0.01**
MARKT	0.01	0.02	0.003	0.02
INVCOND	**0.06***	**0.03**	**0.06***	**0.03**
DIVERSE	**-0.14*** **	**0.04**	**-0.16*** **	**0.03**
POPUL	<0.0001	<0.0001	<0.0001	<0.0001
POPULGrowth	**-0.02*** **	**0.01**	**-0.02*** **	**0.008**
D1.PCI	**-0.00002*** **	**<0.0001**	**-0.00002*** **	**<0.0001**
Constant	**7.84*** **	**0.73**	**7.88*** **	**0.72**
Obs.	*600*		*600*	
No. of groups	*40*		*40*	
Avg. obs./group	*15*		*15*	
Wald χ^2	*83.01****		*100.38****	
	Model (2) Neighborhood Center			
	Model A		Model B	
	Coef.	*SE*	*Coef.*	*SE*
COVID	**0.26*** **	**0.05**	**0.26*** **	**0.05**
MASKM	0.002	0.03	0.01	0.03
L.MASKM			0.01	0.03
UNEMPL	**-0.01*** **	**0.005**	**-0.01*** **	**0.005**
RENPROB	**-0.01*** **	**0.006**	**-0.01*** **	**0.006**
MARKT	0.03	0.03	0.02	0.03
INVCOND	**0.07*** **	**0.03**	**0.08*** **	**0.03**
DIVERSE	**-0.21*** **	**0.03**	**-0.20*** **	**0.03**
POPUL	<0.0001	<0.0001	<0.0001	<0.0001
POPUL$_{Growth}$	-0.005	0.01	-0.003	0.01
D1.PCI	<0.0001	<0.0001	<0.0001	<0.0001
Constant	**7.01*** **	**0.44**	**6.99*** **	**0.45**
Obs.	*600*		*600*	
No. of groups	*40*		*40*	
Avg. obs./group	*15*		*15*	
Wald χ^2	*81.99****		*89.83****	

Note: This table presents the results for the Prais-Winsten regression (panel-specific AR, autocorrelation is calculated based on the autocorrelation of residuals, heteroskedastic panels) for GICAPR. MASKM is 1 if public mask mandate was in place; 0 if not. L.MASKM is the lag of the respective variable. All other variables are as defined in Table 4-1.

, **, and * denote statistical significance at the 10, 5, and 1 % level respectively.*

Governmental restrictions in response to COVID-19 are temporary. While impacting the short-term risk perception of investors as captured by the going-in cap rate, they should have a negligible impact on the long-term risk perception. We capture this longer-term risk perception using the pre-tax yield (*PTYLD*) required by respondents to the Situs RERC survey, which is their required return (IRR) for the entire holding period. The average holding period for Situs RERC respondents regarding regional and neighborhood shopping centers is 10 years, of which the two-year COVID period represents a small fraction. To assess whether our findings for regional malls are indeed driven by shifts in the short-term risk perception due to temporary COVID-19 restrictions, we estimate our model using the pre-tax yield as the dependent variable in our model in Equation 4-1.

The results of this robustness check are presented in Table 4-4. The insignificant coefficient on the interaction effect of *REPUBGOV* and *COVID* suggests that our results in Table 4-2 were indeed due to the short-term shift in risk perception resulting from temporary COVID-19 restrictions. One explanation for the insignificant coefficient on *REPUBGOV* is that in the long term, i.e., over a 10-year holding period, the party affiliation of governors and policy implications are uncertain and thus, do not have an impact on the long-term risk perception of retail investors.

Table 4-4: Robustness Check: Required Pre-Tax Yield

	Regional Mall	
	Coef.	*SE*
COVID	**0.39*****	**0.08**
REPUBGOV	-0.05	0.05
REPUBGOV#COVID	-0.06	0.04
UNEMPL	**-0.02****	**0.01**
RENPROB	**-0.02***	**0.01**
MARKT	0.002	0.02
INVCOND	0.05	0.04
DIVERSE	**0.19*****	**0.04**
POPUL	<0.0001	<0.0001
$POPUL_{Growth}$	**-0.03*****	**0.01**
D1.PCI	**-0.00002****	**<0.0001**
Constant	**9.15*****	**0.81**
Obs.	*600*	
No. of groups	*40*	
Avg. obs./group	*15*	
Wald χ^2	*76.80****	

Note: This table presents the results for the Prais-Winsten regression (panel-specific AR, autocorrelation is calculated based on the autocorrelation of residuals, heteroskedastic panels) for PTYLD. All variables are as defined in Table 4-1.

