Essays on Mutual Fund Flows, Value Corrections and Price Pressure in Global Real Estate Stocks

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Contents

1 Introduction

Fund managers' income is tied directly to assets under management (AuM). Thus, their income generally increases with more AuM. One way to increase AuM is through an outperforming investment strategy. Firstly, since a good performance by construction rise the AuM. Secondly, outperforming funds receive higher inflows and thereby increase the AuM.

In this dissertation, we study the determinants of mutual fund flows. We first investigate how price pressures may be driven by the mean reversion behavior of mispriced stocks. Next, we explore an investment strategy on earnings surprises and the effect of investor attention.

In chapter 2, we use mutual fund flows and their determinants to examine the performance-chasing behavior of mutual fund investors. The consensus in the literature is that investors exhibit great sensitivity to past fund performance. Most studies find that investors disproportionate chase top-performing funds, and observe low fund flow sensitivity to poor-performing funds. Chevalier and Ellison (1997) note there is a moral hazard risk for fund managers due to the convex flow-performance relationship. Because they are dependent on AuM, they may accept extraordinary risks to increase a probability of attaining higher returns and inflows. Investors want returns optimized as well, but they want fund managers to remain cognizant of the associated risks.

Consistent with this 'moral hazard' effect, (Brown et al. (1996)) provide evidence that mid-year 'loser' funds tend to increase fund volatility toward the end of the year in order to increase returns. Our analysis uses monthly data from the Morningstar Direct investment research database on a fund-level basis for the January 1999 through December 2014 period. Our mutual fund flow model is based on a piecewise linear regression model (Sirri and Tufano (1998)).

Earlier studies relied on approximated flows because exact fund flow data were not available. However, since 1996, funds have been required to report precise dollar amounts to the SEC. Our results show a slightly overestimated flow sensitivity to high performance in the models that have approximated rather than exact fund flows. Indeed, exact fund flows are preferable, but both are highly susceptible to data entry issues, which can bias our estimation results.

In our mutual fund data, we find numerous observations that indicate unrealistically high or low fund flows that stem from data entry issues. There are two ways to handle outliers: 1) winsorize them (replace them with more plausible values), or 2) trim (exclude) them. We note that winsorizing may lead to biased results, since the true value of a positive (negative) outlier might be very low (high). Applying both procedures, we only find evidence for a convex flow-performance relationship when we winsorized outlying fund flows. When we exclude the outliers, we find evidence of fund flow sensitivity to low-performing funds.

Moreover, we find evidence for fund flow sensitivity to low-performing funds in case of each outlier treatment procedure once we apply a model controlling for past fund flows (Cashman et al. (2014)). We also find that controlling for persistence dramatically increases each fund flow model's explanatory power. This indicates that investors tend to incorporate information at varying time intervals (Del Guercio and Tkac (2002); Cashman et al. (2014)).

Our first paper shows that both model selection and outlier treatment impact fund flow sensitivity to past performance. Our results have important implications for the moral hazard effect of fund managers taking extraordinary risks to increase returns. They also suggest a delayed reaction on the part of investors to financial news.

In chapter 3, we analyze the correction speed of deviations between stock prices and fundamental values. In a fully efficient market, stock mispricing should be corrected immediately. Assuming that the net asset value (NAV) adequately proxies for a stock's fundamental value, high and persistent differences between them should be impossible. However, NAV spreads tend to fluctuate widely, and we do find that stocks may be highly over- or undervalued. A fundamental issue is how to take advantage of such mispricings. Therefore, the question is: What determines the correction speed of a stock price toward its fundamental value? Or, to put it more simply: What determines the mean reversion speed of the NAV spread? We find it is positively correlated with price pressure potential.

Our analysis is based on the FTSE EPRA/ NAREIT Global Real Estate Index, which includes exchange-traded property-holding companies in countries with fair value-based accounting regimes. Our quarterly sample consists of 219 listed property holding companies from 11 countries over the January 2005 to December 2018 period. To capture the NAV spread's panel dynamics and impact of company-specific control variables, we apply a Blundell and Bond (1998) GMM-System-Estimator. We find proof for the NAV spread's mean reverting behavior towards a long-run mean NAV spread. Moreover, there is evidence that the stocks with the lowest NAV spreads relative to the other stocks in the same country tend to mean-revert the fastest.

According to the literature, online search volume is related to noise trader attention, since professional investors have access to databases like Reuters or Bloomberg (Da et al. (2011)). Remarkably, we find evidence that noise trader attention, as measured by Google searches for a company's name, slows the mean reversion speed of NAV spreads. Moreover, we find a positive dependence between NAV spreads of distinct companies in the same country. We can thus demonstrate that companies with higher levels of online search volume have a greater impact on other companies. In contrast, companies with low levels of online search volume do not impact other companies.

We also show that noise trader attention slows the assimilation of financial news into stock prices. Only the market sentiments of companies with high levels of attention (as measured by the NAV spread) are incorporated into the NAV spreads. We illustrate that the highest price pressure potential exists for undervalued stocks[1] with low levels of online search volume on a quarterly basis.

In chapter 4, we study the earnings momentum of property holding companies. In a fully efficient market, earnings information should be immediately incorporated into stock prices. However, a common market phenomenon is that earnings surprises are followed by extraordinarily high returns (Feng et al. (2014); Price et al. (2012); Bron et al. (2018)). This earnings momentum is revert to a result of investors misreaction to past earnings news (Chan et al. (1996); Hong and Stein (1999)).

Some research cites a link between investor attention and market reactions to earnings announcements (DellaVigna and Pollet (2009); Hirshleifer et al. (2009)).

[1] We term undervalued stocks that stocks with the lowest NAV spreads compared to the other companies in the same country.

In chapter 3, we find that online search attention slows the incorporation speed of news. In this regard, earnings are associated with a source of information about a company's future prospects (Chan et al. (1996)). We expect investor attention to intensify the post-earnings drift. Therefore, we test the impact of noise trader attention on property holding companies' future returns after the announcement of surprisingly high earnings, and pose the question: Does investor attention intensify earnings momentum?

Our data include monthly company-level information on 368 property holding companies that are members of the FTSE EPRA/NAREIT Global Real Estate Index. Our sample ranges from January 2005 to September 2019, and covers 12 industrialized countries. Relying on a Carhart four-factor model, we find evidence of earnings momentum. Our findings contradict earlier studies that observe an outperformance for holding periods up to twelve months Bron et al. (2018)). We find evidence only for the one-month holding period.

We find further that stocks with high Google search volume outperform the benchmark. Remarkably, we find that Google search volume significantly intensifies earnings momentum. As we noted, the literature typically finds that earnings momentum is related to misreactions to earnings news (Chan et al. (1996); Hong and Stein (1999)). Chapter 3 also shows that noise trader attention, as measured by Google search volume, slows the incorporation speed of financial information into stock prices. Noise trader attention seems to intensify earnings momentum.

In advance, we explore the driver of outperformance: earnings, or online search volume. We assume that positive earnings surprises attract the attention of noise traders. We posit that this attention then slows down the speed of information incorporation into stock prices, thereby increasing earnings momentum. Our results confirm this hypothesis by showing that post-earnings drift Granger-causes post-attention drift.

In sum, our results imply that, on a monthly basis, stocks with earnings surprises and high levels of online search attention to generate the highest returns.

2 Is the Flow-Performance Relationship Really Convex? - The Impact of Data Treatment and Model Specification

This paper is the result of a joint project with René-Ojas Woltering and Steffen Sebastian

Abstract This paper challenges the convexity of the flow-performance relationship, according to which investors strongly chase top-performing funds, while fund flows exhibit little to no sensitivity to past performance within the segment of poorly performing funds. Our results suggest that the flow-performance relationship is not convex, but rather linear. In contrast to prior studies, we use reported (i.e., exact) instead of approximated fund flow data, we trim (instead of winsorize) outliers, and we account for persistence in fund flows. We find that each factor contributes to serious biases. For example, investor reactions to poor performance only appear insignificant when outliers are winsorized instead of trimmed. And it is even more evident that fund investors flee poorly performing funds when the model incorporates lagged flows to account for fund flow persistence. Furthermore, our results provide evidence that the degree to which investors chase top-performing funds appears to be slightly upward biased if approximated fund flows are used. Our findings have important implications for the potential moral hazard of fund managers.

2.1 Introduction

The mutual fund literature provides strong evidence that investors are highly sensitive to past fund performance. However, most studies also find that investors tend to disproportionately chase top-performing funds, while showing little to no fund flow sensitivity to poorly performing funds (Ippolito (1992), Sirri and Tufano (1998), Berk and Green (2004), Del Guercio and Tkac (2002), and Huang et al. (2007)). This phenomenon has been dubbed the convexity of the flow-performance relationship.

The flow-performance relationship has important implications for fund managers and asset management firms, because their fee income is usually tied to the amount of assets they have under management. Berk and Green (2004) even argue that the flow-performance relationship directly determines the degree to which fund volume is affected by past performance.

According to Chevalier and Ellison (1997), a convex flow-performance relationship leads to an agency conflict between fund managers and investors. This is because managers are incentivized to manipulate risk to increase the probability of high returns and high inflows, while investors want managers to maximize risk-adjusted returns. Consistent with this '"moral hazard effect', Brown et al. (1996) empirically demonstrate that 'mid-year "loser' funds tend to increase fund volatility in the latter part of the annual assessment period. The authors also show that this effect increases over their sample period, during which industry growth and investor awareness of fund performance increased.

These studies have some commonalities. First, most had to approximate fund flows using fund size and returns, because reported fund flow data were not accessible. Approximated flows rely on the assumption that all flows occur at the end of the month, and that any dividends or distributions are reinvested (Chevalier and Ellison (1997)). Both assumptions are somewhat rigid, and raise the question of whether the usage of approximated fund flows may lead to biased regression results.

Since 1996, the Securities and Exchange Commission (SEC) has required funds to report their exact U.S. dollar fund flow. However, although exact fund flows are definitely preferable to approximated flows, both are highly sensitive to data entry issues, which may lead to strong outliers and thus biases in the econometric estimation.

This leads us to the issue of outlier treatment, which is the second potential problem these studies have in common. In order to avoid the regression results being biased by outliers in the sample, most papers winsorize their fund flows, i.e., they replace extreme outliers (positive or negative) with more plausible values, often the 1% to 99% values of the distribution. However, if the erroneousness is due to data entry problems, this approach may lead to serious biases. In this paper, we explain why extreme values should be trimmed instead (i.e., removed from the sample), and not winsorized.

Finally, the majority of past fund flow studies have neglected the potential persistence of fund flows in their empirical models. More recent studies argue that investors tend to react to information at somewhat different time intervals (Del Guercio and Tkac (2002), Cashman et al. (2014)). Therefore, a control for persistence appears to be essential.

In this paper, we reexamine the flow-performance relationship of mutual funds by using reported instead of approximated flows and trimmed instead of winsorized extreme values. We also control for potential persistence of fund flows. Our empirical study is based on monthly data of U.S. mutual funds from 1999 through 2014.

Our key finding is that the winsorization of outliers leads to serious biases. Investors only *appear* insensitive to poor past performance when outliers are winsorized. When they are trimmed instead, we find evidence of a significant investor reaction to poor past performance. The reaction becomes even more obvious when the regression model controls for the persistence of fund flows. Interestingly, even with winsorized fund flows, we find some evidence of investor reaction to poor performance if we control for fund flow persistence. The use of lagged fund flows therefore appears to counteract potential biases from the inappropriate use of winsorization. Moreover, we find that the reaction of investors to superior performance is slightly overestimated if approximated instead of exact flows are used.

Our results challenge the convexity of the flow-performance relationship because we provide evidence that investors are sensitive to both poor and good past performance. Our findings have important implications for the potential moral hazard of fund managers. The lack of convexity implies that investors are withdrawing money for poor-performing funds. Contrary to previous research, fund managers and asset management companies should not be motivated to increase risk in order to benefit from potential strong performance. Our findings reveal that, ultimately, they would be penalized symmetrically for any underperformance that may accompany this risk-taking behavior.

Our paper contributes to a growing strand of literature that challenges the convexity of the flow-performance relationship. Using market share-adjusted fund flows, Spiegel and Zhang (2013) find evidence that investors do flee poor performance. Furthermore, Clifford et al. (2014) document a linear flow-performance relationship for the subsample of the largest mutual funds. Interestingly, both findings rely on modifications of the original research setting. The authors of both papers highlight that their studies should not be taken as a critique of established articles for that reason. It is also important to note that both papers document evidence against a linear flow-performance relationship by focusing on an alternate setting compared to classical studies of the flow performance relationship. Our article is the first to demonstrate a linear flow-performance relationship in a classical setting.

The remainder of this paper is organized as follows. Section 2.2 describes our data and variables and provides some descriptive statistics. Section 2.3 provides the regression results for the flow-performance relationship using our suggested approach. Section 2.4 concludes.

2.2 Base Model, Data Sources, and Sample Description

Base Model

The flow-performance relationship is generally estimated by the following piecewise linear regression model (see, for example, Sirri and Tufano (1998)). The flow ($flow_{i,t}$) of fund i at time t is modeled as a function of the fund's *past return* ($R_{i,t\text{-}1}$), *logarithm of its total net assets* ($lTNA_{i,t\text{-}1}$), *riskiness* ($riskiness_{i,t\text{-}1}$), *expenses* ($Expenses_{i,t\text{-}1}$), and total fund flows into all funds with the same investment objective (*objective* $flow_{i,t}$):

$$\begin{aligned} flow_{i,t} = f(lTNA_{i,t-1}, g(R_{i,t-1}), Riskiness_{i,t-1}, \\ Expenses_{i,t-1}, objective\ flow_{i,t}) \end{aligned} \tag{2.2.1}$$

In particular, we use a fund's relative performance to explain subsequent fund flows. In each time period, all funds within the same investment objective are ranked according to their performance. This variable is called $Rank_{i,t}$, and ranges from 0 to 1. The performance is then separated into three performance percentiles, which allows us to model a potential non-linear relationship between fund flows and past performance. The bottom quantile is specified as:

$$low\ return_{i,t-1} = min(0.2, Rank_{i,t-1}) \tag{2.2.2}$$

The middle quantile is defined as:

$$midreturn_{i,t-1} = min(0.6, Rank_{i,t-1} - low\ return_{i,t-1}) \tag{2.2.3}$$

The top quantile is defined as:

$$\begin{split} high\ return_{i,t-1} = min(0.2, Rank_{i,t-1} - mid\ return_{i,t-1} - \\ low\ return_{i,t-1}) \end{split} \tag{2.2.4}$$

We use rolling twelve-month returns as a measure of fund performance ($R_{i,t}$). This information is generally available to fund investors through the databases of leading mutual fund data providers.

Additionally, we control for fund fees ($Expenses_{i,t}$), because they have a direct impact on fund investors' net performance. As per Sirri and Tufano (1998), we calculate the total fees an average investor would incur to hold a fund by adding one-seventh of the front load to the expense ratio. The front load is divided by seven because the average holding time of a fund investor is seven years.

Next, because investor behavior is likely to differ according to investment objective, we include the variable ($objective\ flow_{i,t}$) to control for sector-level fund flows. This measure is defined as the sum of all flows within a specific investment objective, and is calculated on the basis of the Morningstar variable *prospectus objective*. Because we use two different flow measures in this study, we define the respective objective flows accordingly.

The variable ($lTNA_{i,t}$) is defined as the *natural logarithm of total net assets*. It is essential to control for TNA because the relative impact of an equal dollar flow is higher for a smaller fund than for a larger one.

Finally, we account for fund riskiness, ($Riskiness_{i,t}$), by using the volatility of fund returns over the past twelve months as a further control variable.

Data Sources and Sample Description

Our sample period covers monthly mutual fund data from January 1999 through December 2014. The dataset comes from the Morningstar Direct investment research database. Our sample includes monthly fund-level data on total net assets, reported flows, and fund returns. The net expense ratio and the maximum front load are updated annually. We also control for indicator variables such as the fund's prospectus investment objective, or information on mergers.

Mutual funds typically offer several share classes for the same investment portfolio. We use the fund ID provided by Morningstar in order to aggregate share class-level data at the mutual fund level. To prevent survivorship bias, we include active as well as non-surviving funds.

We use the Morningstar variable *prospectus objective* in order to determine a fund's investment objective. We focus here primarily on equity mutual funds from the following investment objectives: growth and income, aggressive growth, growth, equity-income, income, and small company.

