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Two Essays in Real Estate Dynamics

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TWO ESSAYS IN REAL ESTATE DYNAMICS

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ABSTRACT

TWO ESSAYS IN REAL ESTATE DYNAMICS

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Real estate dynamics encompass a multifaceted interplay of various factors that shape the market. This dissertation presents two distinct essays that delve into critical aspects of real estate dynamics.

In the first essay, we investigate the influence of short-term rentals, specifically Airbnb activity, on neighboring house prices in Hampton Roads, Virginia. By employing robust measures such as active listings, reservations, and their cumulative impact over different periods, we uncover a positive association between prior Airbnb rental activity and housing sales prices. Moreover, we observe a spatial decay effect, where the localized impact diminishes with increasing geographic distance, particularly beyond 500 meters. Further analysis employing quantile regression reveals that the effect of Airbnb rentals is more pronounced for higher-priced homes, while middle-range house prices demonstrate a relatively lower sensitivity to Airbnb activity. These findings contribute to the existing literature by shedding light on the nuanced relationship between Airbnb and housing prices.

The second essay delves into the relationship between media content sentiments and returns of Real Estate Investment Trusts (REITs). Leveraging proprietary investor sentiment measures from Thomson Reuters, including dimensions such as "stress," "emotion vs. fact," "dividends," and "price direction," we employ a multi-step approach to examine their impact on

REIT returns. Through time series regression and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, we establish the statistical significance of media content sentiments in explaining REIT returns and market volatility. Employing Lasso analysis, we identify the sentiment related to "price direction" as the most influential factor impacting excess REIT returns consistently across various REIT types and weighting schemes. Our analysis enhances traditional asset pricing models, improving the adjusted R-squared, and provides insights into the role of media sentiment in shaping REIT returns.

By integrating these two essays, this dissertation contributes to a comprehensive understanding of real estate dynamics. The first essay illuminates the impact of Airbnb activity on house prices, emphasizing the spatial decay effect and differential sensitivity across price distributions. The second essay highlights the significance of media content sentiments in explaining REIT returns and the findings are validated through Covariance-based Structural Equation Modeling (SEM) and path analysis. Collectively, these essays broaden our knowledge of the complex dynamics within the real estate market and provide valuable insights for researchers, policymakers, and market participants alike.

I would like to dedicate this dissertation to my beloved family and friends, whose unwavering support and encouragement have been my constant source of strength throughout this journey. I also dedicate this work to the late **Dr. John Griffith**, the previous chair of finance, whose profound wisdom and guidance continue to inspire me. Furthermore, I am deeply grateful to the dedicated faculty and staff at Strome College of Business, whose invaluable assistance and support have played a significant role in shaping this dissertation. Special appreciation goes to **Katrina Davenport** for her exceptional guidance and unwavering commitment to my academic growth. This dedication is a reflection of the immense gratitude I hold for each individual who has contributed to my academic and personal development.

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ESSAY 1: THE IMPACT OF SHORT-TERM RENTAL ACTIVITY ON HOUSE PRICES

I. INTRODUCTION

Home-sharing platforms provide opportunities for individuals to earn income by opening their homes to tourists and travelers, among others. Brian Chesky and Joe Gebbia started Airbnb, currently the largest platform for home sharing, by renting out air mattresses to conference attendees. Airbnb has grown rapidly in recent years. Figure 1.1 shows the number of nights booked on Airbnb grew from 72.4 million in 2015 to 326.9 million in 2019, more than a 350% increase. Furthermore, it debuted on NASDAQ on December 10, 2020, with an estimated valuation of $86.5 billion, more than the three largest global hotel chains combined.[1] As of March 31, 2022, Airbnb advertises over six million active listings and operates in more than 220 countries and regions around the world, hosting more than one billion guests (Airbnb Newsroom 2022).

[Insert Figure 1.1 here]

This rapid growth has led to disruptions in the real estate market and hotel industry, as well as challenges for cities and municipalities to impose new regulations (Zervas et al., 2017, Koster et al., 2021). It can also impose costs on neighboring residents due to less space for parking, public safety concerns (Gant, 2016) and the increasing cost of living for renters (Barron, Kung, & Proserpio, 2021). On the other hand, the sharing economy can potentially reduce market friction and improve the use of underutilized resources, leading to improved economic efficiency. Farronato and Fradkin (2022) argued that lower prices and better offerings on home-sharing platforms can increase consumer welfare. The controversial impacts of home-sharing platforms,

[1] In particular, Marriott, Hilton, and Intercontinental were worth $84.1 billion combined on Dec. 10, 2020 (Business Insider).

specifically Airbnb, have led to a nascent literature on the broader impacts of home-sharing platforms.

Critics argue that a concentration of short-term rentals (STR) in a neighborhood can cause negative externalities such as higher levels of noise, littering, and less space for parking and safety concerns in the neighborhood (Gant, 2016). There are also broader societal concerns such as increasing inequality (Schor, 2017), financial hardship (Daniels & Grinstein-Weiss, 2019), and lowering city livability (Barrios et al., 2020, Erhardt et al., 2019). For example, Filippas et al. (2020) found that home-sharing platforms, such as Airbnb, increase the cost of living for local renters while benefitting local landlords and non-resident tourists. Regarding the benefits to landlords, Barron et al. (2021) showed that Airbnb hosts with multiple properties decreased housing supply in local markets, which in turn led to higher rents and home values. However, scholars have also pointed out the benefits of home-sharing platforms. Sheppard and Udell (2016) discussed that STRs can generate a new income stream for homeowners, which decreases the cost of owning or renting a home, which in turn can increase property values. Although Airbnb is a successful and established platform, little is known about its impact on the broader real-estate market.

In this study, we estimated the impact of Airbnb on housing values in Hampton Roads, Virginia. We used data from a multiple listing service (MLS) for southeast Virginia and consider the sales price, along with a wide variety of housing characteristics. We define three different measures of Airbnb activity using data from the AIRDNA. Our empirical strategy uses a hedonic pricing model and the density of Airbnb rentals around the sold property. Our estimated results show that Airbnb density positively affects housing prices, which is consistent across all three measures. Specifically, our main model shows that within four months prior to a home sale and within 300 meters, an additional active Airbnb listing increases a home's value by 0.39%. Similarly, an additional Airbnb listing with a positive occupancy rate is associated with a 0.40% higher sales price. We also used the total number of reservations as our third measure of Airbnb activity as a proxy for guest traffic in the neighborhood. This measure could capture negative externalities from the STR, yet we find a 2.02% increase in house prices for 100 additional reservations in the neighborhood. We show that the impact is greater closer to the home sale date and diminishes with increasing geographic distance. Finally, using unconditional quantile regression, we find that the impact across the housing price distribution is uneven.

This study contributes to literature in several ways. First, we used multiple measures of Airbnb rental activities. One of the concerns about capturing the true impact of Airbnb rental activity is finding a proper measure for active Airbnb listings. Previous studies have focused on the total number of listings (e.g., Franco & Santos, 2021; Valentin, 2021; Todd et al., 2022) or the number of listings that receive a review in a specific time frame (e.g., Zervas et al., 2017, Sheppard & Udell, 2016, Jiao et al., 2021 and Garcia-López et al., 2020) as active Airbnb activity. This could be an imperfect measure of STR activity because many Airbnb listings may have a short period of activity and be out of business afterward. To address this concern, we defined three different measures of Airbnb activity to ensure that our results show a more robust result of Airbnb rental activity. For our first measure, we used Airbnb listings that were active on the Airbnb website. Second, we used active listings that had at least one reservation (positive occupancy rate) in each subperiod. Finally, we used the sum of the number of reservations to account for guest traffic in the neighborhood. Our estimated results are significant at the standard level and consistent across all three measures.

Second, we used different periods before each house sale to capture the time effect of Airbnb rental activity on house prices. Specifically, we measured Airbnb density for three subperiods: four months before sale, four to eight months before sale, and eight to twelve months before house sale. The estimation results reveal that Airbnb activity closer to the sales date has a stronger effect. In addition, to explore the effect of geographic distance, for each home sale, we drew three concentric rings with different radii: 0–300 m (ring 1), 300–500 m (ring 2), and 500-1000 m (ring 3). We find that the effect of Airbnb activity dissipates with distance.

Finally, this study contributes to the literature by examining how Airbnb activity affects home sales across the house price distribution. For this purpose, we used the unconditional quantile regression method proposed by Firpo et al. (2009). We find that the positive impact of Airbnb activity on house prices is not consistent across the entire house price distribution. It is more pronounced for the 70^{th} and 80th quantiles, while middle-range house prices are less affected by Airbnb activity.

II. BACKGROUND AND LITERATURE REVIEW

This study examines residential real estate sale price transactions and Airbnb activity in Hampton Roads, VA. Home values capitalize on positive and negative externalities; therefore, we concentrate on the theoretical considerations and literature review of how Airbnb activity can be capitalized in the final sale price.

Literature Review

Economic theory suggests that short-term rentals (STRs), our key variable of interest, can cause externalities in the residential housing market. On the negative side, Ke et al. (2021) argued that the presence of Airbnb is positively associated with property-related crimes. More tourists or guests brought by home sharing may lead to more noise or traffic and safety concerns in the neighborhood. This may make the neighborhood a less favorable place to live in and lower the demand and price for properties. For instance, Airbnb created a platform for hosts' neighbors to complain in cases where guests had extensive negative externalities such as noise or misuse of common spaces.[2] Furthermore, Zervas et al. (2017) used a difference-in-differences approach and found that a 10% increase in the number of listings led to a 0.39% decrease in hotel revenues in Texas.

On the positive side, home sharing can result in tourists coming to a neighborhood, which in turn can lead to higher revenue for local businesses and higher demand for property. Farronato and Fradkin (2022) found that neighborhoods that previously saw few tourists without STRs now face more tourists because of home-sharing. Furthermore, Alyakoob and Rahman (2018) found that STRs, specifically Airbnb, positively affect restaurant employment.

Barron et al. (2021) and Sheppard and Udell (2016) were among the first to use statistical methods to investigate the relationship between Airbnb and the real estate market. Sheppard and Udell (2016) used a difference-in-differences approach to examine the relationship between Airbnb listings and the housing market in New York. They showed that doubling the total number of Airbnb listings caused a 6.46% increase in property prices. Barron et al. (2021) investigated how an increasing number of Airbnb listings impacted housing and rental prices using a fixed-effects regression analysis. Their analysis was conducted at the zip code level in the United States. They leveraged Google search trends as an instrumental variable to account for endogeneity. This strategy has become increasingly popular in the recent years. Barron et al. (2021) found that a 1%

[2]See https://www.airbnb.com/neighbors

increase in Airbnb listings led to a 0.018% increase in rents and a 0.026% increase in house prices at a median owner-occupancy rate zip code. Consistent with Barron et al. (2021), Benitez-Aurioles and Tussyadiah (2020) also found that house prices increased more than rents because of Airbnb listings.

Several other studies have focused on the effects of Airbnb on the overall housing market in study areas outside the United States. For example, there is recent empirical work on STRs and the housing market in Portugal (Franco & Santos, 2021), France (Ayouba et al., 2020), Barcelona (Garcia-López et al., 2020), and Iceland (Elíasson and Ragnarsson, 2018), among others. These studies also tend to find a positive relationship between STRs and housing prices. Several studies have also investigated the impact of Airbnb on the housing market and regulation of the platform (e.g., Lee, 2016, Koster et al., 2021). Koster et al. (2021) found that an increase in regulations on the Airbnb platform led to a 50% decrease in Airbnb listings, which in turn caused a 2% decrease in housing prices.

Study Area

We used home sales and Airbnb properties in the major cities of the Virginia Beach-Norfolk-Newport News Metropolitan Statistical Area, broadly referred to as Hampton Roads. These cities include Virginia Beach, Williamsburg, Norfolk, Newport News, Chesapeake, Hampton, Portsmouth, Suffolk, and York. Hampton Roads is a popular tourist destination, especially in summer, because of its warm water beaches. Virginia Beach has made TripAdvisor's top 10 list of the most popular U.S. summer destinations based on hotel booking interest from U.S. travelers (13newsnow.com). In addition to being a tourist area, it has a significant naval presence because of its large military bases. The solid line in Figure 1.2 indicates the total number of Airbnb listings in the study area. The number of listings has grown substantially in recent years, rising from less than a hundred listings in October 2014 to 5,718 at the end of 2019. Another important point is that the number of active Airbnb listings (dashed line) was approximately half of the total listings (3,105 listings) at the end of 2019, and the number of listings with reservations (dotted line) was even lower (2,482 listings). This is one reason that the number of Airbnb listings is an imperfect measure of Airbnb activity.

[Insert Figure 1.2 here]

III. EMPIRICAL DATA

Data Sources

Real estate data were obtained from the Real Estate Information Network (REIN), a southeast Virginia multiple listing service. It includes several structural housing characteristics for all homes listed for sale with a real estate agent within the Hampton Roads region over our sample period. After dropping sales with missing observations, the real estate data include 114,561 sales from January 2015 to December 2019 and a wide range of housing characteristics ranging from age, size of the living area, and number of bathrooms to exterior features such as the presence of a patio or a shed. We also dropped 0.01 percent top and down outliers for ‘square feet’ observations and .01 percent of top outliers for ‘age’ observations resulting in 114,537 sales. Finally, to retain only the arm’s length transactions, we dropped REOs and short sales resulting in 102,165 sales. A complete list of housing characteristics is shown in Table 1.1. The data also included the postal address of each property, which we used to create longitude and latitude coordinates using the GIS software.

[Insert Table 1.1 here]

We combined MLS data with Airbnb data from AirDNA. AirDNA is a private Airbnb data company that scrapes data from its website. For the Airbnb dataset, we used monthly data from Oct 2014 to December 2019 (Figure 1.2). We use the latitude and longitude coordinates for Airbnb properties and combine it with the housing transactions.

Distance and Time Effects

For each house sold, we drew three concentric rings with different radii: 0–300 m (ring 1), 300–500 m (ring 2), and 500–1000 m (ring 3). Researchers can choose different buffer distances. For example, smaller buffers may capture the most direct impact of Airbnb activities on a property's price, whereas larger buffers may allow for more variations in Airbnb density and capture the broader economic effects of Airbnb activities in the neighborhood. The Airbnb website does not provide the exact locations of listings for the rental owner's confidentiality. Instead, the Airbnb website shifts the geographic coordinates of the listings by up to 150 meters (450 feet).[3] Consequently, all spatial analyses using Airbnb data have inaccuracies or measurement errors of up to 150 m. Considering this measurement error and based on the simple physics fact that the greatest possible error of a measurement is one-half of the measuring unit,[4] we chose 300 m as the minimum measurement for our smallest radius.

To measure time effects, we categorized the Airbnb listing into three phases over a 12-month period, including the month of sale and 11 months prior to the sale. We broke this 12-months period into three 4-month phases. Figure 1.3 provides a visual description of the time-

[3] See http://insideairbnb.com/data-assumptions
[4] See https://www.statisticshowto.com/greatest-possible-error/

period definitions. For example, S - 11 represents eleven months prior to the month of property sale (S).

[Insert Figure 1.3 here]

Measures of STR Activity

To measure STR activity, we used 3 different approaches:

1. **Active**: We counted the number of Airbnb listings that were "Active" at least once in the respective time phase period. As shown in Figure 1.2, the total number of Airbnb listings exceeds the number of active listings. This is because many hosts joined Airbnb and left it or blocked their property from the website after a while. Therefore, we used active listings to capture the effects of STR activity.

2. **Positive Occupancy Rate**: We counted the number of Airbnb listings reserved by a guest at least once in the respective time phase period. This measure is slightly more restrictive than the number of active listings. We used this measure because an Airbnb property can be active on the website, but this does not mean that it is available for or rented by guests. An active Airbnb property (on the website) may not be reserved for a certain period of time for two reasons. First, it could have been because of a lack of demand at that time. Second, even if reservation requests exist, the owner may not be willing to accept guests at that time. To distinguish between these two, we use this second measure to count Airbnb listings with guests at the property.

3. **Sum of Reservations:** We sum the total number of reservations for all Airbnb listings within each ring around a home sale. This measure differs from the first two measures. First, it measures the total number of reservations instead of the number of Airbnb listings. Second,

we counted every reservation for each Airbnb property for each day. In contrast to the first two measures, where we counted being active or having a guest for at least one day as an active listing. This measure includes the intensity of how active the Airbnb rentals are at a location. Our reason for including this is that we expect the number of reservations, which is associated with guest traffic in the neighborhood, to be a better measure for capturing any negative externalities associated with STR activity. This measure is scaled by 100 to obtain comparable results.

We use the example shown in Figure 1.4 to illustrate our measures of geographic distance and timing. Suppose the property is sold in August and all Airbnb properties around the sold property are active on the Airbnb website at least once from May through August (Phase 1). The number of active Airbnb properties for phase 1 and ring 1(0 to 300m) is 3, while the number of active Airbnb properties for phase 1 and ring 2 (300 to 500m) is 2, and the number of active Airbnb properties for phase 1 and ring 3(500 to 1000m) is 9.

