Real Estate in the Sunshine State:
An Analysis of the Impacts of Local Economic Conditions on the Performance of REITs Investing in Florida

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Abstract

This paper studies the effect of local macroeconomic conditions on the annual returns of REITs. Specifically, I look at Florida's economic performance using four fundamental indicators: state GDP, employment, personal consumption expenditure, and consumer sentiment, and assess whether there is a difference in the relationship between the local economy and REIT returns across the firms that are highly concentrated in Florida relative to those that are not. The empirical results initially confirm a higher equity return for firms with a high exposure to Florida. However, the differential in geographic exposure generally does not affect the sensitivity of the returns to the economic variables, with the exception of consumer sentiment, which displays a negative impact on the returns of high exposure REITs. When the economic variables are scaled by the time varying concentrations of each REIT, the coefficients of each variable are still significant, with short term mean reversion detected from the change of the regression coefficients from negative in a lagged regression to positive in a contemporaneous regression. The growth rate of Florida's GDP is the most significant economic indicator. Further analysis shows that its effect varies across property sectors, with significant effects observed in retail, residential, and industrial REITs but not in healthcare REITs.

1. Introduction

In finance, a simple question leads to vast outcomes. When a conjecture is made, it opens a door to growing curiosity that contributes to it continually over time, either with supporting empirical evidence or counterarguments. The development of real estate investment trusts in the 1960s has piqued the attention of investors and economists alike and led to the emergence of simple questions that later translated to an extensive body of literature. Although that body is not as established as in other areas of finance, it is advancing quickly in tandem with academics' desire to understand the unique structure and characteristics of REITs. REITs have become a popular scope of interest for several reasons. Because they are a relatively modern investment vehicle, they offer a valuable opportunity to learn about their behavior and performance. Secondly, because they are neither exclusively stocks nor real estate, their classification as a hybrid asset class provides insights regarding how the two distinct asset classes may be related.[1] Moreover, being publicly traded securities, expansive data is available from these securities to analyze, which reveal more accurate and timely information than what would be collected from the less responsive private real estate market.

In this paper, I am attempting to add to the increasing body of literature that explores the sensitivity of REITs to macroeconomic factors. Such contributions became prevalent after researchers deduced that REITs share similar behavior patterns to stocks, specifically small-capitalization

[1] Brounen, D., & De Koning, S. (2012). 50 years of real estate investment trusts: An international examination of the rise and performance of REITs. *Journal of Real Estate Literature*, *20*(2), 197-223.

stocks[2]. The implications of this finding are pivotal when we consider that stocks have demonstrated sensitivity to economic variables and business cycles, as per the seminal paper by Chen, Roll, and Ross (1986). The authors found that changes in inflation, industrial production, and market risk premium significantly affect stock returns, with the sensitivities varying across time. Researchers were able to extend this framework to other asset classes, including REITs, and found that they can further explore their risk and return behavior once macroeconomic conditions are accounted for. Particularly, Chaudhry, Bhargava, and Weeks (2022) demonstrated that the default risk premium and unanticipated inflation adversely affect REIT returns, while GDP and the federal funds rate have a positive effect on REIT returns. Glackcock and Lu-Andrews (2013) present strong evidence for the relationship between funding liquidity in the REIT market and macroeconomic factors, which in turn influences the market trading liquidity of REITs and consequently their stock prices and returns. As funding liquidity increases, REIT market liquidity increases, with the effect changing across business cycles. The recency of these papers suggests that the conclusions remain relevant today, which is an important assumption because the structure and characteristics of REITs before 1990 differed from those of REITs that went public after 1990[3]. However, many papers that examined REITs prior to 1990 present robust conclusions that still hold. Ling and Naranjo (1997) identify the growth rates in per capita consumption, the treasury bill rate, the term structure, and unexpected inflation as macroeconomic variables that affect commercial real estate returns, which are the underlying assets of REIT.

Rather than looking at macroeconomic variables that proxy for national economic conditions, I have narrowed my scope to focus on local macroeconomic factors related to the state of Florida. My main interest is to investigate whether there is a relationship between local economic conditions in Florida and REITs that have a portion of their real estate portfolio located in Florida. Some papers emerged in the REIT literature that examine geographic concentration and local economic variables, which motivate my interest in this topic and my desire to examine an individual market. Feng and Wu (2022) assert the relationship between local economic growth and REIT growth by discovering that REITs with more assets in higher economic growth areas, proxied by the lagged GDP growth rates, provide higher stock returns to shareholders. Florida is particularly of interest because it is home to 3 of the top 25 MSAs that REITs typically hold commercial real estate properties in. The three MSAs are Miami, Orlando, and Tampa and are characterized by a large population, strong employment growth, and high real estate demand[4]. Florida also has the fourth highest GDP in the nation, with a GDP growth rate exceeding the

[2] Liow, K.H., &Li, X. (2006). Are REITs unique? A comparative analysis of major asset classes. Journal of Real Estate Finance and Economics, 22(2), 299-318.

[3] Brounen, D., & De Koning, S. (2012). 50 years of real estate investment trusts: An international examination of the rise and performance of REITs. *Journal of Real Estate Literature*, *20*(2), 197-223.

[4] Ling, D. C., Naranjo, A., & Scheick, B. (2019). Asset location, timing ability and the cross-section of commercial real estate returns. *Real Estate Economics*, *47*(1), 263-313.

national average from 2010 to 2019[5]. Moreover, Florida is a gateway to international trade and investment due to its primal geographic proximity to Latin America. These attributes collectively make Florida an attractive hub for commercial real estate investment, and a region worth examining independently.

Throughout the paper, I wish to understand whether there is a relationship between a REIT's degree of property portfolio exposure to Florida as a geographic region of interest and its annual returns. If a relationship exists, I will proceed by looking at the effect of changes in or shocks to local macroeconomic conditions on annual REIT returns across different levels of geographic concentration in Florida to analyze the marginal effect of local economic conditions on REITs that are geographically concentrated in Florida relative to REITs that are not. My dataset contains REITs with a wide spectrum of concentration levels in Florida, ranging from 0 to 68 percent. Evidently, the exposure is time-varying for each REIT, and understanding the time varying nature of allocation and disposal of commercial properties in Florida will be helpful in the analysis. I want to detect the extent to which real estate exposure in Florida affects REIT returns in the cross section of REITs and throughout my sample period, which ranges from 1999 to 2021. I will accomplish this by using a panel regression to regress annual returns against a contemporaneous explanatory variable that represents the annual percentage of Florida exposure for REIT i in year t in a categorical format. If the time series and cross-sectional variations in annual REIT returns are significantly explained by changes in the degree of exposure to Florida, I will introduce local economic variables such as the growth rates of GDP, employment, consumption, and consumer sentiment as controls in the panel regression to check for an asymmetric response of annual REIT returns to local economic factors depending on the whether the level of exposure to Florida is low or high. I later define low and high exposure levels depending on the average cross-sectional concentration in Florida in each year.

The remainder of the paper will proceed in the following format. The next section details relevant papers in the literature that review the history of REITs and their performance summary before versus after the IPO boom, the risk and return performance of REITs with respect to the broader equity market, the pricing of macroeconomic factors into general stock returns and REIT returns, and the correlations between REIT returns and local or regional economies. Sections 3 and 4 detail the methodology, data, and descriptive statistics. I present my dataset, introduce my local variables and explain why I selected them to proxy for Florida's economic performance, demonstrate how I construct my Florida Exposure explanatory variable by converting the percentage of exposure for each REIT in each year from a continuous to a categorical variable. I also display my summary

[5] Ibis World . (2022). *Florida Economic Trends, stats & rankings | IBISWorld*. Florida - State Economic Profile. Retrieved April 1, 2023, from https://www.ibisworld.com/united-states/economic-profiles/florida/

statistics and correlation matrices. In section 5, I present my main results and analysis. Lastly, in section 6, I summarize my results and point out further implications in the conclusion.

2. Literature Review

2.1 History of REITs and performance summary after IPO Boom

Commercial Real Estate properties have been known for their profitability and ability to generate stable income streams for investors. However, they are illiquid, expensive, and inaccessible to retail investors. The pillars of investing, such as diversification and portfolio optimization, are difficult to apply to physical properties and real assets because they require substantial access to capital that perhaps only institutional investors can obtain. Even so, trading of commercial real estate by institutional investors will likely sway market prices significantly, especially since trades cannot be done frequently, quickly, and in large volumes as in the stock market. The informational inefficiency and heterogeneity of real estate also increase search costs and induce limits to arbitrage opportunities, causing mispricing to persist. The creation of Real Estate Investment Trusts (REITs) by the US Congress addressed the liquidity problem by designing a structure that enables investors with an ever-increasing appetite for innovative financial instruments to invest in large and diversified portfolios of commercial properties without directly purchasing those properties; through buying shares of stocks in publicly traded real estate companies.

REITs were created as a result of Congress adopting the Real Estate Investment Trust Act in 1960, a period in which one of the biggest US bull markets was witnessed[6]. The legislation allowed retail investors to gain indirect access to income-generating real estate without purchasing such properties. REITs are public companies that have at least 75 percent of their assets and income tied to revenue producing real estate properties spanning residential, retail, office, hotel, industrial, and healthcare, among others, and are required to distribute at least 90 percent of their taxable rental income as dividends to shareholders. As a result of persistent and high dividend payout ratios, REITs enjoy a tax-exempt status at the cost of foregoing cash reserves that could be utilized to expand organically. REITs were prevented from managing their own properties and selecting their tenants as they were only allowed to operate as holding companies until the Tax Reform Act of 1986 relaxed many REIT-related restrictions, thereby expanding their profitability and growth opportunities. Nevertheless, there were only 58 equity REITs on the market with a combined market capitalization of $5.6 billion; owners and developers did not see the advantage in capital

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[6] Duggan, W. (2021, February 9). *This Day in market history: 1960s bull market ends*. Yahoo! Retrieved April 2, 2023, from https://www.yahoo.com/video/day-market-history-1960s-bull-141200691.html

market access at the cost of abiding by operating restrictions because they had sufficient access to debt at low rates and hardly any taxable income.

REITs witnessed an 'IPO Boom' between 1993-1994 in which 95 private U.S. real estate companies went public, significantly expanding the size of the REIT industry and allowing capital to flow from mutual funds, insurance companies, and pension funds. During a period when overbuilding was prominent, properties were highly leveraged, refinancing no longer easy to obtain, and companies ambivalent to liquidate their assets at a loss, private real estate companies resorted to the public equity market. Many followed the footsteps of major companies such as KIMCO ($128M IPO) in 1991 and Taubman ($330M IPO) in 1992, as REIT valuations were optimistically high despite falling real estate prices[7]. By accessing equity markets, REITs were able to reduce their mounting debt, purchase more properties, and execute rapid growth strategies with improved interest coverage ratios. Between 1992 and 1996, the number of equity REITs grew from 82 to 166 with the market capitalization growing from $12.9 billion to $78.3 billion. In 1992, the 20 largest REITs had a collective market capitalization of $3.6 billion, only two of which being valued at more $500 million. Five years into the IPO boom, more than 23 REITs accumulated a market capitalization in excess of $1 billion each[8]. Eventually, more private companies were able to execute successful debt-to-equity conversions, trading volume increased, and conflicts of interests were resolved with the transformation of such companies from 'mutual fund like' to active and self-managed. As of 2022, 167 REITs trade in the NYSE and have a combined value exceeding $1 trillion.[9]

2.2 REIT risk and return performance in relation to stock market

The rise of REITs generated enduring interest among academics, as the current literature addresses many questions concerning their structure, return predictability, and sensitivity to market conditions. There is much to be researched about REITs, understandably so seeing that they span a grey area with pure real estate on one end of the spectrum and pure equity common stock on the other end. Various papers in the finance literature suggest that REITs have comparable return predictability to stock portfolios and are integrated with the general stock market. Seck (1996) found that REIT returns are driven more by equity market effects than direct commercial property. Direct commercial property valuation is appraisal based and infrequent valuations prevent the timely absorption of market information into property prices. Liow and Li (2006) demonstrate that REITs behave similarly to small capitalization stocks and share similar characteristics. Ling and Naranjo (1999) found that the market for real estate securities is integrated with the market for

[7] Brounen, D., & De Koning, S. (2012). 50 years of real estate investment trusts: An international examination of the rise and performance of REITs. *Journal of Real Estate Literature*, *20*(2), 197-223.
[8] Ambrose, B. W., & Linneman, P. D. (1998). *Old REITs and New REITs*. Real Estate Center, Wharton School of the University of Pennsylvania.
[9] *REIT Industry Financial Snapshot*. Nareit. (n.d.). Retrieved April 3, 2023, from https://www.reit.com/data-research/reit-market-data/reit-industry-financial-snapshot

non-real estate securities, with the degree of integration increasing significantly during the IPO boom. Glascock et al. (2000) contend that REITs post 1992 are now more cointegrated with stocks, although they previously behaved similarly to bonds. Li (2016), by covarying expected REIT returns with Fama-French factors, shows that time-varying REIT returns price risks related with the stock market premium and small stock premium, and Gyourko and Keim (1992) find that market returns are significant in explaining real estate stock returns, and in a second paper show that REIT stock returns readily absorb information about market fundamentals in a similar fashion to general stocks; such that the performance of an appraisal-based portfolio can be implied from the lagged performance of real estate stocks.