, **, and * denote statistical significance at the 10, 5, and 1 % level respectively.*

Our results in Table 4-2 indicate that the short-term risk perception of retail real estate investors is higher for Republican-led states than for Democratic-led states (*REPUBGOV*). However, a number of Republican-led states have MSAs with a Democratic-leaning such as Miami in Florida, Austin in Texas, or Atlanta in Georgia. To further assess whether our finding for *REPUBGOV* is driven by the political leaning of the overall state or MSA, we include the political attitudes of an MSA (*REPUBATT*) and its interaction term with COVID in our model. Hereby political attitudes of an MSA are measured based on how the respective MSA voted in the 2020 presidential election.[24] *REPUBATT* is coded 1 if the MSA has voted Republican, based on the 2020 presidential votes, and 0 otherwise.

The results are shown in Table 4-5. The coefficients on *COVID* and *REPUBGOV#COVID* for both mall types are in line with our previous findings in Table 4-2. However, the coefficients on *REPUBGOV* become insignificant for regional and neighborhood malls while the main effect of *REPUBATT* is significantly positive. This suggests that our findings for *REPUBGOV* in Table 4-2 are driven by the political leanings of MSAs. The risk perception of retail real estate investors is higher for Republican-leaning MSAs than Democratic-leaning MSAs, leading to a higher going-in cap rate requirement. The coefficients on the interaction effect of political attitudes and *COVID* are insignificant for both mall types.

One explanation for our findings for *REPUBATT* is that the political attitudes of an MSA proxy for future growth opportunities and thus, favorable demand drivers relevant to retailers and retail real estate investors. In our sample, Democratic-leaning MSAs are significantly larger, racially diverse, and have higher incomes than Republican ones. For our sample, households in Democratic-leaning MSAs also spend significantly more on entertainment, apparel and services, based on the BLS Consumer Expenditure Survey. Another explanation relates to the retail real estate asset market. Democratic-leaning MSAs may receive more attention from commercial real estate investors due to the favorable fundamental conditions in the space market, which increases liquidity in the respective markets and reduces the risk premium required by investors.

Table 4-5: Results for Going-In Cap Rate, State Governor, and Political Attitudes

	Model (1) Regional Mall		**Model (2) Neighborhood Center**	
	Coef.	*SE*	*Coef.*	*SE*
COVID	**0.37*** **	**0.07**	**0.24*** **	**0.06**
REPUBGOV	-0.02	0.04	0.05	0.04
REPUBGOV#COVID	**-0.07*** **	**0.02**	0.03	0.03
REPUBATT	**0.26*** **	**0.07**	**0.09** **	**0.04**
REPUBATT#COVID	-0.01	0.04	-0.01	0.03
UNEMPL	**-0.01** **	**0.006**	**-0.01** **	**0.005**
RENPROB	**-0.02* **	**0.01**	**-0.01** **	**0.006**
MARKT	0.01	0.02	0.03	0.03
INVCOND	**0.06* **	**0.03**	**0.07** **	**0.03**
DIVERSE	-0.02	0.05	**-0.17*** **	**0.04**
POPUL	**<0.0001* **	**<0.0001**	**<0.0001* **	**<0.0001**
POPULGrowth	**-0.02*** **	**0.01**	-0.01	0.01

[24] We obtain the data on MSA-level from Richard Florida (Bloomberg, December 4, 2020), based on U.S. Census Bureau data analyzed by Patrick Adler: https://www.bloomberg.com/news/features/2020-12-04/how-metro-areas-voted-in-the-2020-election.

Table 4-5: Results for Going-In Cap Rate, State Governor, and Political Attitudes *(continued)*

D1.PCI	**-0.00002*****	**<0.0001**	<0.0001	<0.0001
Constant	**7.77*****	**0.76**	**6.93*****	**0.44**
Obs.	*600*		*600*	
No. of groups	*40*		*40*	
Avg. obs./group	*15*		*15*	
Wald χ^2	*118.64****		*133.18****	

Note: This table presents the results for the Prais-Winsten regression (panel-specific AR, autocorrelation is calculated based on the autocorrelation of residuals, heteroskedastic panels) for GICAPR. All variables are as defined in Table 4-1.