[Insert Figure 1.4 here]

Now, suppose that in Figure 1.4, ring 1, Airbnb *A* has no reservation in August, one reservation in July, no reservation in June, and two reservations in May. Airbnb *B* had five reservations in August, three reservations in July, and no reservations in June and July. Finally, Airbnb *C* was not reserved for those months, although it was active on the website. Based on our measures of STR activity for phase 1 and ring 1, we have 3 listings for the first measure (Active), 2 for the second measure (positive occupancy rate), and 11 for the third measure (sum of reservations).

The summary statistics for our variable of interest, Airbnb density, and the dependent variable, log of the inflation-adjusted house sale price (P), are presented in Table 1.2. As mentioned before, our second measure, the number of Airbnb listings with a positive occupancy rate, is slightly more restrictive than the first measure, the number of active listings. Consequently, the mean for Airbnb densities in different phases and rings for the second measure is less than the similar Airbnb densities for our first measure. For example, the mean for Airbnb_Phase1 _Ring3, the number of Airbnb listings in phase 1 and ring 3, is 3.798 for the first measure and 3.212 for the second measure. Furthermore, instead of counting active listings, we summed the total number of reservations in our third measure. All numbers related to this measure in Table 1.2, are scaled by hundred. For instance, Airbnb_Phase1_Ring1, which is the total number of reservations in phase 1 and ring 1, has a mean of 8 and a maximum of 3,113.

[Insert Table 1.2 here]

IV. METODOLOGY

Empirically, the hedonic pricing model is one of the most widely adopted approaches for assessing a homebuyer's willingness to pay for a specific housing characteristic. In this study, Airbnb activity, defined by our three different measures within a certain distance (our three different rings) from a sold property, is included in the regression analyses as a hedonic attribute. We have three sets of models with different assumptions for distance and time to explore the impact of Airbnb listings on housing prices.

Model 1

We start with a pooled cross section model using Airbnb density in the closest ring (ring 1: 0 to 300 m) and in the closest phase (phase 1: months S to S-3) before house sale (Airbnb_Phase1_Ring1).

$$P = \alpha + (Airbnb\_Phase1\_Ring1)\beta_1 + \gamma X + \delta T + \theta M + \epsilon \quad (1)$$

P is the natural log of the inflation-adjusted sale price for all the houses sold during the study period. The house characteristic variables contained in X are those described in Table 1.1. T are time fixed effects including sales year dummy variables to capture macroeconomic changes within a given year and sales month dummy variables to remove seasonality effects. M are location fixed effects, including public school and zip-code-level fixed effects (M), to control for unobserved time-invariant characteristics that may jointly affect housing prices and Airbnb activities, such as commercial activities, infrastructure, and public facilities. Finally, ϵ is the error term.

Model 2 – Time Effect

In this model, we used Airbnb densities in the closest ring (ring 1) but for different time periods before the sale, namely, Airbnb_Phase1_Ring1, Airbnb_Phase2_Ring1 and Airbnb_Phase3_Ring1, to investigate the impact of Airbnb on house prices over time.

$$P = \alpha + (Airbnb\_Phase1\_Ring1)\beta_1 + (Airbnb\_Phase2\_Ring1)\beta_2 + (Airbnb\_Phase3\_Ring1)\beta_3 + \gamma X + \delta T + \theta M + \epsilon \quad (2)$$

Model 3 – Distance Effect

In this model, we used Airbnb densities in the closest ring (ring 1) but for different time periods before the sale, namely, Airbnb_Phase1_Ring1, Airbnb_Phase2_Ring1 and Airbnb_Phase3_Ring1, to investigate the impact of Airbnb on house prices over time.

$$P = \alpha + (Airbnb\_Phase1\_Ring1)\beta_1 + (Airbnb\_Phase1\_Ring2)\beta_2 + (Airbnb\_Phase1\_Ring3)\beta_3 + \gamma X + \delta T + \theta M + \epsilon \quad (3)$$

Unconditional Quantile Regression

Another goal of this study is to estimate the potential Airbnb effect across the complete distribution of house prices. To do so, we used the unconditional quantile regression (UQR) method proposed by Firpo et al. (2009). Compared to the (conditional) quantile regression method developed by Koenker and Bassett (1978), this methodology allows us to estimate the effects on an outcome variable that is not conditioned by the set of covariates included in the model (Fortin et al., 2011).

UQR is based on extending the concept of the influence function to what has been termed the recentered influence function (RIF). The UQR model is estimated by regressing RIF on the covariates.

$$RIF\left(Y; P_{q_\tau}, F_{P_{q_\tau}}\right) = P_{q_\tau} + \frac{(\tau - \mathbf{1}\{P \le P_{q_\tau}\})}{f_y(P_{q_\tau})} = (Airbnb\_Phase1\_Ring1)\beta_1 + \gamma X + \delta T + \theta M + \epsilon \quad (4)$$

Where P_{q_τ} is the natural log of the real sale price, P, at the τth quantile (q). **1** is an indicator function that takes a value of 1 for P below P_{q_τ}; and $f_y(P_{q_\tau})$ is the density of P at the τth quantile.

V. RESULTS

We begin by providing estimates for the hedonic model shown in Equation (1). The results are presented in Table 1.3. The estimates for our three different measures of Airbnb activity in the closest ring (ring 1: 0 to 300 m) and in the closest phase (phase 1: months S to S-3) prior to house sale are reported in columns (1) to (3), and all standard errors are reported in parentheses. The estimate in column (1) shows that one additional active Airbnb property within 300 m of a house in phase 1 increases the sale price by 0.38%[5]. Based on summary statistics (Table 1.2), the average number of Airbnb listings in our data within 300 m of a house in phase 1 is 0.803. Therefore, the average magnitude of the impact of the first measure is approximately 0.30%. Column 2 shows a similar measure of Airbnb activity, positive occupancy, where an additional Airbnb rental increases nearby housing sales by 0.39%. The mean number of Airbnb listings with a positive occupancy rate for the phase 1 and ring 1 is 0.678, yielding an average impact of approximately 0.26% for the second measure.

[Insert Table 1.3 here]

Finally, column 3 displays the impact of the sum of reservations for all Airbnb listings and for all four months in phase 1 (months S to S-3). In this respect, 100 more Airbnb reservations within 300 m of a house are associated with a 1.99% higher home sales price. The mean for the number of Airbnb reservations for phase 1 and ring 1 is 0.08 (scaled by a hundred). Therefore, the average magnitude of the impact for the third measure is approximately 0.16%. This measure differs from the previous two because it measures the intensity of the guest traffic. We included this measure because we expected the number of reservations to be a better measure for capturing any negative externalities associated with STR activity. Although the average magnitude of the impact for this measure is less than the effects of the first two measures, it is still positive, suggesting that the net effect of STR activity on house prices is positive.

[5] Percentage change is calculated using exp(β)-1.

The results in Table 1.4 explore how Airbnb activity in different periods before house sales affects its price. The estimation results for the three measures are reported in columns (1) to (3). Consistent with our expectations, the period closer to the sale has a stronger effect that diminishes over time. For all three measures, we find significant and higher positive coefficients for Airbnb listings in the months of S to S-3 (phase 1) compared to Airbnb listings in the months of S-4 to S-7 (phase 2) and S-8 to S-11 (phase 3). For instance, the estimation results for our third measure in column (3) show that 100 additional Airbnb reservations within 300 m of a house are associated with 1.12%, 0.91%, and 0.58% higher home sale prices in phases 1, 2, and 3, respectively.

[Insert Table 1.4 here]

The results in Table 1.5 show the effect of distance. We expected that closer Airbnb properties would have a greater impact on house sale prices. All results in Table 1.5 are significant, and the direction of the coefficients is consistent for each measure of Airbnb activity. An interesting result here is that all three measures show a negative effect of Airbnb listings in ring 3 (Airbnb listings at 500 to 1000 m distance from houses) on house prices. Although these negative results are statistically different from zero, their magnitudes are very small, indicating that Airbnb listings far from a property (i.e., higher than 500 m) do not have a strong impact on house prices.

[Insert Table 1.5 here]

In particular, Table 1.5, Column (1) shows that for phase1, the month of the house sale and the 3-month period prior to it, one additional Airbnb listing in ring 1 has a 0.39% impact on house prices. The average magnitude of this impact is approximately 0.31%. While an additional Airbnb listing in ring 2 increases the sale price of nearby houses by 0.10%. Finally, one additional Airbnb listing in ring 3 decreases the neighborhood house sale price by 0.07%. The results of the first two measures are similar and consistent. The results in Column (3) reveal that the third measure shows a positive effect of 2.10% on house price for each 100 more reservations in ring 1, with an average magnitude of approximately 0.17%. 100 more reservations in ring 2 are associated with a 1.15% positive effect, and the average magnitude of this effect is 0.11%. Finally, 100 more reservations in ring 3 are associated with a 0.67% negative effect on house sales.

Ordinary least-squares regressions estimate the conditional mean impact of the STR on housing prices. To estimate the impact of Airbnb on higher versus lower house prices, we proceed to the unconditional quantile regression (UQR) model shown in Equation (4). Because the Airbnb impact is concentrated in ring 1 and phase 1, we apply the UQR model to our baseline equation (1). The results are presented in Table 1.6. For the first two measures, the coefficients for all quantiles (first and second rows) are significant at the 1% level. According to our third measure (third row), most quantiles have significant coefficients. The unconditional quantile regression results are consistent for all the three measures. The results reveal that the positive impact of Airbnb density on house prices is not consistent across the entire house price distribution. This relationship is stronger for the 10th, 70th, 80th and 90th quantiles. It seems that middle-range house prices are less affected by Airbnb activity. This result can be seen better in Figure 1.5. In this figure, each panel plots the explanatory variable's UQR coefficient estimates and their associated 95% confidence intervals.

[Insert Figure 1.5 here]

The quantile regression results show that high-priced properties, particularly the 70th and 80th quantiles, are more affected by Airbnb activity. For example, the quantile regression result for the second measure of Airbnb activity (second row) in Table 1.6 shows that both the 70th and 80th quantiles have a coefficient of 0.0057, which is noticeably higher than those of the other quantiles.

Furthermore, the middle price range of houses is less affected by Airbnb activity. For example, the coefficients of the second measure of Airbnb activity for the 40th, 50th, and 60th quantiles are 0.0024, 0.0029, and 0.0039, respectively. One explanation for higher impact of Airbnb activity on upper end of the price distribution could be that many Airbnb properties are located in tourist areas like "Ocean Front" in Virginia Beach, which has more expensive houses. Due to the higher demand for accommodation from tourists in these places, it is reasonable to say that there are more incentives for STR listings in these areas. This leads to a higher demand for higher-priced properties that increase property value. Furthermore, higher STR activity in these areas causes the supply of higher-priced properties to be lower, which in turn increases prices.

VI. CONCLUSION

In previous literature, critics of short-term rentals (STRs) have argued that the concentration of STRs in a neighborhood can cause negative externalities, such as higher levels of noise, littering, less space for parking, and safety concerns in the neighborhood (Gant, 2016) along with increasing inequality (Schor, 2017), financial hardship (Daniels & Grinstein-Weiss, 2019), and lowering city livability (Barrios et al., 2020, Erhardt et al., 2019). However, some studies (e.g., Sheppard & Udell, 2016) discuss the positive side of STRs, such as generating a new income stream for homeowners, decreasing the cost of owning a home, and increasing property values. This study adds to the growing literature by estimating the effect of STRs (Airbnb) on housing values in Hampton Roads, Virginia. Furthermore, we explored the time and distance effects related to Airbnb activity and examined how Airbnb rental activity impacts house prices across the price distribution of home sales.

We used a hedonic regression model to investigate the effects of Airbnb activities on neighboring house prices. For this purpose, we used three different measures of Airbnb activity to examine whether Airbnb's impact on house prices is robust when different measures of Airbnb are used. The main results reveal that Airbnb activity has a positive impact on housing prices. This result is consistent across all three measures. The average magnitude of the impact is approximately 0.30% for the first measure (number of active Airbnb listings), 0.26% for the second measure (number of Airbnb listings with a positive occupancy rate), and 0.16% for the third measure (total number of reservations). The third measure differs from the first two because it measures the intensity of the guest traffic. We expected the number of reservations to be a better measure to capture any negative externalities associated with STR activity. Although the average magnitude of the impact for this measure is less than the effects of our first two measures, it is still positive, which shows that the positive externalities associated with STR activity dominate its negative externalities and that the net effect on house prices is positive.

Furthermore, our distance-effect model reveals that the localized impact diminishes over geographic space (i.e., distances greater than 500 m). For instance, the results for the first measure show that an additional Airbnb listing at 300 m from the property has a 0.39% impact on house prices. While one more Airbnb listing at a 300-to-500 m distance from the property increases its sale price by 0.10%. Finally, one additional Airbnb listing at a 500-to-1000 m distance from the property decreases the house sale price by 0.07%. Moreover, as expected, the period closer to the sale has a stronger effect. For all three measures, we find significant and higher positive coefficients for Airbnb listings in the months of S to S-3 (phase 1) compared to Airbnb listings in the months of S-4 to S-7 (phase 2) and S-8 to S-11 (phase 3).

Finally, we applied an unconditional quantile regression to examine how Airbnb activity affects house prices across its distribution. We find that the effect is strongest for the 70^{th} and 80^{th} quantiles, while the middle price range of houses is less affected by Airbnb activity. It seems that the higher demand for accommodations from tourists in tourist places, which have more expensive houses, provide more incentives for STR listings in these areas. The higher demand for STR listings and the lower supply of higher-priced properties, as a result of higher STR activity in tourist places, push prices up.

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Table 1.1 Description and summary statistic of housing characteristics, Control variables

Variable	Description	Mean	Std. Dev.	Min	Max
Interior Features:					
Bar	=1, if house has bar	0.132	0.339	0	1
Cedar closet	=1, if house has cedar closet	0.017	0.131	0	1
Gas fireplace	=1, if house has gas fireplace	0.325	0.468	0	1
Handicap access	=1, if house has handicap access	0.008	0.091	0	1
Permanent attic stairs	=1, if house has permanent attic stairs	0.023	0.150	0	1
Pull-down attic access	=1, if house has pull-down attic access	0.234	0.423	0	1
Scuttle access	=1, if house has scuttle access	0.224	0.417	0	1
Skylights	=1, if house has skylights	0.069	0.253	0	1
Wood burning stove	=1, if house has wood burning stove	0.018	0.135	0	1
Window treatments	=1, if house has window treatments	0.307	0.461	0	1
Walk-in closet	=1, if house has walk-in closet	0.553	0.497	0	1
Exterior Features:					
Barn	=1, if house has barn	0.005	0.072	0	1
Corner lot	=1, if house has corner lot	0.106	0.308	0	1
Cul-de-sac	=1, if house is on a cul-de-sac	0.167	0.373	0	1
Deck	=1, if house has deck	0.309	0.462	0	1
Golf course lot	=1, if house has golf course lot	0.010	0.097	0	1
Greenhouse	=1, if house has greenhouse	0.002	0.044	0	1
Gazebo	=1, if house has gazebo	0.014	0.117	0	1
Horses allowed	=1, if house is horses allowed	0.008	0.091	0	1
Inground sprinklers	=1, if house has inground sprinklers	0.107	0.309	0	1
Irrigation control	=1, if house has irrigation control	0.029	0.169	0	1
Tagged items	=1, if house has tagged items	0.002	0.046	0	1
Patio	=1, if house has patio	0.319	0.466	0	1
Pump	=1, if house has pump	0.040	0.197	0	1
Rainwater	=1, if house has rainwater system	0.003	0.058	0	1
Shed	=1, if house has shed	0.302	0.459	0	1
Stable	=1, if house has stable	0.002	0.040	0	1
Wells	=1, if house has wells	0.082	0.274	0	1
Wind power	=1, if house has wind power	0.000	0.011	0	1
Wooded	=1, if house is wooded	0.097	0.296	0	1

Table 1.1 (continued):

Variable	**Description**	**Mean**	**Std. Dev.**	**Min**	**Max**
Style Features:					
2 unit condo	=1, if house is 2 unit condo	0.015	0.121	0	1
Apartment	=1, if house is apartment	0.006	0.079	0	1
Bungalow	=1, if house is bungalow	0.021	0.142	0	1
Cape cod	=1, if house is cape cod	0.045	0.207	0	1
Cluster	=1, if house is cluster	0.009	0.093	0	1
Colonial	=1, if house is colonial	0.076	0.266	0	1
Contemp	=1, if house is contemp	0.081	0.273	0	1
Cottage	=1, if house is cottage	0.016	0.126	0	1
Farmhouse	=1, if house is farmhouse	0.003	0.058	0	1
Log cabin	=1, if house is log cabin	0.000	0.012	0	1
Mobilie home	=1, if house is mobilie home	0.000	0.017	0	1
Modular	=1, if house is modular	0.001	0.029	0	1
Other	=1, if house has other style	0.016	0.126	0	1
Quadraville	=1, if house is quadraville	0.013	0.113	0	1
Ranch	=1, if house is ranch	0.275	0.447	0	1
Spanish	=1, if house is spanish	0.001	0.024	0	1
Split-level	=1, if house is split-level	0.009	0.097	0	1
Townhouse	=1, if house is townhouse	0.122	0.327	0	1
Traditional	=1, if house is traditional	0.231	0.421	0	1
Transitional	=1, if house is transitional	0.210	0.407	0	1
Tri-level	=1, if house is tri-level	0.016	0.125	0	1
Twinhouse	=1, if house is twinhouse	0.006	0.077	0	1
Victorian	=1, if house is victorian	0.005	0.072	0	1
Ownership Type:					
Condo	=1, if ownership type is condo	0.155	0.362	0	1
Cooperative	=1, if ownership type is cooperative	0.002	0.040	0	1
Simple	=1, if ownership type is simple	0.843	0.364	0	1
Other:					
Age	Age of the house in years	36505	24.44	2	121
New construct	=1, if house is new construct	0.132	0.339	0	1
Square feet	Living area in ft^2	1972.3	794.15	210	9952
Waterfront	=1, if house is waterfront	0.099	0.299	0	1

Table 1.2 Description and summary statistics for dependent and independent variables.