2.3 Equity returns price macroeconomic factors

As research and interest in equity markets surged, it became an indispensable notion that stock returns are sensitive to macroeconomic factors and local economic conditions. In their seminal paper, Chen, Roll, and Ross (1986) model equity returns as a function of macro variables and demonstrate that they depend on their exposures to economic state variables such as industrial production, changes in the risk premium and yield curve, and inflation. Smajlbegovic (2019) adds to the literature by showing that stock returns and profitability positively correlate with predicted economic conditions. Not only that, but there exists a strong relationship between equity prices and local macroeconomic variables; as Pirinsky and Wang (2006) prove that companies' stock returns are affected by the local macroeconomic variables, specifically GDP and the unemployment rate, of their headquarters' regions. Korniotis and Kumar (2012) established that local stock returns fluctuate with respect to local business cycles, particularly recessionary periods, which stimulate shifts in local risk aversion and produce predictable return patterns. When examining state-constructed portfolios, they earned higher future returns when state-level unemployment rates were high and loan to value ratios were low.

Since some similarities can be found between REITs and non-REIT stocks, and stock markets are exposed to economic forces, one may naturally hypothesize that REITs are also exposed to such economic forces. In Chan et al (1990), unexpected inflation and changes in the risk structure and term spread of interest rates impact equity REIT returns 60% as much as their impact on common stock returns, and Fei et al. (2010) adds that the unemployment rate and inflation rate affect returns. Thus, although equity REITs are less risky than corporate stocks, they do not hedge against systematic conditions. Ling and Naranjo (1997) support the discernable co-movement between macroeconomic events and real estate markets by identifying the growth rate in real per capita consumption as an additional fundamental state variable that bears a risk premium which is consistently priced ex-ante in real estate returns across REIT and appraisal-based portfolios. Prior to their work, risk-adjusted performances of REITs endured an omitted variables problem, as multifactor models that overlooked the role of consumption as a state variable were possibly biased in their predictability of stock returns. The conclusion reaffirms Geltner's (1989) finding about the systematic risk of real estate indices being significantly positively correlated with national consumption. Thus, I include the growth in per capita consumption expenditures as one of my explanatory variables. In more general terms, real estate portfolio betas display procyclical behavior with respect to recessionary periods, according to Glascock (1991), although the effect is temporary and period specific. Lastly, by estimating a two-factor regression model of a sample of REIT returns after 1992 with changes in interest rates and the stock market as covariates, Allen, Madura, and Springer (2000) demonstrate a statistically significant result that supports the sensitivity of REIT returns. Their analysis also suggests that REITs may not completely isolate their stock performance from economic and broader market forces, although they can control their degree of exposure to them.

2.4 Equity returns price macroeconomic factors

Many papers proved that commercial real estate is sensitive to local economic conditions. Given that such properties constitute the underlying assets of REITs, these findings offer valuable implications that we can extend later to test on REIT returns. Plazzi, Torous, and Valkanov (2018) highlight how the expected returns of commercial properties, which rely on expected rent growth and rent-price ratios, are not only time-varying depending on the state of the national economy, but are subject to idiosyncratic fluctuations, such as location differences in the cross-section of properties. It is important to capture the between-property aspect because individual effects stemming from differences in geographic, demographic, and urban factors convey region-specific economic fluctuations and heterogeneous degrees of propagation of national economic shocks across regions. Additionally, Cotter, Gabriel, and Roll (2014) identify MSA allocations as a significant factor in commercial real estate performance, as between-MSA performance differs according to the MSA's exposure to macroeconomic shocks. Feng (2021), relying on the conjecture that changes in local economic conditions should impact the income return and capital appreciation of commercial real estate in such local economies, uses GDP level and GDP growth of different geographic locations to identify a relationship between the local economy and CRE performance. Using a Fama-Macbeth regression, he finds a positive correlation between CRE returns and GDP level and growth. Specifically, the size of the economy, proxied by GDP level, significantly affects CRE income and capital return, and the growth of the economy, proxied by GDP growth rate, significantly affects the capital return. The paper supports the migration of CRE investment from areas with low GDP level but high GDP growth to areas with high GDP level but low GDP growth, reaffirming the conclusion by Ling, Naranjo, and Scheik (2018) that commercial property portfolios have recently been moving to gateway markets, which are regions that enjoy good economic health. It also backs their uncovered evidence for the ability of REIT geographic exposures to explain the cross section of REIT returns, thus influencing portfolio allocations across time toward and away from geographic markets depending on their market conditions and performance.

2.5 Correlation between REIT returns and the local economy

Given the discussed literature above, the natural next step is to hypothesize that, theoretically, REIT returns must also be responsive to the local economic conditions that impact their underlying commercial real estate properties. In fact, this sensitivity should be more easily detectable with REIT stocks, which behave like general stocks, than with commercial properties due to the fact that commercial properties' returns and market values are appraisal based[10]. Appraisals are not done instantaneously and frequently, whereas REIT stock prices appreciate and depreciate continually, so REIT returns are more likely to reflect the general market factors governing the underlying properties than the properties themselves. Prevailing arguments exist for the presence of a 'local beta', which means that the market risks associated with local real estate markets are non-diversifiable and priced into REIT equity returns. Many academics agree with this notion, among them are Zhu and Lizieri (2022). They construct an explanatory variable known as local beta by finding the weighted average sum of the betas of each local property market ($ß_m$) for each firm's property portfolio, with the weights representing the proportion of properties of firm i in MSA m to their total number of properties. $ß_m$, derived for each MSA, reflects the loading of systematic market factors on local commercial real estate. Their results show that as REITs' exposure to the most volatile property markets (high local beta) increases, their returns increase, as highly concentrated REITs' returns increase by 4.7% per a one standard deviation in the local beta measure. Feng and Wu (2021) suggest that local GDP growth affects REIT firm growth through the growth of equity. For each REIT, a value weighted aggregated measure of local GDP growth is constructed in which the GDP growth rate for each MSA is scaled by the net book values of the properties located in that MSA. REIT firm growth at year is regressed against lagged firm level GDP growth. The results indicate that REITs with more assets concentrated in high economic growth areas experience faster growth in their book value and market value of assets. Lastly, Hartzell et al. (2014), by using Herfindahl indices to measure geographic concentration, identify that REITs that employ a geographic diversification strategy are valued lower than REITs with a stronger geographical focus. Their findings relate to my scope, as I will also attempt to observe whether a tighter geographical focus on Florida is a driver of annual returns.

3. Methodology

In Chen et. Al's influential paper, the authors found that changes in industrial production index, the risk-free rate, the inflation rate, and the term structure were statistically significant in predicting stock prices. Based on this framework, many researchers have adopted these economic indicators in subsequent studies as a basis to measure the sensitivity of REIT returns to macroeconomic conditions and shocks. For example, Chan, Hendershott, and Sanders use the factors presented by

[10] Gyourko, J., & Keim, D. B. (1993). Risk and return in real estate: evidence from a real estate stock index. *Financial Analysts Journal*, *49*(5), 39-46.

Chen et. Al to understand how various macroeconomic factors affect real estate returns. The constraint with these widely used factors is that they are broad national indicators, with few regional economies having state-specific indicators that mimic them. Since my aim is to analyze the effect of local economic conditions in the state of Florida on the annual returns of REITs that own or operate properties in Florida, my explanatory variables should be as localized as possible. FRED and other databases do not provide a measure of industrial production that is specific to Florida. Other possible proxies such as the manufacturing production index and capacity utilization rate were also not available. As a proxy for the inflation rate, the consumer price index for Florida urban consumers was found, but is only specific to Miami, which is one out of three MSAs of interest. Lastly, data on the term structure of municipal bonds in Florida may be used, but municipal bonds do not accurately represent economic conditions in a state.

Economic Variables

I collect all my economic variables, excluding the consumer sentiment index, from the St. Louis Fed database (FRED).

A. GDP growth

I examine a time series of the percentage change from the prior year in the all industry total gross domestic product from 1998 – 2021. The data is annual and not seasonally adjusted. FRED constructs the percentage change year over year as follows:

$$GDP_t\,\% = \left(\frac{GDP_t}{GDP_{t-nobsperyear}} - 1\right) * 100$$

Where the subscript $nobsperyear$ denotes the number of observations per year, which differs by frequency.[11] In our case, since the data's frequency is annual, it is set to 1. GDP_t is the most recent estimate of GDP for the given year. Although the estimate for GDP_t is not exactly released at the end of year t to match annual REIT returns conveying the change in the stock price between the end of years t and t – 1, it still reflects total economic activity (as measured by the total production of goods and services) in Florida during year t, so it is concurrent with fluctuations in the stock price. Since GDP is a coincident indicator, it reflects current information rather than information that has already been priced, which affects investors' sentiment in tandem and subsequently stock prices throughout the year

B. Employment growth

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[11] *What formulas are used to calculate growth rates?* Getting To Know FRED. (n.d.). Retrieved April 3, 2023, from https://fredhelp.stlouisfed.org/fred/data/understanding-the-data/formulas-calculate-growth-rates/

A time series of the seasonally adjusted percentage change from the prior year in the total nonfarm employment in Florida from 1998 – 2021 is collected. The percentage change in employment year over year is calculated similarly to the GDP growth variable. Employment reports are released more frequently than GDP reports as the state of Florida releases monthly employment reports compared to annual GDP reports. FRED aggregates higher frequency data series, such as the monthly time series of total nonfarm employment to a lower frequency annual time series by taking the average of the twelve-monthly employment values[12]. Employment growth is an important barometer of the health of the economy because it is closely correlated with consumer spending and economic growth. Employment growth is used in the asset pricing literature, specifically when looking at macroeconomic risk factors and asset returns, as changes in employment patterns affect market volatility, monetary policy, and corporate earnings, which consequently affect stock returns. REITs can use employment growth to identify markets and MSAs with strong job growth, which helps to assess future demand for office, retail, and industrial spaces.

C. Consumption growth

A time series of annual personal consumption expenditures for Florida was used to obtain the percentage change from the prior year from 1998 – 2021. The collected data measures the total spending on goods and services purchased by households residing in Florida. FRED uses the similar aggregation mechanism as in finding GDP and employment growth to calculate consumption growth and convert the data from quarterly to annual. Like GDP, personal consumption is a coincident economic indicator. I employ consumption as a variable following Geltner's (1989) finding that appraisal based real estate returns are sensitive to changes in national consumption, and Ling and Naranjo's (1997) conclusion that excluding the change in per capita consumption as a source of systemic risk in multifactor models that price the sensitivity of real estate returns elicits an omitted variables problem.

D. CSI growth

The University of Florida's Bureau of Economic Research surveys 563 individuals from Florida, to represent an unbiased demographic cross section of Florida, on a monthly basis and asks each respondent a set of questions related to their current personal financial situation, their expected financial situation one year from now, the expected national economic outlook over the next year and the next five years, and whether it is a good time to buy a major household item[13]. UF' CSI

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[12] *What is frequency aggregation?* Getting To Know FRED. (n.d.). Retrieved April 3, 2023, from https://fredhelp.stlouisfed.org/fred/data/understanding-the-data/what-is-frequency-aggregation/#:~:text=Frequency%20aggregation%20converts%20higher%2Dfrequency,the%20lowest%20data%20is%20annual.