2.3 Fund Flow Definitions, Outlier Treatment, and Model Specification

Reported versus Approximated Flows

The SEC has only required mutual funds to report monthly net flows since 1996. For this reason, early studies on the flow-performance relationship approximated fund flows according to the following formula (e.g., Sirri and Tufano (1998)):

$$flow\ approx_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \tag{2.3.1}$$

The accuracy of this commonly used fund flow approximation relies on the assumption that all dividends are reinvested and that all fund flows occur at the end of a respective month. As mentioned earlier, however, there are two concerns with these assumptions. First, because we are assuming fund flows occur at the end of the period, approximated flows neglect the fact that intra-period net flows are also affected by funds' intra-period returns. This factor can lead to dramatic differences between exact and approximated fund flows during months with high absolute flows and/or high absolute returns. Second, the assumption that dividends are completely reinvested may be too rigid. Nevertheless, Clifford et al. (2013) report that the correlation between reported and approximated flows is 99.6%, which is quite high. They interpret this as an indicator of the accuracy of previously used fund flow approximations.

Because funds have been required to report their real U.S. dollar flows to the SEC since 1996, this enables a direct comparison between approximated and reported fund flows. The relative (%) reported flows[2] are calculated as follows:

$$flow_{i,t} = \frac{flow_{i,t}}{TNA_{i,t-1}} \tag{2.3.2}$$

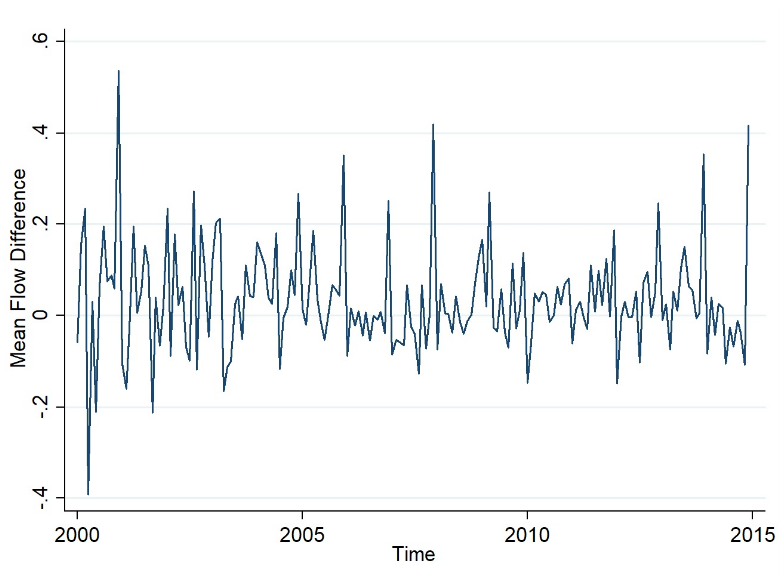
Figure 1 shows the mean differences between aggregated and reported fund flows over our sample period. In each month, we subtract the mean of all approximated fund flows from the mean of all reported mutual fund flows. The graph suggests there are substantial differences that also appear to be subject to seasonality. For example, the flow difference tends to be largest in December, when most funds pay their dividends.

We note that econometric analyses are vulnerable to the omitted variable bias. This is the case if the model leaves out an important variable that is correlated with the dependent variable and one or more of the explanatory variables. Here, we can expect the regression results to be unbiased only if there is no correlation between flow differences, which are driven by dividends, and the other variables of the regression model.

Table 1 shows there is a significant correlation between flow differences and fund flows. The flow difference is correlated with returns. Additionally, we find a relationship between dividends and returns. The correlations between the flow difference and the fund flows, as well as those between dividends and the control variables, are remarkably high. The correlation coefficients between flow differences and the control

[2] We control for fund mergers by calculating the sum of the TNA of all merged funds that flowed into an acquiring fund, and then adjust the respective fund flows accordingly.

Figure 1: Fund Flow Difference over Time



We calculate the mean reported and mean approximated fund flows for each period from 1999 to 2014. Mean flow difference is defined as the difference between mean reported and mean approximated fund flows. Therefore, reported fund flow is given by the ratio of fund flows and total net assets, defined as $Flow_t/TNA_{t\text{-}1}$, where $Flow_t$ is the fund flow reported to the SEC at time textitt, and TNA_t is the fund's total net assets in period textitt. The approximated fund flow is given by $(TNA_t\text{-}TNA_{t\text{-}1}(1+\ R_{i,t\text{-}1}))/\ TNA_{t\text{-}1}$, where $R_{i,t}$ is the fund's monthly return at time textitt. We choose a trimming quantile of 1% in order to cut outlying fund flows from the sample.

Table 1: Correlations among Neglected Factors, Performance, and Control Variables

	flow difference	rep. flow	approx. flow	dividends	L.Return	L.Riskiness	L.Expenses	Objflow	L.lTNA
flow difference	1.0000	-	-	-	-	-	-	-	-
rep. flow	0.1625***	1.0000	-	-	-	-	-	-	-
approx. flow	-0.2171***	0.9279***	1.0000	-	-	-	-	-	-
dividends	0.0147***	-0.0560***	-0.0677***	1.0000	-	-	-	-	-
L.Return	-0.0034*	0.0696***	0.0642***	-0.1025***	1.0000	-	-	-	-
L.Riskiness	-0.0013	-0.0021	0.0063***	-0.3225***	-0.1983***	1.0000	-	-	-
L.Expenses	-0.0077***	0.0111***	0.0174***	-0.2717***	-0.0080***	0.1757***	1.0000	-	-
Objflow	-0.0053***	0.1359***	0.1112***	0.0932***	0.0496***	-0.0913***	-0.0301***	1.0000	-
L.lTNA	0.0029*	-0.1863***	-0.1899***	0.1368***	0.0537***	-0.0876***	-0.2643***	0.0018	1.0000

The sample includes U.S. mutual funds with investment objectives of growth and income, aggressive growth, growth, equity-income, income, and small company, as classified by Morningstar from 1999 to 2014. The Table shows the correlations between variable flow difference, defined as the difference between reported and approximated flows, and several sample variables. The reported flow is defined as the ratio of fund flows and total net assets, given by $Flow_t/TNA_{t\text{-}1}$, where $Flow_t$ is the fund flow reported to the SEC at time t, and $(TNA_t$ is the fund's total net assets in period textitt. The approximated fund flow is defined as $(TNA_t\text{- } TNA_{t\text{-}1}(1+ R_{i,t\text{-}1}))/\ TNA_{t\text{-}1}$, where $R_{i,t}$ is the fund's monthly return at time t. In the correlogram, we show the joint correlations among: flow difference, reported flows, approximated flows, dividends, last period's rolling annual returns, fund riskiness (volatility of the last year's monthly return), fund's total expenses (net expense ratio plus one-seventh of the front load), objective flows (mean flows per investment objective), and logarithm of the last month's total net assets. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

variables are rather moderate.

Together, the correlations and the mean flow differences suggest that using approximated instead of reported flow data may lead to biased regression results. Thus, we formulate our first hypothesis as follows:

Hypothesis 1: *The use of approximated instead of exact fund flows leads to biased regression results for the flow-performance relationship.*

Trimming versus Winsorizing of Outliers

The statistical literature cites various reasons that observations may take on extreme values. In social statistics, for example, outliers may occur when an older person overstates his age. This occurs particularly in rural or underdeveloped regions, where birth documents may be non-existent. In this case, it is appropriate to replace extremely positive outliers by more plausible, yet also high, outliers. In other words, the value should be winsorized in order to avoid having the overly high outlier drive the sample (Ghosh and Vogt (2012)). Winsorization replaces any positive (negative) extreme values with more moderate maximum (minimum) values, for example, the ninety-ninth (first) percentile.

Data entry issues, which may occur through, e.g., typing errors, are another potential reason for erroneous outliers. Here, a seemingly very high number could be a very small number in reality. In this case, winsorization could lead to biased regression results because the explanatory variables should predict a very low value instead of a very high one. Thus, trimming (excluding outliers completely from an analysis when they exceed (or fall below) a certain threshold) would be more appropriate. We conduct a plausibility check regarding the most extreme outliers in our sample, and find that the vast majority appear to be due to data entry problems. Thus, we argue that, in the mutual fund literature, trimming should clearly be preferred over winsorization with respect to fund flows.

There is no consensus in the mutual fund flow literature on how to treat outliers, however. Some studies, such as, e.g., Elton et al. (1996), Clifford et al. (2014), Casavecchia (2016), and Ferreira et al. (2012), winsorize them, while others trim outlying values (e.g., Huang et al. (2007), Spiegel and Zhang (2013) and Cashman et al. (2014)). In contrast, (Chevalier and Ellison (1997) and Sirri and Tufano (1998)) aim to ensure high data quality in their sample by cross-checking their data with other databases, while leaving outliers unchanged.

In this study, we examine how the estimated flow-performance relationship differs depending on whether outliers are winsorized or trimmed. We trim and winsorize both reported and approximated fund flows at the 1% and 99% percentiles.

In the mutual fund literature, winsorizing 1% of the most extreme values is the most commonly used approach (see, for example, Clifford et al. (2013), Elton et al. (1996), Casavecchia (2016), and Ferreira et al. (2012)). Clifford et al. (2014) winsorize at the 2.5% percentiles. On the other hand, Huang et al. (2007) trim at the 2.5% percentiles and Spiegel and Zhang (2013) at the 5% percentiles while Cashman et al. (2014) eliminate observations with inflows below -12% and outflows above 50%.

Table 2 provides the summary statistics for our flow measures and some control variables for the entire sample period, as well as for December 2000, December 2007, and December 2014.[3] The numbers reveal that trimmed flows generally have a substantially lower mean than winsorized flows. In untabulated results, we find that about half the 1% highest outflows (those which we define as outliers) are actually associated with positive returns, and about one-quarter with extraordinary returns. It is thus doubtful that the highest outflows are associated with high returns. This supports our argument that outliers tend to be driven by data entry issues, and hence should be trimmed, not winsorized.

Following Sirri and Tufano (1998), we also provide a graphical representation of the flow-performance relationship. For each investment objective, and for each month, all funds are ranked according to their performance over the previous twelve months, and then split into twenty quantiles. We calculate the average net flow (%) into each of the twenty performance quintiles in the following month.

Figure 2 illustrates the relationship between the funds' money growth rates and past performance. The upper panel (A) shows the resulting flow-performance relationship for different trimming thresholds. It is obvious that lower thresholds lead to more convex flow-performance relationships. In contrast, higher trimming quantiles

[3] The variable riskiness is based on the fund returns of the past twelve months. Therefore, the first analyzable observation is January 2000.

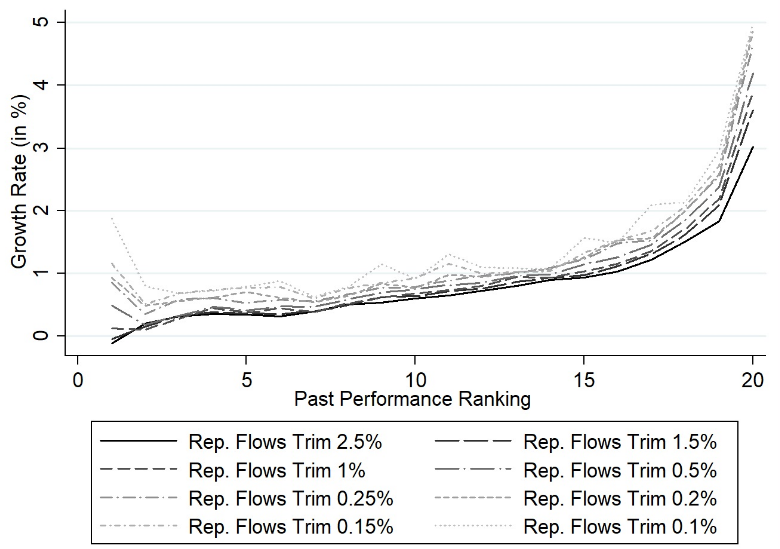
Table 2: Summary Statistics on Fund Flows, Performance, and Control Variables

	Entire Time Span			2000			2007			2014		
	Mean	Deviation	Observations	Mean	Deviation	Observations	Mean	Deviation	Observations	Mean	Deviation	Observations
Trim Rep. Flows												
reported flow	1.00	5.68	302,932	1.17	6.61	689	0.38	5.09	1,625	0.08	5.78	2,371
TNA (billion USD)	1.72	6.39		2.75	8.01		2.12	8.45		1.98	8.47	
Front Load	0.90	1.52		0.91	1.66		0.92	1.56		0.78	1.31	
Net Expense Ratio	1.07	0.53		1.13	0.49		1.05	0.50		1.02	0.52	
Expenses	1.20	0.62		1.26	0.60		1.18	0.60		1.13	0.59	
Trim App. Flows												
approx. flow	1.00	5.96	334,837	0.65	6.84	792	0.00	5.43	1,747	-0.25	6.33	3,559
TNA (billion USD)	1.72	6.44		2.51	7.51		2.06	8.18		1.91	7.70	
Front Load	0.89	1.51		0.92	1.65		0.91	1.54		0.83	1.37	
Net Expense Ratio	1.07	0.52		1.13	0.49		1.04	0.50		1.03	0.52	
Expenses	1.19	0.62		1.26	0.60		1.17	0.60		1.15	0.60	
Winsor. Rep. Flows												
reported flow	1.09	7.33	306,838	1.36	8.75	701	0.17	6.10	1,654	-0.20	7.34	2,440
TNA (billion USD)	1.70	6.36		2.71	7.95		2.09	8.38		1.93	8.35	
Front Load	0.89	1.51		0.89	1.65		0.93	1.56		0.77	1.30	
Net Expense Ratio	1.07	0.53		1.13	0.49		1.05	0.50		1.03	0.52	
Expenses	1.20	0.62		1.26	0.60		1.18	0.60		1.14	0.59	
Winsor. App. Flows												
approx. flow	1.10	7.73	339,176	0.52	8.67	812	0.00	7.06	1,772	-0.43	8.16	3,656
TNA (billion USD)	1.70	6.40		2.45	7.43		2.04	8.13		1.87	7.61	
Front Load	0.88	1.51		0.91	1.66		0.91	1.55		0.82	1.36	
Net Expense Ratio	1.07	0.53		1.14	0.49		1.05	0.50		1.03	0.52	
Expenses	1.20	0.62		1.27	0.60		1.18	0.60		1.15	0.60	

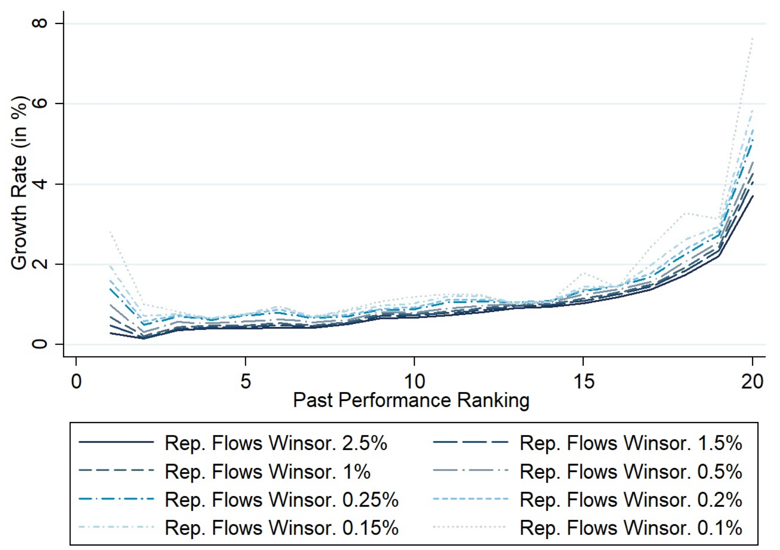
The sample includes U.S. mutual funds with the investment objectives of growth and income, aggressive growth, growth, equity-income, income, and small company, as classified by Morningstar from 1999 to 2014. The Table lists the information for four samples using different outlier detection methods. Each trims or winsorizes at the 1% percent level, but using either approximated or exact flow definitions, resulting in four different samples. Thus, reported flow is defined as the ratio of fund flows and total net assets, given by $Flow_t/TNA_{t\text{-}1}$, where $Flow_t$ is the fund flow reported to the SEC at time t, and TNA_t is the fund's total net assets in period t. Approximated fund flow is defined as $(TNA_t$ - $TNA_{t\text{-}1}$ $(1+ R_{i,t\text{-}1}))/$ $TNA_{t\text{-}1}$, where $R_{i,t}$ is the fund's monthly return at time t. Each sample includes either the approximated or reported fund flows. Additionally, each sample includes funds' total net assets, load fees, and annual net expense ratios. Each dataset contains the variable "Expenses," which is estimated as the annual expense ratio plus one-seventh of the load fees, where the factor of 7 represents the average holding period of an initial fund. For each variable, the mean and standard deviation are reported.