Variable	Description	Mean	Std. Dev.	Min	Max
Independent variable:					
Measure 1: “Active” Airbnb					
Airbnb_Phase1 _Ring1	Number of Airbnb in phase1 and ring 1	0.803	4.15	0	138
Airbnb_Phase1 _Ring2	Number of Airbnb in phase1 and ring 2	1.028	4.232	0	143
Airbnb_Phase1 _Ring3	Number of Airbnb in phase1 and ring 3	3.798	12.038	0	267
Airbnb_Phase2 _Ring1	Number of Airbnb in phase2 and ring 1	0.684	3.692	0	136
Airbnb_Phase3 _Ring1	Number of Airbnb in phase3 and ring 1	0.588	3.407	0	137
Measure 2: “Positive Occupancy Rate”					
Airbnb_Phase1 _Ring1	Number of Airbnb in phase1 and ring 1	0.678	3.588	0	138
Airbnb_Phase1 _Ring2	Number of Airbnb in phase1 and ring 2	0.875	3.739	0	130
Airbnb_Phase1 _Ring3	Number of Airbnb in phase1 and ring 3	3.212	10.66	0	255
Airbnb_Phase2 _Ring1	Number of Airbnb in phase2 and ring 1	0.563	3.156	0	134
Airbnb_Phase3 _Ring1	Number of Airbnb in phase3 and ring 1	0.478	2.790	0	128
Measure 3: Sum of Reservations					
Airbnb_Phase1 _Ring1	Number of reservations in hundreds in phase1 and ring 1	0.080	0.481	0	31.13
Airbnb_Phase1 _Ring2	Number of reservations in hundreds in phase1 and ring 2	0.102	0.487	0	16.05
Airbnb_Phase1 _Ring3	Number of reservations in hundreds in phase1 and ring 3	0.368	1.372	0	37.27
Airbnb_Phase2 _Ring1	Number of reservations in hundreds in phase2 and ring 1	0.061	0.381	0	21.83
Airbnb_Phase3 _Ring1	Number of reservations in hundreds in phase3 and ring 1	0.052	0.341	0	24.05
Dependent variable:					
P	Natural log of the inflation adjusted house sale price	12.25	0.558	6.767	15.21

Note: For each house sold, we drew three concentric rings with different radii: Ring 1, 0–300 m; Ring 2, 300–500 m; and Ring 3, 500–1000 m.
Phase 1 includes the month of sale and the three months before that. For example, if a house is sold in August; thus, Phase 1 includes May, June, July, and August. Phase 2 includes the fourth month before the sale and three months before that. Suppose a house is sold in August; thus, Phase 2 includes January, February, March, and April. Phase 3 includes the eighth month before the sale and three the months before that. Suppose that a house is sold in August; thus, Phase 2 includes September, October, November, and December.

Table 1.3 Model 1: OLS regression estimates, all three measures.

	Measure (1) **Active**	**Measure (2)** **Positive Occupancy**	**Measure (3)** **Sum of reservations**
Airbnb_Phase1 _Ring1	0.0038*** (0.0002)	0.0039*** (0.0002)	0.0197*** (0.0018)
Zip code dummies	Yes	Yes	Yes
School district dummies	Yes	Yes	Yes
Year of sale dummies	Yes	Yes	Yes
Month of sale dummies	Yes	Yes	Yes
N	102165	102165	102165
adj. R-sq	0.783	0.783	0.783

Note: Standard errors are in parentheses. Standard errors for the regression were obtained using 500 bootstrap replicates. $*$ $p < 0.1$. $**$ $p < 0.05$. $***$ $p < 0.01$.
The coefficients of the control variables introduced in Table 1.1, are not included in this table. The complete version of this table is available upon request.

Table 1.4 Model 2: Time Effect, all three measures

	Measure (1) **Active**	**Measure (2)** **Positive Occupancy**	**Measure (3)** **Sum of reservations**
Airbnb_Phase1_Ring1	0.0037***	0.0022***	0.0112***
	(0.0006)	(0.0005)	(0.0030)
Airbnb_Phase2_Ring1	-0.0005	0.0012*	0.0091**
	(0.0008)	(0.0006)	(0.0040)
Airbnb_Phase3_Ring1	0.0007	0.0013**	0.0058
	(0.0007)	(0.0006)	(0.0039)
Zip code dummies	Yes	Yes	Yes
School district dummies	Yes	Yes	Yes
Year of sale dummies	Yes	Yes	Yes
Month of sale dummies	Yes	Yes	Yes
N	102165	102165	102165
adj. R-sq	0.783	0.783	0.783

Note: Standard errors are in parentheses. Standard errors for the regression were obtained using 500 bootstrap replicates. ∗ $p < 0.1$. ∗∗ $p < 0.05$. ∗∗∗ $p < 0.01$.
The coefficients of the control variables introduced in Table 1.1, are not included in this table. The complete version of this table is available upon request.

Table 1.5 Model 3: Distance Effect, all three measures

	Measure (1) **Active**	**Measure (2)** **Positive Occupancy**	**Measure (3)** **Sum of reservations**
Airbnb_Phase1 _Ring1	0.0039*** (0.0002)	0.0041*** (0.0003)	0.0208*** (0.0022)
Airbnb_Phase1 _Ring2	0.0010*** (0.0003)	0.0009** (0.0003)	0.0114*** (0.0027)
Airbnb_Phase1 _Ring3	-0.0007*** (0.0001)	-0.0007*** (0.0001)	-0.0067*** (0.0009)
Zip code dummies	Yes	Yes	Yes
School district dummies	Yes	Yes	Yes
Year of sale dummies	Yes	Yes	Yes
Month of sale dummies	Yes	Yes	Yes
N	102165	102165	102165
adj. R-sq	0.783	0.783	0.783

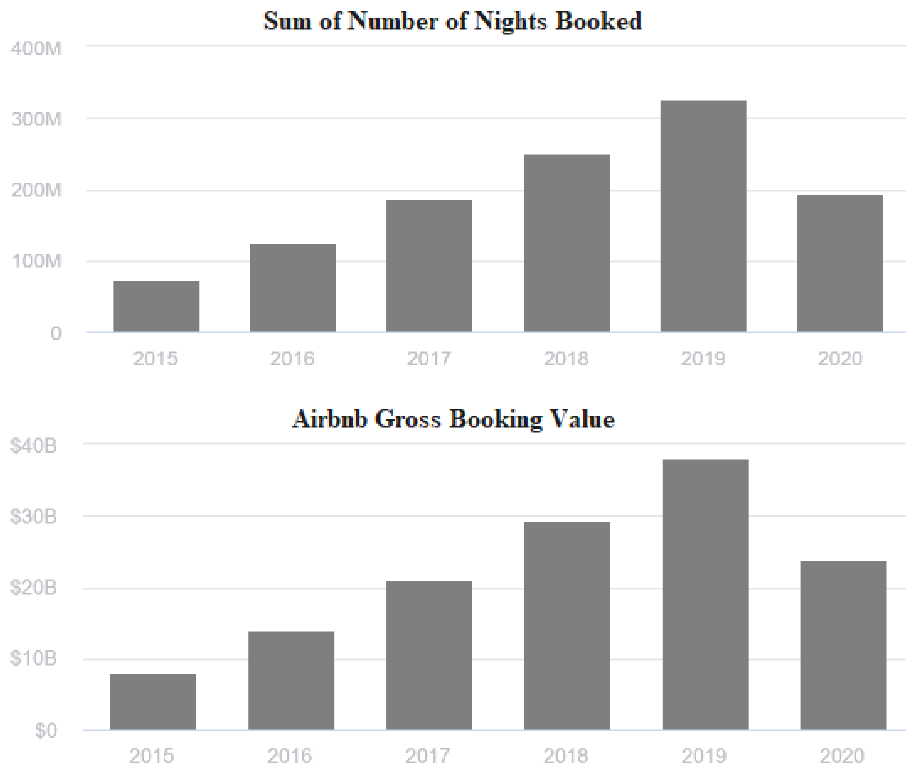
Note: Standard errors are in parentheses. Standard errors for the regression were obtained using 500 bootstrap replicates. ∗ $p < 0.1$. ∗∗ $p < 0.05$. ∗∗∗ $p < 0.01$.
The coefficients of the control variables introduced in Table 1.1, are not included in this table. The complete version of this table is available upon request.

Table 1.6 Unconditional Quantile Regression Result, all three measures.

	0.10 Quantile	0.20 Quantile	0.30 Quantile	0.40 Quantile	0.50 Quantile	0.60 Quantile	0.70 Quantile	0.80 Quantile	0.90 Quantile
Measure (1): Airbnb _Phase1_Ring1	0.0041***	0.0025***	0.0021***	0.0024***	0.0029***	0.0039***	0.0057***	0.0052***	0.0043***
	(0.0008)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
Measure (2): Airbnb _Phase1_Ring1	0.0044***	0.0026***	0.0020***	0.0024***	0.0029***	0.0039***	0.0057***	0.0057***	0.0048***
	(0.0009)	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Measure (3): Airbnb _Phase1_Ring1	0.0205***	0.0075*	0.0037	0.0090***	0.0135***	0.0213***	0.0339***	0.0359***	0.0330***
	(0.0064)	(0.0039)	(0.0034)	(0.0028)	(0.0025)	(0.0026)	(0.0030)	(0.0032)	(0.0040)
Zip code dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School district dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of sale dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of sale dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	102165	102165	102165	102165	102165	102165	102165	102165	102165
adj. R-sq	0.282	0.394	0.474	0.533	0.579	0.605	0.611	0.573	0.472

Note: Standard errors are in parentheses. Standard errors for the quantile regression were obtained using 500 bootstrap replicates. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.
The coefficients for the control variables introduced in Table 1, Panel A, are not included in this table. The complete version of this table is available upon request.

Figure 1.1 Airbnb Growth



Source: WALSTREETZEN

Figure 1.2 Number of Airbnb listings in Hampton Roads, Virginia, OCT 2014-DEC 2019

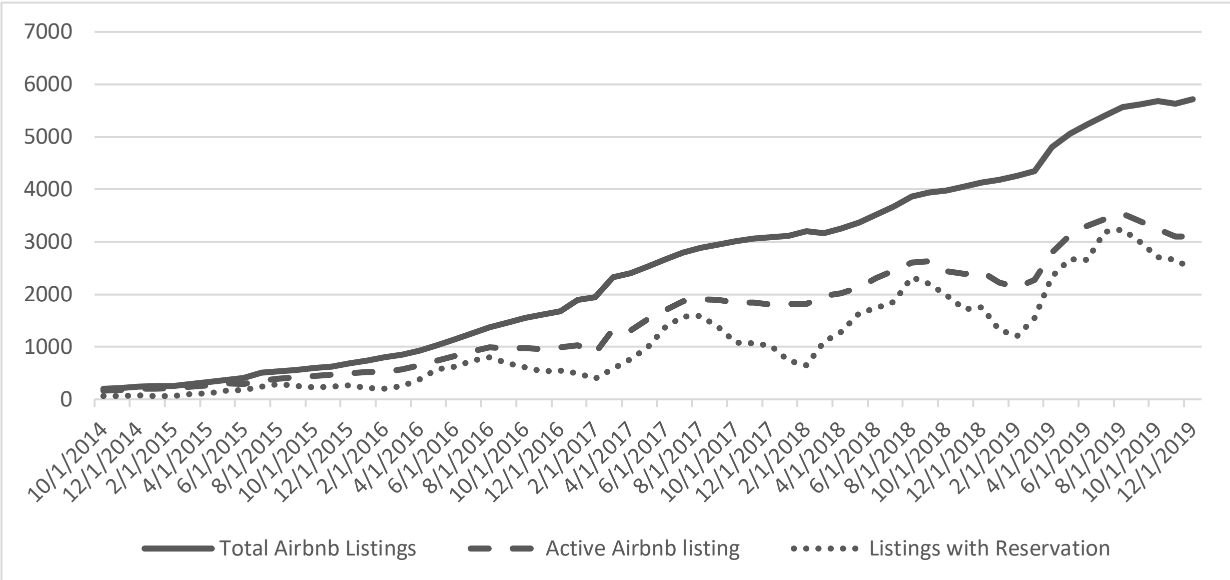
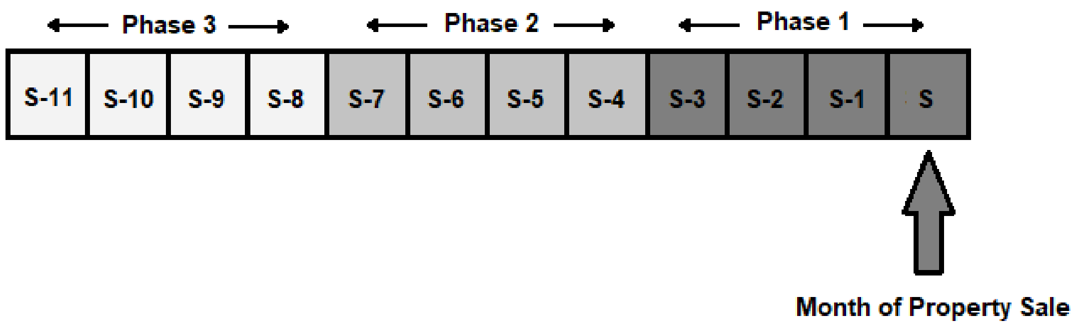


Figure 1.3 Airbnb activity by time.



We broke the 12-months period before each sale (including the month of sale and eleven months prior to the sale) into three 4-Months phases. For example, for a house sold in August (S), Phase 2 would include January (S-7), February (S-6), March (S-5), and April (S-4).