[13] B.E.B.R. – Bureau of Economic and Business Research. (n.d.). Retrieved April 3, 2023, from https://bebr.ufl.edu/florida-consumer-sentiment/

calculations follow the University of Michigan's consumer sentiment index, with the same base year used, which is 1966. I aggregate the end of month index figures to an annual basis by taking a 12-month average. I find the year over year percentage change in consumer price index as follows:

$$CSI_t\ \% = \left(\frac{CSI_t}{CSI_{t-1}} - 1\right) * 100$$

REIT Data

I obtain REIT stock data from the Bergstrom Real Estate Center at the University of Florida for 171 equity REITs. For each REIT, the dataset contains a description of the property sector it operates in, its annual returns as of the end of each year, and its total concentration in Florida at the end of each year. Annual returns in each year are measured by finding the percentage change in the REIT's closing stock price at the end of the year from the closing price at the beginning of the year. The REIT dataset contains firms that IPO after 1998, firms that halt operations before 2021, and firms that have never owned or operated properties in Florida from their year of inception until either their year of dissolution or the end of the sample period in 2021 (whichever comes earlier). Since my aim is to observe annual returns between 1998 and 2021, I only include REITs that are in operation as of the beginning of the sample period but keep any firms that halt operations or have no available data in any year during the sample period to avoid survivorship bias. I exclude REITs that have no exposure to Florida for the entirety of the sample period to avoid negatively skewing my Florida concentration measure, as my aim is to study REITs that have invested in Florida properties whether as of the beginning or eventually during the sample period

Florida Concentration

Total Florida concentration predictor variable is calculated for each REIT in each year as:

$$CON_{it} = \frac{\sum_{j=1}^{N} Florida\_Propertysqft_{ij}}{\sum_{k=1}^{M}\sum_{j=1}^{N} State\_Propertysqft_{ijk}}$$

Where $Florida\_Propertysqft_{ij}$ is the value in square footage of property j located in Florida and the sum of square feet is found for all commercial real estate properties going from j = 1 to N for REIT i. $State\_Propertysqft_{ijk}$ is the value in square footage of property j located in one state and summed over all properties going from j = 1 to N for REIT i in that state. The result is summed over all states going from k = 1 to M for REIT i. The denominator assumes that each REIT's portfolio is geographically diversified across several MSAs or at least in one other geographic location outside of Florida.

The average cross-sectional concentration is calculated as:

$$FL\_CON_t = \frac{\sum_{i=1}^{N} CON_{it}}{N}$$

Where the cross section in each year contains all the REITs in the sample.

Annual Florida concentration is a continuous variable. It does reveal whether a REIT is geographically concentrated in Florida due to the cross-sectional and time series dispersion in annual concentration. To convert CON_{it} to a more relative measure, I compare it to FL_CON_t each year. if CON_{it} is greater than FL_CON_t, REIT i will be classified as high concentration and low concentration otherwise, since it is above the average cross-sectional concentration, but only in the year at which FL_CON_t is evaluated. Since FL_CON_t is time varying, CON_{it} is compared to it each year to account for the fact that REITs vary their allocation decisions in Florida over time depending on market demand, economic conditions, the regulatory environment, supply and demand dynamics, and the competitive landscape.

After classifying each REIT into high or low concentration. I create the following indicator variable:

$$HIGHLOW_{it} = \begin{cases} 1 \; if \; CON_{it} > FL\_CON_t \\ 0 \; otherwise \end{cases}$$

Since our data includes both cross-sectional and time-series components, I will utilize panel regressions to first identify a relationship between the level of geographic exposure to Florida and annual REIT returns. Since the REITs in my sample will display individual-level variation that may not have been captured by the data, I will utilize a fixed-effects panel regression. Fixed-effects is useful to control for unobservable characteristics associated with each individual firm that may correlate with the independent variables such that the covariance between the independent variable and the error term is not zero. However, since the economic data is time-varying and identical in the cross-section of REITs, I will also utilize a random-effects panel regression. To assess the suitability of each model, I will rely on the Lagrange Multiplier test, which tests for the presence of individual varying effects. If the null hypothesis can be rejected, it will be necessary to control for cross-sectional heterogeneity by using an individual fixed effects regression. If the null hypothesis fails to be rejected, I will use a time fixed effects regression.

4. Data and Descriptive Statistics

I begin my analysis with the dataset obtained from the Bergstrom Real Estate Center. The dataset compiles the REITs' names, main operating sectors, annual stock returns, and annual Florida concentration measured by square footage from 1998 – 2021. Although some papers in the literature use book or market value to measure concentration, using square footage is a more relevant proxy for the size of the REITs' portfolio allocation toward a specific location. Firstly, book values could distort exposure due to depreciation expense. Second, market values are appraisal based and appraisals are not updated contemporaneously with evolving information about market fundamentals. The market value available in year t may not be as relevant to that year as it was to previous years. Hence, under or overpricing may arise in that year, leading to under or over estimation of Florida exposure. Changes in square footage can reflect the acquisition and disposal of properties by portfolio managers depending on current market conditions. Additionally, square footage provides a more homogenous measure of exposure in the cross section of REITs than book and market values, enabling the comparability of exposure across REITs. This is especially important when we take into account the fact that the sample REITs operate in different sectors that may not apply uniform valuation mechanisms.

I exclude REITs that IPO after 1998 to avoid lookahead bias and REITs that have never invested in Florida from 1998 – 2021. I keep REITs that invest in Florida in any given year but cease operations during the sample period and have missing data to avoid survivorship bias. I also keep REITs that have zero exposure in Florida as of 1998 but increase or decrease exposure subsequently, in addition to REITs that have some exposure in 1998 but cut exposure to zero subsequently in the sample period. Consequently, I have 43 REITs which I analyze over 24 years, yielding 1032 observations. Two firms – Post Properties Inc and Equity One Inc contain missing data. Upon first examining the data, I observe cross-sectional and time series variation in REIT-level exposures (by % square feet) to the Florida market. As exposure varies across time within each REIT, the average FL exposure varies in the cross section of all 43 REITs in each year.

I create three Florida exposure groups to allocate the sample REITs; high (above average), low (below average), and 75th quartile. For each year, I compute an equally weighted cross-sectional average REIT concentration and the 75th quartile concentration. I then compare each REIT's annual concentration to those values; where if it is above the average concentration in that year, I allocate it to the high exposure group, if it is above the 75th quartile concentration, I allocate it to the 75th quartile group, and if it is below the average concentration, I allocate it to the low exposure group. I repeat the process for the entire sample period and constantly rebalance the portfolios' components by regrouping the REITs at the end of every year in the sample period according to the average cross sectional Fl exposure in that year. For any given exposure group, the combination of REITs in year t may not be the same as the combination in year t+1, because we construct a time-varying measure of geographic concentration in Florida. I compute the time-varying measure of average Fl concentration as stated in the methodology.

The concentration is calculated at the end of each year t. If REIT i's concentration (%) exceeds Con_t, it is added to the high exposure portfolio. N is fixed so that if a REIT's concentration is zero at any given year, this observation is still factored into the average cross-sectional exposure of that year. Ignoring zero exposure observation will overstate the cross-sectional average.

The reallocation of REITs into and out of exposure portfolios is necessary to account for the time variation and individual variation in Fl exposure. A REIT in 1998 would be considered above average if its exposure to Florida exceeded the average REIT concentration in that year of 9.6%. Later on, its exposure in a given year may be below the average REIT concentration in that year, so it should not remain in the above average exposure group in that year. Analyzing the raw data shows that although a short-term persistence exists in exposure, it dissipates in the long term, in which a REIT that begins the sample period with a certain degree of Fl exposure does not necessarily maintain it for the entire time horizon.

The methodology above is consistent with what Ling, Naranjo, and Scheick observe when analyzing the cross-sectional and time series variation of MSA exposures of REITs over time and REIT returns. They find that MSA exposures that are significant in explaining REIT returns in a given year differ substantially over their sample period. In a given year, MSAs that do not have significant explanatory power do have significant coefficients, whether positive or negative, in another year. For this reason, the authors construct time-varying measures of geographic concentrations across their MSAs of interest that adjust at the beginning of each year for the duration of their sample period. For each REIT, they allocate each of its properties into its corresponding MSA and calculate the % of the REIT's geographic exposure to a given MSA by summing the market value of its properties in that MSA and dividing the result by total sum of properties across all MSAs, repeating the process each year. Similarly, Fl exposure values that do not have significant explanatory power do have significant explanatory power in another period, depending on whether they are above or below the time varying average exposure. For this reason, I repeat the classification each year. Figure 1 shows that any REIT with an annual concentration exceeding 10% is deemed above average before 2000, but 10% will be slightly below average in 2009.

By constructing exposure groups to categorize the REITs in the sample, I create equally weighted REIT portfolios that follow an investment criterion related to the extent of Florida exposure. The portfolio is monitored at the end of each year to ensure it meets the investment criterion. If a REIT no longer satisfies the criterion, adjustments must be made. This logic is similar to selling stocks that do not meet investment criteria and buying stocks that do. The rebalancing at the end of each year does not necessitate that the number of REITs in each portfolio be fixed in each year. Thus, the number of REITs in the high exposure portfolio in year t is not necessarily equal to the number in the subsequent year.

Figure 1: Average Fl concentration in the cross section of REITs in the sample from 1998-2021

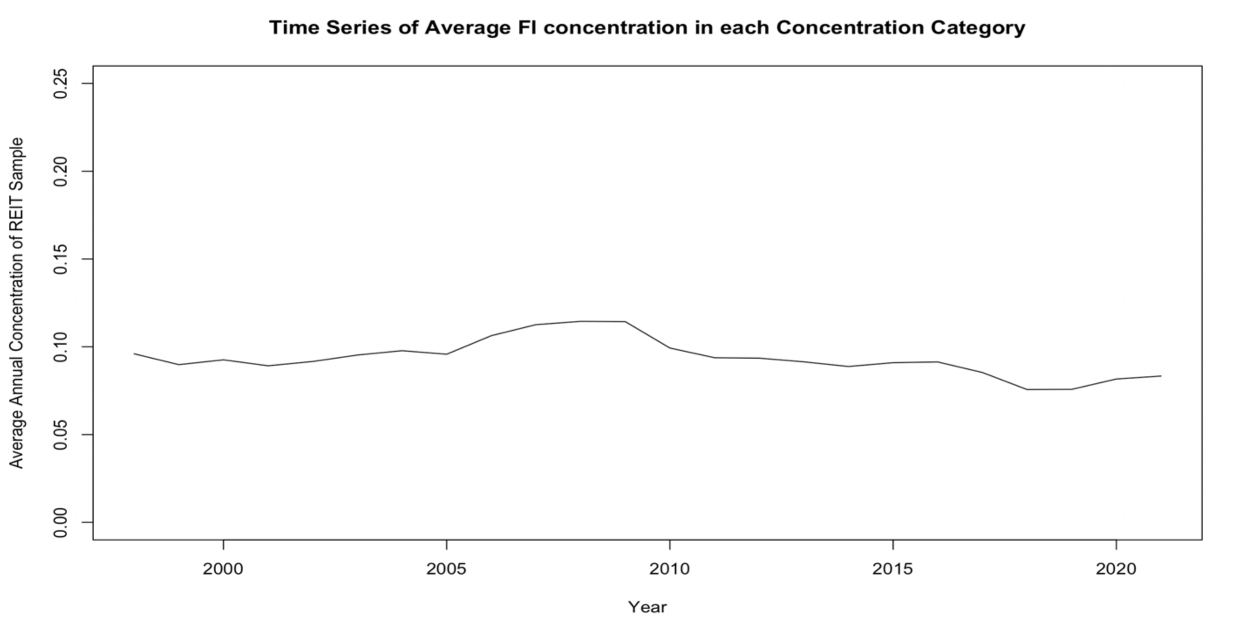
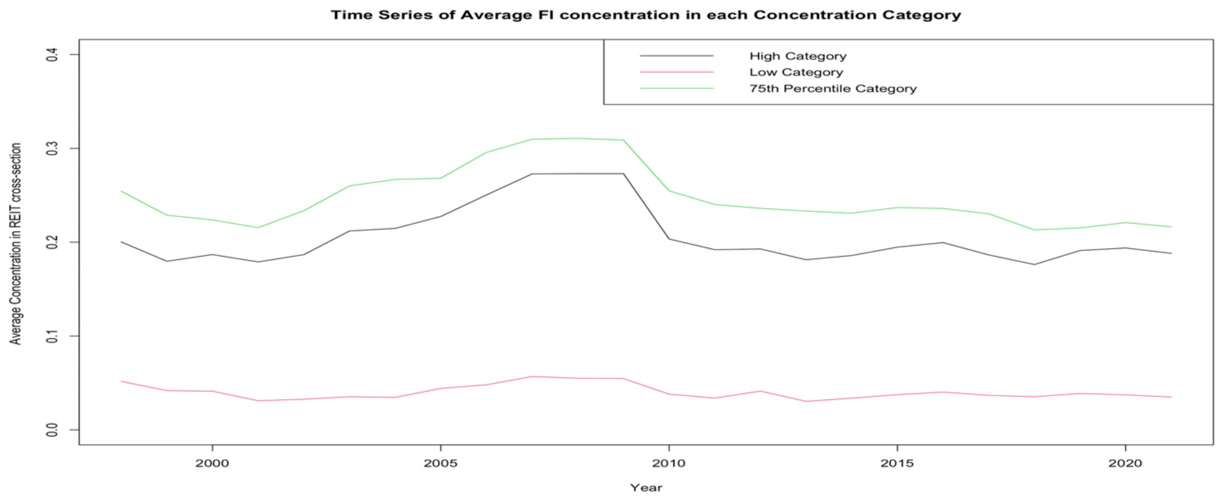