Figure 2: Flow-Performance Relationship Using Different Outlier Treatment Methods

A: Trimmed Data



B: Winsorized Data



For each period from 1999 to 2014, funds are ordered within their respective investment objective (growth and income, aggressive growth, growth, equity-income, income, and small company), and ranked into twenty equal clusters based on their respective rolling annual returns. For each rank, we calculate the respective mean growth rate of the funds within that cluster. Growth rate is defined as the ratio of fund flows and total net assets, as follows: $Flow_t/TNA_{t\text{-}1}$, where $Flow_t$ is the fund flow reported to the SEC at time textitt. We apply eight different trimming or winsorizing quantiles (0.1%, 0.15%, 0.2%, 0.25%, 0.5%, 1%, 1.5%, and 2.5%) in order to treat outlying fund flows. This results in eight distinct samples. The upper graph plots a line for each sample showing the respective combination of mean growth rate and prior return ranking for trimming. The lower figure replicates this graph for winsorizing.

lead to more linear flow-performance relationships.

The lower panel (B) illustrates the flow-performance relationship using winsorized data, treated at the same thresholds as in (A). As with the case of trimming, we find a less convex flow-performance relationship for higher winsorizing thresholds. Yet the relationship is more convex than (B), even when higher thresholds are applied. The comparison of the 1% winsorized and trimmed flow-performance graphs in Figure 3 reveals that the flow-performance relationship is less convex (or more linear) when the outliers are trimmed instead of winsorized. In particular, the lowest performance quintiles are associated with smaller fund flows.

We suspect that winsorizing leads to retaining attenuated versions of incorrect values. The inclusion of these values influences the shape of the flow-performance relationship and may affect empirical conclusions. Thus, we formulate our hypothesis regarding the effect of outliers on the bottom performance quantile as follows:

Hypothesis 2: *Winsorizing instead of trimming outliers hides investor sensitivity to poor performance.*

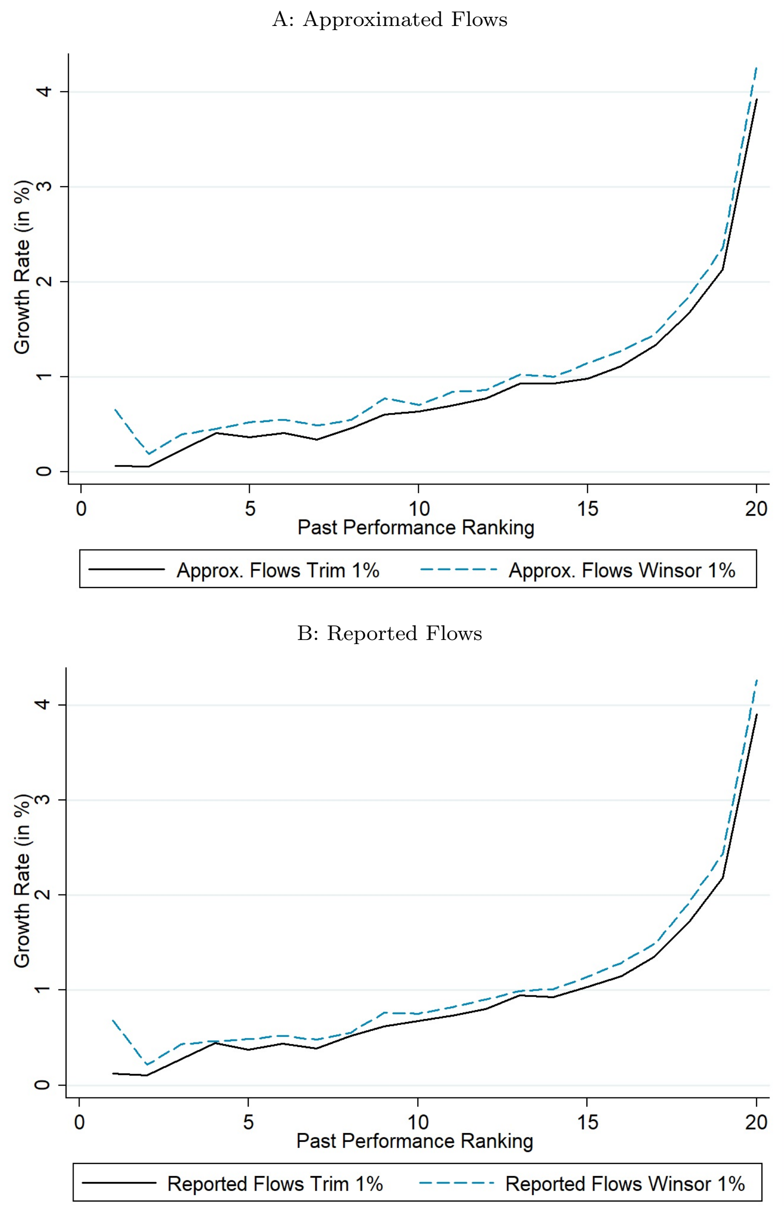
Accounting for Fund Flow Persistence

More recent studies have emphasized the importance of controlling for the persistence of fund flows when examining the flow-performance relationship (see, e.g., Del Guercio and Tkac (2002), Johnson (2007), and Cashman et al. (2014)). Cashman et al. (2014) argue that fund investors react to performance changes rather sluggishly. In other words, they react to new information in a learning process over different time intervals. Furthermore, the authors argue that using twelve lags prevents any bias due to potential seasonal patterns in the monthly fund flows.

While these studies do not focus primarily on the shape of the flow-performance relationship, we argue that fund flow persistence is likely to be an important factor in our setting because its neglect may lead to biased regression results. Therefore, we formulate our third hypothesis as follows:

Hypothesis 3: *Neglecting persistence leads to a biased flow-performance relationship.*

Figure 3: Flow-Performance Relationship Using Trim and Winsorize at 1%



For each period from 1999 to 2014, funds are ordered within their respective investment objectives (growth and income, aggressive growth, growth, equity-income, income, and small company), and ranked into twenty equal clusters based on their respective rolling annual returns. For each rank, we calculate the respective mean growth rate of the funds within that cluster. We apply two different outlier treatment methodologies to either trim or winsorize at the 1% quantile, resulting in two distinct samples. We then plot a line for each sample showing the respective combination of mean growth rate and prior return ranking. In the upper panel, the growth rate is given by $(TNA_t\text{- } TNA_{t\text{-}1}(1+ R_{i,t\text{-}1}))/TNA_{t\text{-}1}$, where $R_{i,t}$ is the fund‘s monthly return at time textitt. In the lower panel, the growth rate is defined as the ratio of fund flows and total net assets, defined as $Flow_t/TNA_{t\text{-}1}$, where $Flow_t$ is the fund flow reported to the SEC at time textitt.

To examine the impact of fund flow persistence on the shape of the flow-performance relationship, we estimate an alternative model that includes twelve lags of monthly fund flows in addition to the initial base specification:

$$\begin{aligned} flow_{i,t} = f(\sum_{j=1}^{12} flow_{i,t-j}, lTNA_{i,t-1}, g(R_{i,t-1}), Riskiness_{i,t-1}, \\ Expenses_{i,t-1}, objective\ flow_{i,t}) \end{aligned} \tag{2.3.3}$$

2.4 Regression Results

Table 3 contains the regression results for the flow-performance relationship using diverse approaches. We test three hypotheses, each of which refers to an alternative way to estimate the flow-performance relationship relative to the standard approach. In particular, we vary: 1) reported versus approximated flows, 2) trimmed versus winsorized outliers, and 3) controlling for versus neglecting fund flow persistence. We also test whether the results for reported versus approximated fund flows differ depending on whether the data are trimmed or winsorized, and we test whether these four specifications are affected by whether we control for persistence. In total, this results in eight different specifications. The respective regression results are in Table 3. All regressions are estimated using the Fama-MacBeth procedure (Fama and MacBeth (1973)).

The sample includes U.S. mutual funds with the investment objectives of growth and income, aggressive growth, growth, equity-income, income, and small company, as classified by Morningstar from 1999 to 2014. The Table lists the information for four samples using different outlier detection methods. Each trims or winsorizes at the 1% percent level, but using either approximated or exact flow definitions, resulting in four different samples. Thus, reported flow is defined as the ratio of fund flows and total net assets, given by $Flow_t/TNA_{t-1}$, where $Flow_t$ is the fund flow reported to the SEC at time *t*, and TNA_t is the fund‘s total net assets in period *t*. Approximated fund flow is defined as $(TNA_t - TNA_{t-1} (1+ R_{i,t-1}))/ TNA_{t-1}$, where $R_{i,t}$ is the fund‘s monthly return at time t. Each sample includes either the approximated or reported fund flows. Additionally, each sample includes funds’ total net assets, load fees, and

Table 3: Regression Results of the Fama-MacBeth Two-Step Procedure

	Winsorize		Trim		Winsorize		Trim	
VARIABLES	Model (i) Approx.	Model (ii) Reported	Model (iii) Approx.	Model (iv) Reported	Model (viii) Approx.	Model (vii) Reported	Model (vi) Approx.	Model (v) Reported
L.lowReturn	0.919	0.992	1.613***	1.824***	1.699***	1.487**	2.659***	2.234***
	(0.773)	(0.707)	(0.554)	(0.490)	(0.571)	(0.573)	(0.258)	(0.298)
L.midReturn	2.166***	2.201***	2.120***	2.138***	1.154***	0.962***	0.883***	0.804***
	(0.136)	(0.118)	(0.113)	(0.0999)	(0.113)	(0.0960)	(0.0718)	(0.0689)
L.highReturn	15.50***	16.25***	15.48***	15.47***	8.204***	6.741***	5.825***	4.756***
	(0.914)	(0.970)	(0.741)	(0.725)	(0.718)	(0.701)	(0.448)	(0.412)
L.Riskiness	0.0454*	0.00872	0.0315	-0.00457	0.0332	0.0126	-0.0401***	-0.0442***
	(0.0254)	(0.0252)	(0.0197)	(0.0203)	(0.0243)	(0.0234)	(0.0134)	(0.0124)
L.Expenses	-0.268***	-0.291***	-0.242***	-0.251***	-0.149***	-0.162***	-0.108***	-0.114***
	(0.0375)	(0.0370)	(0.0293)	(0.0299)	(0.0314)	(0.0297)	(0.0208)	(0.0211)
Objflow	0.532***	0.518***	0.674***	0.642***	0.327***	0.294***	0.204***	0.207***
	(0.0270)	(0.0312)	(0.0303)	(0.0338)	(0.0248)	(0.0296)	(0.0224)	(0.0237)
L.log(TNA)	-0.528***	-0.502***	-0.390***	-0.377***	-0.309***	-0.258***	-0.142***	-0.130***
	(0.0146)	(0.0149)	(0.00886)	(0.0101)	(0.00966)	(0.0109)	(0.00571)	(0.00709)
Constant	9.187***	8.862***	6.305***	6.254***	4.852***	4.094***	1.955***	1.876***
	(0.353)	(0.367)	(0.255)	(0.270)	(0.247)	(0.261)	(0.148)	(0.175)
L.flow	-	-	-	-	0.101***	0.197***	0.258***	0.306***
	-	-	-	-	(0.00757)	(0.0128)	(0.00755)	(0.0119)
L2.flow	-	-	-	-	0.112***	0.121***	0.132***	0.125***
	-	-	-	-	(0.00675)	(0.0102)	(0.00575)	(0.00741)
L3.flow	-	-	-	-	0.0850***	0.0790***	0.0836***	0.0812***
	-	-	-	-	(0.00631)	(0.00804)	(0.00487)	(0.00620)
L4.flow	-	-	-	-	0.0494***	0.0543***	0.0526***	0.0414***
	-	-	-	-	(0.00620)	(0.0119)	(0.00456)	(0.0103)
L5.flow	-	-	-	-	0.0517***	0.0430***	0.0395***	0.0388***
	-	-	-	-	(0.00606)	(0.00781)	(0.00457)	(0.00566)
L6.flow	-	-	-	-	0.0438***	0.0406***	0.0330***	0.0378***
	-	-	-	-	(0.00617)	(0.00968)	(0.00445)	(0.00638)
L7.flow	-	-	-	-	0.0246***	0.0209***	0.0136***	-0.00222
	-	-	-	-	(0.00581)	(0.00627)	(0.00403)	(0.0148)
L8.flow	-	-	-	-	0.0258***	0.0353**	0.0276***	0.0280***
	-	-	-	-	(0.00533)	(0.0142)	(0.00421)	(0.00543)
L9.flow	-	-	-	-	0.0209***	0.0198**	0.0139***	0.0234*
	-	-	-	-	(0.00562)	(0.00961)	(0.00444)	(0.0134)
L10.flow	-	-	-	-	0.00467	0.000111	0.0130***	0.0143
	-	-	-	-	(0.00531)	(0.0149)	(0.00376)	(0.0103)
L11.flow	-	-	-	-	0.0136***	0.00286	0.00765**	0.0123*
	-	-	-	-	(0.00460)	(0.00992)	(0.00346)	(0.00634)
L12.flow	-	-	-	-	0.0206***	0.0227***	0.0169***	0.00997
	-	-	-	-	(0.00398)	(0.00793)	(0.00324)	(0.0100)
Observations	339,176	306,838	334,837	302,932	327,312	264,244	295,985	239,416
Number of groups	179	179	179	179	179	179	179	179
R-squared	0.058	0.063	0.072	0.075	0.224	0.308	0.329	0.374
Adj. R-squared	0.055	0.059	0.069	0.071	0.221	0.305	0.326	0.371

This table shows Fama and MacBeth (Fama and MacBeth (1973)) regression results using a U.S. mutual fund sample with the investment objectives of growth and income, aggressive growth, growth, equity-income, income, and small company from 1999 to 2014. The table reports regression coefficient estimates using fund flows as the dependent variable. It lists the information for four samples using different fund flow definitions and outlier detection methods. Each trims or winsorizes at 1%, but using either approximated or exact fund flow definitions, resulting in four distinct samples. The reported flow is thus defined as the ratio of fund flows and total net assets given by $Flow_t/TNA_{t-1}$, where $Flow_t$ is the fund flow reported to the SEC at time t, and TNA_t is the fund's total net assets in period t. The approximated fund flow is defined as $(TNA_t - TNA_{t-1}(1+ R_{t-1}))/ TNA_{t-1}$, where R_t is the fund's monthly return at time t.

Column (i) shows the results incorporating approximated fund flows that are winsorized at the 1% level. Column (ii) contains the regression results for the case of using fund flows as reported to the SEC instead of the approximated version. Columns (iii) and (iv) replicate the specifications in columns (i) and (ii), this time trimming instead of winsorizing the outliers. Columns (v) to (viii) replicate the analysis of the first four columns, this time controlling for fund flow persistence. The independent variables include fund i's relative performance measure to time t to explain subsequent fund flows. In each time period, all funds within the same investment objective are then ranked according to their performance. This variable is called $Rank_{i,t}$, and ranges from 0 to 1. Next, the performance is separated into three performance percentiles, which allows us to model a potential non-linear relationship between fund flows and past performance: The bottom quantile is defined as: low $\text{return}_{\text{i,t-1}} = \min(0.2, \text{Rank}_{\text{i,t-1}})$, the middle quantile is defined as: mid $\text{return}_{\text{i,t-1}} = \min(0.6, \text{Rank}_{\text{i,t-1}}$ - low $\text{return}_{\text{i,t-1}})$, and the high-performance quantile is defined as: high $\text{return}_{\text{i,t-1}} = \min(0.2, \text{Rank}_{\text{i,t-1}}$ - mid $\text{return}_{\text{i,t-1}}$ - low $\text{return}_{\text{i,t-1}})$. We use rolling twelve-month returns as a measure of fund performance ($R_{i,t}$). We also control for the volatility of fund i's monthly returns from the preceding year, the fund's past period total expenses (given by the annual expense ratio plus one-seventh of the load fees), the objective flows, defined as the growth rate of all funds in the same investment category, and the log of the fund's last month total net assets. Standard errors are in parentheses, and p-values are denoted by asterisks (***0.01, **0.05, *0.1).

annual net expense ratios. Each dataset contains the variable "Expenses," which is estimated as the annual expense ratio plus one-seventh of the load fees, where the factor of 7 represents the average holding period of an initial fund. For each variable, the mean and standard deviation are reported.