, **, and * denote statistical significance at the 10, 5, and 1 % level respectively.*

4.6 Conclusion

Political uncertainty and governmental regulations have been found to impact the decision-making of residential and commercial real estate market participants (e.g., Ambrose & Diop, 2021; Asquith, 2019; Diamond *et al*., 2019a, 2019b; Luo *et al*., 2021; Monfared & Pavlov, 2019; Schuetz *et al*., 2011; Suzuki & Asami, 2020). However, no previous study has investigated the impact of government risk due to governmental restrictions on the risk perception of investors. We fill this gap in the literature by using the COVID-19 pandemic as a natural quasi-experiment separating the pre-COVID period (2018/2019) and COVID period (2020/2021) as well as governmental restrictions affecting MSAs along the political affiliation of state governors as government risk proxy.

Using MSA-level going-in cap rates that reflect ex-ante risk premiums required by investors and thus, their risk perception, we find that the COVID-19 pandemic yielded a risk premium compared to the pre-COVID period for neighborhood and regional shopping centers. However, in states with a Republican governor, which proxies for shorter and fewer governmental restrictions, investors required a lower going-in cap rate for regional malls during the COVID-19 period than in Democratic-led states. This provides evidence for the impact of government risk on the short-term risk perception of investors in a shopping center type significantly affected by mask mandates, social distancing, and store occupancy limitations, which in turn impacted the desire of shoppers to leisurely shop and eat out for extended periods. On the other hand, we find no effect for neighborhood shopping centers, which can be explained with the essential nature of their tenants (e.g., grocery stores). Further analysis suggests that mask mandates as a type of governmental regulation explain higher risk going-in cap rates, and that pandemic-related governmental restrictions have no impact on the long-term risk perceptions of retail investors. Last, we show that the political leaning of an MSA impacts the risk perception of investors. Explanations include the signaling effect of political attitudes about factors that impact future space and asset market conditions.

Future studies may use our findings as a starting point to investigate the relation of political decision-maker attitudes and risk perception. Depending on their political attitudes and interests, decision-makers at commercial real estate development or investment firms may vary in their assessment of risk related to governmental regulations (e.g., rent control, COVID-restrictions) and political climate in a geographical market. Other studies could examine our findings on racial-ethnic diversity in more depth and use them as a starting point for analyzing other dimensions of diversity (e.g., socio-economic status, age, sexual orientation, religious beliefs) and their impact on investor risk perception. Such investigations could help understand the dynamics underlying our findings on the political attitudes of an MSA and their impact on investor risk perception.

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5 Conclusion

5.1 Executive Summary

Research comprising this dissertation highlights that the changing retail landscape impacts the risk perception of investors in general-purpose shopping centers and asset pricing. While threats emerging from an increased online and discount competition as well as the recent COVID-19 pandemic have been found to impact risk perception and asset pricing overall, the results also show that investors do not only price general uncertainties, but consider property-type and -characteristic specific risks when valuing assets and making pricing decisions.

Regional and super-regional shopping centers as well as their anchor tenant groups have been found to be especially vulnerable to retail industry disruptions. This suggests that centers focused on non-essential goods, leisure shopping and food in the premium and mid-tier price-segment represent a greater overall risk to investors. Accordingly, investors have been found to be more sensitive towards disruptions impacting retailers when making pricing decisions with these types of centers. Representative examples derived in this dissertation comprise e-commerce sales, the industry-level stock market performance of department stores as well as government-imposed restrictions related to the COVID-19 pandemic.

On the other hand, neighborhood and community centers, with discount-focused and convenience-oriented tenant groups primarily covering essential goods, show more resilience towards a changing retail landscape, which affects the risk perception of investors accordingly. These types of shopping centers are impacted to a lesser degree by retail industry disruptions, or only when looking at centers within that category that are considered of higher risk due to overall center quality and location.

Although all three articles are consistent in terms of direction, sensitivity, and thus, overall risk perception due to potential threats facing the retail industry, they offer nuanced insights. The following provides a respective overview of these considerations and implications.