Figure 1 shows the average annual Fl exposure in the REIT cross section over time. The average is equally weighted. On average, in any given year, a REIT will invest 9.361% of its property portfolio in Florida. The minimum average exposure in the REIT cross section is 7.564% and the maximum is 11.448%. In 2018, the average REIT invested 7.564% of its assets in Florida properties. In

2008, the average REIT invested 11.448% of its assets in Florida properties. The highest figures recorded for average Fl exposure across all REITs occurred between 2007 and 2009. Average Fl exposure declined by 1.5% after 2009 and never returned to the levels recorded between 2007 and 2009 as of 2021. Between 2003 and 2009, National Health Investors had the highest exposure in both the cross section and throughout the sample period (67.67%). Since the financial crisis, no REIT in the sample had comparable Fl exposure to National Health Investors; maximum Fl Exposure in the cross section ranged from 43.91% to 48.03% after 2010.

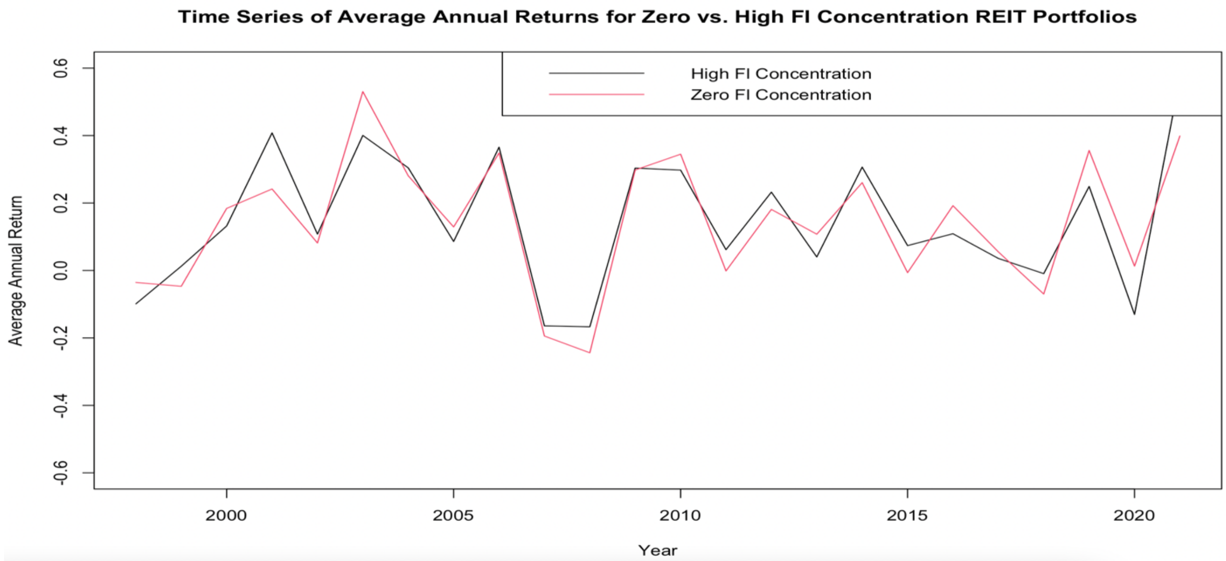
Figure 2: Average annual Fl concentration by exposure group from 1998 – 2021



We can observe from figure 2 that REITs belonging in the high and 75th percentile categories exhibit more volatile behavior than those in the low category in terms of the proportion of their real estate asset portfolio concentrated in Florida, especially in the years preceding the financial crisis and after 2009. Between 2002 and 2007, a persistent increase in the cross-sectional average exposure is noted for the high and 75th percentile categories. Despite the varying composition of REITs across the years in each portfolio, the average in the cross section consistently increases and is not skewed by any removals or additions of REITs from the portfolios. This shows that the exposure pattern or behavior throughout the years is not an individual specific phenomenon, rather it is observed regardless of which REITs are in which exposure category.

For comparability purposes, I also create a zero-exposure group to classify any REITs that had no properties in Florida in a given year. Many REITs in the sample invest in and divest from Florida through time, but some divest completely and reacquire some assets subsequently. In figures 3 to 6, I compute the average annual returns in the cross section of REITs in each exposure group from 1998 – 2021 and plot them in a time series.

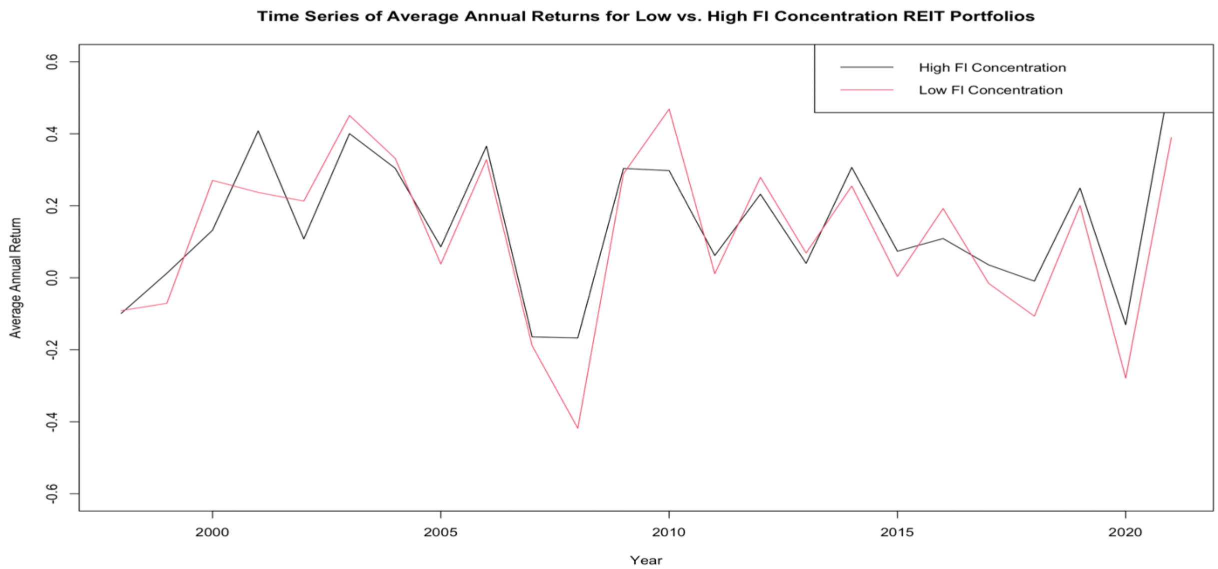
Figure 3: Comparing the average annual returns between the zero exposure REIT subgroup and the high (above average) exposure REIT subgroup



For zero exposure and high exposure, we observe similar volatility patterns across time. In the 2000-2002 bear market, the annual returns of a portfolio simulating the high exposure group is higher, and the decline in annual returns during the financial crisis is less steep. After the Covid-crisis, average annual returns for the high exposure groups rise more sharply.

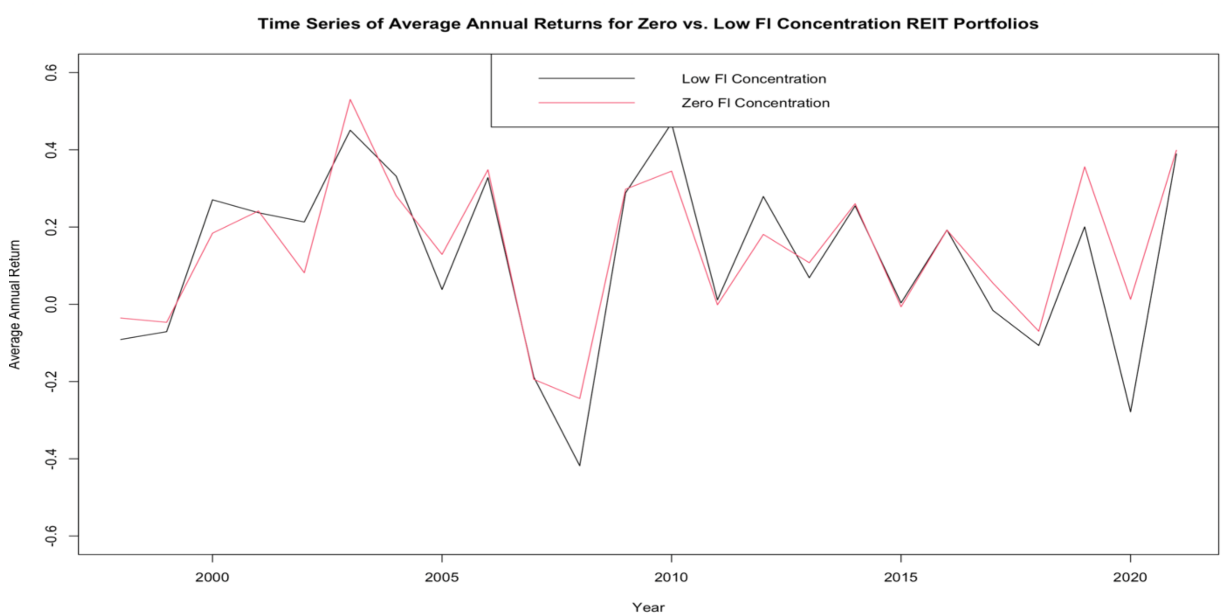
Figure 4: Comparing the average annual returns between the low (below average) exposure REIT subgroup and the 75th percentile exposure REIT subgroup

Figure 5: Comparing the average annual returns between the low (below average) exposure REIT subgroup and the high (above average) exposure REIT subgroup



Similar patterns to Figures 3 and 4 are observed in the 2000-2002 bear market, financial crisis, and Covid crisis. There is a more persistent outperformance in average annual returns from 2016 – 2020 for the high exposure group when compared to the low exposure group versus when compared to a portfolio of REITs that do not invest in Florida at all.

Figure 6: Comparing the average annual returns between the low (below average) exposure REIT subgroup and the zero exposure REIT subgroup



A low-exposure portfolio is more severely impacted by the financial crisis than a zero-exposure portfolio and underperforms from 2016-2020. We can imply from this figure that exposure to Florida in broader terms may not drive outperformance, rather a high degree of exposure is what drives outperformance relative to portfolios that are not as geographically concentrated in Florida.

The following table presents the summary statistics for the high, low, and 75th quantile exposure portfolio groups. Throughout the sample period, the portfolio groups' REIT composition does not remain constant. Each REIT either remains in its preceding year's portfolio or is regrouped depending on the current year's average Florida concentration in the REITs' cross section. Regrouping accounts for the fact that the exposure to Florida within each REIT is time varying, which distorts average exposure every year. The low Fl exposure group has the lowest standard deviation, suggesting that there is low volatility in the average annual concentration throughout the sample period. The smooth line in figure 2 displays no evidence of volatility: an average annual Fl exposure of 3% is considered low (below average) in 2001 and in 2013. The high Fl exposure group displays a higher standard deviation with slightly higher volatility in average annual Fl exposure. The 75th percentile group contains that highest volatility, with average annual concentration ranging from 21% to 65%. The low group has the lowest mean annual returns compared to the high and 75th percentile group. The mean annual returns for those two groups are almost similar, but the latter group's returns are more volatile, offering higher return but greater risk.