Figure 1.4 Example of Airbnb density for three different rings

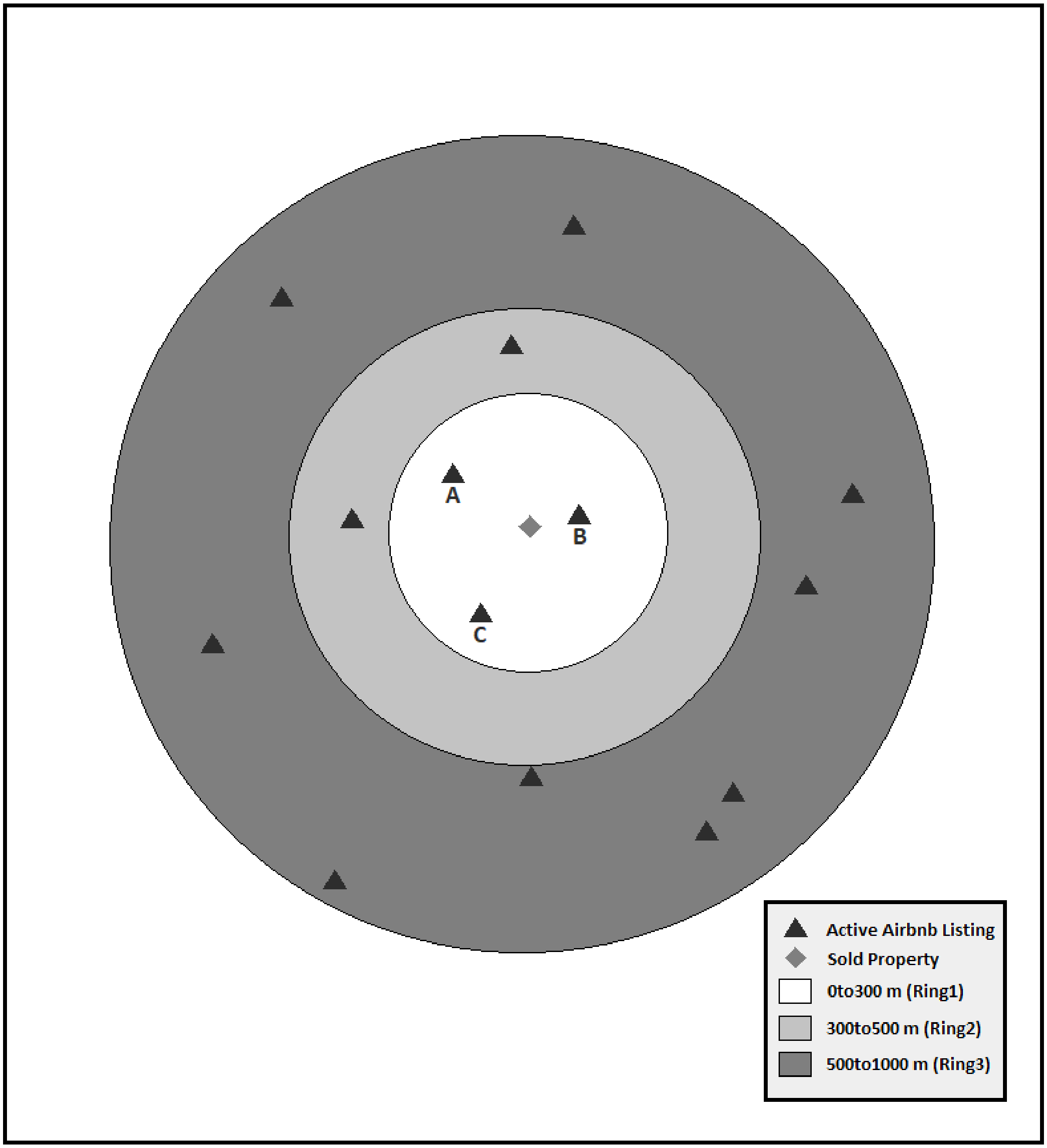
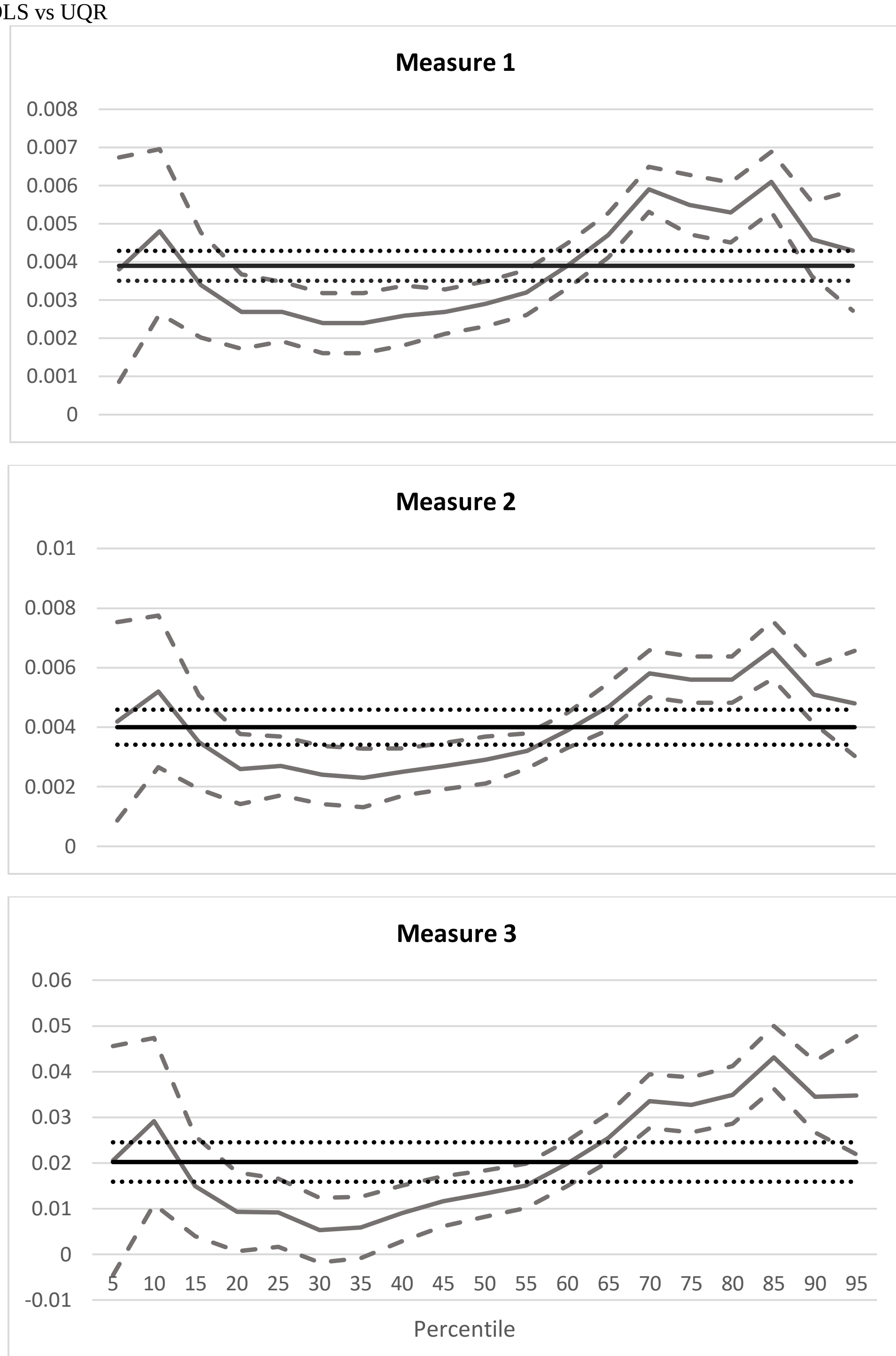


Figure 1.5 OLS vs UQR



This figure displays the estimated increase in house price associated with Airbnb listings for phase 1 and ring 1. Each panel plots an explanatory variable's UQR coefficient estimates and their associated 95% confidence intervals (dashed line) at 19 quantile points from the 5th to 95th percentile. The solid horizontal line in each figure is the OLS coefficient estimate and associated 95% confidence interval (dotted line). Note: Scale for measure3 is different from measures 1 and 2.

ESSAY 2: EXAMINING THE INTERACTION BETWEEN MEDIA CONTENT INVESTOR SENTIMENT AND REIT RETURN AND VOLATILITY

I. INTRODUCTION

Real Estate Investment Trusts (REITs) have gained significant popularity as investment vehicles, offering investors exposure to the real estate market without the complexities of direct property ownership. The performance of REITs is influenced by various factors, including macroeconomic indicators, market conditions, and investor sentiment (Lin, Rahman & Yung, 2009). In recent years, the role of media content and its impact on financial markets has garnered considerable attention (e.g., Yu et al., 2023; Shen et al., 2021; Duz Tan & Tas, 2021). Understanding how media content sentiments interact with REIT returns and volatility is crucial for investors, analysts, and policymakers in making informed decisions and managing risks in the real estate market.

The objective of this research is to comprehensively examine the interaction between media content sentiments and REIT performance. We utilize proprietary investor sentiment measures developed by Thompson Reuters MarketPsych, focusing on four sentiments: “stress”, “emotions vs. facts”, “dividends”, and “price direction”. These sentiments capture different dimensions of investor sentiment, reflecting market participants' attitudes and beliefs.

The significance of media content sentiments in financial markets has been widely recognized. Media content, including news articles, social media posts, and analyst reports, can shape investor perceptions and influence trading decisions. Positive or negative sentiment expressed in media content can potentially impact market sentiment, leading to changes in asset prices and volatility (Lee, Jiang & Indro, 2002; Shu & Chang, 2015). Therefore, analyzing the relationship between media content sentiments and REIT performance is crucial for understanding the drivers of returns and volatility in this sector.

To explore this relationship, we adopt a multi-step approach. In Step 1, we employ time series regression to examine the statistical significance of the four media content sentiments and a market premium factor in explaining the excess returns of REITs across different types of REITs and weighting schemes. By including these sentiments as independent variables, we aim to determine their ability to explain the variation in REIT returns beyond traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM) and the Fama-French 3-factor model (Fama & French, 1993). The results will provide insights into the extent to which media content sentiments contribute to explaining REIT returns.

To account for potential autocorrelation and volatility clustering in the data, Step 2 involves an autocorrelation check and the application of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. These models capture the volatility patterns and autocorrelation in squared returns, allowing us to better understand the dynamics of volatility in the context of media content sentiments. This step is crucial in addressing any potential biases and improving the robustness of our analysis.

In Step 3, we employ Lasso analysis to identify the most influential media content sentiment on REIT excess returns. Lasso analysis is a regression technique that helps identify the most relevant variables in the presence of multiple predictors. By identifying the sentiment that has the highest effect on REIT returns, we can understand the specific drivers of performance within the context of media content sentiments.

Finally, to validate the relationships established in previous steps, Step 4 employs Covariance-based Structural Equation Modeling and path analysis. SEM is a statistical technique used to evaluate complex structural models based on covariance matrices. Path analysis allows us to assess the overall fit of the model, estimate the strength and significance of relationships, and evaluate the direct and indirect effects of media content sentiments on REIT returns. This step provides a robust framework for understanding the complex interplay between media content sentiments, price direction, and REIT performance.

By following this comprehensive research approach, we aim to provide valuable insights into the role of media content sentiments in driving REIT returns and volatility. The findings from this study will contribute to the growing literature on investor sentiment, media effects, and financial market dynamics. Additionally, the results will have practical implications for investors, analysts, and policymakers, enabling them to better understand the drivers of REIT performance and make informed decisions in the ever-evolving real estate market.

II. LITERATURE REVIEW

Effect Real Estate Investment Trusts (REITs) and Market Efficiency:

Real Estate Investment Trusts (REITs) have become a popular investment choice, offering investors exposure to the real estate market while enjoying the benefits of liquidity and diversification (Miles and Mc Cue (1982)). The efficient market hypothesis posits that financial markets quickly incorporate all available information into asset prices, rendering it difficult for investors to consistently outperform the market (Fama, 1970). However, several studies have challenged the notion of market efficiency in the context of REITs (e.g., Almudhaf, Aroul &

Hansz, 2020; Adekoya, Oduyemi & Oliyide, 2021), suggesting that non-traditional factors, including sentiment and media content, play a role in driving their returns and volatility.

Investor Sentiment and Financial Markets:

Investor sentiment refers to the prevailing attitudes, beliefs, and emotions of market participants, which can influence their investment decisions and subsequent asset prices. Traditional models of asset pricing, such as the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model, primarily focus on systematic risk factors. However, recent research has emphasized the role of investor sentiment as an additional explanatory factor for asset returns (e.g., Baker & Wurgler, 2006; Baker, Wurgler & Yuan, 2012; Huang et al., 2015). Media content, including news articles and social media posts, can shape investor sentiment, leading to deviations from fundamental valuations and affecting market outcomes (Tetlock, 2007).

Media Content and Financial Markets:

Media content plays a crucial role in disseminating information to market participants. It can have a significant impact on investor sentiment, influencing their perceptions, attitudes, and subsequent trading decisions. Research has shown that media content sentiments, such as positive or negative news, can affect asset prices, trading volume, and volatility. Studies have examined the relationship between media content and various financial markets, including stocks, bonds, and commodities (e.g., Tetlock, 2007; Engelberg & Parsons, 2011). However, the literature on the impact of media content sentiments on REIT returns and volatility remains limited.

The Interaction between Media Content and REIT Returns:

A growing body of research has been dedicated to investigating the interaction between sentiments expressed in media content and the performance of Real Estate Investment Trusts (REITs). Ruscheinsky, Lang and Schäfers (2018) conducted a study that provided compelling evidence of a leading relationship between media sentiment and future movements in the REIT market. Their findings suggested that a sentiment measure that encompasses both positive and negative sentiments yield superior results compared to one that focuses solely on one polarity. Another study by Freybote (2016) demonstrated that investor sentiment in the commercial real estate market not only influences pricing decisions in the REIT stock market but also affects the REIT bond market. However, it is worth noting that these studies have primarily focused on a limited number of sentiment factors, such as news tone, and have also tended to examine specific types of investors exclusively.

Thomson Reuters MarketPsych and Sentiment Measures:

Thomson Reuters MarketPsych is a prominent provider of sentiment measures derived from textual analysis of media content. These measures capture various dimensions of investor sentiment, including stress, emotions vs. facts, dividends, and price direction. The proprietary nature of these sentiment measures enables researchers to gain insights into market sentiment beyond traditional sentiment proxies. Several studies have utilized MarketPsych sentiment measures in analyzing different financial markets, highlighting their usefulness in understanding investor behavior and market dynamics (e.g., Shen, Najand & Chen, 2023; Griffith, Najand & Shen, 2020; Audrino & Telereva, 2019; Sun, Najand & Shen, 2016).

Analytical Techniques - Time Series Regression, Autocorrelation, Lasso, SEM:

To investigate the relationship between media content sentiments and REIT returns, a range of analytical techniques can be applied. Time series regression allows for the estimation of the statistical significance and explanatory power of sentiment measures in explaining REIT returns beyond traditional asset pricing models. Autocorrelation checks and GARCH models help account for serial correlation and volatility clustering in the data, ensuring robustness in the analysis. Lasso analysis can identify the most influential sentiment factor, providing insights into the specific drivers of REIT performance. Lastly, SEM and path analysis validate the relationships established and assess their overall fit.

In conclusion, the literature reviewed demonstrates the importance of investor sentiment and media content in driving REIT returns and volatility. The use of proprietary sentiment measures, such as those provided by Thompson Reuters MarketPsych, enables a comprehensive analysis of sentiment dimensions beyond traditional proxies. This research aims to contribute to the existing literature by employing a multi-step approach that incorporates various analytical techniques to examine the relationship between media content sentiments and REIT performance. The findings from this study will enhance our understanding of the role of sentiments in shaping the real estate market, enabling investors, analysts, and policymakers to make informed decisions and manage risks in the dynamic REIT sector.

III. DATA

Our research relies on data obtained from the Thomson Reuters Marketpsych Indices (TRMI), which undergoes regular updates to capture real-time insights from a diverse range of premium news sources, global internet news coverage, and various social media platforms

(Peterson (2013)). By incorporating sentiments from both professional and individual investors, the TRMI offers a comprehensive understanding of market sentiment dynamics.

The TRMI combines news and social media content using lexical analysis techniques to extract sentiment indices. MarketPsych, for the professional investor category, collects textual data from reputable sources such as The New York Times, The Wall Street Journal, Financial Times, Seeking Alpha, and other commonly accessed sources. Additionally, less formal news sources like Yahoo! and Google News are included. In terms of social media, the TRMI aggregates data from over 2 million sources, including platforms like StockTwits, Yahoo! Finance, Blogger, chat rooms, and various other outlets. MarketPsych's data collection process involves analyzing over 2 million news articles and posts on a daily basis. As a result, the TRMI provides a valuable compilation of high-quality news content and a diverse range of social media sources, forming a strong foundation for our research.

For our analysis, we have selected four TRMI sentiment measure. These measures include “stress”, “price direction”, “emotion vs. fact”, and “dividends”. Each sentiment index represents a 24-hour rolling average score of references to the specific measure in the news and social media. All measures range from -1 to 1, except for stress, which ranges from 0 to 1. The definitions of our selected sentiment measures in the TRMI are shown in Figure 2.1.

[Insert Figure 2.1 here]

To analyze the returns of US Real Estate Investment Trusts (REITs), we obtained the necessary data from the Center for Research in Security Prices (CRSP) database[6]. Our study specifically focuses on the average total REIT returns, along with the two main categories of

[6] https://www.crsp.org/

REITs: equity REITs and mortgage REITs. We considered both value-weighted and equally weighted average returns to ensure robust findings. Additionally, we incorporated additional factors such as market premium, HML (Fama-French value factor), SMB (Fama-French size factor), and risk-free rate using publicly available data from the Kenneth French data library[7]. The data frequency for our analysis is daily, covering the period from January 1, 2013, to December 31, 2019. The choice to commence our analysis in 2013 was driven by the availability of abundant sentiment data derived from media content in the TRMI during that period, while also minimizing the presence of missing variables (Figure 2.2).

[Insert Figure 2.2 here]

Table 2.1 provides descriptive statistics and a correlation matrix for the variables (sentiments and REIT excess returns) used in this study. The REIT excess return is positively correlated with price direction, emotions vs. facts, and dividends, and negatively correlated with stress.

[Insert Table 2.1 here]

IV. METHOD AND RESULTS

Regression Analysis and Model Comparison

In the first step of our methodology, we employed time series ordinary least squares (OLS) regression to investigate the relationship between our four sentiment measures and the excess return of REITs. Our initial model (Model 1) included the market premium factor along with our four sentiment measures (stress, emotions vs. facts, price direction, and dividends) as independent

[7] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

variables. We also compared our findings with the Capital Asset Pricing Model (CAPM) and the three-factor model. Furthermore, we extended Model 1 by including additional factors, namely the HML factor and the SMB factor, resulting in Model 2.

Model 1 can be represented as follows:

$$\text{Excess REIT Return}_t = \beta_0 + \beta_1\text{Stress}_t + \beta_2\text{Pricedirection}_t + \beta_3\text{Emtionvsfact}_t + \beta_4\text{Dividends}_t + \beta_5\text{MKT}_t + \epsilon_t \quad (1)$$

Model 2 incorporates the additional factors and is represented as follows:

$$\text{Excess REIT Return}_t = \beta_0 + \beta_1\text{Stress}_t + \beta_2\text{Pricedirection}_t + \beta_3\text{Emtionvsfact}_t + \beta_4\text{Dividends}_t + \beta_5\text{MKT}_t + \beta_6\text{SMB}_t + \beta_7\text{HML}_t + \epsilon_t \quad (2)$$

CAPM and Fama-French- 3factor employed for the purpose of comparison, are delineated as follows:

$$\text{CAPM: Excess REIT Return}_t = \beta_0 + \beta_5\text{MKT}_t + \epsilon_t \quad (3)$$

$$\text{3-facor: Excess REIT Return}_t = \beta_0 + \beta_5\text{MKT}_t + \beta_6\text{SMB}_t + \beta_7\text{HML}_t + \epsilon_t \quad (4)$$

In these models, the "Excess REIT Return" represents the excess returns of the REITs being examined at time t, while Stress_t, Pricedirection_t, Emtionvsfact_t *and* Dividends_t are our previously mentioned sentiment measures. MKT_t, SMB_t and HML_t represent the market factor, size factor (Small Minus Big), and value factor (High Minus Low), respectively. The coefficients β_0 *to* β_7 reflect the respective risk premiums associated with intercept and each factor, and ϵ_t denotes the error term.