Paper 1 | Chapter 2

Is E-Commerce an Investment Risk Priced by Retail Real Estate Investors? An Investigation

Focusing on institutional-grade shopping centers across the US over the period of 2000 to 2018, the paper finds that e-commerce sales have a significantly negative relation with total returns of general-purpose shopping centers in the next quarter. This informative value is driven by capital returns, providing evidence that e-commerce as an investment risk is indeed priced by retail real estate investors. The results are robust to different measures of e-commerce sales. While consistent across mall types, the effect is stronger for regional and super-regional malls than neighborhood and community shopping centers. Explanations for this difference include the types of tenants in these different malls and the varying impact of e-commerce on their business. Compared to the first decade of the twenty first century, technological innovations such as smart phones and mobile internet resulted in a small positive effect of e-commerce sales on capital returns for regional and super-regional shopping centers in the second decade (2010-2018). Explanations for this effect include multiple channel retailing strategies and a stronger focus on experiential shopping, which are benefitting brick-and-mortar stores in shopping centers. The study finds no relation between e-commerce sales and income returns. This lack of a short-term impact of online sales on income returns can be explained with how retail leases are structured.

The paper complements literature investigating the impact of e-commerce on retail real estate markets by providing first evidence that e-commerce represents a risk to investors that affects retail property pricing. This is an especially relevant step towards closing the scholarly gap, as existing studies were predominantly conducted in the early days of e-commerce, have yielded contradicting conclusions, and widely neglected the investor perspective.

Implications to retail real estate investors include the evidence that e-commerce indeed represents a risk that affects asset pricing with investors relying on online sales in the previous quarter to make pricing decisions in the current. The results for the smart phone period and regional and super-regional shopping centers further suggest that new retailing strategies integrating online shopping and the physical store environment reduce the risk for retail real estate investors.

Paper 2 | Chapter 3

Tenant Stock Market Performance and Retail Real Estate Prices

In order to assess the validity of the tenant quality measure used in the empirical study, the paper first shows that the stock market performance of non-discount department stores predicts retail real estate investor sentiment and total returns for general-purpose shopping centers in the next quarter.

Using a sample of 5,507 mall transactions in California over the period of 2000 to 2020, the paper provides evidence that the stock market performance of non-discount department stores has a positive relation with transaction prices for shopping centers in lower quality locations (suburban) and of lower property quality. The stock market performance of discount department stores only has informative value for transaction prices of malls with the highest risk to investors. Overall, the informative value of tenant stock market performance for transaction prices is highest for higher risk tenants and properties with a higher difficulty to replace anchor tenants. In this context, the results suggest that location and then property quality are most important.

The paper contributes to studies investigating tenant quality on landlord-level variables as well as to a wider literature on asset pricing in the context of commercial real estate markets by introducing industry-level stock market performance as a tenant-specific factor in a hedonic pricing model. Furthermore, the paper contributes to the commercial real estate sentiment literature by providing evidence that the stock market performance of a major tenant group affects the sentiment of commercial real estate investors.

As for practical implications, the study is of value to investors considering that it shows the stock market performance of a major tenant group to contain information that predicts asset prices and thus, can be used in the investment decision-making process.

Paper 3 | Chapter 4

Government Risk and Real Estate Investor Risk Perception

Focusing on MSA-level going-in cap rates over the period of 2018/2019 (pre-COVID) and 2020/21 (COVID), the paper shows that overall, the pandemic yielded a risk-premium compared to the pre-COVID period for general-purpose shopping centers. However, for states with Republican governors, which proxy for shorter and fewer COVID-19 restrictions, investors in regional malls required a lower going-in cap rate in the pandemic period than for states with Democratic governors. This suggests that the risk perception shifted as a result of governmental restrictions in response to the pandemic. This effect does not exist for neighborhood shopping centers, whose tenants were not as affected by COVID-19 restrictions. Robustness checks suggest that these findings can be explained with mask mandates as one type of governmental restrictions, and that restrictions do not impact the long-term risk perception of retail real estate investors as captured by the pre-tax yield (IRR) over the entire holding period. The paper also indicates that political attitudes in an MSA impact investor risk perception. Compared to Democratic-leaning MSAs, investors require a higher going-in cap rate for Republican-leaning populations, irrespective of mall type. One explanation is the signaling effect of political attitudes about factors that influence future space and asset market conditions.