First, we replicate the standard approach to estimating the flow-performance relationship by using approximated fund flow data, winsorized at the first and ninety-ninth percentiles. The respective regression results are in column (i) of Table 3, and confirm the convexity of the flow-performance relationship. While investors are highly sensitive to medium and high levels of past performance, the reaction of fund flows within the low performance quantile is not statistically different from zero. The adjusted R-squared is rather low, at only 5.8%, and the control variables all have the expected sign, except for the impact of riskiness, which appears to be positively correlated with fund flows.

Column (ii) contains the regression results for the same specification. However, in this case, we use the fund flows reported to the SEC, instead of the approximated version. The regression results are overall very similar to those in column (i). We still find no evidence of investor reaction in the low performance fractile. Thus, the use of approximated instead of reported fund flows does not appear to have an impact on the shape of the flow-performance relationship (Hypothesis 1). Nevertheless, there are some minor improvements that suggest reported fund flow data should be preferred when available. For example, the adjusted R-squared increases from 5.8% to 6.3%, and the impact of fund return volatility is no longer significant, which makes sense if we assume that most investors are not risk-tolerant.

Columns (iii) and (iv) replicate the specifications in columns (i) and (ii), this time by trimming instead of winsorizing the outliers. Remarkably, by using trimmed data, the reaction to poor performance becomes significant for both specifications. The sensitivity of fund flows to poor performance is even stronger than the reaction to medium performance levels. The top performance reaction parameter remains the one with the highest significance.

Note that these results are consistent with Hypothesis 2: Investors appear sensitive to poor performance only when outliers are eliminated instead of winsorized. In other words, the (unjustified) winsorization of outliers masks investor sensitivity to poor performance, which may lead to incorrect conclusions. The R-squared of the specifications in columns (iii) and (iv) are also considerably higher than in the models using winsorized data.

Columns (v) to (viii) replicate the analysis of the first four columns, this time controlling for fund flow persistence. Interestingly, we observe that the reaction in the bottom performance quantile becomes significant for both outlier treatment approaches. This suggests that controlling for fund flow persistence may heal the shortcomings of winsorization to some extent. However, the sensitivity is still considerably more pronounced when outliers are trimmed and not winsorized (Approach 1). Overall, the results are consistent with Hypothesis 3: The neglect of fund flow persistence masks investor sensitivity to poor performance.

Again, it does not seem to make a big difference whether reported or exact flows are used. However, the relationship in the low-performance area is about 50% stronger for the trimmed dataset compared to the winsorized dataset. There is also some evidence that the use of approximated fund flows leads to a slight overestimation of investors' reactions to superior performance. In the trimmed dataset, we can reject the hypothesis that the high performance reaction parameters are equal, independent of the fund flow definition, with a p-value of 2%. Therefore, we also find some evidence for Hypothesis 1.

Comparing the results for both datasets (trimmed versus winsorized), we can reject the hypothesis that the low-performance reaction parameters are equal. This result is once more in line with Hypothesis 2, suggesting that winsorizing leads to a biased estimate for the bottom quantile. Compared to the middle quantile, the low-performance parameter is significantly different and several times higher for both approaches. Investors' reactions to superior performance remain extraordinarily high, and deviate significantly from the other performance reaction parameters. However, we identify a dramatic reduction in parameter magnitude that is reduced by half when we control for fund flow persistence. This result supports Hypothesis 3, because the flow-performance relationship shifts in a meaningful way.

Additional evidence in favor of our preferred specification (model viii) is provided by the expected negative sign of the impact of the control variable riskiness, and by the R-squared, which is substantially higher than in all other regression specifications.

In summary, our findings reveal that the flow-performance relationship is highly sensitive to the way outliers are treated and to controlling for persistence. In contrast, we find that using approximated flows only slightly overestimates investors' reactions to strong performance. Hence, the way data are cleaned before being incorporated into an analysis, and controlling for persistence, are of major importance.

Winsorizing (instead of trimming) fund flows leads to a serious downward bias for the low-performance parameter, and, depending on the model specification, even to insignificance. We suspect that the bias for the winsorized dataset is due to data entry issues.

Controlling for persistence may heal the shortcomings of using winsorized data to some extent. We interpret the shift in the shape of the flow-performance relationship for the winsorized dataset after controlling for persistence as follows: The attenuated versions of outliers that are retained in the considered sample are smoothed out. Therefore, the outliers of the most extreme outflows are a purely random process. A moderate or even high return that is followed by an erroneous extreme outflow in the following period biases the short-run influence of past returns to fund flows. They have no influence on the immediate subsequent month. Thus, these outliers show an immediate effect that has no long-run influence on the flow-performance relationship. Consequently, after controlling for persistence, their influence weakens, and the poor performance relationship transforms into a significantly positive parameter.

In summary, our research suggests investors do punish poor performance across the broad spectrum of mutual funds and not only in modified cases of the original research question as in the studies of Spiegel and Zhang (2013) and Clifford et al. (2014). Importantly, and in contrast to the prevailing school of thought, our research findings do not imply that there is a potential misalignment of incentives between fund managers and investors. As the flow-performance relationship is linear, fund managers do not have an incentive to take excessive risk in order to benefit from asymmetric reactions of investors.

2.5 Conclusion

This study readdresses the well-established convexity of the flow-performance relationship by using a new combination of state-of-the-art methods and new data. In particular, we use reported instead of approximated fund flows, we trim instead of winsorize outliers, and we follow the recent literature by controlling for fund flow persistence.

Through the combination of these approaches, three major findings emerge. First, we find substantial differences between approximated and reported fund flows. The neglected part of approximated fund flows exhibits seasonal patterns. The differences are particularly pronounced during December, when dividends are paid. Importantly, we find significant correlations between the neglected part of the fund flow approximations and the commonly incorporated variables used to model fund flows. Because common econometric analyses rely on the assumption that none of the neglected factors are correlated with the explanatory variables, this may lead to biased estimates. We find evidence that investors' reactions to strong performance is slightly overestimated in the models that use approximated instead of exact fund flows, as reported to the SEC. Therefore, we recommend using reported fund flows when available.

Second, we find that the winsorization of outliers leads to an insignificant flow-performance relationship in the low-performance quantile. In contrast, when outliers are trimmed, the coefficient on fund flow sensitivity with respect to poor performance becomes positive and significant. Surprisingly, the reaction is significantly stronger than even medium performance levels. We suspect that winsorizing leads to the inclusion of incorrect values, and may be causing biased estimates.

Third, we find that controlling for persistence also substantially impacts the shape of the flow-performance relationship, because the reaction of fund flows to poor performance becomes even stronger. Overall, we find that mutual fund investors strongly react to both strong and poor past performance. This is consistent with a linear, rather than a convex, flow-performance relationship.

Our findings have important implications for the potential moral hazard of fund managers. Previous studies, such as Chevalier and Ellison (1997), Brown et al. (1996), and Sirri and Tufano (1998), suggest fund managers are incentivized to take on risk in order to increase fund flows. They argue that the reward for extraordinarily high returns is very high, while the penalty for extraordinarily low performance is more modest. However, those studies incorporated outliers, neglected fund flow persistence, and used approximated fund flows.

Our approach sheds a new light on the debate regarding potentially perverse incentives for fund managers and the asset management industry. Poor performance is associated with lower fund flows, and hence does have an impact on assets under management and fee income. Managers should therefore avoid excessive risk-taking. Ultimately, we find that the rewards for high performance are much more comparable to the penalties for low performance than prior studies have suggested.

3 What Determines the Mean Reversion Speed of NAV Spreads?

This paper is the result of a joint project with René-Ojas Woltering, Christian Weis and Steffen Sebastian.

Abstract In this paper, we study the mean reversion behavior of NAV spreads for a global sample of 219 listed real estate stocks. We find NAV spreads for companies trading at a high discount to mean revert fastest. Remarkably, we also provide evidence that online search attention impacts the mean reversion speed of NAV spreads: Stocks with lower levels of online search attention mean-revert significantly faster than those with higher levels. Our global research setting allows us to show that a country's average NAV spread has an impact on the NAV spreads of individual stocks. Ultimately, we find that the NAV spread of companies receiving high levels of online search attention has a disproportionately high impact on the NAV spreads of other companies.

3.1 Introduction

Deviations of share price from fundamental value have long intrigued the financial literature. In the case of listed real estate companies, the net asset value (NAV) provides a particularly compelling proxy for a firm's fundamental value. The real estate literature explaining the NAV spreads REITs and REOCs can be divided into two strands. One strand argues in favor of the so-called rational approach, according to which the NAV spread can be fundamentally explained by financial determinants (see for example Capozza and Korean (1995); Benveniste et al. (2001); Clayton and MacKinnon (2000); Cronqvist et al. (2001); Bond and James (2003); Gentry et al. (2004); Brounen and Laak (2005); Ghosh et al. (2020). A second strand of literature argues that the existence of NAV spreads is a market anomaly, often tied to irrational investor sentiment (Lee et al., 1999). 'Noise traders' have long been suspected of being a source of undue fluctuations in NAV spreads (see for example, (Lee et al., 1999; Elton et al., 1998)). This assumption is also consistent with Ke (2015), who finds for real estate that increasing institutional share ownership tends to narrow NAV spreads. Lending further support to the irrational explanation, Woltering et al. (2018) show that an investment strategy of buying those global REITs and REOCs that trade at the largest discounts to NAV, while short-selling those trading at the highest premiums can lead to substantial risk-adjusted returns. More recently, (Letdin et al., 2022) decompose the NAV spread into a rational, or factor-based component, and into an irrational, or sentiment-related component. The authors find that an investment strategy based on exploiting sentiment-related part of the NAV-spread leads to even higher risk-adjusted returns than an investment strategy that is purely based on raw NAV spreads. This finding also suggests that the sentiment-related part of the NAV spread is a market anomaly, which is not consistent with the notion of fully efficient financial markets.

A fundamental question in finance is how to take advantage of mispricings of stocks. Assuming that the NAV is an adequate proxy for the intrinsic value of a stock it would be straightforward to invest (divest) in the most underpriced (overpriced) stocks according to this measure. However, NAV spreads may persist for long periods of time. Hence, a potentially even more important investment criterion than the level of the NAV spread is how to find stocks whose share price will quickly adjust to their intrinsic value after the impact of an exogenous shock to the NAV spread. The higher the mean reversion speed, the higher the potential to generate significant risk-adjusted returns. If investors systematically exploit such mispricings, the anomaly should disappear over time. Hence, another angle to examine NAV-based investment strategies is to look at the speed of mean reversion of the NAV spread, which is the time duration until the NAV spread of a particular REIT or REOC corrects toward its long-run mean after the impact of an exogenous one-unit shock. For the potential success of NAV spread-based investment strategies, the mean reversion speed of the NAV spread may be as important as the level of the spread. In this paper, we thus seek to answer the research question: What determines the mean reversion speed of NAV spreads? We use the Blundell-Bond (1998) GMM-System-Estimator to capture the dynamic impact of company-specific control variables. Our empirical analysis is based on a global sample of FTSE EPRA/NAREIT Global Real Estate Index property-holding companies in countries with fair value-based accounting regimes. This setting allows us to measure the company's NAVs as a proxy for fundamental value. In total, our sample consists of 219 listed property-holding companies across 11 countries over the 2005-2018 period.

The real estate literature provides some evidence for the mean reversion of NAV spreads (see for example (Liow and Li, 2006; Patel et al., 2009)). We contribute to this strand of the literature by documenting which factors impact the mean reversion speed of NAV spreads of property-holding companies. In particular, we find that companies with the highest NAV discounts mean-revert the fastest to long-run mean, and those with medium leverage ratios tend to mean-revert the fastest. We also find that the NAV spread of smaller companies revert faster to their mean compared to large companies. Moreover, our global research setting enables us to innovate by examining the role of country-wide NAV spreads on an individual firm's NAV spread. We document a positive and statistically significant impact of the country-wide NAV spread, which can be interpreted as a spillover effect. Moreover, we find that stocks from the same country, with the highest Google search attention, have a disproportionate effect on other stocks' NAV spreads in that country. We term this the 'spillover effect' of online search attention on other stocks.

In light of the article of (Letdin et al., 2022), we have a special interest in the potential impact of investor sentiment regarding the level and the mean reversion speed of NAV spreads. (Da et al., 2011) find that the Google search volume is a direct proxy of retail investor attention and that it is a predictor of stock price movements. We thus examine how online search attention as measured by google search data impacts the mean reversion of NAV spreads. In the context of listed real estate companies, (Jandl and Fuerst, 2015) only find a marginal impact of online search attention on NAV spreads. While we also find only an insignificant impact of online search attention on the level of the NAV spread, we contribute to the literature by documenting that online search attention impacts the speed of mean reversion of the NAV spread. In particular, we find that the NAV spread of listed real estate companies with a low level of online search attention tends to mean revert faster. Or in other words, firms with medium to high levels of online search attention tend to be associated with more prolonged NAV spreads.

The remainder of this paper is structured as follows. Section 3.2 introduces the related literature and presents our hypotheses. Section 3.3 describes the data and provides descriptive statistics. The empirical specification is presented in Section 3.4, while Section 3.5 illustrates the empirical results. Section 3.6 concludes.

3.2 Literature Review and Hypothesis

The validity of the efficient market hypothesis (EMH) has been debated in the literature for decades. Under the EMH, the price of a share equals its intrinsic value at all times. In this regard, supporters of the EMH argue that the NAV spread is merely compensation for higher risk (Davis et al., 2000). On the other hand, this theory has early opponents, such as Shiller et al. (1983), who have stressed that stock price volatility is too high to be attributable solely to fundamental information.

What Drives Stock Price Deviations from NAV?

For property-holding companies, the NAV spread was initially described by Adams and Venmore-Rowland (1990), who present a theoretical rather than an empirical approach. Later empirical studies find that a certain part of the NAV spread can be explained by rational factors, although they generally fail to capture higher fluctuations through time.[4] Thus, we can divide the financial literature on NAV spreads into two broad approaches: 'rational' and 'noise trader'.

The rational approach assumes that share price deviations from NAV are caused by a set of rational company-specific factors, such as size, taxation, risk factors, debt levels, and shareholder structure. The NAV spread is explained by the general assumption of a company's fair value measured by its future return expectations, corrected by potential risk.

Traditional (rational) factors do not capture market cycles. These characteristics challenge the rational approach, since they imply dramatic shifts in fundamental

[4] See, e.g., Capozza and Korean (1995); Benveniste et al. (2001); Clayton and MacKinnon (2000); Cronqvist et al. (2001); Bond and James (2003); Gentry et al. (2004); Brounen and Laak (2005); Ghosh et al. (2020).

factors over time (Mueller and Pfnuer, 2013). Financial researchers note that these higher fluctuations are driven mainly by market sentiment (Morri and Benedetto, 2009).

De Long et al. (1990b) attribute this phenomenon to the presence of two types of traders: 1) rational institutional investors, and 2) individual/retail traders (i.e., noise traders). In this regard, Lee et al. (1999) and Elton et al. (1998) assume that noise trader risk generates noisy fluctuations in NAV spreads. This assumption is in line with Ke (2015), who finds for real estate that increasing institutional share ownership tends to narrow NAV spreads. Furthermore, Lee et al. (1999) argue that price deviations to fundamentals result from irrational agents trading on correlated sentiment.

Another implication of Lee et al. (1999) is that the investor group trading the underlying properties differs from that group trading the property companies' shares. If the investor groups were equal, sentiment changes would influence both markets equally: The property and the stock market would be equally risky. The assets held primarily by real estate companies tend to be traded by professional investors. Share prices of property-holding companies are highly influenced by somewhat unprofessional retail traders. In this regard, Barkham and Ward (1999) find that real estate company shares provide a vehicle by which noise traders may influence the property market. And Patel et al. (2009) stress that NAV spread levels of property-holding companies capture macroeconomic risk.

What Determines the Mean Reversion Speed of NAV Spreads?

In a fully efficient market, NAV spreads follow a white noise process. The NAV spread of the current period should be independent of that of the previous period. The real estate financial literature provides some evidence for the mean reversion of NAV spreads (see Liow (2003); Liow and Li (2006); Chiang (2009); Patel et al. (2009)). But, to the best of our knowledge, we are the first to study which factors impact the mean reversion speed of NAV spreads of property-holding companies.