To ensure the robustness of our results, we considered both value-weighted and equally weighted average REIT excess returns as dependent variables. The outcomes of our regression analysis are presented in Table 2.2. In both models, all coefficients for our variables are statistically significant at the 1% level, except for stress, which is significant at the 5% level. These results hold consistently for both value-weighted and equally weighted average REIT excess returns.

[Insert Table 2.2 here]

In terms of model fit, we examine the adjusted R-squared values. For value-weighted excess returns, Model 1 yields an adjusted R-squared of 35.7%, demonstrating a 2% improvement in predictive power compared to the CAPM model (adj R-squared = 33.7%) and a 1.2% improvement compared to the three-factor model (adj R-squared = 34.5%). Model 2 further enhances the predictive power with an adjusted R-squared of 36.6%, surpassing the performance of our initial model. Similar patterns emerge for equally weighted excess returns, where Model 1 achieves an adjusted R-squared of 43.2%, outperforming the three-factor model (adj R-squared = 42.9%) and the CAPM model (adj R-squared = 41.2%). Model 2 demonstrates the highest predictive power with an adjusted R-squared of 44.8%.

These findings indicate that incorporating our sentiment measures in the regression models enhances their ability to explain the variations in REIT excess returns, surpassing the predictive power of traditional models such as the CAPM and the three-factor model.

To further investigate the predictive power improvement of our sentiment measures, we conducted an analysis specifically focusing on the two largest categories of REITs: Equity REITs and Mortgage REITs. The procedure for this analysis was similar to the previous analysis, and we examined both value-weighted (VW) and equally weighted (EW) excess REIT returns.

The results of this analysis are presented in Table 2.3. In Panel A, which displays the results for Equity REITs, we observed consistency with our previous findings. The only difference was that the coefficient for the HML factor was not statistically significant for EW excess REIT returns.

In terms of model fit and predictive power, the results were similar to the previous analysis. For VW excess returns, the adjusted R-squared values were 33.3% for the CAPM model, 34.2% for the 3-factor model, 35.2% for Model 1, and 36.2% for Model 2. Regarding EW excess returns, the adjusted R-squared values were as follows: 39.2% for the CAPM model, 40.5% for the 3-factor model, 41.1% for Model 1, and 42.3% for Model 2.

[Insert Table 2.3 here]

Moving on to Panel B, which presents the results for Mortgage REIT returns, we observed overall consistency with the previous findings. However, for our "dividends" sentiment measure, the coefficients were not statistically significant for both VW and EW excess returns, as well as for both Model 1 and Model 2. This could be attributed to the distinct income sources and investment strategies of these REIT types. Equity REITs primarily rely on rental income and property appreciation, while mortgage REITs generate income from interest earned on mortgage investments. The significant relationship between dividend sentiment and equity REIT returns suggests that investor sentiment regarding dividends directly affects equity REIT performance, as dividends form a significant part of their income stream. In contrast, the non-significant relationship between dividend sentiment and mortgage REIT returns may be due to the interest rate sensitivity of mortgage REITs and the relative importance of other sentiment variables tied to interest rates or credit market conditions. Instead, sentiment measures related to interest rates or mortgage rates might be more relevant for Mortgage REITs. Despite this, the increase in adjusted R-squared and predictive power remained consistent. For VW excess returns, the adjusted R-squared values were 25% for the CAPM model, 25.7% for the 3-factor model, 26.4% for Model 1, and 27% for Model 2. For EW excess returns, the adjusted R-squared values were as follows:

30.9% for the CAPM model, 34.4% for the 3-factor model, 35.7% for Model 1, and 35.7% for Model 2.

It is worth noting that in this analysis, Model 1 did not outperform the 3-factor model in terms of explanatory power for Mortgage REIT returns. However, Model 2 still exhibited the best fit among the different models. Additionally, the lower adjusted R-squared values for Mortgage REITs, such as 25% for the CAPM model, indicate that Mortgage REIT returns exhibit greater divergence from the stock market compared to Equity REIT returns.

Sentiment measures and stock return volatility: GARCH Model

Sentiment measures have the potential to influence both stock returns and volatility, although the precise nature of this relationship remains a topic of ongoing research. Previous studies, such as those conducted by Lee et al. (2002) and Verma and Verma (2007), have found evidence supporting the impact of sentiment on both the mean and variance of stock returns. To delve deeper into this relationship, we employ a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, a widely used framework for analyzing the effect of sentiment measures on stock returns' mean and volatility.

The GARCH model, introduced by Bollerslev (1986), addresses the limitations of ARCH(p) models by incorporating lags of conditional variance as regressors. In our analysis, we adopt the GARCH(1,1) specification, which has proven effective in capturing the dynamics of conditional volatility. This model is characterized by the following equation:

$$h_t = \omega + \gamma \varepsilon_{t-1}^2 + \delta h_{t-1} \tag{5}$$

Here, h_t represents the conditional volatility at time t, ω is the intercept term, γ captures the impact of the lagged squared error term (ε_{t-1}^2), and δ reflects the persistence of past volatility (h_{t-1}).

In our analysis, we apply the GARCH (1,1) model to both Model 1 and Model 2. Model 1 incorporates the sentiment measures along with the market premium factor (MKT), while Model 2 includes additional factors such as the Small Minus Big factor (SMB) and the High Minus Low factor (HML). The respective equations for the models are presented as follows:

GARCH Model 1:

$$\text{Excess REIT Return}_t = \beta_0 + \beta_1\text{Stress}_t + \beta_2\text{Pricedirection}_t + \beta_3\text{Emtionvsfact}_t + \beta_4\text{Dividends}_t + \beta_5\text{MKT}_t + \epsilon_t$$

$$h_t = \omega + \gamma\varepsilon_{t-1}^2 + \delta h_{t-1} \tag{6}$$

GARCH Model 2:

$$\text{Excess REIT Return}_t = \beta_0 + \beta_1\text{Stress}_t + \beta_2\text{Pricedirection}_t + \beta_3\text{Emtionvsfact}_t + \beta_4\text{Dividends}_t + \beta_5\text{MKT}_t + \beta_6\text{SMB}_t + \beta_7\text{HML}_t + \epsilon_t$$

$$h_t = \omega + \gamma\varepsilon_{t-1}^2 + \delta h_{t-1} \tag{7}$$

Table 2.4 presents the estimates of the GARCH(1,1) models. The first row corresponds to the value-weighted excess return as the dependent variable in Model 1, while the second row represents the value-weighted excess return in Model 2. Rows 3 and 4 present the results for the equally weighted excess REIT return in Models 1 and 2, respectively. In the last column, we include the result of Akaike's Information Criterion (AIC) from our OLS regression analysis to compare the model fit with the GARCH models.

[Insert Table 2.4 here]

The GARCH models demonstrate a good fit to the data, with all coefficients being statistically significant. Among the sentiment measures included in the models, Price direction has the most significant impact and is statistically significant at the 1% level across all models. The coefficients for conditional volatility are also highly statistically significant, indicating the presence of volatility clustering. Moreover, by comparing the AIC values of the GARCH and OLS models, we can observe that the GARCH models exhibit lower AIC values, indicating an improvement in the goodness of fit compared to the OLS models. This suggests that incorporating sentiment measures in the GARCH framework enhances the model's ability to capture and explain the volatility dynamics of REIT returns.

The findings pertaining to Equity and Mortgage REITs align with the overall results discussed here, however they are not included in this section, for brevity. A comprehensive analysis of these specific categories can be made available upon request, providing a deeper insight into the influence of sentiment measures on different types of REITs. Additionally, in the subsequent stages of our analysis, we concentrate solely on value-weighted excess returns to streamline the presentation of models, tables, and graphs in this paper. Nevertheless, the outcomes for other categories can be supplied upon request for a more comprehensive examination.

Identification and Selection of Key Sentiments: Lasso Analysis

At this step, we employ the Lasso (Least Absolute Shrinkage and Selection Operator) method to further explore the relationship between media content sentiments and the return of Real Estate Investment Trusts (REITs). The Lasso method is a powerful statistical technique that enables us to identify the most influential predictors among a set of variables. By simultaneously performing variable selection and regularization, Lasso shrinks the coefficients of less important predictors towards zero, effectively reducing their impact on the outcome variable. This approach helps address challenges such as overfitting and multicollinearity, which are common in studies with numerous predictors.

The utilization of Lasso in our research offers two main benefits. Firstly, it allows us to verify the predictive power of our selected media content sentiments. Secondly, it aids in identifying the key sentiments that significantly influence REIT returns, thereby providing valuable insights for the existing literature.

To determine the optimal model, we considered three different indirect estimation criteria: AIC, SBC, and adjusted R-squared. These criteria help us select the model that minimizes the estimated prediction error. The results of the Lasso selection analysis, shown in Table 2.5, indicate the following effects:

Step 0: Intercept, Step 1: priceDirection, Step 2: stress, Step 3: emotionVsFact, Step 4: dividends

[Insert Table 2.5 here]

According to the AIC-based Lasso selection, the effect of dividends was found to have the highest influence on REIT returns. This suggests that including all four sentiments in the model leads to the best fit. Additionally, in line with the outcomes of the AIC-based Lasso analysis, the adjusted R-squared criterion further supports the superior explanatory power attained by incorporating the effect of dividends. These results emphasize the significance of including all four sentiments for optimizing the model's performance. Conversely, in the SBC-based Lasso selection, the effect of priceDirection was determined to have the strongest impact, indicating that including priceDirection alone yields the best fit, and adding other sentiments does not significantly improve the model.

Furthermore, Figure 2.3 visually presents the Lasso analysis for the three aforementioned criteria. In the AIC-based and adjusted R-squared -based analyses, the best fit occurs at the far left of the graph, as indicated by the vertical line. However, when observing the line illustrating adjusted R-squared changes, it is evident that priceDirection has the highest effect on adjusted R-squared changes, while the other three sentiments contribute to adjusted R-squared improvement at a relatively lower rate compared to priceDirection. In the SBC analysis, the best fit is observed at a point corresponding to 0.036 on the x-axis, where the effect of other sentiments is close to zero.

[Insert Figure 2.3 here]

Overall, the Lasso analysis suggests that including all four sentiments can yield a better fit for predicting REIT returns. However, it is notable that the price direction sentiment exhibits the strongest effect compared to the other sentiments.

Optimal Model Selection and Path Analysis

Finally, we employ Covariance-based Structural Equation Modeling (SEM) and path analysis to further investigate the relationships established between media content sentiments and the performance of REITs. SEM is a comprehensive statistical technique that allows for the examination of complex relationships among multiple variables simultaneously. By modeling both the observed and latent variables, SEM enables us to assess the direct and indirect effects of media content sentiments on REIT returns.

The use of SEM in our research is particularly valuable for several reasons. Firstly, SEM provides a holistic approach to analyzing the interplay between media content sentiments and REIT performance, considering both the measured variables (such as sentiment dimensions) and latent constructs (such as investor sentiment). This allows us to capture the underlying mechanisms and dynamics at play in a more comprehensive manner.

Secondly, SEM facilitates the evaluation of the overall model fit and goodness-of-fit indices, which provide statistical evidence regarding the validity and reliability of our proposed model. By examining fit indices such as the chi-square test, standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA), Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), and Schwarz Bayesian Criterion (SBC), we are able to assess the degree to which our model aligns with the observed data. This comprehensive evaluation enables us to determine the robustness and reliability of the relationships between media content sentiments and REIT returns.

Path analysis, a component of SEM, enables us to estimate and interpret the direct and indirect effects of the predictor variables on the outcome variable. By quantifying the strength and significance of these paths, we gain insights into the specific pathways through which media content sentiments influence REIT returns. This allows us to understand the relative importance of each sentiment dimension in driving the overall effect on REIT performance.

By integrating SEM and path analysis into our research framework, we aim to provide a comprehensive understanding of the complex interrelationships between media content sentiments and REIT performance. This approach allows us to go beyond simple correlation analyses and uncover the underlying mechanisms and dynamics that drive these relationships. The findings from

SEM and path analysis will enhance our understanding of how media content sentiments influence REIT returns.

In summary, SEM and path analysis offer a robust and comprehensive framework for analyzing the complex relationships between media content sentiments and REIT performance. By utilizing these techniques, we can assess the direct and indirect effects of media content sentiments, evaluate model fit, and uncover the specific pathways through which these sentiments influence REIT returns.

We conducted a series of Structural Equation Modeling (SEM) and Path analyses to examine the relationship between media content sentiments and REIT returns. Initially, we developed Model 1, which included all four sentiments predicting the excess return directly. The model diagram and results from the analysis, presented in Figure 2.4 and the corresponding results table, indicate significant paths between all sentiments and the excess return. Specifically, Pricedirection and EmotionVsFact had significant effects at the 1% level, while Stress and Dividends showed significant effects at the 10% level. Variance analysis revealed that the exogenous variables had small, estimated variance parameters, indicating consistency and reliability in their measurement. However, the error variable (Return) exhibited larger variance (0.71354), suggesting the presence of measurement error or inconsistency in the observed indicators.

[Insert Figure 2.4 here]

Moving forward, we extended the analysis to Model 2, which considered both direct and indirect effects of sentiment variables on the excess return. The model diagram and the results, presented in Figure 2.5 and the corresponding table, demonstrated significant indirect effects of

Stress on Dividends, Dividends on EmotionVsFact, and EmotionVsFact on Pricedirection, all at the 1% level. The direct effects remained consistent with the findings from Model 1. The variance analysis results were also similar to those of the previous model.

[Insert Figure 2.5 here]

In Model 3, we focused solely on the indirect effects of Stress, Dividends, and EmotionVsFact, along with the direct effect of Pricedirection on the excess return. All path estimates in this model were significant at the 1% level, and the variance analysis results were consistent with the previous models. The model and its related results are shown in Figure 2.6 and its corresponding results table.

[Insert Figure 2.6 here]

Furthermore, we explored additional models by excluding Stress and Dividends separately, resulting in Models 4, 5, 6, 7, 8, and 9. The decision to exclude these variables was based on their lower significance levels in the initial models. In addition, as indicated by the Lasso analysis results, these variables and especially stress has the weakest effect on predicting REIT return, specifically in terms of improving adjusted R-squared and AIC. Figures 2.7 to 2.12, along with their corresponding results table, present these models and results for them. The significance of the estimated parameters and variance parameters remained consistent across these models.

[Insert Figure 2.7 here]

[Insert Figure 2.8 here]

[Insert Figure 2.9 here]

[Insert Figure 2.10 here]

[Insert Figure 2.11 here]

[Insert Figure 2.12 here]

To assess the goodness of fit among the introduced models, we utilized various criteria outlined earlier, as presented in Table 2.6. Notably, all the estimated parameters associated with the paths in our nine models were found to be statistically significant. Therefore, our focus shifted towards comparing the models based on their overall fit and identifying the model that demonstrated the best relative performance. It is important to note that comparing the first three models with the rest of the models is not appropriate, particularly when considering information-theoretic fit indices such as AIC, CAIC, and SBC. This discrepancy arises from the fact that the first three models include four sentiment variables, while the other models consist of three sentiment variables. Consequently, these fit indices tend to favor models with a lower number of included variables, leading to an unfair comparison between the different model groups.

[Insert Table 2.6 here]

We then proceeded to evaluate the models using the chi-square test. It is important to note that the chi-square test statistic tends to favor models with a higher number of parameters and does not account for model parsimony. Consequently, models with direct effects (Model 1, 4, and 7) exhibited a perfect fit according to this criterion. However, while these models fit the data well, they may not provide a concise explanation of the observed data. Thus, relying solely on the chi-square statistic as a criterion for model comparison is not recommended. Upon analyzing the chi-square results, we found that models 2, 3, 6, 8, and 9 yielded p-values below the significance threshold of 0.05, indicating a rejection of the null hypothesis of good fit for these models.

Another criterion we considered is the standardized root mean square residual (SRMR). The SRMR measures the discrepancy between the fitted covariance matrix and the observed covariance matrix in a standardized manner. It is important to note that the SRMR does not account for model parsimony. As indicated in the table, models with fewer degrees of freedom tend to have smaller SRMR values. Typically, a model with an SRMR below 0.05 is considered acceptable. Applying this criterion to our analysis, we find that Model 2 and Model 3 are either not acceptable or marginally acceptable due to their SRMR values exceeding the threshold.

We also examined the root mean square error of approximation (RMSEA) as another criterion for model evaluation. The RMSEA considers both model fit and parsimony. The criterion for accepting a model is typically an RMSEA value below 0.05. In our analysis, Models 2, 3, 8, and 9 do not meet this criterion and are therefore deemed not acceptable. This suggests that these models have a relatively poor fit to the data, considering both the model's complexity and the observed covariance matrix.