The article adds to literature on the impact of governmental regulations and political risks on real estate market participants by offering first evidence of government risk due to governmental restrictions affecting the risk perception of investors of a non-housing property type. Furthermore, this paper contributes to an emerging stream of literature investigating the impact of the COVID-19 pandemic on commercial real estate markets.

As for investors, the paper shows that the uncertainty associated with active government indeed weighs on investor sentiment and therefore affects pricing decisions. However, in the case of the recent pandemic, the shifts in risk perception are found to be only short-term, as COVID-19 restrictions are temporary.

5.2 Final Remarks and Outlook

Due to the nature of the underlying empirical studies, this dissertation is based on data from past events. However, the insights are relevant for the future, both for subsequent scientific analyses and implications for industry participants. As the market continues evolving rapidly, new challenges will likely emerge. Consequently, understanding the impact of retail industry trends on investor risk perception and hence, retail asset pricing will remain a concern for retail real estate investors in the future.

For example, while COVID-19-related regulations continue to ease down, the role of government intervention will most likely remain relevant. As the industry is currently entering the next market cycle, new government intervention related to, e.g., inflation, employment or supply chain shortages can be expected. The dissertation shows that when legislation is active, the associated uncertainty can weigh on investor sentiment, affecting asset pricing.

Another recent example further underscores the relevance of assessing tenant quality. The industry's two largest bankruptcies in 2020 involved non-discount department store chains JC Penney and Neiman Marcus, which were already in distress before the pandemic. Both companies had assets of more than $7.5 billion when they filed for Chapter 11 bankruptcy in mid-2020.[25] This is a suitable example for how tenant quality and stock performance were most likely able to indicate changes in retail asset values.

At the same time, the pandemic has accelerated a long overdue adaption in the retail industry. After two decades of great uncertainty about the future of brick-and-mortar retail, it has thus become increasingly clear in recent years that online and brick-and-mortar retail can coexist and are even interdependent. However, ongoing technological evolution and online retail will surely continue to be a force shaping the sector going forward. While this dissertation is primarily concerned with the uncertainties and negative impact on asset pricing, it also addresses how recent technological trends could have a positive impact. A closer look at the market indicates that physical retail will not disappear, albeit transform fundamentally: The industry is seeing shifts toward experience-oriented or mixed-use shopping centers to create the drawing power formerly stemming from one or two key anchor tenants. Such developments open up an exciting area for future research to examine how technological and societal trends are evolving the industry, creating new opportunities for retail real

[25] Surveyed by bankruptcydata.com.

estate investors. Therefore, this dissertation provides a starting point for further investigation into how investors' risk perceptions can affect asset pricing from a different angle.

While each concluding chapter presents various ideas for specific future research related to the respective focus of analysis (see Chapters 2.6, 3.7, 4.6), collaborative areas for future studies directly adding to this dissertation are multifold. One possible approach is a more detailed examination of the behavior and perceptions of different types of investors (e.g., institutional vs. non-institutional, local vs. national). Mainly due to insufficient data, this dissertation has considered the investor pool as a whole. However, it can be expected that, for example, more sophisticated investors, who have greater access to more data and information overall, behave differently when exposed to a particular risk than less sophisticated investors. Future studies could therefore focus on how distinct types of retail real estate investors use information differently, have varying sensitivities, and are therefore influenced variably when making pricing decisions. If appropriate data sets become available in the future, such an analysis is encouraged to advance the comprehension of findings presented here. Similarly, subsequent research should expand the analysis geographically, within the US or beyond. Due to restricted data access, the first paper investigates the US market as a whole (Chapter 2) while the second paper (Chapter 3) solely focuses on the California market. However, the final contribution (Chapter 4) gives indications of the differences that can result from underlying market environments across states and their submarkets. While this represents a limitation of this work, it provides the opportunity to focus future research accordingly. Finally, this dissertation predominantly focuses on a short-term risk perspective throughout all articles. Future studies can examine the long-term relations of the issues raised here.

Altogether, recent scientific studies on the retail real estate market are severely limited. While the contribution of this dissertation towards filling this gap is comparatively small when considering the picture as a whole, it aims at providing equal impetus and motivation to spur future studies in this area. This is particularly important as the retail market remains highly disrupted, requiring continuous scrutiny and reassessment to comprehend underlying fundamentals. Understanding of what drives retail asset pricing will therefore continue to be a concern for real estate investors, and risk perception has proven to be a determining factor.