Table 1: Summary Statistics for Sample REITs Grouped by Florida Exposure: 1998 – 2021

Group 1: High (Above Average) FL Exposure			
Concentration		Annual Returns	
Minimum	0.1761	Minimum	-0.1670
Maximum	0.2730	Maximum	0.5697
Mean	0.2079	Mean	0.1469
Median	0.1933	Median	0.1084
Standard Deviation	0.0307	Standard Deviation	0.1970
Group 2: Low (Below Average) FL Exposure			
Concentration		Annual Returns	
Minimum	0.0304	Minimum	-0.4182
Maximum	0.0569	Maximum	0.4687
Mean	0.0402	Mean	0.1190
Median	0.0378	Median	0.1964
Standard Deviation	0.0077	Standard Deviation	0.2331
Group 3: 75th Quartile FL Exposure			
Concentration		Annual Returns	
Minimum	0.2132	Minimum	-0.1793
Maximum	0.6535	Maximum	0.6535
Mean	0.1514	Mean	0.1514
Median	0.1097	Median	0.1097
Standard Deviation	0.2093	Standard Deviation	0.2093

Table 1: After categorizing the REITs into high, low, and 75th percentile for the duration of the sample period, I find the cross sectional average annual Fl concentration and return in each year t. Then, I compute the average and standard deviations for these values in addition to the minimum, maximum, and median.

Besides exposure groups, I break down the sample REITs by property sector and form property type portfolios to classify each REIT. I compute the summary statistics for annual Florida concentration and annual returns in each sector in table 2. We observe that diversified REITs have the highest mean annual returns and the highest standard deviation in both annual returns and annual exposure, while office REITs have the lowest standard deviation in annual returns. The high variability in returns for diversified REITs confirms Gyourko and Nelling's (1996) conclusion that REIT diversification across property types may be a naïve diversification strategy. The trend for office REITs may have changed after the Covid-19 pandemic as office property investments look less lucrative due to the changed work environment. These impacts were only captured in the last year of the sample period, so they may not be noticeable enough to skew the mean. Hotel REITs exhibit the lowest mean in annual returns and annual exposure across all groups, and specialized REITs have the highest mean Fl exposure. Industrial and residential sector types have comparable average annual returns and volatility.

Table 2: Summary Statistics for Sample REITs grouped by sector (1998 – 2021):

	Healthcare	Hotel	Industrial	Office	Residential	Retail	Specialized	Diversified
Returns (%)								
Min	-0.3036	-0.5138	-0.5571	-0.2939	-0.2922	-0.3676	-0.2065	-0.4765
Max	0.7308	0.6860	0.6333	0.4086	0.6606	0.5293	0.8368	1.0521
Mean	0.1361	0.0654	0.1455	0.0750	0.1464	0.1214	0.1686	0.1687
SD	0.2310	0.2862	0.2401	0.2043	0.2326	0.2459	0.2668	0.3281
Median	0.1261	0.0845	0.1384	0.1106	0.1273	0.0956	0.1294	0.1113
Exposure (%)								
Min	0.0081	0.0000	0.0790	0.0354	0.1081	0.0667	0.1071	0.0102
Max	0.1871	0.0377	0.1049	0.0790	0.1601	0.1122	0.1935	0.4252
Mean	0.0840	0.0031	0.0896	0.0477	0.1347	0.0950	0.1425	0.0910
SD	0.0501	0.0106	0.0074	0.0103	0.0178	0.0135	0.0253	0.1109
Median	0.0679	0.0000	0.0887	0.0446	0.1273	0.0983	0.1386	0.0470

After grouping the firms into their respective property sector groups, I subdivide each sector group into a high and low exposure subgroup relying on my previous methodology of computing the average annual concentration in the REITs' cross section at each year. For each sector group, I compare each REIT in the cross section to its corresponding year's average concentration and categorize it into an above or below average subgroup within its property sector, accordingly, repeating the same steps for all 24 years. Although each sector group contains the same combination of REITS across time (since each REIT's property type focus is unchanged), the exposure subgroups contain a different combination of REITs every year due to their annual reclassification between the high and low exposure subgroups. The results show that for all property sectors, with the exception of hotel and diversified, we note a marginal effect of the degree of geographic concentration in Florida on annual REIT returns. I demonstrate from these results that the return pattern is not a phenomenon specific to a single property sector as the effects are observed between sectors.

Summary Statistics for High vs Low Exposure REITs Groups within each Property Sector: 1998-2021								
	Healthcare	Hotel	Industrial	Office	Residential	Retail	Specialized	Diversified
High Exposure: Average Returns (%)								
Mean	0.1313	0.000	0.1728	0.1248	0.1540	0.1399	0.1943	0.1657
SD	0.1524	0.000	0.1938	0.1685	0.2261	0.2435	0.2994	0.2154
Low Exposure: Average Returns (%)								
Mean	0.1138	0.0654	0.1365	0.0695	0.1397	0.1136	0.0794	0.1700
SD	0.2066	0.2862	0.2643	0.2149	0.2716	0.2472	0.2622	0.3707
High Exposure: Average Fl Concentration (%)								
Mean	0.2278	0.000	0.2837	0.2226.	0.2113	0.1862	0.1774	0.2285
SD	0.1545	0.000	0.0161	0.0187	0.0404	0.0172	0.0264	0.1152
Low Exposure: Average Fl Concentration (%)								
Mean	0.0255	0.0031	0.0249	0.0115	0.0078	0.0321	0.0764	0.0344
SD	0.0100	0.0106	0.0076	0.0064	0.0129	0.0110	0.0075	0.0318

I sub-divided each sector group into high and low exposure sub-groups to classify REIT i in year t, repeating the process for all i = 1, 2, …, 43 and t = 1, 2, …, 24, taking the average across time for each sub-group within each sector afterwards. For REITs falling under the hotel sector group, all the REITs had below average exposure. I set the summary statistics for the high exposure sub-group within the hotel sector to 0.000 to account for the absence of data. The summary statistics show that returns are higher in high exposure groups than low exposure groups, with the exception of diversified REITs. The most notable differences in annual returns between high and low exposure groups are in the industrial, office, and specialized REIT property sectors.

In addition to annual Fl concentration, I consider a set of macroeconomic variables as my explanatory variables: All industry total Florida Gross State Product growth rate, the total nonfarm employment growth rate, the personal consumption expenditure growth rate in Florida, and the Florida consumer sentiment index growth rate. I collected data from 1998 – 2021 to create lagged explanatory variables that can estimate the effects of annual REIT returns in the subsequent year. This is based on Feng and Zhu's finding that REIT firm growth is positively correlated with the lagged firm-scaled measure of economic growth, which follows from Ling, Naranjo, and Scheick's methodology of lagging the economic variables in the panel regression. However, for regression models testing the effects of contemporaneous variables, I use the data from 1999 – 2021. Table 4 presents my descriptive statistics.

Table 4: Summary Statistics for explanatory variables: 1998 – 2021	
GDP: All Industry Total in Florida (% Change from Year Ago)	
Min	-3.6577
Max	12.4320
Mean	4.840
St. Deviation	3.652
Total Nonfarm Employment (% Change from Year Ago)	
Min	-6.2736
Max	4.5955
Mean	1.3489
St. Deviation	2.8411
Personal Consumption Expenditure (% Change from Year Ago)	
Min	-2.8636
Max	15.6238
Mean	5.073
St. Deviation	3.5680
Florida Consumer Sentiment Index (% Change from Year Ago)	
Min	-16.696
Max	56.969
Mean	15.76
St. Deviation	7.7088

Annual data for GDP, Employment, and Consumption are taken from the FRED database.[1] Monthly data for Florida CSI are taken from UF's Bureau of Business and Economic Research and are averaged to obtain annual data. Growth rates are determined by finding the percentage change from the prior year. GDP, Employment, Consumption, and CSI growth are lagged by 1 year in the panel regression, so REIT returns between 1999 – 2021 are regressed against the economic variables from 1998 – 2020. Since I am also looking at contemporaneous relationships, I collect data on the economic variables for 2021.

Table 5 displays the correlation matrix for the state variables. I initially compute the correlations between the explanatory variables while excluding the y variable of annual returns. For comparative purposes, I organize the sample REITs into two portfolio groups: high (above average) and zero exposure. This helps me detect whether REITs are responsive at all to any regional shocks to Florida's economy even if they are fully divested from properties in that region. I compute the correlation matrices between the economic variables and the average annual returns in each of the portfolios. To broadly observe whether contemporaneous and lagged variables interact differently with REIT returns, I find correlations between lagged variables and returns and contemporaneous variables and returns respectively for each exposure portfolio.

Table 5: Correlation Matrix for Economic Variables 1998 – 2021

	GDP %	Emp %	Cons %	Florida CSI
GDP %				
Emp %	0.8507			
Cons %	0.8819	0.8122		
Florida CSI %	0.1831	0.3875	0.0486	

GDP % is the percent change from the end of year t – 1 to year t in the all industry total gross state product in Florida observed from 1998 to 2021. Emp % is the percent change from the end of year t – 1 to year t in the total nonfarm employment in Florida observed from 1998 to 2021. Florida CSI % is the annual percent change in the consumer sentiment index which surveys Florida residents. Monthly collected data is averaged over twelve months to yield annual observations. The annual data is taken from 1998 to 2021. Cons % is the percent change from the end of year t – 1 to year t in personal consumption expenditure recorded from 1998 to 2021.

Table 6: Correlation Matrix for Economic Variables (no lags) and Average Annual Returns of the High Exposure REIT Group[1] between 1999 – 2021

	Return	GDP %	Emp %	Cons %	Florida CSI
Return					
GDP %	0.4011				
Emp %	0.2860	0.8486			
Cons %	0.4468	0.8807	0.8105		
Florida CSI	0.2149	0.1710	0.3760	0.0367	
Correlation Matrix for Economic Variables (no lags) and Average Annual Returns of the Zero Exposure REIT Group between 1999 – 2021					
Return					
GDP %	0.3313				
Emp %	0.2534	0.8486			
Cons %	0.2121	0.8807	0.8105		
Florida CSI	0.3712	0.1710	0.3760	0.0367	

[1] In the upper half of the table, the variables GDP %, Emp %, Consumption %, and Florida CSI % are contemporaneous. Average annual portfolio returns in year t are predicted from state variables in year t. When there are no lags, all the economic variables are positively correlated with the average annual returns of the high exposure group and the low exposure group. Correlations between the predictor variables and annual returns decline in a zero-exposure portfolio, except for CSI growth. CSI growth and per capita consumption expenditures are very weakly correlated. Predicted consumption patterns for the next 12 months do not reveal valuable information about current consumption patterns.

Table 7: Correlation Matrix for lagged Economic Variables* and Average Annual Returns of the High Exposure REIT Group[2]

	Return	GDP %	Emp %	Cons %	Florida CSI
Return					
GDP %	-0.2114				
Emp %	-0.3800	0.8557			
Cons %	-0.3137	0.8669	0.8809		
Florida CSI	-0.3054	0.3123	0.4592	0.2364	

Correlation Matrix for lagged Economic Variables* and Average Annual Returns of the Zero Exposure REIT Group

Return					
GDP %	0.2222				
Emp %	0.0399	0.8557			
Cons %	0.0421	0.8669	0.8809		
Florida CSI	0.0694	0.3123	0.4592	0.2364	

*GDP %, Emp %, Consumption %, and Florida CSI % are lagged by 1 year and correlation is measured between these variables at the end of year t – 1 and average annual return at the end of year t. Observations for those variables are taken in 1998. Average annual returns for the high exposure REIT groups in year t are negatively correlated with GDP %, Emp %, Consumption %, and Florida CSI % in year t -1. GDP % is highly correlated with Emp % when lagged by 1 year and when there are no lags. GDP % is highly correlated with Cons %. Emp % in year t is highly correlated with Cons %. Florida CSI is negatively correlated with high exposure group REIT returns, but the correlation weakens to almost zero for the zero exposure REIT group returns. A portfolio of REITs that is fully divested from Florida during 1998 to 2021 is insignificantly correlated with lagged macroeconomic variables, with increased correlations in the contemporaneous case.