We posit that market participants identify market anomalies, and systematically invest in undervalued companies (or divest overvalued (premium) companies). Thus, companies with extraordinarily low (high) NAV spreads mean-revert faster. We also expect the speed of mean reversion may be driven by company size as the same dollar amount of buying and selling pressure could have a disproportionate price pressure effect on smaller companies. Moreover, the leverage ratio likely impacts the mean reversion speed. We posit further that there is an optimal capital structure, and that extreme leverage ratios (both very high and very low) decrease mean reversion speed. Further, we suspect that the CAPM beta may have an impact on the mean reversion speed of the NAV spread.

Impact of Online Search Attention

Over the past decade, research using online data from search engines, social networks, internet encyclopedias, microblogging, and image hosting websites has exploded.[5] Google Trends is an especially valuable and accessible data source. In this context, the financial literature finds a positive correlation between the volume of Google search queries and trading activity (Veiga et al., 2013).

Da et al. (2011) find that Russell 3000 stocks with abnormal rising online search attention are linked to short-run overperformance and long-run price reversals. Bijl et al. (2016) use S&P 500 companies, and Hervé et al. (2019) use French companies. Both find virtually identical results. In this context, Da et al. (2011) argue that extraordinary increases in Google search requests are tied to increasing retail trader attention. They note that individual stockholders tend to rely more heavily on Google to obtain company investment information. Professional investors have access to more robust platforms such as Bloomberg or Reuters (Da et al., 2011).

Kristoufek (2013) provides evidence that stocks with higher online search attention tend to be riskier. Bijl et al. (2016) develop a trading strategy for investing in companies that have lower Google attention. They find that, if transaction costs are neglected, the strategy would beat the market; once transaction costs are controlled for, the strategy would fail.

In the case of real estate markets, Wu and Brynjolfsson (2015) and Beracha and

[5] See, e.g., Moat et al. (2013); Bordino et al. (2012); Gilbert and Karahalios (2010); Mao et al. (2011); Bollen et al. (2011); Preis et al. (2013).

Wintoki (2013) show the predictive power of Google Trends. Wu and Brynjolfsson (2015) illustrates that Google search terms are correlated with future house prices and sales. Beracha and Wintoki (2013) find further evidence of the predictive power of online search intensity on future home price changes. Rochdi and Dietzel (2015) develop an investment strategy based on Google Trends data using the MSCI US REIT Index. They find that Google Trends investment strategies may substantially outperform the benchmark. Moreover, the use of data on online search requests is applied to the NAV spread puzzle of property-holding companies.

Jandl and Fuerst (2015) use Google Trends data as a proxy for information demand. However, they find no economically relevant impact on the level of NAV spreads. We posit that online search attention may influence the level of NAV spreads. Reflecting the findings of previous research, we formulate our first hypothesis as follows:

Hypothesis 1a: *The level of the NAV spread is related to the level of online search attention.*

Google search requests on a company's name are connected with high information demand. The question is whether that demand is rational, or the result of noise trader attention or bad news. To answer this question, we test whether the mean reversion speed of the NAV spread toward its long-run mean increases (decreases) depending on whether a company is the subject of higher (lower) levels of Google search requests. If it increases, this would be due to rational information demand. If it decreases, it would be related to rising levels of noise trader attention or to bad news. We assume that high levels of Google search requests are related to high levels of noise attention, and therefore slow the mean reversion speed. We thus formulate our next hypothesis as follows:

Hypothesis 1b: *Online search attention slows the mean reversion speed of NAV spreads.*

Spillover Effect of Online Search Attention to other Stocks

De Long et al. (1990a) posit that noise trader sentiment is stochastic. Under this assumption, there should be no relationship between the NAV spread of a specific company and its countrywide average NAV spread. Nevertheless, the real estate finance literature reports a relationship between the two (Barkham and Ward, 1999; Clayton and MacKinnon, 2000; Mueller and Pfnuer, 2013). Woltering et al. (2018) find evidence that the key to outperform the market is to invest in the most underpriced stocks relative to the average NAV spread in a specific country. This result suggests that there is a dependency between a company specific NAV spread and the average NAV spread in a specific country. Ambrose et al. (2007) find that REIT return correlations are driven by investor sentiment. In our study we go one step further and we assume that the stocks in a country that receive the highest online search attention will disproportionately affect other stocks' NAV spreads in that country. A clear understanding of such spillovers driven by online search attention is crucial for analyzing the dynamics of the NAV spread and could be applied to improve investment strategies. Our result might suggest that investing in the most underpriced stocks relative to an average online search attention weighted NAV spread in a specific country leads to extraordinary returns. Therefore, we formulate our next hypothesis as follows:

Hypothesis 2: *The spillover effect to other stocks increases with rising levels of online search attention.*

3.3 Data

Our sample consists of quarterly company-level data on 219 property-holding companies in 11 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, and United Kingdom) from March 2005 to December 2018. This allows a high degree of comparability of accounting information across countries due to the adoption of IFRS in many countries. We chose the sample from the constituents of the FTSE EPRA/ NAREIT Global Real Estate Index, which are provided by the European Public Real Estate Association (EPRA) in conjunction with the National Association of Real Estate Investment Trusts (NAREIT) and the Financial Times Stock Exchange (FTSE). The constituents include listed companies with relevant real estate activities. To ensure index quality, the FTSE EPRA/NAREIT Global Real Estate Index mandates four qualities for the underlying property companies: 1) minimum free-float market capitalization, 2) minimum liquidity requirement, 3) minimum share of EBITDA (75%) from relevant real estate activities, and 4) publication of audited annual accounting reports in English.

Following Weis et al. (2021), we limit the sample to property-holding companies from countries with fair value-based accounting regimes.[6] In this regard, the introduction of International Financial Reporting Standards (IFRS) in 2005 considerably improved the comparability of accounting data across nations (Ball, 2006). IFRS accounting, in contrast to historical cost-based accounting, reports assets at fair value. For real estate companies, the assets consist mainly of regularly valued properties. Assuming that other assets and liabilities are also reported close to their market value, the book value of equity of real estate companies can be interpreted as a 'sum of the parts' estimate of the company value, where each property is evaluated using specific risk-adjusted discount rates. This provides a unique framework in which to analyze discrepancies between stock prices and approximations of the fundamental value across countries.

Our dataset consists of fundamental company-specific financial data collected from Thomson Reuters Datastream. To gauge online search attention, we gathered data from Google Trends. We merely include countries with a minimum of 100 observations and at least 5 observations to each specific period. To prevent survivorship bias, we include active as well as deleted FTSE EPRA/NAREIT Global Real Estate Index constituents.

Variable Definitions

Our data includes NAV spreads, company size, leverage, and CAPM beta. We define the NAV spread ($spread_{i,t}$) of property-holding company i in period t as the relative

[6] Our empirical sample is based on REITs and REOCs from countries which report according to IFRS: Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, and United Kingdom. IFRS requires companies to disclose the market value of investment properties. US REITs and REOCs are not part of our sample as they report according to US-GAAP. Under US-GAAP, book values are based on historically depreciated real estate acquisition costs, so they cannot be a basis for the calculation of NAV-spreads.

difference between NAV per share ($NAV_{i,t}$) and the unadjusted share price ($price_{i,t}$).

$$spread_{i,t} = \frac{price_{i,t}}{NAV_{i,t}} - 1 \tag{3.3.1}$$

We calculate the ($NAV_{i,t}$) of company i in period t by dividing Thomson Reuters' common equity (i.e., book value of equity) by its number of shares. A positive (negative) NAV spread is expressed as a premium (discount) to NAV. To determine value, middle, and growth portfolios, we rank the NAV spread on a country level at the end of each quarter. We define three distinct binary indicator variables that equal 1 if a company belongs to the respective cluster, and 0 otherwise: A quintile of stocks with high discounts to NAV ($SPREAD1_{i,t}$), the middle three quintiles ($SPREAD2_{i,t}$), and a quintile of stocks with the highest premiums to NAV ($SPREAD3_{i,t}$).

We measure size ($size_{i,t}$) by the natural logarithm of a company's market capitalization. To define small, medium, and large companies, we use ranks of company size on country-level. We cluster the sample into three groups of company sizes, and define three binary indicator variables that equal 1 if a company belongs to the respective cluster, and 0 otherwise: A quintile of stocks with small companies ($SIZE1_{i,t}$), the middle three quintiles ($SIZE2_{i,t}$), and a quintile of stocks with large companies ($SIZE3_{i,t}$).

Leverage ($leverage_{i,t}$) is the ratio of a company's total debt to total assets. Similarly to the above, we cluster the sample on country-level into three groups of leverage. We define three distinct binary indicator variables that equal 1 if a company belongs to the respective cluster, and 0 otherwise: A quintile of stocks with a low leverage ratio ($LEV1_{i,t}$), the middle three quintiles ($LEV2_{i,t}$), and a quintile of stocks with high leverage companies ($LEV3_{i,t}$).

Additionally, we derive the respective 24-month rolling CAPM betas for each stock in our sample on a quarterly basis. To this end, we use monthly data on a company's total return, the risk-free rate, and the monthly return of the market portfolio proxy as follows:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{iM,t}(r_{m,t} - r_{f,t}) + u_{i,t} \tag{3.3.2}$$

The CAPM beta ($CAPM\ beta_{i,t}$) of company i in period t is represented by the parameter $\beta_{iM,t}$. $r_{i,t}$ is the total return of REIT i in month t, $r_{f,t}$ is the risk-free rate, and $r_{m,t}$ is the monthly return of the market portfolio proxy. The data on $r_{f,t}$ and $r_{m,t}$ come from Kenneth French's website.[7]

We rank CAPM beta on country-level at the end of each quarter, and again define three dummy variables that equal 1 if a company belongs to the respective cluster, and 0 otherwise: A quintile of stocks with low CAPM beta companies ($CAPM1_{i,t}$), the middle three quintiles ($CAPM2_{i,t}$), and a quintile of stocks with high CAPM beta companies ($CAPM3_{i,t}$).

Next, we measure the spillover effect (i.e., the dependence of the countrywide average NAV spread on a specific company's NAV spread) by calculating the average NAV spread in the operating country of each company ($ctrspread_{i,t}$). Thus, for each company i, we calculate by quarter t the market capitalization ($mcap_{i,t}$) weighted average NAV spread of the other companies in that country. $n_{i,t}$ represents the number of the other companies in the country of company i in period t. [8]

$$ctrspread_{i,t} = \frac{\sum_{j=1, j\neq i}^{n_{i,t}} spread_{j,t}\ mcap_{j,t}}{\sum_{j=1, j\neq i}^{n_{i,t}} mcap_{j,t}} \tag{3.3.3}$$

We again use Google Trends to measure online search attention. We obtain data on monthly worldwide search requests of the respective company name without limiting to a specific filter (e.g., categories such as finance, real estate, etc.). We leave company names as is in the majority of cases, but remove certain endings (such as Inc. and Corp.) where necessary.

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

[8] To prevent misleading correlations, we exclude company i from this aggregation.

Google Trends data are only accessible in a weighted form relative to other companies. For the highest search volume across all companies through time, the value is ranked 100. If a company receives no search requests over a particular point in time, the value is set to 0. Moreover, Google Trends only allows downloading of five time series on relative search requests simultaneously. Thus, we develop our own algorithm in order to determine a ranking for each company name relative to other companies' names across time.[9] In this paper, we calculate average search requests on a quarterly basis.

Uncorrected Google search requests on a specific company's name tend to be error-prone, since a given company may have a specific shareholder structure, size, location, or investment segment that can lead them to receive significantly higher (lower) levels of search requests than others. Our aim is to measure extraordinarily high or low search requests on a specific company as compared to the number of requests it received in the past. Therefore, we standardize our quarterly Google search volume $gsv_{i,t}$ by subtracting past years' average volume, and dividing it by the standard deviation of quarterly volume over the past year $\sigma_{gsv,i,t}$.

$$sgsv_{i,t} = \frac{gsv_{i,t} - \frac{1}{4}\sum_{j=0}^{3} gsv_{i,t-j}}{\sigma_{gsv,i,t}} \tag{3.3.4}$$

We name this variable standardized Google search volume (SGSV). The SGSV ($sgsv_{i,t}$) data on company i in period t is ranked quarterly. We cluster the sample on a country level into three SGSV groups at the end of each quarter. We define three distinct binary indicator variables that equal 1 if a company belongs to the respective cluster, and 0 otherwise: A quintile of stocks with low SGSV ($SGSV1_{i,t}$), the middle three quintiles ($SGSV2_{i,t}$), and a quintile of stocks with high SGSV ($SGSV3_{i,t}$).

In order to capture the spillover effect of online search attention on other stocks, we calculate market capitalization weighted average NAV spreads on a quarterly basis

[9] The algorithm downloads multiple datasheets, with the name of the first company in each one and four other company names as well. Once downloaded, we are able to combine the datasheets.

within each of our SGSV clusters on a country level.[10]

As an additional control, we consider companies' investment sectors (office, retail, hotel, industrial, residential, diversified, or specialty), as well as binary country identification variables. To prevent outliers misleadingly driving our results, we winsorize the NAV spread, the logarithm of the company's market capitalization, and leverage at a 2.5/97.5 level.

Descriptive Statistics

Table 4 provides the summary statistics of the NAV spread, size, leverage, and CAPM beta of the global sample for each country from March 2005 to December 2018. We report statistics on the mean, standard deviation, and median. In our observation period, we find a 17.45% average NAV spread premium on a global level, with a mean company size of 129.00 billion USD. The NAV spread is highest in Canada with 74.72%, and lowest in Hong Kong with -17.94%. Overall, we observe a substantial degree of variation in NAV spreads across countries.

Table 5 shows the statistics on a sector level. Property-holding companies in the investment segment of specialty properties show the highest NAV spread with 55.88%, while the lowest NAV spread is seen for companies investing in diversified property with 9.12%. The correlations among the NAV spread, its lagged value, and its explanatory variables are given in Table 6. We find a statistically significant positive correlation between the NAV spread and the previous period's NAV spread, size, leverage, and country average NAV spread. We find a statistically significant negative correlation between the previous period's CAPM beta and the NAV spread. There is no statistically significant correlation between lagged SGSV and the NAV spread.

[10] As with $ctrspread_{i,t}$, we exclude company i from this aggregation to avoid any misleading correlations between one and the same company.