We further examined information-theoretic fit indices, including the Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), and Schwarz Bayesian Criterion (SBC). These indices take into account both the model's goodness of fit and its parsimony. Across these indices, Model 5 consistently emerges as the best-performing model among the competing alternatives. Notably, Model 5 demonstrates good absolute fit, as evidenced by its low SRMR value of 0.005. Moreover, even when considering the model fit chi-square test statistic, Model 5 stands out as the only model with a degree of freedom greater than zero that meets this criterion. Overall, the information-theoretic fit indices strongly support Model 5 as the most favorable choice, suggesting its optimal balance between model fit and simplicity.

In conclusion, the findings from the path analysis indicate that Model 5 exhibits the best overall fit among the alternative models considered. This model not only performs good but also demonstrates superior fit compared to the other models. Therefore, Model 5 emerges as the most suitable choice for capturing the relationships and predicting the outcomes in our analysis. However, it is important to acknowledge that the direct effect models (Model 1, Model 4, and Model 7) could also be considered viable options given their satisfactory fit. Ultimately, the selection of the optimal model should be based on careful evaluation of the specific research objectives, theoretical considerations, and the trade-off between complexity and fit.

V. CONCLUSION

In this study, we have examined the interaction between media content sentiments and Real Estate Investment Trusts (REITs) returns and volatility. By utilizing proprietary investor sentiment measures developed by Thompson Reuters MarketPsych, we have gained valuable insights into the role of media content sentiments in shaping the performance of REITs. Our research has contributed to the existing literature by employing a comprehensive multi-step approach, incorporating various analytical techniques to analyze the relationship between sentiments and REIT performance.

First, our time series regression analysis revealed that the four media content sentiments, namely stress, emotions vs. facts, dividends, and price direction, along with a market premium factor, were statistically significant in explaining the excess returns across different types of REITs and weighting schemes. These sentiments provided explanatory power beyond traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model. These findings highlight the importance of considering media content sentiments as a valuable addition to existing models when seeking a deeper understanding of REIT returns.

To account for potential biases and volatility clustering, we conducted autocorrelation checks and employed Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. Our results confirmed the presence of volatility clustering and provided insights into the dynamics of volatility in the context of media content sentiments. These findings have implications for risk management and the modeling of REIT returns, considering the role of sentiments in driving volatility patterns.

Furthermore, through Lasso analysis, we identified that that including all four sentiments can yield a better fit for predicting REIT returns. However, it is notable that the price direction sentiment exhibits the strongest effect compared to the other sentiments. In addition, we validated the relationships established in previous steps through Covariance-based Structural Equation Modeling (SEM) and path analysis. These analyses provided a robust framework for understanding the complex interplay between media content sentiments and REIT performance. The findings supported the overall fit of the model and confirmed the direct and indirect effects of media content sentiments on REIT returns.

In conclusion, this research has shed light on the significant role of media content sentiments in driving the performance of REITs. By utilizing proprietary sentiment measures, incorporating various analytical techniques, and following a comprehensive approach, we have contributed to the existing literature on investor sentiment, media effects, and financial market dynamics. The findings from this study have practical implications for investors, analysts, and policymakers, enabling them to make informed decisions, manage risks, and better understand the drivers of REIT performance in the ever-evolving real estate market. Future research may expand on this study by considering additional sentiment dimensions, incorporating alternative data sources, and exploring the impact of sentiment on other aspects of the REIT market, such as liquidity and market efficiency.

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Table 2.1-Descriptive statistics and correlations.

	Stress	Emotionvsfact	Pricedirection	Dividends	REIT-VW	EREIT-VW	MREIT-VW	REIT-EW	EREIT-EW	MREIT-EW
Panel A:										
N	1762	1762	1762	1762	1762	1762	1762	1762	1762	1762
Mean	0.0439	0.3697	0.0099	0.0036	0.0391	0.0409	0.0330	0.0401	0.0413	0.0333
Std Dev	0.0120	0.0705	0.0094	0.0038	0.8614	0.8830	0.8298	0.8031	0.8537	0.7975
Min	0.0106	0.0715	-0.0538	-0.0169	-4.57	-4.71	-4.18	-4.24	-4.49	-4.07
Max	0.1167	0.7111	0.1542	0.0332	3.44	3.37	4.52	3.5	3.31	4.19
Panel B:										
Stress	1.0000									
Emotionvsfact	0.2355	1.0000								
Pricedirection	-0.1528	-0.2877	1.0000							
Dividends	-0.1221	-0.2559	0.0567	1.0000						
REIT-VW	-0.0635	-0.0004	0.1781	0.0399	1.0000					
EREIT-VW	-0.0626	-0.0024	0.1749	0.0400	-	1.0000				
MREIT-VW	-0.0431	0.0177	0.1487	0.0186	-	-	1.0000			
REIT-EW	-0.0590	0.0076	0.1809	0.0343	-	-	-	1.0000		
EREIT-EW	-0.0588	0.0047	0.1762	0.0379	-	-	-	-	1.0000	
MREIT-EW	-0.0411	0.0196	0.1582	0.0043	-	-	-	-	-	1.0000

Note: REIT-VW represents the value-weighted average of US REIT excess return, EREIT-VW denotes the value-weighted average of US equity REIT excess return, and MREIT-VW signifies the value-weighted average of US mortgage REIT excess return. Similarly, REIT-EW corresponds to the equally weighted average of US REIT excess return, EREIT-EW represents the equally weighted average of US equity REIT excess return, and MREIT-EW indicates the equally weighted average of US mortgage REIT excess return.

Table 2.2- OLS result

	CAPM		3-Factor		Model 1		Model 2	
	VW	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**	**EW**
MKT	0.6022*** (0.0201)	0.6211*** (0.0177)	0.6030*** (0.0204)	0.5976*** (0.0177)	0.5897*** (0.0199)	0.8756*** (0.0119)	0.5905*** (0.0201)	0.5865*** (0.0180)
SMB			-0.0721** (0.0342)	0.2137*** (0.0297)			-0.0755** (0.0336)	0.2104*** (0.0290)
HML			-0.1567*** (0.0332)	-0.0084*** (0.0289)			-0.1619*** (0.0327)	-0.0131*** (0.0280)
Stress					-3.7409*** (1.4211)	-3.3163*** (1.2451)	-3.8373*** (1.4115)	-3.5314*** (1.2280)
Emotionvsfact					0.7863*** (0.2557)	0.8108*** (0.2240)	0.7979*** (0.2539)	0.7699*** (0.2209)
Pricedirection					11.9863*** (1.8381)	11.1168*** (1.6106)	12.1463*** (1.8257)	10.8013*** (1.5883)
Dividends					10.4578** (4.4982)	9.0899** (0.0175)	10.6299** (4.4666)	9.4785** (3.8857)
N	1762	1762	1762	1762	1762	1762	1762	1762
adj. R-sq	0.337	0.412	0.345	0.429	0.357	0.432	0.366	0.448

Note: Standard errors are in parentheses. Standard errors for the regression were obtained using 500 bootstrap replicates. $*$ $p < 0.1$. $**$ $p < 0.05$. $***$ $p < 0.01$.

MKT denotes the market premium factor, SMB represents the Fama-French size factor (Small minus Big), and HML signifies the Fama-French 3-factor value factor (High minus Low).

Table 2.3- Equity and Mortgage REIT result

	CAPM		3-Factor		Model 1		Model 2	
	VW	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**	**EW**
Panel A: Results for Equity REIT Return								
MKT	0.6136***	0.6440***	0.6152***	0.6213***	0.9818***	0.6322***	0.6027***	0.6099***
	(0.0207)	(0.0191)	(0.0209)	(0.0192)	(0.0147)	(0.0189)	(0.0207)	(0.0190)
SMB			-0.0845**	0.1938***			-0.0878**	0.1907***
			(0.0351)	(0.0323)			(0.0346)	(0.0318)
HML			-0.1700***	-0.0377			-0.1753***	-0.0426
			(0.0341)	(0.0314)			(0.0336)	(0.0309)
Stress					-3.7544**	-3.4786***	-3.8530***	-3.7056***
					(1.4623)	(1.3477)	(1.4510)	(1.3340)
Emotionvsfact					0.7635***	0.8177***	0.7772***	0.7800***
					(0.2631)	(0.2425)	(0.2610)	(0.2399)
Pricedirection					11.9421***	11.4219***	12.1244***	11.1447***
					(1.8915)	(1.7433)	(1.8768)	(1.7254)
Dividends					10.6086**	10.3060**	10.7845**	10.7158**
					(4.6288)	(4.2661)	(4.5916)	(4.2212)
N	1762	1762	1762	1762	1762	1762	1762	1762
adj. R-sq	0.333	0.392	0.342	0.405	0.352	0.411	0.362	0.423
Panel B: Results for Mortgage REIT Return								
MKT	0.5003***	0.5344***	0.4900***	0.5079***	0.7718***	0.7458***	0.7425***	0.7122***
	(0.0206)	(0.0190)	(0.0209)	(0.0189)	(0.0158)	(0.0138)	(0.0149)	(0.0126)
SMB			0.1308***	0.2950***			0.3435***	0.4430***
			(0.0350)	(0.0316)			(0.0298)	(0.0251)
HML			0.0866**	0.1235***			0.6798***	0.6975***
			(0.0341)	(0.0308)			(0.0272)	(0.0229)
Stress					-2.6144*	-2.4282*	-2.6492*	-2.5813**
					(1.4645)	(1.3493)	(1.4587)	(1.3156)
Emotionvsfact					0.8142***	0.7796***	0.7912***	0.7256***
					(0.2635)	(0.2427)	(0.2624)	(0.2366)
Pricedirection					10.0181***	10.0650***	9.8023***	9.5901***
					(1.8943)	(1.7453)	(1.8867)	(1.7016)
Dividends					6.1710	2.9540	6.2351	3.2323
					(4.6357)	(0.0189)	(4.6160)	(4.1630)
N	1762	1762	1762	1762	1762	1762	1762	1762
adj. R-sq	0.250	0.309	0.257	0.344	0.264	0.323	0.270	0.357

Note: Standard errors are in parentheses. Standard errors for the regression were obtained using 500 bootstrap replicates. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

MKT denotes the market premium factor, SMB represents the Fama-French size factor (Small minus Big), and HML signifies the Fama-French 3-factor value factor (High minus Low).

Table 2.4-GARCH result

Model		Intercept	Stress	PriceDirection	EmotionvsFact	Dividends	MKT	SMB	HML	ARCH (1)	GARCH (1)	AIC	OLS AIC
VW	1	-0.244**	-2.738**	11.185***	.612**	8.160*	0.584***	-	-	0.051***	0.929***	3608.515	3703.609
		(-2.31)	(-2.10)	(7.46)	(2.54)	(1.78)	(36.61)			(5.84)	(76.08)		
	2	-0.249**	-2.798**	11.256***	0.621***	7.997*	0.589***	-0.073**	-0.177***	0.052***	0.926***	3580.018	3680.22
		(-2.36)	(-2.18)	(7.82)	(2.60)	(1.75)	(35.80)	(-2.43)	(-6.19)	(5.82)	(71.58)		
EW	1	-0.280***	-2.478**	11.134***	0.687***	6.988*	0.604***	-	-	0.048***	0.934***	3138.832	3237.935
		(-3.01)	(-2.24)	(8.40)	(3.22)	(1.79)	(42.42)			(5.30)	(75.35)		
	2	-0.261***	-2.541**	11.014***	0.654***	7.452*	0.575***	0.201***	-0.023	0.048***	0.932***	3089.495	3189.235
		(-2.86)	(-2.35)	(8.24)	(3.09)	(1.92)	(39.90)	(7.49)	(-0.91)	(5.42)	(73.56)		

Note: Standard errors are in parentheses. Standard errors for the regression were obtained using 500 bootstrap replicates. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

Table 2.5- Lasso result

Step	Effect entered	Number of effects in	AIC	SBC	Adj r2	Parameter estimate
0	Intercept	1	1239.4028	-519.1230	0	-0.359039
1	Price Direction	2	1187.9138	-565.1378*	0.0293	17.343451
2	Stress	3	1189.0138	-558.5635	0.0293	-3.374424
3	Emotion vs Fact	4	1187.5555	-554.5476	0.0306	0.918329
4	Dividend	5	1178.2892*	-558.3398	0.0363*	9.676591

* Optimal Value of Criterion

Note: The asterisk (*) indicates the optimal value for different criteria. For the AIC (Akaike Information Criterion) and adjusted R-squared, the asterisk appears after the effect of "dividend" enters the model, indicating that including all sentiment variables provides improved predictive power. However, for the SBC (Schwarz Bayesian Criterion) criterion, the asterisk appears after the effect of "Price direction" enters the model, indicating that "Price direction" alone offers superior predictive power according to this criterion.

Table 2.6- Comparison of models fit

Models	1	2	3	4	5	6	7	8	9
Df	0	3	6	0	1	3	0	1	3
p-value	.	<0.0001	<0.0001	.	0.4792	0.0291	.	<0.0001	<0.0001
SRMR	0	0.0648	0.0682	0	0.005	0.0186	0	0.0278	0.0355
RMSEA	.	0.1339	0.0992	.	0	0.0337	.	0.0896	0.0635
AIC	30	121.77	128.05	20	18.50	23.01	20	33.14	38.33
CAIC	127.11	199.46	186.32	84.74	76.77	68.33	84.74	91.41	83.65
SBC	112.11	187.46	177.32	74.74	67.77	61.33	74.74	82.41	76.65

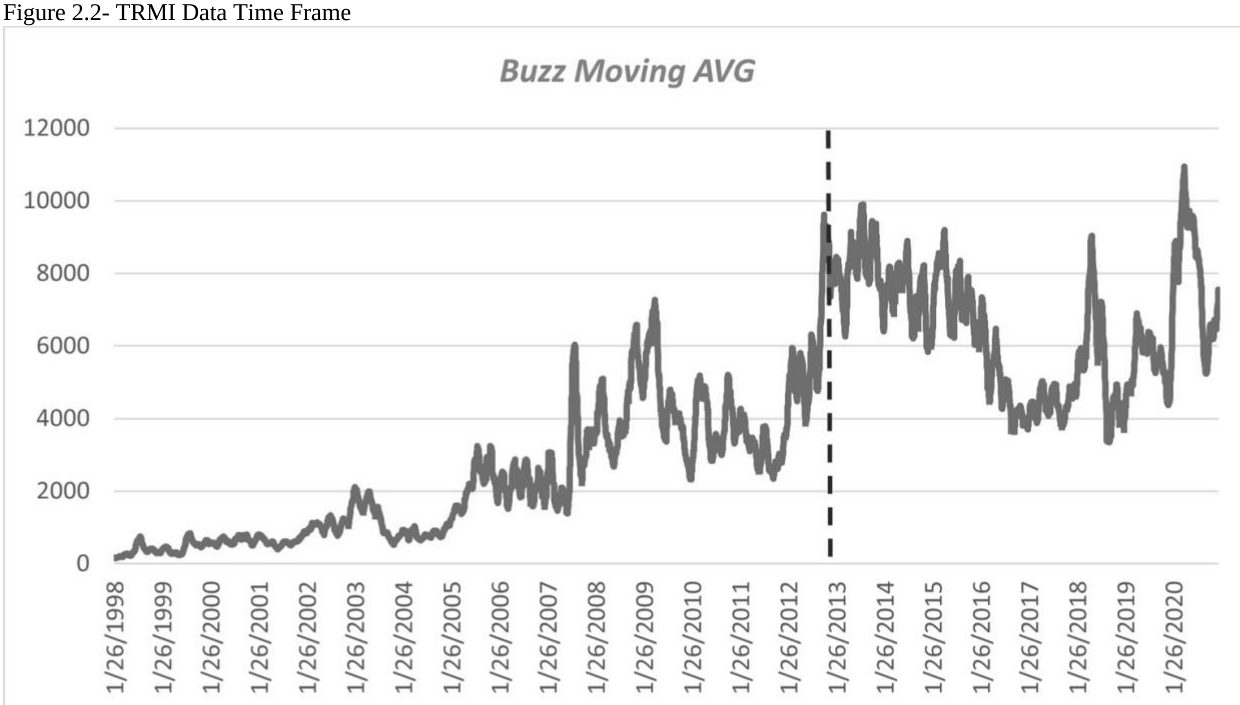
Note: Df represents the degree of freedom for each model. p-value of Chi-square, SRMR (Standardized Root Mean Square Residual), and RMSEA (Root Mean Square Error of Approximation) are absolute criteria for assessing good fit. Typically, p-values greater than 0.05, SRMR values less than 0.05, and RMSEA values less than 0.05 are considered indicative of a good fit.
AIC (Akaike Information Criterion), CAIC (Consistent Akaike Information Criterion), and SBC (Schwarz Bayesian Criterion) are comparative criteria, where lower values indicate a better fit among the competing models.

Figure 2.1-Sentiment measures and definitions.