5. Empirical Results

For my sample period (1999 to 2021), I conduct regression analysis on annual REIT returns and their concurrent annual concentrations in Florida, which is measured by a REIT's square footage in Florida real estate properties as a percentage of its total square footage of owned properties across all geographic locations in its portfolio. The aim is to run a simple OLS regression to broadly measure how much real estate exposure in Florida affects annual REIT returns. Since I classify the REITs in my sample into high concentration or low concentration categories each year depending on its corresponding year's average cross-sectional exposure, I use an indicator variable in my regression instead of a continuous variable denoting concentration. The indicator (HIGHLOW) is set to one if REIT's exposure to Florida properties is above the average cross-sectional concentration in that year and 0 otherwise. The use of a categorical variable standardizes and simplifies my desired definition of concentration, as my goal is to measure a difference in returns across levels of exposure and not a difference in returns per a one-unit increase in the percentage of concentration. Additionally, it also allows me to account for the time varying dispersion in average exposure since the definition of high exposure is relative and should not be assumed constant as of the beginning of the sample period.

Table 8 displays the results for the following ordinary least squares regression:

$$R_{it} = \alpha_{it} + \beta_1 HIGHLOW_{it} + \epsilon_{it}$$

The OLS regression coefficient for the forecasting variable is reported. The indicator variable is statistically significant at the 5% alpha level; when HILOW = 1, on average, the mean response function is 3.999% higher for the high concentration group than the low concentration group. It can be implied that in a given year, there is a positive relationship between a REIT holding commercial properties in Florida in an amount (measured by square feet) exceeding the equally weighted average Fl concentration in that year and its annual returns.

Table 8: One variable OLS regression summary statistics (1998 – 2021)

Variable	Coefficient	t statistic	P-value
Intercept	0.12185	10.426	0.000***
HILOW	0.03999	2.087	0.0372*
Residual Standard error			0.287
Adjusted R-squared			0.0035
F-statistic			4.354

However, the OLS model is naïve and merely gives a descriptive insight. It ignores the underlying cross-sectional and time-varying effects. This model also assumes that we are selecting random and independent samples at different points in time and treats every REIT-year combination as an individual observation, ignoring heterogeneity and correlations between the combined error term and the predictor. It is important to recognize the inherent unobserved heterogeneity, and that the trend in annual returns could stem from a time dependent or entity dependent component that we do not define. Thus, the regression is biased and inconsistent. The low adjusted R-squared implies that exposure alone caries little explanatory power, which might disappear if we introduce controls.

To solve the omitted variables problem, I utilize panel regressions, which hold time-specific unobservable factors constant over the observation span and introduce a temporal dimension. I create an unbalanced panel, since I have missing data for two entities Since a pooled OLS does not solve the assumption violations that we encounter in the naïve regression, I run a fixed effects regression and begin with testing for individual fixed effects as follows:

$$R_{it} = \beta_1 HIGHLOW_{it} + \alpha_i + \epsilon_{it}$$

Where α_i accounts for the differences between individual firms that are constant over time. The estimated coefficient represents a common effect of exposure on returns across all entities controlling for individual heterogeneity. I also run a fixed effects panel regression to control for unobserved effects that are constant across entities but vary over time:

$$R_{it} = \beta_1 HIGHLOW_{it} + \lambda_t + \epsilon_{it}$$

Where λ_t accounts for variables that change over time. A panel regression with time fixed effects captures whatever a set of t – 1 dummy variable would capture, including any variables that are present for all REITs in a given time period and that may influence annual returns. Table 9 represents summary statistics for individual and time fixed effects panel regressions. Within each REIT, the level of exposure does not significantly impact annual returns. Between REITs, the level of exposure is significant in explaining concurrent REIT returns. However, it is implied by the Lagrange multiplier test that it is not as crucial to control for REIT firm characteristics as it is to control for macroeconomic variables when estimating the predictability of REIT returns. We conclude that the estimated relationship between annual Fl exposure and annual REIT returns in an individual fixed effects model is insignificant and not affected by omitted variable bias due to factors that are constant over time, but significant and responsive to omitted variable bias arising from factors that are constant across entities in a time fixed effects model. Of course, this conclusion may vary by looking at different sample periods.

Table 9: Summary statistics of panel regression with indicator variable (1999-2021)

Individual effects within model	Coefficient	t statistic	P-value
Variable			
HIGHLOW	0.04981	1.3012	0.1935
R-squared			0.0018
F-statistic			1.6930
Lagrange Multiplier test: (H_0 = individual effects are not significant)			
P-value			0.9992
Time effects within model			
Variable			
HIGHLOW	0.02985	2.2232	0.02644*
Adjusted R-squared			0.00525
F-statistic			4.9425
Lagrange Multiplier test: (H_0 = time effects are not significant)			
P-value			0.0000***

This table shows the effect of contemporaneous Fl exposure on REIT returns, using a sample period from 1999-2021. After controlling for individual specific unobservable factors, the effect of exposure on returns is no longer significant. However, a LaGrange multiplier test indicates that we should fail to reject the null hypothesis that individual effects are not significant. Although using a fixed effect estimator helps obtain a consistent estimate of beta, there is no need to eliminate the time invariant unobserved component because it does not significantly correlate with the regressor, thus not affecting the zero-covariance assumption between the predictor variable (HIGHLOW) and the correlation coefficient. On the other hand, a time fixed effects regression shows that a change in Fl exposure at year t from 0 to 1 significantly affects returns at year t after excluding unobserved variables that vary over time but are constant across entities.

Since time effects are significant, I introduce our specified macroeconomic variables, GDP %, EMP %, CSI %, CONS% as controls to our panel regression. I run the two following regressions, in which the first tests for the combined effects of Fl exposure at year t and lagged economic variables at year t – 1 on annual returns at year t, and the second introduces interaction terms. Specifically, I interact each of the lagged economic variables with the HIGHLOW indicator variable to test for differences in the lagged local economic effects across the levels of Florida exposure on annual returns. By using interaction terms, I can answer the question: By how much will a REIT's sensitivity to economic conditions change depending on how geographically concentrated their portfolio currently is in Florida?

In a five-factor model with the aforementioned economic variables, whether or not you are highly exposed to Florida relative to the average concentration of the sample REITs in Florida in the same year does not significantly affect your returns. As illustrated in table 10, lagged GDP and employment growth are statistically significant, while lagged per capita consumption and CSI growth are only significant at the 10% level. The explanatory power of the level of geographic exposure dissipates, as most of the variation in returns is explained by time-varying controls. In a multi-factor model with highly correlated economic variables, issues with collinearity arise. To investigate whether and how the economic variables separately affect REIT returns across different levels of Fl exposure, I run the following regression for each individual variable. I find that there is no significant evidence to support that lagged local macroeconomic effects on annual REIT returns vary across geographic exposure levels.

$$R_{it} = \alpha_i + \beta_1 HIGHLOW_{it} + \beta_2 Economicvar_{t-1} + \beta_3 HIGHLOW * Economicvar + \epsilon_{it}$$

Table 10: Summary statistics of panel regression with lagged economic variables (1999-2021)

Variable	Coefficient	t statistic	P-value
A) Five-factor model			
HIGHLOW	0.0544	1.4799	0.13924
GDP %	2.7001	4.4467	0.000***
EMP %	-3.6606	-4.1516	0.000***
CSI %	-0.2782	-1.8755	0.0610
CONS %	-1.565	4.4467	0.0669
Adjusted R^2			0.0437
B) Interaction terms			
Model 1			
HIGHLOW	0.0503	1.0624	0.2883
GDP %	-1.2634	-3.4766	0.000***
HIGHLOW_GDP	-0.0533	-0.0897	0.9299
Model 2			
HIGHLOW	0.0534	1.3992	0.1621
EMP %	-2.5662	-6.0787	0.000***
HIGHLOW_EMP	-0.1966	-0.2838	0.7766
Model 3			
HIGHLOW	0.0581	1.5361	0.1248
CSI %	-0.5597	-3.5767	0.000***
HIGHLOW_CSI	-0.2787	-1.0694	0.2852
Model 4			
HIGHLOW	0.0436	0.8687	0.3852
CONS %	-2.1959	-5.0923	0.000***
HIGHLOW_CONS	-0.0227	-0.0319	0.9745

The table above displays the combined and individual effects of the lagged macroeconomic variables on annual REIT returns. We can see that the effect of the lagged economic factors in year t – 1 are not significantly different across low and high levels of geographic exposure to Florida in year t. The predictive power of exposure disappears as the effect of a REIT's exposure in year t on its corresponding year's equity returns changes from positive and significant in a one-factor panel regression with time fixed effects to positive but not significant when the effects of the economic variables are combined and isolated.

To check whether the results above change for contemporaneous economic variables, I run the same fixed effects panel regressions. In the following five factor panel regression, I estimate the combined effects of geographic exposure and economic concentration in year t on REIT returns in year t:

$$R_{it} = \alpha_i + \beta_1 HIGHLOW_{it} + \beta_2 GDP_t + \beta_3 EMP_t + \beta_4 CSI_t + \beta_5 CONS_t + \epsilon_{it}$$

The same results hold for the indicator variable. In a multi-factor model with contemporaneous economic variables, most of the returns' sensitivities are explained by changes in the local macro-economic conditions in that year than by changes in exposure levels. However, this model differs in that consumption growth and CSI growth are significant and have positive coefficients, implying that REIT returns are more responsive to changes in consumption expenditure patterns that occur between the end of year t and the end of year t – 1 than to changes occurring between the end of years t – 1 and t – 2. The explanatory power of GDP weakens as the p-value increases, but a positive coefficient is reported in the lagged and contemporaneous model. The adjusted R-squared increases from 0.0437 to 0.1419, which is expected due to the addition of model parameters that are common across all firms. As we introduce time-varying economic factors, the panel dataset becomes more time-dominant and the effects of heterogeneity in the cross-sections are reduced, increasing the R-squared. Employment growth is significant as in the lagged model but maintains a negative coefficient. Table 11 displays the results of running a separate panel regression for each contemporaneous economic variable with an interaction term between the HIGHLOW indicator variable corresponding with the following regression:

$$R_{it} = \alpha_i + \beta_1 HIGHLOW_{it} + \beta_2 Economicvar_t + \beta_3 HIGHLOW * Economicvar + \epsilon_{it}$$

Table 11: Summary statistics of panel regression with contemporaneous economic variables (1999-2021)			
Variable	Coefficient	t statistic	P-value
Model 1			
HIGHLOW	0.0461	1.0235	0.3063
GDP %	2.3551	7.5612	0. 000***
HIGHLOW_GDP	-0.2375	-0.4510	0.6521
Model 2			
HIGHLOW	0.0434	1.1292	0.2591
EMP %	2.5457	6.2907	0.000***
HIGHLOW_EMP	-0.6754	-0.2838	0.3275
Model 3			
HIGHLOW	0.0290	0.7853	0.4325
CSI %	1.2062	8.0540	0.000***
HIGHLOW_CSI	-0.7969	-3.2292	0.0012**
Model 4			
HIGHLOW	0.0304	0.6610	0.5088
CONS %	2.3182	7.2547	0.000***
HIGHLOW_CONS	0.1812	0.3368	0.7363

In a separate regression for each variable, the coefficients for GDP, Employment, CSI, and Consumption growth are all negative when lagged and positive when contemporaneous. Interestingly, the interaction term between CSI growth and HIGHLOW is negative and statistically significant. Although a positive change in consumer sentiment between the end of year t and year t – 1 positively effects the level of REIT returns, the effect is not uniform across all levels of geographic exposure to Florida. REITs whose portfolio exposure to Florida exceeds the average cross-sectional exposure in a given year are negatively impacted in their annual returns by a positive change to consumer sentiment from the prior year. This result is unusual because behavioral finance theory demonstrates that asset returns increase when consumers and investors are optimistic and decrease when they are pessimistic about the future direction of the economy. Consumer sentiment is a leading economic indicator which predicts changes in economic activity based on consumers' predicted buying patterns in the next 12 months. Because the CSI at the end of year t reflects predicted economic activity for year t + 1, it could be possible that the following year's returns for high-concentration REITs will be positive or less negative as a way of correcting the over-reaction in the prior year that led to the decrease in returns. For the remaining economic variables, the interaction terms are not significant and do not suggest a difference in return sensitivity to local economic conditions between above average versus below average concentration portfolios.