Table 4: Countrywise Summary Statistics on NAV spreads and Control Variables

	N	Stocks	Mean	SD	median		N	Stocks	Mean	SD	median
World						Hong Kong					
spread	5544	219	18.62%	60.33%	10.02%	spread	484	27	-9.90%	56.88%	-28.55%
company size (bn USD)	5544	219	3.64	5.78	1.69	company size (bn USD)	484	27	9.14	10.53	4.97
leverage	5544	219	40.53%	14.87%	40.93%	leverage	484	27	24.35%	9.04%	25.03%
CAPM beta	5544	219	0.18	0.60	0.13	CAPM beta	484	27	0.07	0.53	0.06
Google Trends	5544	219	4.41	0.95	10.57	Google Trends	484	27	3.33	0.51	8.42
Australia						Japan					
spread	408	19	16.10%	46.98%	13.67%	spread	1086	36	48.05%	65.96%	43.04%
company size (bn USD)	408	19	4.20	6.80	1.46	company size (bn USD)	1086	36	5.23	7.53	2.37
leverage	408	19	33.64%	9.77%	34.79%	leverage	1086	36	44.49%	9.59%	44.26%
CAPM beta	408	19	0.18	0.42	0.11	CAPM beta	1086	36	0.21	0.64	0.18
Google Trends	408	19	4.64	1.01	8.50	Google Trends	1086	36	5.96	0.95	15.46
Belgium						Singapore					
spread	240	6	13.65%	22.57%	13.27%	spread	632	20	3.66%	48.44%	-3.38%
company size (bn USD)	240	6	0.85	0.72	0.50	company size (bn USD)	632	20	3.65	2.85	2.57
leverage	240	6	41.41%	12.99%	45.85%	leverage	632	20	33.91%	9.94%	34.29%
CAPM beta	240	6	0.03	0.24	-0.02	CAPM beta	632	20	0.20	0.31	0.17
Google Trends	240	6	0.78	0.68	0.56	Google Trends	632	20	2.00	0.68	3.02
Canada						Sweden					
spread	194	10	78.27%	75.48%	69.35%	spread	267	8	17.51%	45.75%	21.70%
company size (bn USD)	194	10	2.32	2.80	1.13	company size (bn USD)	267	8	1.76	1.23	1.54
leverage	194	10	60.19%	10.34%	59.92%	leverage	267	8	47.65%	15.57%	51.39%
CAPM beta	194	10	0.16	0.47	0.09	CAPM beta	267	8	0.29	0.95	0.15
Google Trends	194	10	2.51	1.18	2.71	Google Trends	267	8	3.97	3.60	3.49
France						Netherlands					
spread	422	11	42.63%	72.57%	31.51%	spread	205	7	-0.70%	25.03%	-2.54%
company size (bn USD)	422	11	3.72	3.48	2.62	company size (bn USD)	205	7	3.16	2.28	2.10
leverage	422	11	46.44%	14.77%	49.00%	leverage	205	7	37.02%	5.83%	38.18%
CAPM beta	422	11	0.16	0.51	0.13	CAPM beta	205	7	0.15	0.35	0.15
Google Trends	422	11	8.72	2.20	12.97	Google Trends	205	7	8.15	1.96	8.70
Germany						United Kingdom					
spread	476	21	18.28%	68.88%	9.18%	spread	1130	54	-2.43%	43.52%	-2.38%
company size (bn USD)	476	21	1.81	3.14	0.72	company size (bn USD)	1130	54	1.63	2.42	0.56
leverage	476	21	51.46%	17.31%	54.69%	leverage	1130	54	38.43%	15.19%	36.80%
CAPM beta	476	21	0.11	0.86	0.11	CAPM beta	1130	54	0.23	0.66	0.12
Google Trends	476	21	2.91	1.18	4.87	Google Trends	1130	54	4.19	0.51	12.10

Our sample includes quarterly FTSE EPRA/NAREIT REIT data from 11 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, and United Kingdom) from January 2005 to December 2018. The table summarizes the data on a worldwide and country-level on the NAV spread ($\mathrm{spread}_{\mathrm{i,t}}$), defined as ($\mathrm{price}_{\mathrm{i,t}}/\mathrm{NAV}_{\mathrm{i,t}}$ - 1), where $price_{i,t}$ is the unadjusted share price of company i in period t, $NAV_{i,t}$ is NAV per share of company i in period t, market capitalization in billions USD ($size_{i,t}$) of company i in period t, ratio of a company's total debt to total assets ($leverage_{i,t}$) of company i in period t, 24-month CAPM beta ($CAPM\ beta_{i,t}$) of company i in period t, and quarterly Google search volume of company i's name ($gsv_{i,t}$) in period t. For each variable, the mean, standard deviation, and median are reported.

Table 5: Sectorwise Summary Statistics on NAV spreads and Control Variables

	N	Stocks	mean	sd	p50		N	Stocks	mean	sd	p50
Diversified						Residential					
spread	2799	80	10.70%	59.15%	-0.72%	spread	555	30	18.11%	64.47%	7.57%
company size (bn USD)	2799	80	5.21	7.67	2.24	company size (bn USD)	555	30	2.10	3.40	1.09
leverage	2799	80	35.89%	14.66%	35.84%	leverage	555	30	51.33%	14.25%	53.29%
CAPM beta	2799	80	0.17	0.61	0.12	CAPM beta	555	30	0.07	0.80	0.13
Google Trends	2799	80	5.47	13.24	0.68	Google Trends	555	30	3.28	4.78	1.47
Hotel						Retail					
spread	97	6	-2.08%	77.58%	-2.06%	spread	983	33	25.98%	56.02%	15.18%
company size (bn USD)	97	6	0.93	0.85	0.61	company size (bn USD)	983	33	4.12	5.17	2.27
leverage	97	6	36.89%	17.85%	44.38%	leverage	983	33	34.84%	14.32%	35.47%
CAPM beta	97	6	0.19	0.48	0.01	CAPM beta	983	33	0.15	0.43	0.11
Google Trends	97	6	1.05	0.68	0.98	Google Trends	983	33	5.17	9.76	1.14
Industrial						Specialty					
spread	479	22	9.22%	37.09%	7.82%	spread	151	5	61.98%	71.35%	42.15%
company size (bn USD)	479	22	1.65	1.89	1.04	company size (bn USD)	151	5	0.80	0.48	0.67
leverage	479	22	38.53%	12.08%	39.19%	leverage	151	5	53.20%	14.40%	52.64%
CAPM beta	479	22	0.12	0.47	0.10	CAPM beta	151	5	0.11	0.34	0.09
Google Trends	479	22	0.71	0.79	0.51	Google Trends	151	5	1.53	2.14	0.51
Office											
spread	1010	43	23.46%	64.51%	13.67%						
company size (bn USD)	1010	43	3.10	3.17	2.11						
leverage	1010	43	44.10%	13.21%	43.59%						
CAPM beta	1010	43	0.29	0.65	0.18						
Google Trends	1010	43	1.60	2.18	0.65						

The sample includes quarterly FTSE EPRA/NAREIT REIT data from 11 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, and United Kingdom) from January 2005 to December 2018. The table summarizes data on a sector level over 7 sectors (Diversified, Hotel, Industrial, Office, Residential, Retail, and Speciality) on the NAV spread ($\mathrm{spread}_{\mathrm{i,t}}$), defined as ($\mathrm{price}_{\mathrm{i,t}}/\mathrm{NAV}_{\mathrm{i,t}}$ - 1), where $price_{i,t}$ is the unadjusted share price of company i in period t, $NAV_{i,t}$ is NAV per share of company i in period t, market capitalization in billions USD ($logsize_{i,t}$) of company i in period t, ratio of a company's total debt to total assets ($leverage_{i,t}$) of company i in period t, 24-month CAPM beta ($CAPM\ beta_{i,t}$) of company i in period t, and quarterly Google search volume of company i's name ($gsv_{i,t}$) in period t. For each variable, the mean, standard deviation, and median are reported.

Table 6: Correlations among NAV spreads, Rational Determinants, and Sentiment Variables

	spread	L.spread	L.size	L.leverage	L.CAPM beta	L.ctrspread	L.gsv
spread	1.000						
L.spread	0.906***	1.000					
L.size	0.255***	0.243***	1.000				
L.leverage	0.172***	0.167***	-0.280***	1.000			
L.CAPM beta	-0.030*	-0.018	0.035**	-0.040***	1.000		
L.ctrspread	0.469***	0.506***	0.097***	0.190***	-0.089***	1.000	
L.sgsv	0.009	0.003	-0.010	-0.004	-0.005	-0.002	1.000

The sample includes quarterly FTSE EPRA/NAREIT REIT data on 11 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, and United Kingdom) from January 2005 to December 2018. The table shows the correlations between the variable NAV spread ($\mathrm{spread}_{\mathrm{i,t}}$), defined as ($\mathrm{price}_{\mathrm{i,t}}/\mathrm{NAV}_{\mathrm{i,t}}$ - 1), where $price_{i,t}$ is the unadjusted share price of company i in period t, $NAV_{i,t}$ is the NAV per share of company i in period t, and several lagged sample variables. The NAV spread of company i in the previous period ($\mathrm{spread}_{\mathrm{i,t-1}}$), the logarithm of the market capitalization in billions of USD ($logsize_{i,t\text{-}1}$) of company i in the previous period, the ratio of total debt to total assets ($leverage_{i,t\text{-}1}$) of company i in the previous period, the 24-month CAPM beta of company i in the previous period $CAPM\ beta_{i,t\text{-}1}$, the countrywide average NAV spread ($ctrspread_{i,t\text{-}1}$) calculated for each company i individually as the market capitalization weighted quarterly average NAV spreads of the other companies in the respective country in the previous period, and the quarterly Google search volume of company i's name in the previous period *t-1* ($gsv_{i,t\text{-}1}$). Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

3.4 Empirical Specification

Base Model

We describe today's NAV spread ($spread_{i,t}$) of company i at time t as a function of previous periods' NAV spreads ($spread_{i,t\text{-}1}$), previous periods' countrywide average NAV spreads in the respective country of company i ($ctrspread_{i,t\text{-}1}$), a set of control variables (*controls*), and controls for sector and country. a_i represents the panel fixed effect of company i, and $e_{i,t}$ is a white noise shock to time t.

$$spread_{i,t} = \alpha\ spread_{i,t-1} + \beta\ ctrspread_{i,t-1} + controls + a_i + e_{i,t} \tag{3.4.1}$$

The idea behind our model is that there are two fundamental market correction mechanisms affecting the NAV spread. The first is the mean reversion behavior of the NAV spread correcting the NAV spread toward its long-run mean; the second is the spillover effect correcting a company's NAV spread toward its countrywide average.

Note that the autoregressive parameter α determines the mean reversion speed of the NAV spread toward its long-run mean after the impact of an exogenous shock $e_{i,t}$. Therefore, we assume that the value of parameter α is between 0 and 1 ($0 < \alpha < 1$). This assumption assures the mean reversion behavior of the NAV spread. The closer α moves to 0, the higher the mean reversion speed of the NAV spread after the impact of an exogenous shock. In the case of $\alpha = 0$, a deviation from the long-run mean NAV spread at time t would be corrected completely in the subsequent period $t+1$. If $\alpha = 1$, the previous period's NAV spread would be fully reversed into the current period's NAV spread.

We assume the value of β is between 0 and 1 ($0 < \beta < 1$). The higher parameter β, the stronger the spillover effect adjusting a company's NAV spread toward the countrywide average. For $\beta = 1$, 100% of the country-specific average NAV spread would spill over into the company-specific NAV spread. For $\beta = 0$, we observe no spillover effect.

The vector *controls* includes company-specific rational determinants that include the previous period's logarithm of company size, leverage, and CAPM beta, as well as country- and sector-specific dummy variables. Using this specification, we are able to model the dynamics of the NAV spread while simultaneously considering those deviations.

Measuring the Speed of Mean Reversion

Our interest in this paper concerns the mean reversion speed of the NAV spread. In this regard, the IRF of the NAV spread measures the effect of an exogenous one-unit shock occurring at time t (that is, $e_{i,t} = 1$, as in Equation (5)) on future values of the NAV spread. The IRF quantifies the mean reversion speed of the NAV spread. The h-th horizon of our IRF is given by:

$$IRF(h) = \alpha^h \quad for\ h = 0, 1, 2, ..., \tag{3.4.2}$$

An unbiased estimate of α allows us to calculate an unbiased scalar estimate of the mean reversion speed the half-life of a one-unit shock. This is the duration until an exogenous one-unit shock corrects to half its initial magnitude. The smaller parameter α, the higher the mean reversion speed.[11]

We measure the impact of company-specific information on mean reversion speed by adding interaction terms of the lagged NAV spread and dummy variables indicating this information to our base model. The sum of the parameter α and the parameter on the interaction term indicates the mean reversion speed. Thus, a significantly negative (positive) parameter on the interaction term indicates a higher (lower) mean reversion speed for this specific information.

To measure the mean reversion speed at different NAV spread levels, we add interaction terms indicating the high discount portfolio (SPREAD1) or the high premium portfolio (SPREAD3) and the lagged NAV spread to our base model. We posit that

[11] Equation 6 does not take into account feedback effects. This effect occurs since a one-unit-shock on company i in period 0 has an impact on the other companies ($j \neq i$) in period 1 while the other companies effect company i in period 2. The regression parameters in table 7 and 8 show that the beta coefficient is (at 0.1) so small that the feedback effect is practically irrelevant. In unreported results we have calculated the impulse response functions as shown in figure 4 and 5 including the feedback effect. The results had no discernible differences.

high discount stocks mean-revert quickest. Thus, we expect a significantly negative parameter on the interaction term of SPREAD1 and the lagged NAV spread. To test the impact of company size, we include interaction terms of the lagged NAV spread and the binary variables indicating small (SIZE1) or large (SIZE3) company. We expect to find higher mean reversion for small companies, and thus a significantly negative parameter on the interaction term of SIZE1 and lagged NAV spread.

Furthermore, we posit that the leverage ratio will impact the mean reversion speed of the NAV spreads. Therefore, we add interaction terms of the lagged NAV spread and dummy variables indicating low (LEV1) or high leverage ratios (LEV3). We expect to find slower mean reversion for both, and thus significantly positive parameters on both interaction terms. In order to test whether the CAPM beta impacts the mean reversion speed of the NAV spread, we allow interaction terms of the lagged NAV spread and binary variables indicating low (CAPM1) and high CAPM beta (CAPM3). We posit that companies with low CAPM betas will mean-revert the quickest. We thus expect a negative parameter on the interaction term of CAPM1 and the lagged NAV spread.

Analyzing the Impact of Online Search Attention

Under Hypothesis 1a, we posit that shifting SGSV levels affect the level of the NAV spread. To prove this assumption, we add the variable SGSV to our base model. We expect a significant impact.

As stated in Hypothesis 1b, our aim is to measure the relationship between mean reversion speed and SGSV. Therefore, we add interaction terms of SGSV and the autoregressive coefficient for both low and high SGSV to our base model. We expect a significantly negative parameter on the interaction term between low SGSV and the lagged NAV spread.

Analyzing the Spillover Effect of Online Search Attention

Under Hypothesis 2, we posit higher spillover effects from companies with higher levels of online search attention. To test this notion, we use a piecewise linear specification, and replace the variable $ctrspread_{i,t-1}$ in our base specification with the online search attention cluster-specific aggregates. We expect no to find significant dependence on companies within the SGSV1 cluster. We expect a rather small spillover effect from SGSV2 companies, and that the effect from the SGSV3 cluster will be the highest.

Estimation Procedure

In our empirical specification, we include the lagged NAV spread and the countrywide average NAV spread. To control for country and sector specifics, we include binary variables that represent the country and company's operational sector. We also add a panel fixed effect to capture company-specific long-run NAV spreads. Using this specification, we aim to capture the dynamics and country and sector characteristics of the global dataset. Running a common panel estimation would lead to endogeneity bias, as the fixed effect appear to be correlated with the lagged dependent variable. An endogeneity bias may also arise with the countrywide average NAV spread. This calls for a dynamic panel estimator. We use a Blundell-Bond (1998) GMM-System-Estimator, and instrumentalize the lagged NAV spread and the interactions with the lagged NAV spread. We also instrumentalize the countrywide average NAV spread and the SGSV clusters of the countrywide average NAV spread (a detailed explanation is provided in the Appendix).

3.5 Regression Results

Table 7 and table 8 provides the results of the Blundell-Bond (1998) regression. In table 7 model (i) shows the base model, models (ii) to (v) capture the impact of company-specific information on the mean reversion speed of the NAV spread. In table 8 model (i) analyzes the impact of SGSV on the level of the NAV spread, models (ii) and (iii) examine the impact of SGSV on the mean reversion speed of the NAV spread and the spillover effect of online search attention, and models (iv) examines a robustness test by examining all the impacts discussed above simultaneously. In each specification, we model the NAV spread as a function of the lagged NAV spread, the countrywide average NAV spread, leverage, the natural logarithm of company size, and CAPM beta. The Arellano-Bond test for zero autocorrelation in first-differenced errors finds no evidence of autocorrelation in the residuals in any of our specifications. This is an indicator for correct specification. Furthermore, in no case we can reject the Sargan test at any rational significance level, proving that the set of instruments is chosen reasonably.

Our analysis shows the following results. We find a positive impact of size and a negative effect of leverage on the NAV spread. Therefore, large companies and companies with low leverage tend to trade at a high premium to the NAV. Surprisingly, we find no significant impact of CAPM beta. Regarding the relevance and impact of these factors on the NAV spread, the real estate literature finds heterogeneous results (Rehkugler et al., 2012). For example, Clayton and MacKinnon (2000), Capozza and Korean (1995), and Brounen and Laak (2005) report a positive impact of company size due to economies of scale, while Bond and James (2003) detect no significant impact. In contrast, Barkham and Ward (1999) and Morri and Benedetto (2009) find that company size tends to negatively impact NAV spreads.

The literature reports even more heterogeneous results for the impact of leverage. Bond and James (2003), Brounen and Laak (2005), Ke (2015), and Morri and Benedetto (2009) find that increasing leverage is related to higher discounts to NAVs. In contrast, Clayton and MacKinnon (2000), Morri and Benedetto (2009), and Nellessen and Zuelch (2011) cite a positive impact of leverage on the NAV spread. And Barkham and Ward (1999) and Rehkugler et al. (2012) find no significant relationship between leverage and the NAV spread. Bond and James (2003) and Morri and Benedetto (2009) use the CAPM beta as a proxy for risk, and find evidence of a negative impact. Our results on the impact of the CAPM beta are in line with those of Brounen and Laak (2005).