Index	**Description:** *Investor sentiment references in news and social media to...*	Range
stress	arousal and intensity, weighted towards distress	0 to 1
emotionVsFact	all emotional sentiments, net of all factual and topical references	-1 to 1
priceDirection	price increases, net of references to price decreases	-1 to 1
dividends	dividends rising, net of references to dividends falling	-1 to 1

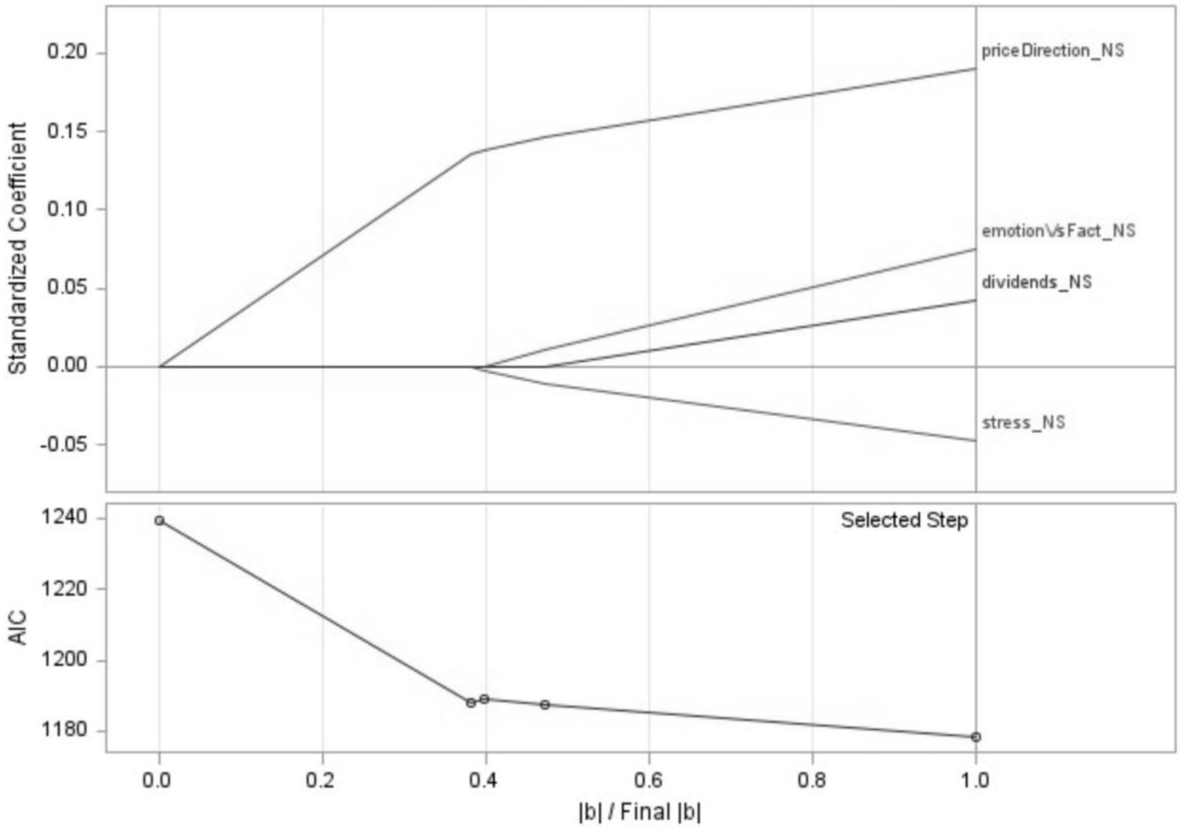
The definitions of emotional indicator data in the table are provided by the Thomson Reuters MarketPsych Indices (TRMI)

Figure 2.2- TRMI Data Time Frame



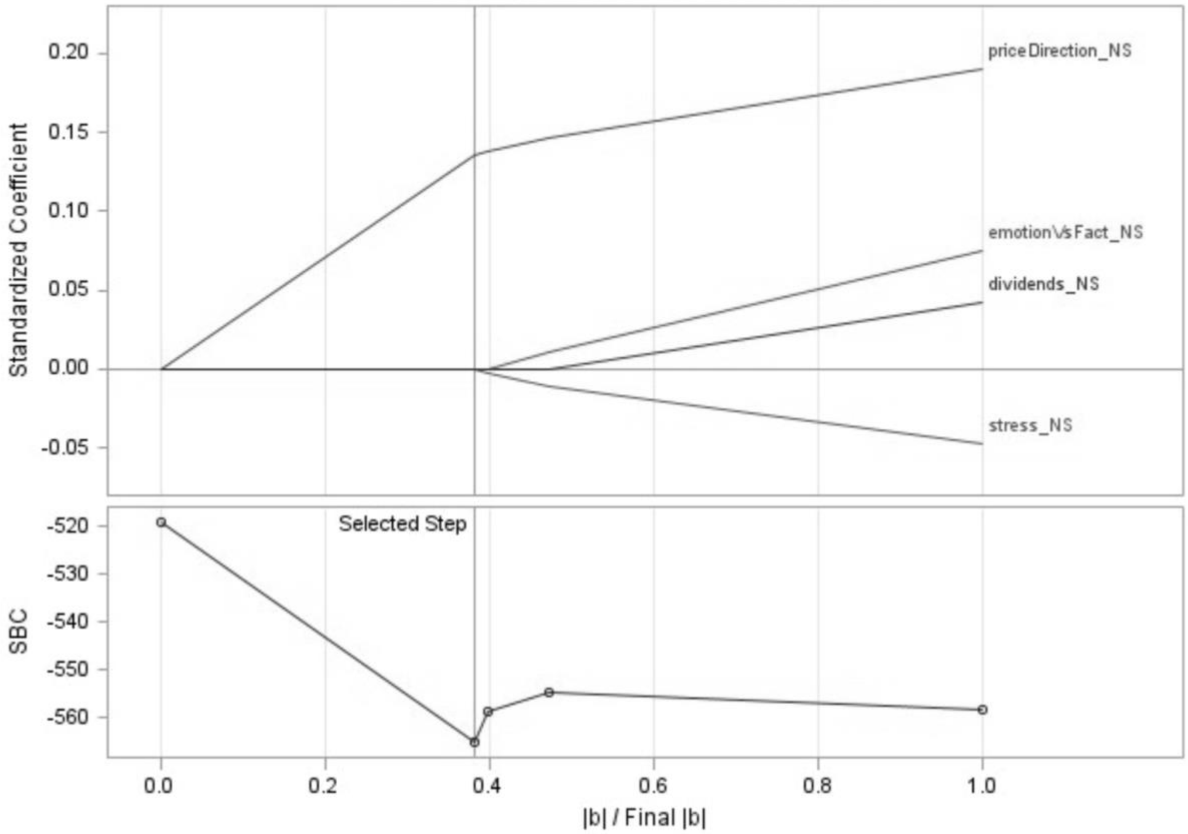
Note: The graph illustrates the monthly moving average of BUZZ in the TRMI dataset, representing the total reaction of investors captured from news and social media. A significant increase is observed in 2013, indicating a substantial rise in data availability and the inclusion of emotional data, enabling a more comprehensive assessment of investor reactions.

Figure 2.3-Lasso Analysis



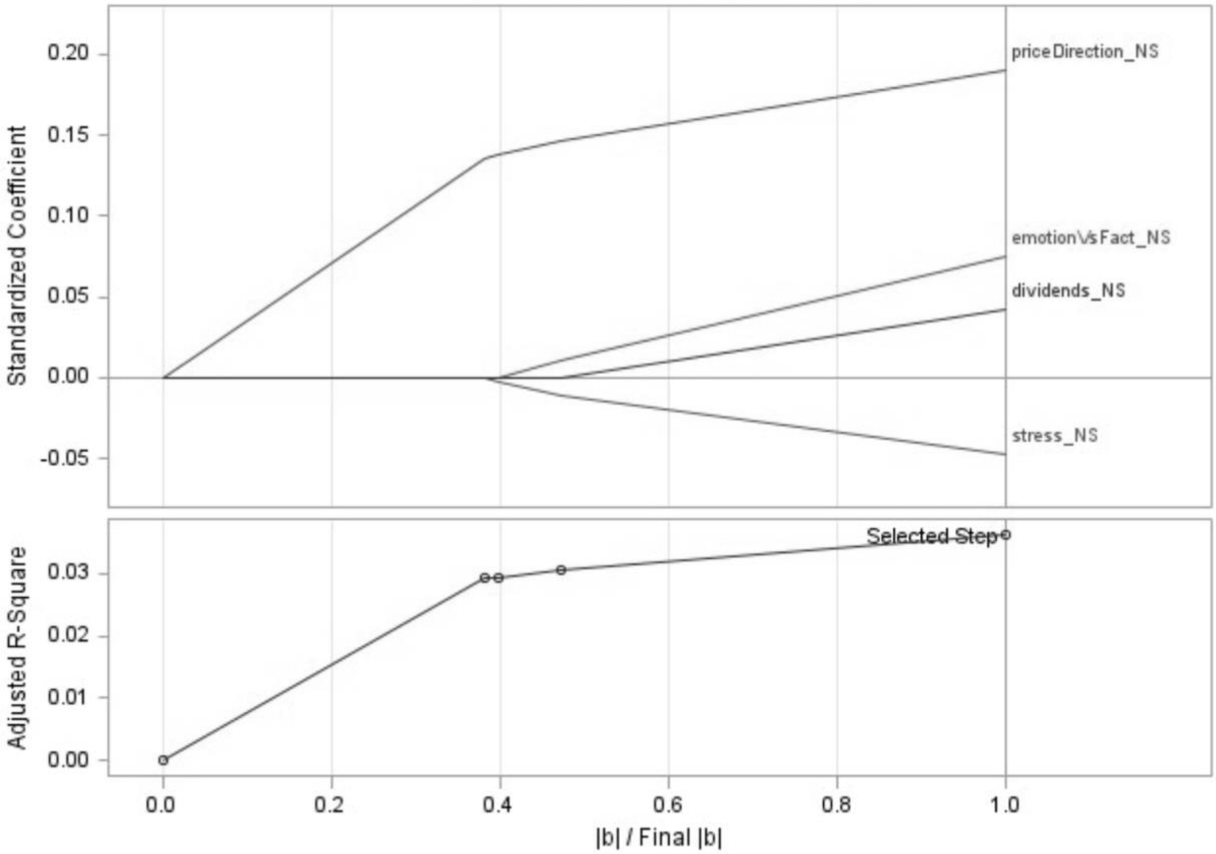
The graphs visually demonstrate the process of Lasso analysis in determining the optimal effects based on different criteria. For the AIC (Akaike Information Criterion) a vertical line appears after the effect of "dividend" enters the model, indicating that including all sentiment variables leads to improved predictive power.

Figure 2.3-Continued



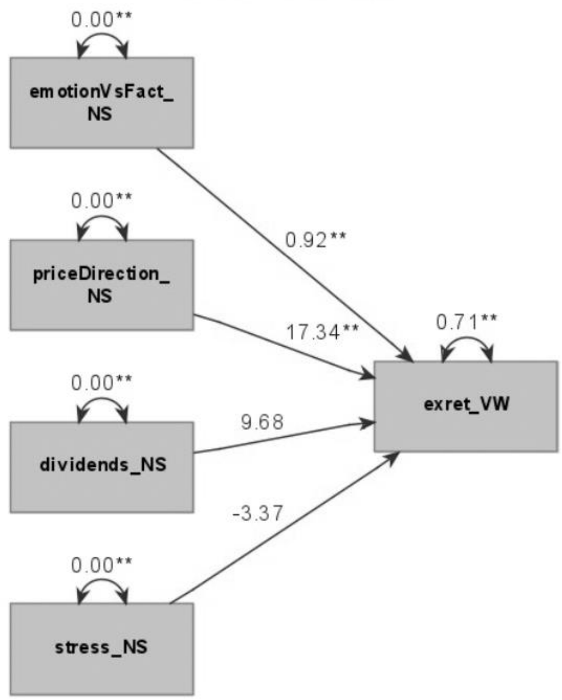
The graphs visually demonstrate the process of Lasso analysis in determining the optimal effects based on different criteria. For the SBC (Schwarz Bayesian Criterion) criterion, the vertical line appears after the effect of "Price direction" enters the model, suggesting that "Price direction" alone provides superior predictive power according to this criterion.

Figure 2.3-Continued



The graphs visually demonstrate the process of Lasso analysis in determining the optimal effects based on different criteria. For R-squared, a vertical line appears after the effect of "dividend" enters the model, indicating that including all sentiment variables leads to improved predictive power.

Figure 2.4-Model 1



PATH List

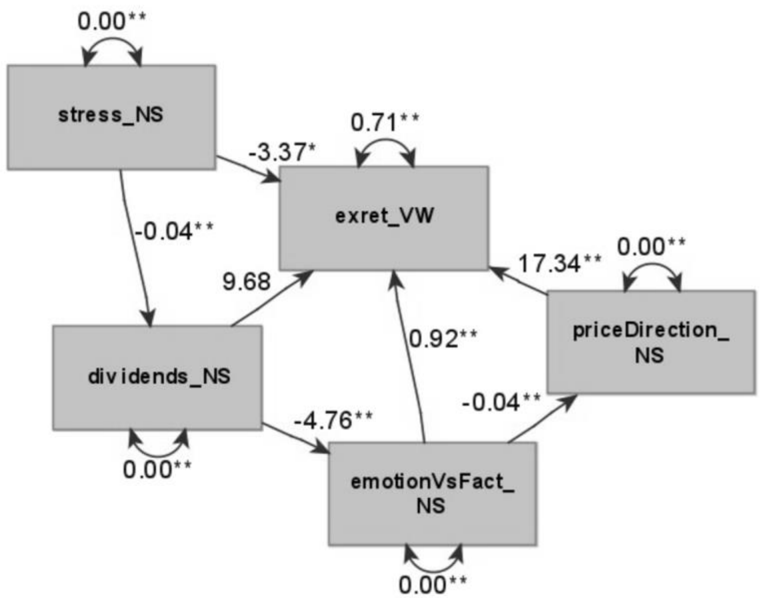
Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Stress	===>	**Return**	_Parm1	-3.37442	1.73719	-1.9425	0.0521
Dividends	===>	**Return**	_Parm2	9.67659	5.49903	1.7597	0.0785
emotionVsFact	===>	**Return**	_Parm3	0.91833	0.31249	2.9388	0.0033
priceDirection	===>	**Return**	_Parm4	17.34345	2.23623	7.7557	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**stress**	_Add01	0.0001440	<0.0001	29.6732	<0.0001
	emotionVsFact	_Add02	0.00497	0.0002	29.6732	<0.0001
	priceDirection	_Add03	0.0000889	<0.0001	29.6732	<0.0001
	dividends	_Add04	0.0000144	<0.0001	29.6732	<0.0001
Error	**Return**	_Add05	0.71354	0.02405	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

Figure 2.5-Model 2



PATH List

Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Stress	===>	**Dividends**	_Parm1	-0.03862	0.03862	-5.1623	<0.0001
Dividends	===>	**emotionVsFact**	_Parm2	-4.75546	0.42804	-11.1099	<0.0001
emotionVsFact	===>	**priceDirection**	_Parm3	-0.03778	0.00306	-12.3665	<0.0001
Stress	===>	**Return**	_Parm4	-3.37442	1.68987	-1.9969	0.0458
Dividends	===>	**Return**	_Parm5	9.67659	5.52430	1.7516	0.0798
emotionVsFact	===>	**Return**	_Parm6	0.91833	0.30697	2.9916	0.0028
priceDirection	===>	**Return**	_Parm7	17.34345	2.23623	7.7912	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**stress**	_Add01	0.0001440	<0.0001	29.6732	<0.0001
Error	**emotionVsFact**	_Add02	0.00465	0.0002	29.6732	<0.0001
	priceDirection	_Add03	0.0000818	<0.0001	29.6732	<0.0001
	dividends	_Add04	0.0000142	<0.0001	29.6732	<0.0001
	Return	_Add05	0.71354	0.02405	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

Figure 2.6-Model 3

PATH List

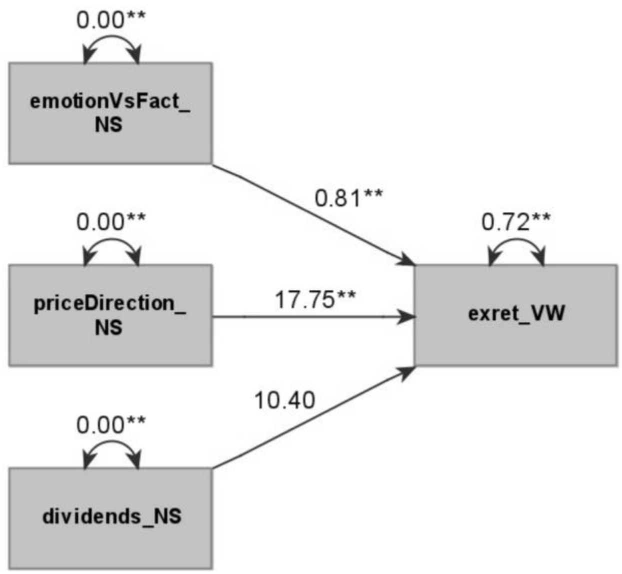
Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Stress	===>	**Dividends**	_Parm1	-0.03862	0.00748	-5.1623	<0.0001
Dividends	===>	**emotionVsFact**	_Parm2	-4.75546	0.42804	-11.1099	<0.0001
emotionVsFact	===>	**priceDirection**	_Parm3	-0.03778	0.00306	-12.3665	<0.0001
priceDirection	===>	**Return**	_Parm4	16.27894	2.14272	7.5973	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**stress**	_Add01	0.0001440	<0.0001	29.6732	<0.0001
Error	**emotionVsFact**	_Add02	0.00465	0.0002	29.6732	<0.0001
	priceDirection	_Add03	0.0000818	<0.0001	29.6732	<0.0001
	dividends	_Add04	0.0000142	<0.0001	29.6732	<0.0001
	Return	_Add05	0.71853	0.02421	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