Possible reasons for why the predictive power of geographic exposure is only significant at the 5% alpha level in a one factor model and no longer significant with the inclusion of time varying controls are ample. Firstly, the heterogeneity of Florida concentration in the cross section is not as high as one would expect. Although the differences in concentration as measured by square-footage are not fully uniform, they are also not fully dispersed. A simple scatterplot of geographic concentration for any given year reveals that REITs with above 40 percent concentration by square feet are outliers, with the majority of REITs in the sample having a concentration between 0 to 20 percent. For the entirety of the sample period, the proportion of REITs with an annual concentration between 0 to 20 percent is at least 80 percent in any year, and the proportion of REITs with an annual concentration exceeding 30% ranges between 5 and 12 percent. In only 7 out of the 24 years in our sample period, annual concentration surpassed 50%. However, two REITs at most in any year in that subperiod had such exposure density. Such REITs match the desired specification of what constitutes a highly geographically concentrated firm, but they are scarce in the data set and their presence does not skew the average concentration considerably. The equally weighted average de-emphasizes those highly concentrated REITs and emphasizes those with 0 percent concentration. As a result, the definition of high concentration for this sample is relaxed to place equal importance on a firm with 20% exposure and another firm with more than double that exposure despite the stark differences in their investment strategy and risk profile. This leads to the firms that are truly highly concentrated to be considered outliers in theory when they are not in practice. If we had 100% exposure cases in the cross section for each year, the spread in annual concentration between firms would be wider, and the increased heterogeneity will be more insightful in the panel regressions such that the time-varying effects will not be as significant, and the cross-sectional variation will be observed after introducing economic variables as controls.

Another reason is that REITs, even those headquartered in Florida, do not have a high exposure to Florida to begin with. Although Florida contains 3 cities falling under the top MSA category (Miami, Orlando, and Tampa), the total number of major cities in that category are 25, according to Ling, Naranjo, and Scheik, with the top gateway markets being Boston, Chicago, Los Angeles, New York, San Francisco and Washington DC. These gateway markets have the greatest allocations of investments, with a lower allocation towards the remaining cities. This implies that REIT returns are more likely to be responsive to changes in geographic exposure to gateway cities than to non-gateway cities, especially since investments in gateway markets are drastically higher. In fact, it is observed in the authors' panel regression results examining the effect of geographic exposure on the cross section of REIT returns: the relationship between annual excess returns and the percentage of a firm's total RE portfolio located in gateway markets is positive and statistically significant. However, a breakdown by MSA shows that the relationship is not statistically significant, as Tampa is the only Florida MSA with significant p-values.

Nevertheless, a panel regression with only local economic variables produces significant results that cannot be ignored merely because geographic exposure to Florida in the time series and cross section is not high enough. In table 10, a fixed effects panel regression of lagged and contemporaneous economic variables produces significant results for all the variables. Whether lagged or contemporaneous, the GDP growth rate is positively related to REIT returns. The continuation of positive returns suggests that GDP carries a positive but short-term momentum effect on REIT stocks. Returns respond positively to information related to GDP that is at least one year old and respond to information arising as recently as year t similarly to how it responds to older information. The p-value in the contemporaneous regression is still significant but increases slightly, which signifies that the returns may not instantly respond to newly emerging information about GDP growth and thus will not fully price them in the same year. We also note that returns respond negatively to increases in employment growth at the end of year t – 1 and at the end of year t, and returns are more responsiveness to concurrent changes to CSI and per capita consumption growth than prior year changes. It can be implied that investors still rely on past year information about consumer sentiment and consumption patterns, but once newer information emerges prior data becomes less valuable to them. Overall, the predictability of returns using contemporaneous variables is stronger, since the adjusted R^2 increases by almost 10 percent.

Table 12: Summary statistics of panel regression with economic variables (1998 – 2021)

Panel A: Lagged		Coefficient	t-statistic	P-value
GDP %		2.7035	4.4494	0.000***
EMP %		-3.6156	-4.1003	0.000***
CSI %		-0.2721	-1.8342	0.0670
CONS %		-1.6270	-1.9081	0.0567
Adjusted R^2	0.0443			
Panel B: Contemporaneous				
GDP %		1.4954	4.4494	0.0084**
EMP %		-4.8478	-6.9196	0.000***
CSI%		1.3907	10.1005	0.000***
CONS %		4.0725	7.0420	0.000***
Adjusted R^2	0.1417			

Although our aim was to inspect whether the effect of economic variables on REIT returns changes across high and low levels of geographic exposure to Florida, we deduced that the marginal effect of exposure on returns disappear when introducing such economic variables to our panel data. In general, REIT returns are explained more by changes to local economic conditions, in which the changes are not necessarily economic shocks, than by altering the firms' degree of exposure from low to high. However, it is important to consider that in any given year a REIT may have zero exposure to Florida, and because its annual concentration falls below the average concentration corresponding to that year, it will still be included in the low-exposure portfolio. Thus, the indicator variable is set to zero whether a REIT's exposure falls below the average in the cross section or has a concentration of zero. As a result, we have an identifiability problem that leads us to conclude that changes to local economic conditions affect REIT returns regardless of whether or not a REIT chooses to dispose of its Florida-based properties from its portfolio to have a concentration of zero in Florida in any year. Using this conclusion, we make a generalization that REIT returns are always entirely exposed to Florida's local economic conditions. A possible solution would be to scale each REIT's exposure to the local economy to the proportion of its assets located in Florida, because a REIT's sensitivity should be limited to the extent of its exposure to Florida, especially if it is geographically diversified across different MSAs and accordingly across different regional economic variables.

I scale each economic variable as follows, repeating the step for each REIT:

$$Concentration_t * Econvar_t$$

Where the concentrations for each REIT are calculated as follows:

$$Concentration_t = \frac{Florida\_squareft_t}{\sum_{j=1}^{n} MSA\_squareft_{jt}}$$

Where $MSA\_squareft_{jt}$ measures the total proportion of properties in each MSA by square feet in a given year t and is summed over all the MSAs composing the property portfolio of a REIT in that year. Concentration displays cross sectional and time series variation, and each of the economic variables display only time series variation. The product of concentration and any of the specified economic variables now displays cross-sectional and time series variation. As a result, the REITs in our sample are no longer uniformly exposed to the economic variables as we construct firm-specific economic growth measures, in line with Feng and Wu's methodology. Indirectly, we account for possible unobserved heterogeneity between firms, arising from different investment strategies and attitudes towards geographic concentration/diversification that lead portfolio managers to allocate investments towards Florida differently across space and time. Table 13 displays the results from running a fixed effects panel regression after scaling the economic variables. In the lagged regression, scaled GDP and employment growth are still significant. The results concerning the explanatory power of lagged GDP is consistent with what is prevalent in the literature. Feng and Wu found a positive correlation between local GDP growth and expected stock returns in the following year, suggesting that higher economic growth is associated with better future stock performance. CSI becomes significant at the 5% alpha level and per capita consumption growth becomes significant at the 1% alpha level in explaining REIT returns when they are scaled by geographic exposure. Changes in consumer sentiment and per capita consumption are negatively related to future REIT returns. In the contemporaneous regression, GDP growth is no longer significant when it is scaled, and employment growth is significant at the 1% alpha level. REIT returns may not instantaneously price recent information about GDP growth, which proxies for economic growth, rather their responsiveness is detected one year ahead. CSI and consumption growth are still significant. We can deduce that, whether or not CSI growth is scaled, its relevance to REIT returns increases once new information is collected and becomes available to investors. It may be that CSI at the end of year t – 1 reveals information about year t that has already been incorporated in the stock price. Many economists agree that although CSI has considerable predictive power, its marginal value decreases when used in conjunction with other economic variables, especially those that are highly correlated to CSI. Meanwhile, CSI at the end of year t reveals newer information concerned with the following year, with such information not being reflected in the stock price. Overall, lagged CSI contains information that is outdated enough to no longer be as relevant to investors as the information contained in contemporaneous CSI. The future economic conditions it predicted have already manifested in the following year and became incorporated in the stock returns.

Table 13: Summary statistics of panel regression with scaled economic variables (1999 – 2021)

Panel A: Lagged	Coefficient	t-statistic	P-value
GDP %	17.0766	3.6829	0.000***
EMP %	-16.1067	-3.4655	0.000***
CSI %	-2.1843	-2.0761	0.0382*
CONS %	-13.3579	-2.6174	0.009**
Panel B: Contemporaneous			
GDP %	0.3207	0.9372	0.9372
EMP %	-11.5445	-2.7743	0.0056**
CSI%	4.7830	5.1187	0.000***
CONS %	14.9452	3.6474	0.000***

It is necessary to run univariate regressions for each economic variable to isolate the effects of GDP, Employment, CSI, and per capita consumption expenditures on REIT returns. Multicollinearity problems are prevalent in a four-factor model of local economic variables, especially between GDP, Employment, and Consumption. Table 14 shows that the estimated coefficients for all the economic variables are negative in lagged regressions but positive in contemporaneous regressions, which shows that the signs of the coefficients in the multivariate panel regression are not totally accurate. For example, the persistence in negative performance that is explained by lagged and contemporaneous employment growth is not present when we estimate the effects separately. For each variable, we observe high and positive contemporaneous effects. The lagged effects are almost as high but steer in the opposite direction.

Table 14: Summary statistics of panel regression for each individual variable scaled for geographic exposure (1999 – 2021)

Panel A) Lagged	Coefficient	P-value	R^2
GDP %	-4.6977	0.0072**	0.0078
EMP %	-11.9058	0.000***	0.0281
CSI %	-3.0894	0.000***	0.0129
CONS %	-7.0899	0.000***	0.0140
Panel B) Contemporaneous			
GDP %	7.4471	0.000***	0.0253
EMP %	7.9973	0.000***	0.0154
CSI %	3.2232	0.000***	0.0177
CONS %	8.1478	0.000***	0.0269

This table displays the results of a univariate regression done for each economic variable. Each lagged variable is scaled for geographic exposure in year t – 1. Each contemporaneous variable is scaled for geographic exposure in year t. Predictability increases slightly for GDP %, CSI %, CONS % when returns are regressed against contemporaneous variables as the R-squared increases.

The differences in the estimated coefficients between lagged and contemporaneous regressions for each local variable suggest subsequent mean reversion as we do not observe evidence of persistence or momentum in annual REIT returns. Mean reversion is the presence of transitory components in equity prices, in which subsequent period returns are positively autocorrelated with past returns over short horizons (three to twelve months as demonstrated by Jegadeesh and Titman) but are negatively autocorrelated over longer horizons. If past returns are high, they are likely to be low in later periods. However, this conclusion depends heavily on the duration of the holding period, the sample period under study, and the time interval or frequency at which the returns are being analyzed. Although there is not enough or widespread mention about mean reversion in the REIT context in the finance literature, a study by Graff and Young (1997) tests for serial persistence in monthly sample intervals and observes performance reversals in REIT returns. In a more generalized context, many studies demonstrate that equity securities that initially outperform have weaker long-term performance. The accepted reasoning is that equities experience a temporary shock which causes their prices to increase or decrease by more than the expected value of the new information, but over time they inevitably return to a fundamental value, which is the 'would be' value of the stock in the preceding period if it had behaved in accordance with the efficient market hypothesis. In the context of our study, the temporary shock constitutes the reaction to information carried from changes in local macroeconomic factors, which proxy for current and predicted economic conditions. Specifically, GDP growth, measured by the percent change of the most recent reading from a year ago, proxies for current changes in Florida's output during the year and thus its economic growth. A positive change to GDP causes annual REIT returns to increase significantly in tandem, but to start decreasing as significantly in the following year. The estimated coefficient of lagged CSI growth being approximately equal in magnitude but opposite in direction to contemporaneous CSI growth suggests that changes in consumer sentiment reported by Florida residents do not enhance predictability in the long term because the reversal that follows a year later almost completely erases the initial overreaction. The case is similar for employment growth, perhaps because the information derived from this variable can be derived from other indicators that are stronger predictors of REIT return performance. However, the mean reversion observed from employment growth is stronger. This may be due to employment growth being a lagging indicator that does not shift in tandem with the economy. At the end of year t, stock prices seem to have already reflected all available information related to employment growth with no new information to price. Employment growth in year t – 1 is not only a lagging indicator by definition but contains old information at this point that may have been fully realized. We can also conclude that although mean reversion is noted for GDP growth and per capita consumption growth, the overreaction from the positive shock still leaves a trace in the following year as the reversal is not as high in magnitude as the initial spike in returns.