Under the assumption that noise trader risk is stochastic, there should be no cross-time or cross-country relationships among NAV spreads (De Long et al., 1990a). Our results challenge this assumption. Importantly, we find that the parameter on the lagged NAV spread is greater than 0 and smaller than 1 in each specification. This result proves the mean reversion behavior of NAV spreads. In each specification, we also find that the countrywide average NAV spread of the other companies exhibits a statistically significant positive impact. This is evidence for the existence of a

Table 7: Estimation Results of the Blundell Bond 1998 System GMM Estimator

Specification	(i)	(ii)	(iii)	(iv)	(v)
Variables	spread	spread	spread	spread	spread
L.spread	0.636***	0.752***	0.702***	0.615***	0.667***
	(0.045)	(0.092)	(0.051)	(0.055)	(0.045)
L.spread L.SPREAD1		-0.347***			
		(0.105)			
L.spread L.SPREAD3		-0.072			
		(0.086)			
L.spread L.SIZE1			-0.115*		
			(0.063)		
L.spread L.SIZE3			-0.073		
			(0.062)		
L.spread L.LEV1				0.153**	
				(0.074)	
L.spread L.LEV3				0.114*	
				(0.067)	
L.spread L.CAPM1					-0.066
					(0.059)
L.spread L.CAPM3					0.044
					(0.051)
L.ctrspread	0.116***	0.106**	0.123***	0.115***	0.109***
	(0.038)	(0.046)	(0.033)	(0.035)	(0.0279)
L.logsize	0.163***	0.147***	0.130***	0.142***	0.127***
	(0.025)	(0.013)	(0.015)	(0.016)	(0.015)
L.leverage	-0.588***	-0.344**	-0.395***	-0.164	-0.448***
	(0.187)	(0.139)	(0.121)	(0.112)	(0.112)
L.CAPMbeta	-0.011	-0.005	-0.008	-0.006	-0.004
	(0.024)	(0.017)	(0.021)	(0.019)	(0.020)
Observations	5,544	5,544	5,544	5,544	5,544
NumberofCompanies	219	219	219	219	219
m1	-6.862	-6.823	-6.929	-6.970	-6.938
m2	1.215	1.027	-6.929	1.173	1.174
Sargan	199.852	199.244	193.874	199.196	196.750
(df)	248	458	458	458	458

This table summarizes our Blundell-Bond (1998) estimation results using a quarterly sample of FTSE EPRA/NAREIT REIT data from 11 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, and United Kingdom) from March 2005 to December 2018. The table reports the coefficient estimates for separate regressions using the NAV spread ($\mathrm{spread}_{\mathrm{i,t}}$) as the dependent variable, defined as ($\mathrm{price}_{\mathrm{i,t}}/\mathrm{NAV}_{\mathrm{i,t}}$ - 1), where $price_{i,t}$ is the unadjusted share price of company i in period t, and $NAV_{i,t}$ is the NAV per share of company i in period t. The independent variables used in the regression include the NAV spread of company i in the previous period ($\mathrm{spread}_{\mathrm{i,t\text{-}1}}$), the logarithm of the market capitalization in billions of USD ($logsize_{i,t\text{-}1}$) of company i in the previous period, the ratio of total debt to total assets ($leverage_{i,t\text{-}1}$) of company i in the previous period, the 24-month CAPM beta ($CAPM\ beta_{i,t\text{-}1}$) of company i in the previous period, and the countrywide average NAV spread of the other companies in the respective country ($ctrspread_{i,t\text{-}1}$) calculated individually for each company i in the previous period. For differing specifications, we allow interaction terms between the lagged NAV spread and the lagged binary variables for different NAV spread levels, company sizes, leverage ratios, and CAPM beta levels. The low NAV spread dummy variable (SPREAD1) is therefore identified as the lower quintile of NAV spreads (the highest discount to NAV), the high NAV spread portfolio (SPREAD3) is the upper quintile, and each NAV spread cluster is determined quarterly on country-level. We denote small companies (SIZE1) as the lower quintile of company size, large companies (SIZE3) as the upper quintile, and each SIZE cluster is determined quarterly on country-level. Moreover, we denote low leverage (LEV1) as the lower quintile of leverage, high leverage (LEV3) as the upper quintile, and each leverage cluster is determined quarterly on country-level. CAPM1 is a dummy variable for low CAPM beta representing the lower quintile of CAPM beta, high CAPM beta (CAPM3) is the upper quintile, and each CAPM cluster is determined quarterly on country-level. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Notes:

1. Country and sector dummies are included in all specifications.
2. Heteroscedasticity and autocorrelation (HAC) robust standard errors are in parentheses, and p-values are denoted by asterisks (***0.01, **0.05, *0.1).
3. m1 and m2 are first- and second-order tests on autocorrelation in the first-differenced residuals. Under the null hypothesis, there is no serial correlation. The test statistic is asymptotically standard normal distributed.
4. Sargan is a test of overidentifying restrictions. The null hypothesis assumes instrument validity. The test statistic is chi-squared distributed, with degrees of freedom reported in parentheses.
5. The instruments used in each equation are:

L2.spread, L2.logsize, L2.leverage, L2.CAPM beta, DL.spread, LD.logsize, LD.leverage, LD.CAPM beta

Specification (i) additionally uses:

L2.ctrspread, DL.ctrspread

Specification (ii) additionally uses:

L2.ctrspread, DL.ctrspread, L2.spread L2.SPREAD1, L2.spread L2.SPREAD3

Specification (iii) additionally uses:

L2.ctrspread, DL.ctrspread, L2.spread L2.SIZE1, L2.spread L2.SIZE3

Specification (iv) additionally uses:

L2.ctrspread, DL.ctrspread, L2.spread L2.LEV1, L2.spread L2.LEV3

Specification (v) additionally uses:

L2.ctrspread, DL.ctrspread, L2.spread L2.CAPM1, L2.spread L2.CAPM3

where:

L2.x identifies the second lag of a respective variable x.

DL.x is the lag of first difference of a respective variable x.

Table 8: Estimation Results of the Blundell Bond 1998 System GMM Estimator

Specification	(i)	(ii)	(iii)	(iv)
Variables	spread	spread	spread	spread
L.spread	0.642***	0.688***	0.677***	0.804***
	(0.048)	(0.042)	(0.036)	(0.056)
L.spread L.SPREAD1				-0.240***
				(0.083)
L.spread L.SPREAD3				-0.067
				(0.047)
L.spread L.SIZE1				-0.062
				(0.049)
L.spread L.SIZE3				-0.028
				(0.035)
L.spread L.LEV1				0.103***
				(0.036)
L.spread L.LEV3				0.057
				(0.037)
L.spread L.CAPM1				-0.055*
				(0.033)
L.spread L.CAPM3				0.070**
				(0.029)
L.spread L.SGSV1		-0.075*		-0.050*
		(0.044)		(0.028)
L.spread L.SGSV3		0.029		0.015
		(0.051)		(0.023)
L.ctrspread	0.117***	0.107***		
	(0.039)	(0.032)		
L.ctrspreadSGSV1			0.005	0.004
			(0.019)	(0.015)
L.ctrspreadSGSV2			0.029	0.012
			(0.022)	(0.017)
L.ctrspreadSGSV3			0.059***	0.039***
			(0.013)	(0.012)
L.logsize	0.158***	0.141***	0.125***	0.081***
	(0.025)	(0.021)	(0.016)	(0.009)
L.leverage	-0.612***	-0.287***	-0.402***	-0.136
	(0.173)	(0.132)	(0.137)	(0.101)
L.CAPMbeta	-0.014	-0.008	-0.010	0.002
	(0.023)	(0.020)	(0.022)	(0.017)
L.SGSV	0.005	-0.001	0.007	0.005
	(0.005)	(0.006)	(0.005)	(0.005)
Observations	5,544	5,544	5,544	5,544
NumberofCompanies	219	219	219	219
m1	-6.826	-6.923	-6.965	-7.112
m2	1.124	1.038	1.180	1.210
Sargan	201.318	195.324	192.722	181.489
(df)	248	458	668	1508

This table summarizes our Blundell-Bond (1998) estimation results using a quarterly sample of FTSE EPRA/NAREIT REIT data from 11 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, and United Kingdom) from March 2005 to December 2018. The table reports the coefficient estimates for separate regressions using the NAV spread ($\mathrm{spread}_{\mathrm{i,t}}$) as the dependent variable, defined as ($\mathrm{price}_{\mathrm{i,t}}/\mathrm{NAV}_{\mathrm{i,t}}$ - 1), where $price_{i,t}$ is the unadjusted share price of company i in period t, and $NAV_{i,t}$ is the NAV per share of company i in period t. The independent variables used in the regression include the NAV spread of company i in the previous period ($\mathrm{spread}_{\mathrm{i,t\text{-}1}}$), the logarithm of the market capitalization in billions of USD ($logsize_{i,t\text{-}1}$)

of company i in the previous period, the ratio of total debt to total assets ($leverage_{i,t\text{-}1}$) of company i in the previous period, the 24-month CAPM beta ($CAPM\ beta_{i,t\text{-}1}$) of company i in the previous period, and the countrywide average NAV spread of the other companies in the respective country ($ctrspread_{i,t\text{-}1}$) calculated individually for each company i in the previous period. For differing specifications, we allow interaction terms between the levels of online search attention. Standardized Google search volume (SGSV) is defined by subtracting the past year's average Google search volume from the quarterly Google search volume, and dividing it by its standard deviation within the past year. We define low SGSV (SGSV1) as the lower quintile of SGSV, medium SGSV (SGSV2) as the middle three quintiles, and high SGSV (SGSV3) as the upper quintile. Each SGSV cluster is determined quarterly on country-level. Additionally, we include the country average NAV spread within each SGSV cluster within those of low SGSV ($\mathrm{ctrspread}_{\mathrm{SGSV1,i,t\text{-}1}}$), medium SGSV ($\mathrm{ctrspread}_{\mathrm{SGSV2,i,t\text{-}1}}$), and high SGSV ($\mathrm{ctrspread}_{\mathrm{SGSV3,i,t\text{-}1}}$) of company i in the previous period. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Notes:

1. Country and sector dummies are included in all specifications.
2. Heteroscedasticity and autocorrelation (HAC) robust standard errors are in parentheses, and p-values are denoted by asterisks (***0.01, **0.05, *0.1).
3. m1 and m2 are first- and second-order tests on autocorrelation in the first-differenced residuals. Under the null hypothesis, there is no serial correlation. The test statistic is asymptotically standard normal distributed.
4. Sargan is a test of overidentifying restrictions. The null hypothesis assumes instrument validity. The test statistic is chi-squared distributed, with degrees of freedom reported in parentheses.
5. The instruments used in each equation are:

Specification (i) additionally uses:
L2.ctrspread, DL.ctrspread, L2.SGSV, DL.SGSV
Specification (ii) additionally uses:
L2.ctrspread, DL.ctrspread, L2.SGSV, DL.SGSV, L2.spread L2.SGSV1, L2.spread L2.SGSV3
Specification (iii) additionally uses:
L2.SGSV, DL.SGSV, L2.ctrspreadSGSV1, L2.ctrspreadSGSV2, L2.ctrspreadSGSV3, DL.ctrspreadSGSV1, DL.ctrspreadSGSV2, DL.ctrspreadSGSV3
Specification (iv) additionally uses:
L2.SGSV, DL.SGSV, L2.spread L2.SGSV1, L2.spread L2.SGSV3, L2.ctrspreadSGSV1, L2.ctrspreadSGSV2, L2.ctrspreadSGSV3, DL.ctrspreadSGSV1, DL.ctrspreadSGSV2, DL.ctrspreadSGSV3
where:
L2.x identifies the second lag of a respective variable x.
DL.x is the lag of first difference of a respective variable x.

spillover effect. The parameter is highest in model (i) of Table 8, where 11.7% of the countrywide average NAV spread spills over, and lowest in model (ii) of Table 7, where the percentage is 10.6%.

Furthermore, we suspect that mean reversion speed depends on company-specific accounting and financial information. Table 7, Column (ii), shows that the interaction term of the lagged NAV spread and lagged SPREAD1 is significantly negative. Therefore, high discount stocks mean-revert more quickly than medium discount stocks. However, mean reversion speed does not differ significantly between the medium and high premium clusters.

Graphical analysis of the IRF in Figure 4 provides further insights into the mean reversion behavior of the NAV spread. The IRF of the high discount portfolio reaches half-life within the first quarter. The middle portfolio absorbs a one-unit shock significantly more slowly, taking three quarters to reach half-life. We interpret this phenomenon as a consequence of investor behavior. This is because systematically investing in undervalued stocks (or divesting overvalued stocks) can lead to price pressure and a higher mean reversion speed of companies with high discounts (premia) to NAV.

Note that we also expect to find some correlation between mean reversion speed and company size. We posit this is because market participants identify market anomalies and systematically invest in undervalued companies. Assuming they invest equally in small and large companies, we expect the NAV spread of smaller companies to mean-revert more quickly. Table 7, Column (iii) shows a significantly negative parameter on the interaction term of the lagged NAV spread and the lagged SIZE1 dummy variable. This indicates that smaller companies mean-revert more quickly than the sample. The IRFs for small, medium, and large companies are shown in Figure 4. Each IRF reaches half-life within the second quarter, although we note some differences.

Table 7, Column (iv) shows that the parameters on the interaction terms on both low leverage (LEV1) and the lagged NAV spread, and high leverage (LEV3) and the lagged NAV spread, are positive and significantly different from zero. We expect there is an optimal capital structure, and that both positive and negative deviations slow the mean reversion speed. Figure 4 shows the respective IRFs. The IRF of the medium leverage portfolio reaches half-life within the second quarter. Both the high and low leverage portfolios absorb a one-unit shock significantly more slowly. In both cases, half-life is reached within the third quarter.

Table 7, Column (v) adds the interaction terms of the CAPM beta and the lagged NAV spread to our base model. We find no significant coefficient for the interaction term of the lagged NAV spread and the CAPM beta ranking. Therefore, we find no proof that companies with low CAPM betas mean-revert more quickly than those with high CAPM betas. The respective IRFs are in Figure 4.

Hypothesis 1a posits a relationship between SGSV and the level of the NAV spread. To test this assumption, we add the variable SGSV in Table 8, Column (i). Contradicting Hypothesis 1a, we find that the variable is statistically insignificant. We suspect that SGSV influences the mean reversion speed of the NAV spread, but not the level of the NAV spread.

Under Hypothesis 1b, we expect a relationship between the mean reversion speed and the level of SGSV. Therefore, we expect companies with high SGSV to mean-revert more slowly than those with lower levels of SGSV. In Table 8, Column (ii), we interact these binary variables on Google search requests with our lagged NAV spread in order to determine the mean reversion speed in case of low (high) SGSV. We find that the interaction term between the lagged NAV spread and lagged SGSV1 is significantly negative. However, surprisingly, mean reversion speed does not differ substantially between the medium and high SGSV clusters. Therefore, low levels of SGSV increase the mean reversion speed of the NAV spread. The IRFs for the different levels of SGSV are shown in Figure 4. The IRF of the SGSV1 portfolio reaches half-life the fastest. The SGSV2 portfolio takes significantly longer to absorb a one-unit shock. Both IRFs reach half-life within the second quarter.

In their study on Russell 3000 stocks, Da et al. (2011) find that retail traders rely heavily on Google for information, while more professional traders have access to sophisticated databases such as Reuters or Bloomberg. In the real estate literature, the Google search volume on a company name is usually interpreted as information demand (Jandl and Fuerst, 2015). Rochdi and Dietzel (2015) also interpret Google search volume as information demand, and use macroscopic search terms like real estate company, funds, realty trusts, etc. With the SGSV, we can identify abnormal Google searches at a specific point in time compared to other companies in a specific country. High SGSV may be a proxy for bad news or rising noise trader attention. We posit that low SGSV levels indicate decreasing levels of market sentiment, which lead to higher mean reversion speeds toward the long-run NAV spread.