Figure 2.7-Model 4



PATH List

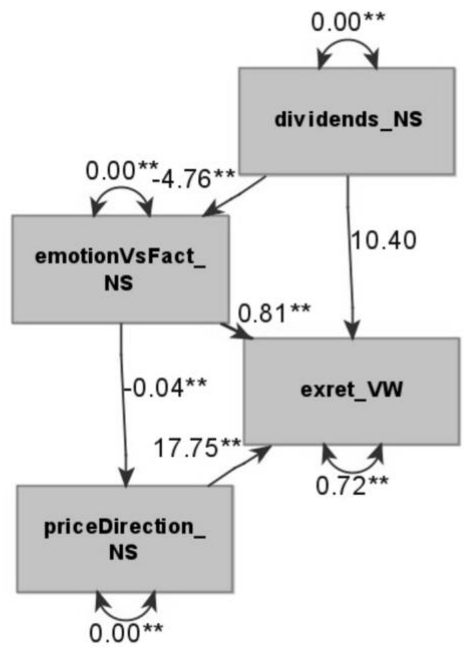
Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Dividends	===>	**Return**	_Parm1	10.39932	5.49231	1.8934	0.0583
emotionVsFact	===>	**Return**	_Parm2	0.80845	0.30766	2.6278	0.0086
priceDirection	===>	**Return**	_Parm3	17.75113	2.22874	7.9646	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**emotionVsFact**	_Add01	0.00497	0.0002	29.6732	<0.0001
	priceDirection	_Add02	0.0000889	<0.0001	29.6732	<0.0001
	dividends	_Add03	0.0000144	<0.0001	29.6732	<0.0001
Error	**Return**	_Add04	0.71507	0.02410	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

Figure 2.8-Model 5



PATH List

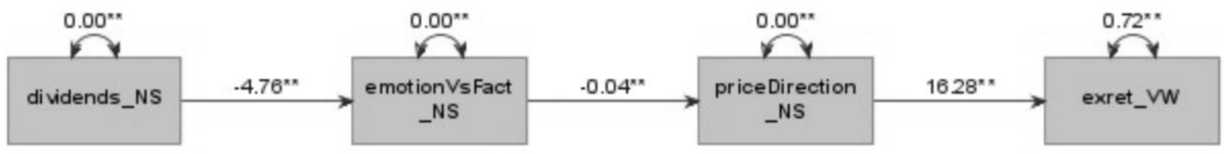
Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Dividends	===>	**emotionVsFact**	_Parm1	-4.75546	0.42804	-11.1099	<0.0001
emotionVsFact	===>	**priceDirection**	_Parm2	-0.03778	0.00306	-12.3665	<0.0001
Dividends	===>	**Return**	_Parm3	10.39932	5.49153	1.8937	0.0583
emotionVsFact	===>	**Return**	_Parm4	0.80845	0.30730	2.6308	0.0085
priceDirection	===>	**Return**	_Parm5	17.75113	2.22843	7.9658	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**dividends**	_Add01	0.0000144	<0.0001	29.6732	<0.0001
Error	**emotionVsFact**	_Add02	0.00465	0.0002	29.6732	<0.0001
	priceDirection	_Add03	0.0000818	<0.0001	29.6732	<0.0001
	Return	_Add04	0.71507	0.02410	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

Figure 2.9-Model 6



PATH List

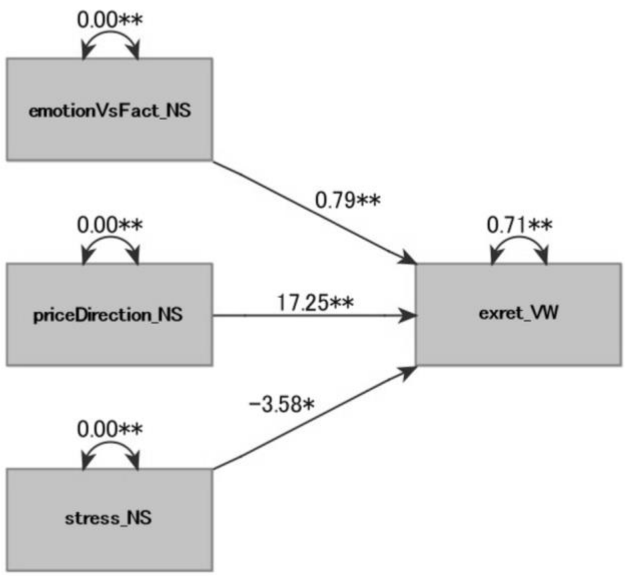
Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Dividends	===>	**emotionVsFact**	_Parm1	-4.75546	0.42804	-11.1099	<0.0001
emotionVsFact	===>	**priceDirection**	_Parm2	-0.03778	0.00306	-12.3665	<0.0001
priceDirection	===>	**Return**	_Parm3	16.27880	2.14272	7.5973	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**dividends**	_Add01	0.0000144	<0.0001	29.6732	<0.0001
Error	**emotionVsFact**	_Add02	0.00465	0.0002	29.6732	<0.0001
	priceDirection	_Add03	0.0000818	<0.0001	29.6732	<0.0001
	Return	_Add04	0.71853	0.02421	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

Figure 2.10-Model 7



PATH List

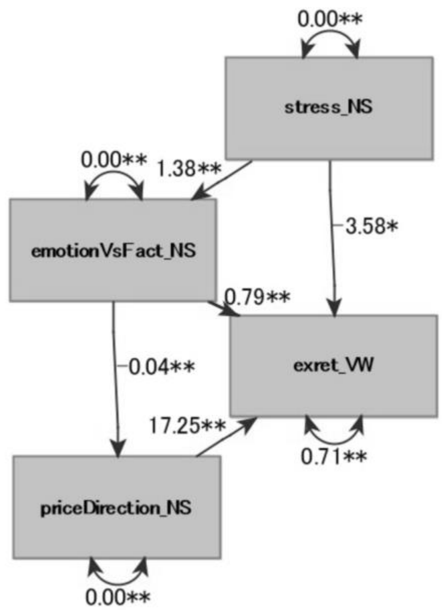
Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Stress	===>	**Return**	_Parm1	-3.58126	1.73473	-2.0644	0.0390
emotionVsFact	===>	**Return**	_Parm2	0.78990	0.30411	2.5974	0.0094
priceDirection	===>	**Return**	_Parm3	17.25256	2.23760	7.7103	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**stress**	_Add01	0.0001440	<0.0001	29.6732	<0.0001
	emotionVsFact	_Add02	0.00497	0.0002	29.6732	<0.0001
	priceDirection	_Add03	0.0000889	<0.0001	29.6732	<0.0001
Error	**Return**	_Add04	0.71479	0.02409	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

Figure 2.11-Model 8



PATH List

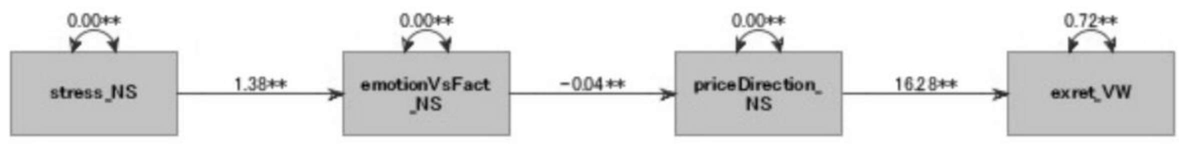
Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Stress	===>	**emotionVsFact**	_Parm1	1.38415	0.13611	10.1697	<0.0001
emotionVsFact	===>	**priceDirection**	_Parm2	-0.03778	0.00306	-12.3665	<0.0001
Stress	===>	**Return**	_Parm3	-3.58126	1.72729	-2.0733	0.0381
emotionVsFact	===>	**Return**	_Parm4	0.78990	0.30573	2.5837	0.0098
priceDirection	===>	**Return**	_Parm5	17.25256	2.22800	7.7435	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**stress**	_Add01	0.0001440	<0.0001	29.6732	<0.0001
Error	**emotionVsFact**	_Add02	0.00470	0.0002	29.6732	<0.0001
	priceDirection	_Add03	0.0000818	<0.0001	29.6732	<0.0001
	Return	_Add04	0.71479	0.02409	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

Figure 2.12-Model 9



PATH List

Path			Parameter	Estimate	Std Error	t Value	Pr > |t|
Stress	===>	**emotionVsFact**	_Parm1	1.38415	0.13611	10.1697	<0.0001
emotionVsFact	===>	**priceDirection**	_Parm2	-0.03778	0.00306	-12.3665	<0.0001
priceDirection	===>	**Return**	_Parm3	16.27880	2.14272	7.5973	<0.0001

Variance Parameters

Variance Type	Variable	Parameter	Estimate	Std Error	t Value	Pr > |t|
Exogenous	**stress**	_Add01	0.0001440	<0.0001	29.6732	<0.0001
Error	**emotionVsFact**	_Add02	0.00470	0.0002	29.6732	<0.0001
	priceDirection	_Add03	0.0000818	<0.0001	29.6732	<0.0001
	Return	_Add04	0.71853	0.02421	29.6732	<0.0001

Note: The above table presents the estimates for each presented path in the path analysis model, along with their corresponding standard errors, t-values, and p-values. The estimates indicate the strength and direction of the relationships between the variables. The bottom table provides the variance results of the path analysis, including estimates for variances, their standard errors, t-values, and p-values. The estimates for variances represent the variability of the latent variables in the path analysis model.

APPENDIX: DEFINITIONS OF VARIABLES

AIC: AIC stands for Akaike Information Criterion. It is a measure used for model selection, balancing the goodness of fit with the complexity of the model. AIC penalizes models with a larger number of parameters, aiming to select the model that provides the best balance between fit and parsimony. Lower AIC values indicate better model fit.

Airbnb_Phase1_Ring1: Density of Airbnb listings within a certain measure in Phase 1 and Ring 1. It represents the concentration or abundance of Airbnb rental activity in a specific area during Phase 1 and within the first ring of geographic proximity.

Airbnb_Phase1_Ring2: Density of Airbnb listings within a certain measure in Phase 1 and Ring 2. It represents the concentration or abundance of Airbnb rental activity in a specific area during Phase 1 and within the second ring of geographic proximity.

Airbnb_Phase1_Ring3: Density of Airbnb listings within a certain measure in Phase 1 and Ring 3. It represents the concentration or abundance of Airbnb rental activity in a specific area during Phase 1 and within the third ring of geographic proximity.

Airbnb_Phase2_Ring1: Density of Airbnb listings within a certain measure in Phase 2 and Ring 1. It represents the concentration or abundance of Airbnb rental activity in a specific area during Phase 2 and within the first ring of geographic proximity.

Airbnb_Phase3_Ring1: Density of Airbnb listings within a certain measure in Phase 3 and Ring 1. It represents the concentration or abundance of Airbnb rental activity in a specific area during Phase 3 and within the first ring of geographic proximity.

CAIC: CAIC stands for Consistent Akaike Information Criterion. It is a modification of AIC that takes into account the sample size. Similar to AIC, CAIC also penalizes model complexity, with lower values indicating better model fit.

Df: Df stands for degrees of freedom. It refers to the number of independent pieces of information available in a statistical analysis. In the context of model fit assessment, it represents the difference between the number of observed variables and the number of estimated parameters.

dividends: This sentiment captures investor sentiment regarding changes in dividend payments. It reflects the net sentiment towards rising dividends, considering references to falling dividends. The range of values for dividends sentiment is from -1 (indicating a negative sentiment towards dividend changes) to 1 (indicating a positive sentiment towards dividend changes).

emotionVsFact: This sentiment captures all emotional sentiments expressed by investors in news and social media, net of factual and topical references. It represents the overall emotional tone in investor sentiment, regardless of whether it is positive or negative. The range of values for emotionVsFact sentiment is from -1 (indicating predominantly negative emotions) to 1 (indicating predominantly positive emotions).

EREIT-EW: Equity REIT Equally Weighted (EW) represents the equally weighted average of excess returns for US Equity Real Estate Investment Trusts (EREITs). It focuses specifically on the equally weighted performance of equity REITs.

EREIT-VW: Equity REIT Value Weighted (VW) represents the value-weighted average of excess returns for US Equity Real Estate Investment Trusts (EREITs). It focuses specifically on the performance of equity REITs within the broader REIT market.

HML: HML represents the Fama-French 3-factor value factor (High minus Low). It captures the performance difference between high book-to-market (value) stocks and low book-to-market (growth) stocks, emphasizing the value effect in asset pricing models.

MKT: MKT represents the market premium factor. It is a factor that captures the excess return of the overall market or a broad market index, indicating the performance of the overall market beyond the risk-free rate.

Month of sale dummies: Month of sale dummies are binary variables that represent different months in which house sales take place. Each dummy variable captures a specific month, allowing for the examination of seasonal patterns and month-to-month variations in house prices. A value of 1 indicates that the sale occurred in the corresponding month, while a value of 0 indicates otherwise.

MREIT-EW: Mortgage REIT Equally Weighted (EW) represents the equally weighted average of excess returns for US Mortgage Real Estate Investment Trusts (MREITs). It examines the equally weighted performance of mortgage REITs.

MREIT-VW: Mortgage REIT Value Weighted (VW) represents the value-weighted average of excess returns for US Mortgage Real Estate Investment Trusts (MREITs). It examines the performance of mortgage REITs, which primarily invest in mortgages and mortgage-backed securities.

P: It represents the natural logarithm of the inflation-adjusted house sale price. The variable P captures the sale price of houses after adjusting for inflation, providing a standardized measure for comparison and analysis.

priceDirection: This sentiment focuses on investor sentiment related to price changes in the market. It reflects the net sentiment towards price increases, taking into account references to price decreases. The range of values for priceDirection sentiment is from -1 (indicating a negative sentiment towards price changes) to 1 (indicating a positive sentiment towards price changes).

p-value (Chi-square): The p-value represents the probability of observing a Chi-square test statistic as extreme as, or more extreme than, the actual observed value, assuming the null hypothesis is true. A p-value less than a predefined significance level (often 0.05) indicates statistical significance.

REIT-EW: REIT Equally Weighted (EW) represents the equally weighted average of excess returns for US Real Estate Investment Trusts (REITs). It provides an alternative measure of REIT performance where each REIT is given equal weight in the portfolio.

REIT-VW: REIT Value Weighted (VW) represents the value-weighted average of excess returns for US Real Estate Investment Trusts (REITs). It measures the performance of a portfolio of REITs based on their market value weights.

RMSEA: RMSEA stands for Root Mean Square Error of Approximation. It is a measure of how well the model fits the data, taking into account both the discrepancy and the complexity of the model. It provides an estimate of the average discrepancy between the observed covariance matrix and the model-implied covariance matrix, with lower values indicating a better fit.

SBC: SBC stands for Schwarz Bayesian Criterion, also known as the Bayesian Information Criterion (BIC). It is another measure used for model selection, balancing fit and complexity. Like AIC and CAIC, SBC penalizes models with more parameters. Lower SBC values indicate better model fit and parsimony.

School district dummies: Similar to zip code dummies, school district dummies are binary variables that capture the presence of specific school districts. Each dummy variable represents a different school district, allowing for the consideration of school district effects on house prices. A value of 1 indicates that the property falls within the corresponding school district, while a value of 0 indicates otherwise.

SMB: SMB represents the Fama-French size factor (Small minus Big). It measures the performance difference between small-cap stocks and large-cap stocks, highlighting the size effect in asset pricing models.

SRMR: SRMR stands for Standardized Root Mean Square Residual. It is a measure of the discrepancy between the observed covariance matrix and the model-implied covariance matrix. It provides an overall measure of how well the model fits the data, with lower values indicating a better fit.

stress: A measure of arousal and intensity in investor sentiment, primarily reflecting distress-related sentiments. It represents the weighted sentiment towards negative emotions associated with market stress. The range of values for stress sentiment is from 0 (indicating low distress) to 1 (indicating high distress).

Year of sale dummies: Year of sale dummies are binary variables that represent different years in which house sales occur. Each dummy variable captures a specific year, enabling the analysis of temporal variations in house prices. A value of 1 indicates that the sale occurred in the corresponding year, while a value of 0 indicates otherwise.

Zip code dummies: These are binary variables used to indicate specific zip code locations. Each dummy variable represents a different zip code, allowing for the inclusion of geographical variations in the analysis. A value of 1 indicates that the property is located within the corresponding zip code, while a value of 0 indicates otherwise.

VITA

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- Fall 2022 | Online | ***REST 454- Real Estate Investment Analysis*** | (4.33)
- Summer 2022 | In-class | ***FIN 323- Introduction to Financial Management*** | (N/A)
- Spring 2022 | Online | ***FIN 434- Management of Financial Institutions*** | (4.15)
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