Also, in the context of our study, mean reversion is observed during a shorter interval for REIT returns than what is commonly observed in the finance literature, in which price reversals occur several years after investing in past "winner" or "loser" stocks while momentum extends over a one-year horizon. This supports the notion that REITs behave like general non-REIT stocks but are not completely identical in their performance characteristics to stocks. GDP growth seems to be the most relevant predictor of annual returns for firms that allocate a proportion of their portfolio in Florida. Although some degree of price reversal is observed over the following year, the coefficient in the lagged regression indicates that REIT stock price changes as predicted by GDP growth do not return to a fundamental level, at least not within the next year. Investors do pay attention to changes in Florida's GDP, understandably so since the economy of the state of Florida is the fourth largest in the US. The effect of the size of the local economy is documented in the REIT literature, as Feng concluded that the income return and capital appreciation of commercial real estate are significantly positively impacted by the size of the economy, which is measured by local GDP. Accordingly, Florida's economy is not fully negligible, so an economic variable proxying for Florida's economic growth is influential. Theoretically, if we construct a weighted average measure of GDP across all geographic areas in which a REIT is invested, Florida's GDP would still be emphasized due to its size. Overall, I find that the scaled firm-level local macroeconomic measures are positively associated with the equity value of REITs that allocate assets in Florida in the short term. If an investor is forming a momentum-based investment strategy of buying REIT stocks that respond positively to positive economic shocks related to Florida's GDP, they will not realize positive returns if their holding period exceeds one year, and cumulative returns will be low.

To see whether the effect of GDP growth on concurrent REIT returns varies by the property type in which the REIT is specialized, I categorized my REITs into portfolios of different property sectors and run a fixed effects panel regression for each portfolio. In the previous panel regressions that combined all REITs in the panel data, property type may have been an unobservable individual-variant component. By accounting for property type, we can check for heterogeneity in the response to GDP growth between REITs belonging to different property sectors. In table 15, the p-values demonstrate that the effects of contemporaneous GDP growth are not uniform across property types. Retail REITs' returns in year t are significantly positively impacted by a positive change to GDP between the end of years t and t – 1. This sensitivity can be explained by the fact that the retail sector fluctuates with business cycles and economic conditions. Residential REITs are significant at the 1 percent alpha level, and industrial REITs are significant at the 5% level. Office REITs are not sensitive to changes in GDP, which is expected as the pandemic's impacts on the office industry and remote work landscape was only observed in two years in our sample period and should not skew the results radically. Healthcare REITs are not at all sensitive to changes in GDP, as the underlying properties and the healthcare industry are recession-proof and the demand for healthcare is inelastic. The differences in the estimated coefficients for GDP growth and their significance on contemporaneous REIT returns suggest that diversification across property types and sectors can provide a hedge against changes to GDP. However, persistent negative changes to GDP (reduction in GDP growth between the end of years t – 1 and t) implies an economic downturn and a recession, to which commercial real estate is susceptible since rent growth, net operating income, and vacancy rates can be impacted regardless of the intended use of the commercial real estate property. Realistically, perhaps only properties used for healthcare related purposes and thus healthcare REITs are not significantly impacted by negative GDP growth.

Table 15: Summary statistics of panel regressions for annual REIT returns against scaled GDP growth by property type (1999 – 2021)

Property type	Coefficient	p-value	R^2
Retail			
GDP %	11.1027	0.000***	0.0378
Residential			
GDP %	8.8954	0.0029**	0.0585
Office			
GDP %	10.2437	0.1894	0.0157
Industrial			
GDP %	11.7382	0.0311*	0.0378
Healthcare			
GDP %	1.364	0.6149	0.0019

Observing the lowest p-value in the regression of retail REITs' annual returns against contemporaneous GDP growth also supports Gyourko and Nelling's empirical results. They conduct a property type analysis by running a regression of equity betas for REITs between 1988 – 1992 against the percentage of REIT i's investment in healthcare, industrial, office residential, and retail property sectors. Their results show that as the percentage of portfolio allocation towards retail properties increases, so does the REIT's equity beta, indicating that retail-focused REITs have higher systematic risk. Retail REITs' sensitivity to changes in Florida's GDP growth verify that the retail sector is procyclical, which affects retail tenants' operating income and cashflows.

6. Conclusion

The empirical evidence shows that REITs are sensitive to changes in the degree of investment allocation towards real estate in Florida. A firm's annual returns increase by almost 3 percent on average when its geographic concentration is above the time varying average concentration across REITs as opposed to when it is below the average. My aim was to identify whether there was a significant differential in the effect of local economic conditions on annual REIT returns across high and low levels of geographic exposure to Florida. After accounting for the growth rates in GDP, employment, personal consumption expenditure, and consumer sentiment, I find that the significant result obtained disappears. Only the interaction term between the indicator variable HIGHLOW and CSI growth produce significant results in a contemporaneous panel regression, where a positive change in CSI is associated with lower returns for a highly concentrated REIT.

I can attribute this phenomenon for the following reasons. Firstly, the dispersion in Florida exposure is not as stark as previously anticipated. Secondly, the exposure amounts are not high in the first place; as we do not observe firms that have extremely high concentration values, such as a concentration exceeding 50 percent, specifically after the financial crisis. REIT portfolio managers are not necessarily diversifying geographically across all regions. At the same time, they do not view geographic concentration in one state as a viable investment strategy. The summary statistics imply that REITs are more likely to be concentrated in a property sector than in a geographic region. If the exposure values were higher than what was observed in the dataset, or more frequently observed, so that a concentration above 50 percent is not an outlier, the indicator variable and the interaction terms with the local economic variables may have been significant.

To avoid an overgeneralization from claiming that the impacts of changes in local economic conditions propagate uniformly across all the REITs in our sample, the time varying geographic concentration is multiplied with each economic variable for each REIT to produce scaled economic variables. All four scaled economic factors are significant in a multifactor lagged regression, but GDP growth is not significant in a contemporaneous regression, suggesting that REITs take time to price information related to Florida's GDP. However, conducting univariate regressions shows all the economic variables to be statistically significant in explaining annual returns. The change in the signs of the coefficient estimates for each variable between lagged and contemporaneous regression signals that REIT stocks may exhibit mean reverting behavior over short horizons. The degree of mean reversion varies across the economic variables, with the strongest mean reversion observed for employment growth. For growth rates in CSI and consumption, subsequent year returns seem to fall back almost exactly to their fundamental value as the mean reversion occurs in the same magnitude as the initial spike in the stock price. For GDP growth, the lagged regression suggests that REIT stock prices do not fully return to their fundamental value within a one-year time horizon, suggesting that GDP carries the most influential and persistent effect on returns among the set of economic factors. However, the impact of GDP growth on annual returns varies by property type, with retail REITs displaying higher sensitivity to scaled GDP growth and healthcare REITs not being sensitive.

The results have implications for existing literature by verifying that REITs are indeed sensitive to macroeconomic factors similarly to other asset classes. Although REITs are an innovative financial instrument that provide retail and institutional investors a higher degree of stability arising from dividend payouts and income producing assets, they are not a perfect hedge against broad as well as regional economic forces. My study focused on using ex-post data to explain historical REIT returns, assuming that the sensitivity of returns to macroeconomic factors will be constant over time. However, many economists agree that sensitivities and loadings on systematic risks have a time-varying nature. Fama and Macbeth pioneered a famous regression method that allows beta coefficients of the independent variables to vary across time. It would be interesting to analyze the changes in the relationship between the scaled economic factors and annual REIT returns over time, especially once commercial real estate investment in Florida increases in the future and REIT portfolios become more exposed to regional macroeconomic conditions due to changing investment allocation strategies.

References

Allen, M.T., Madura, J. & Springer, T.M. REIT Characteristics and the Sensitivity of REIT Returns. *The Journal of Real Estate Finance and Economics* **21**, 141–152 (2000). https://doi.org/10.1023/A:1007839809578

Ambrose, B. W., & Linneman, P. D. (1998). *Old REITs and New REITs*. Real Estate Center, Wharton School of the University of Pennsylvania.

Brounen, D., & De Koning, S. (2012). 50 years of real estate investment trusts: An international examination of the rise and performance of REITs. *Journal of Real Estate Literature*, *20*(2), 197-223.

Chan, K. C., Hendershott, P. H., & Sanders, A. B. (1990). Risk and Return on Real Estate: Evidence from Equity REITs. *Real Estate Economics, 18* (4), 431-452. http://dx.doi.org/10.1111/1540-6229.00531

Chaudhry, M. K., Bhargava, V., & Weeks, H. S. (2022). Impact of economic forces and fundamental variables on REIT returns. *Applied Economics*, *54*(53), 6179-6201.

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of business*, 383-403.

Cotter, J., Gabriel, S., & Roll, R. (2015). Can housing risk be diversified? A cautionary tale from the housing boom and bust. *The Review of Financial Studies*, *28*(3), 913-936.

Fei, P., Ding, L., & Deng, Y. (2010). Correlation and volatility dynamics in REIT returns: performance and portfolio considerations. *The Journal of Portfolio Management*, *36*(2), 113-125.

Feng, Z., & Wu, Z. (2022). Local economy, asset location and REIT firm growth. *The Journal of Real Estate Finance and Economics*, *65*(1), 75-102.

Geltner, D. (1989). Estimating real estate's systematic risk from aggregate level appraisal-based returns. *Real Estate Economics*, *17*(4), 463-481.

Glascock, J., & Lu-Andrews, R. (2014). An examination of macroeconomic effects on the liquidity of REITs. *The Journal of Real Estate Finance and Economics*, *49*, 23-46.

Glascock, J. L. (1991). Market conditions, risk, and real estate portfolio returns: Some empirical evidence. *The Journal of Real Estate Finance and Economics*, *4*, 367-373.

Glascock, J. L., Lu, C., & So, R. W. (2000). Further evidence on the integration of REIT, bond, and stock returns. *The Journal of Real Estate Finance and Economics*, *20*, 177-194.

Graff, R., & Young, M. (1997). Serial persistence in equity REIT returns. *Journal of Real Estate Research*, *14*(3), 183-214.

Gyourko, J., & Keim, D. B. (1992). What does the stock market tell us about real estate returns?. *Real Estate Economics*, *20*(3), 457-485.

Gyourko, J., & Nelling, E. (1996). Systematic risk and diversification in the equity REIT market. *Real Estate Economics*, *24*(4), 493-515.

Hartzell, J. C., Sun, L., & Titman, S. (2014). Institutional investors as monitors of corporate diversification decisions: Evidence from real estate investment trusts. *Journal of Corporate Finance*, *25*, 61-72.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of finance*, *56*(2), 699-720.

Korniotis, George M. and Kumar, Alok, State-Level Business Cycles and Local Return Predictability (March 6, 2012). Journal of Finance, Forthcoming, Available at SSRN: https://ssrn.com/abstract=1094560 or http://dx.doi.org/10.2139/ssrn.1094560

Li, Y. (2016). Time variation of expected returns on REITs: Implications for market integration and the financial crisis. *Journal of Real Estate Research*, *38*(3), 321-358.

Naranjo, A., & Ling, D. C. (1997). Economic risk factors and commercial real estate returns. *The Journal of Real Estate Finance and Economics*, *14*, 283-307.
Ling, D. C., & Naranjo, A. (1999). The integration of commercial real estate markets and stock markets. *Real Estate Economics*, *27*(3), 483-515.

Ling, D. C., Naranjo, A., & Scheick, B. (2019). Asset location, timing ability and the cross-section of commercial real estate returns. *Real Estate Economics*, *47*(1), 263-313.

Liow, K.H., &Li, X. (2006). Are REITs unique? A comparative analysis of major asset classes. Journal of Real Estate Finance and Economics, 22(2), 299-318.

Pirinsky, C., & Wang, Q. (2006). Does corporate headquarters location matter for stock returns?. *The Journal of Finance*, *61*(4), 1991-2015.

Alberto Plazzi, Walter Torous, Rossen Valkanov, Expected Returns and Expected Growth in Rents of Commercial Real Estate, *The Review of Financial Studies*, Volume 23, Issue 9, September 2010, Pages 3469–3519, https://doi.org/10.1093/rfs/hhq069

Seck, D. (1996). The substitutability of real estate assets. *Real Estate Economics*, *24*(1), 75-95.

Smajlbegovic, E. (2019). Regional economic activity and stock returns. *Journal of Financial and Quantitative Analysis*, *54*(3), 1051-1082.

Zhu, B., & Lizieri, C. (2022). Local beta: Has local real estate market risk been priced in REIT returns?. *The Journal of Real Estate Finance and Economics*, 1-37.