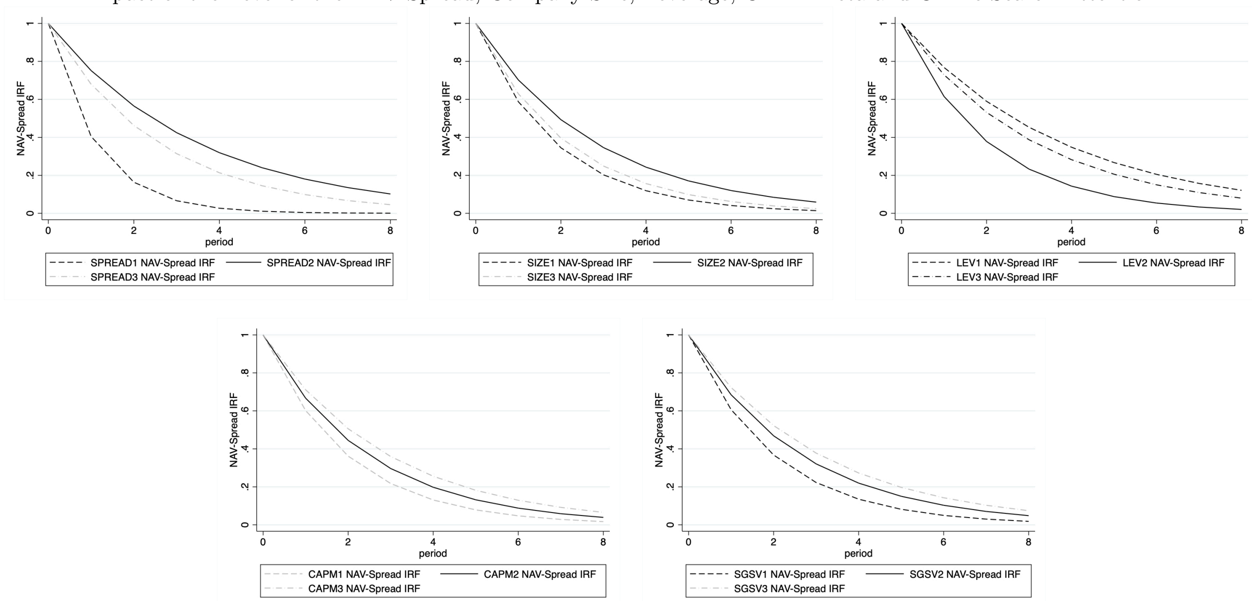
Hypothesis 2 assumes that the spillover effect is related to the level of online search attention. We apply a piecewise linear regression that allows us to calculate separately the sensitivity of an individual company's NAV spread to the countrywide average NAV spread for each SGSV cluster. We posit that the spillover effect increases with rising levels of SGSV. Table 8, Column (iii) controls for distinct spillover effects in the SGSV1, SGSV2, and SGSV3 clusters. We find a spillover from the SGSV3 cluster of approximately 5.9%. The spillover effects from companies within the SGSV2 and SGSV1 clusters are statistically insignificant. Therefore, our results are in line with those of Hypothesis 2. In summary, our findings proof that the spillover effect is highly sensitive to the level of SGSV.

Table 8, Column (iv) captures our test on robustness and controls for each of the impacts discussed above simultaneously. Therefore, we control the base effect of the variable SGSV, and capture the impact of each company-specific information and SGSV on the mean reversion speed of the NAV spread, and a control for the distinct spillover effects in the SGSV1, SGSV2, and SGSV3 clusters. The parameter on the interaction term of SGSV1 and the lagged NAV spread is significantly negative. However, the parameter on the interaction term of SGSV3 and the lagged NAV spread is insignificant. Thus, we find proof for the validity of hypothesis 1b, SGSV has a negative impact on the mean reversion speed of the NAV spread. Morevoer, we find evidence for hypothesis 2. The spillover effect increases with rising levels of SGSV. The spillover from the SGSV3 cluster is approximately 3.9% and there are no statistically significant spillover effects from companies within the SGSV2 and SGSV1 clusters. The parameter on the interaction term of SPREAD1 and the lagged NAV spread is significantly negative. However, the parameter on the interaction term of SPREAD3 and the lagged NAV spread is insignificant. Thus, using this specification, we find further proof that companies with high discounts to NAV mean revert quickest. However, the mean reversion speed of companies with a high premium to NAV does not significantly differ from the base group. Using this specification, we find that the CAPM beta has a negative impact on the mean reversion speed of the NAV spread. The parameter on the interaction between lagged NAV spread and CAPM1 is significantly negative and the parameter on the interaction between lagged NAV spread and CAPM3 is significantly positive. Accordingly, rising levels of CAPM beta lower the mean reversion speed of the NAV spread. The parameter on the interaction between lagged NAV spread and LEV1 is positive and statistically significant while the parameter on the interaction between lagged NAV spread and LEV3 is insignificant. Accordingly, the mean reversion speed of the NAV spread of companies with low leverage is significantly slower while high leverage has no impact on the mean reversion speed. Both parameters on the interaction terms of SIZE1 (and SIZE3) and the lagged NAV spread are insignificant. Thus, using this specification, we find no proof that size has an impact on the mean reversion speed of the NAV spread.

The IRFs for the different levels of SPREAD, SIZE, leverage, CAPM, and SGSV are shown in Figure 5. The IRF of the base portfolio is shown in each graph as solid line. We find that it takes four quarters to reach half-life after the impact of a one-unit shock within this portfolio. Graph 1 shows that the IRF of the high discount portfolio reaches half-life within the second quarter. The IRFs for small, medium, and large companies are shown in Graph 2. We need to highlight that using this specification we find no statistically significant difference in the mean reversion speed between small, medium, and large companies. Graph 3 shows that the IRF of the low leverage portfolio reaches half-life within the eighth quarter. Graph 4 shows the IRFs for different levels of CAPM beta. We find that the IRF of the CAPM1 portfolio

Figure 4: Impulse Response Function After the Impact of an Exogenous One-Unit Shock

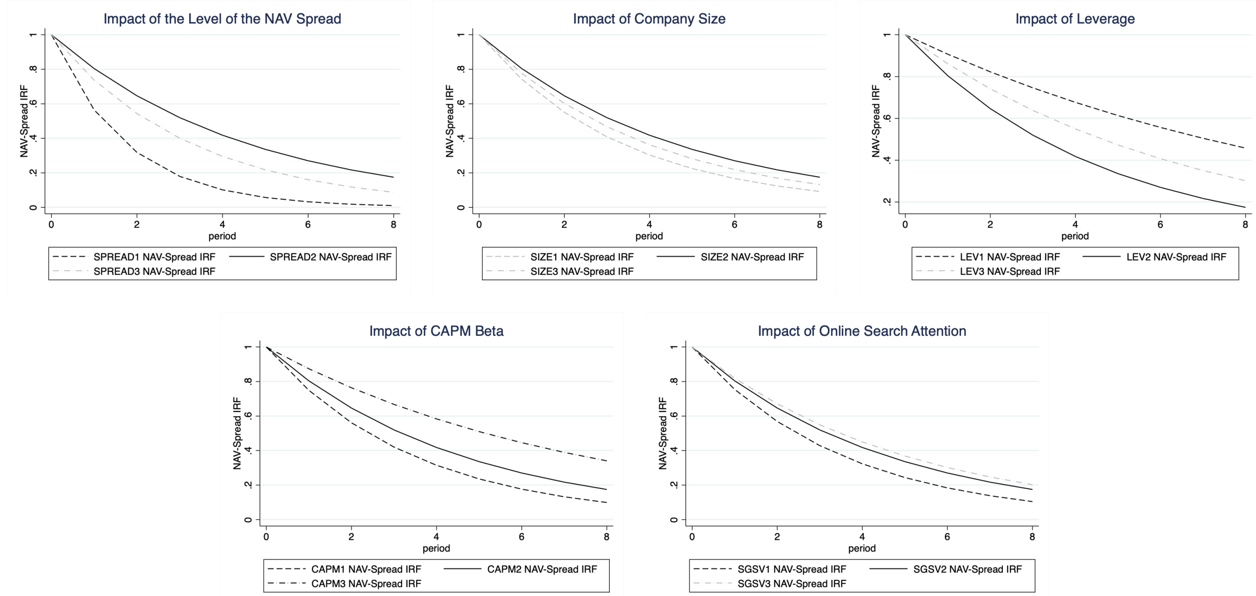
Impact of the Level of the NAV Spread, Company Size, Leverage, CAPM Beta and Online Search Attention



This graph shows the impulse response functions (IRF) of the NAV spreads after the impact of an exogenous one-unit shock. NAV spread ($\mathrm{spread}_{i,t}$) is defined as ($\mathrm{price}_{i,t}/\mathrm{NAV}_{i,t}$ - 1), where $price_{i,t}$ is the unadjusted share price of company i in period t, and $NAV_{i,t}$ is the NAV per share of company i in period t. Graph 1 plots different lines for different levels of the NAV spread (SPREAD). The graph distinguishes IRFs regarding the previous quarter's NAV spread level. Therefore, we denote a value portfolio (SPREAD1) as the lower quintile of SPREAD (the highest discount to NAV), a middle portfolio (SPREAD2) as the middle three quintiles, and a growth portfolio (SPREAD3) as the upper quintile. Graph 2 distinguishes IRFs regarding the previous quarter's company size as represented by market capitalization. We denote small companies (SIZE1) as the lower quintile of company size, medium companies (SIZE2) as the middle three quintiles, and large companies (SIZE3) as the upper quintile. Graph 3 distinguishes IRFs regarding the previous quarter's leverage. We define leverage as the ratio of a company's total debt to total assets. Therefore, we denote low leverage (LEV1) as the lower quintile of leverage, medium leverage (LEV2) as the middle three quintiles, and high leverage (LEV3) as the upper quintile. Graph 4 distinguishes IRFs regarding the previous quarter's CAPM beta as represented by the 24-month CAPM beta. Therefore, we denote low CAPM beta (CAPM1) as the lower quintile of CAPM beta, medium CAPM beta (CAPM2) as the middle three quintiles, and high CAPM beta (CAPM3) as the upper quintile. Graph 5 plots different lines for different levels of standardized Google search volume (SGSV). We define SGSV by subtracting the past year's average Google search volume from the quarterly Google search volume, and dividing it by its standard deviation within the past year. The graph distinguishes IRFs regarding the previous quarter's SGSV. Therefore, we denote low SGSV (SGSV1) as the lower quintile of SGSV, medium SGSV (SGSV2) as the middle three quintiles, and high SGSV (SGSV3) as the upper quintile. Each SPREAD, SIZE, leverage, CAPM, and SGSV cluster is determined quarterly on country-level.

Figure 5: Impulse Response Function After the Impact of an Exogenous One-Unit Shock

Impact of the Level of the NAV Spread, Company Size, Leverage, CAPM Beta and Online Search Attention



This graph shows the impulse response functions (IRF) of the NAV spreads after the impact of an exogenous one-unit shock. NAV spread ($\text{spread}_{\text{i,t}}$) is defined as ($\text{price}_{\text{i,t}}/\text{NAV}_{\text{i,t}}$ - 1), where $price_{i,t}$ is the unadjusted share price of company i in period t, and $NAV_{i,t}$ is the NAV per share of company i in period t. Graph 1 plots different lines for different levels of the NAV spread (SPREAD). The graph distinguishes IRFs regarding the previous quarter's NAV spread level. Therefore, we denote a value portfolio (SPREAD1) as the lower quintile of SPREAD (the highest discount to NAV), a middle portfolio (SPREAD2) as the middle three quintiles, and a growth portfolio (SPREAD3) as the upper quintile. Graph 2 distinguishes IRFs regarding the previous quarter's company size as represented by market capitalization. We denote small companies (SIZE1) as the lower quintile of company size, medium companies (SIZE2) as the middle three quintiles, and large companies (SIZE3) as the upper quintile. Graph 3 distinguishes IRFs regarding the previous quarter's leverage. We define leverage as the ratio of a company's total debt to total assets. Therefore, we denote low leverage (LEV1) as the lower quintile of leverage, medium leverage (LEV2) as the middle three quintiles, and high leverage (LEV3) as the upper quintile. Graph 4 distinguishes IRFs regarding the previous quarter's CAPM beta as represented by the 24-month CAPM beta. Therefore, we denote low CAPM beta (CAPM1) as the lower quintile of CAPM beta, medium CAPM beta (CAPM2) as the middle three quintiles, and high CAPM beta (CAPM3) as the upper quintile. Graph 5 plots different lines for different levels of standardized Google search volume (SGSV). We define SGSV by subtracting the past year's average Google search volume from the quarterly Google search volume, and dividing it by its standard deviation within the past year. The graph distinguishes IRFs regarding the previous quarter's SGSV. Therefore, we denote low SGSV (SGSV1) as the lower quintile of SGSV, medium SGSV (SGSV2) as the middle three quintiles, and high SGSV (SGSV3) as the upper quintile. Each SPREAD, SIZE, leverage, CAPM, and SGSV cluster is determined quarterly on country-level.

reaches half-life quickest within the third quarter. The CAPM3 portfolios mean reverts with a significantly slower speed. It takes five quarters to reach half-life. The IRFs for the different levels of SGSV are shown in Graph 5. The IRF of the SGSV1 portfolio reaches half-life quickest within the third quarter. The SGSV2 and the SGSV3 portfolio absorb a one-unit shock slower and the IRFs reach half-life within the fourth quarter.

Overall, the results in Table 7 and 8 confirm that the level of the NAV spread and leverage impact the mean reversion speed of the NAV spread. Moreover, we find a higher mean reversion speed for companies with low SGSV levels. We also find that the spillover effect to other companies is related to the level of SGSV.

3.6 Conclusion

This study analyzes the mean reversion behavior of NAV spreads for a global sample of 219 listed real estate companies. We contribute to the literature by modelling for a first time what drives the speed of mean reversion for NAV spreads. We find that the mean reversion speed is the fastest for companies with high NAV discounts and medium levels of leverage. Our global setting also allows us to expand the literature by documenting the role of average country-wide NAV spreads, which have a positive and statistically significant impact on a company's NAV spread. Remarkably, we find evidence that stocks with the highest online search attention have a disproportionate impact on the NAV spreads of other stocks in that country. Most importantly, we are the first to study the impact of online search attention on the NAV spread's mean reversion behavior.

Our findings have two major practical implications. First, we contribute to the debate as to whether online search attention is a proxy for rational information demand or to 'noisy' retail trader attention. If high levels of online search attention were associated with a faster NAV spread mean reversion, we would conclude a rational correction procedure is taking place, which results from rational information demand. However, our results suggest the opposite is the case: low levels of online search attention are associated with faster NAV spread mean reversion. Consequently, mid to high levels of online search attention are associated with prolonged NAV spreads, lending support to the noise trader argument.

Secondly, our findings contribute to the recent literature on NAV spread-related investment strategies. (Letdin et al., 2022) document the benefits of an investment strategy that seeks to exploit the sentiment-driven component of NAV spreads. We show that higher levels of online search attention decrease mean reversion speeds, hence lowering potential gains from the investment strategy proposed by (Letdin et al., 2022). On the other hand, we find that lower levels of online search attention are associated with, faster mean reversion, thus favoring sentiment-related investment strategies aimed at beating the market.

4 Does Investor Attention Intensify Earnings Momentum?

This paper is the result of a joint project with René-Ojas Woltering and Steffen Sebastian.

Abstract We examine the performance and interaction between earnings momentum and Google search attention using a global sample of 368 property-holding companies from 2005:1 to 2019:9 in the FTSE EPRA/NAREIT Global Real Estate Index. The portfolio returns are analyzed on a risk-adjusted basis employing a Carhart four-factor model. First, we show that high earning REITs and REITs with high levels of unexpected Google search volume outperform in the subsequent month followed by a long-term reversal. Second, we find that unexpected Google search attention intensifies earnings momentum. Third, we find that the attention-based momentum Granger causes earnings momentum.

4.1 Introduction

Malkiel and Fama (1970) claim that financial markets are efficient, however, evidence from financial literature suggests that both earnings momentum (post-earnings-drift) and attention-based investment strategies generate abnormal returns (Bron et al. (2018); Chan et al. (1996); Da et al. (2011); Joseph et al. (2011); Yung and Nafar (2017)). The post-earnings-drift in REITs can be attributed to the serial correlation between real estate assets and rental income growth (An et al. (2016); Case and Shiller (1988)). On the other hand, the outperformance after unexpected Google attention can be attributed to the limited attention resources of individual investors when selecting stocks from a large pool (Barber and Odean (2008)). The attention-based momentum (post-attention-drift) is predominantly caused by high levels of unexpected Google search attention (Bank et al. (2011); Da et al. (2011); Joseph et al. (2011); Yung and Nafar (2017)).

A behavioral explanation for the earnings momentum is poor market reaction to new information (De Bondt and Thaler (1985); Kahneman and Tversky (1977);

Shiller (1980)) and positive earnings surprises being an indicator for good news (Feng et al. (2014)). In advance, attention is a key factor explaining how investors react to news (Hou et al. (2009)), and Moniz et al. (2011) find that news flow signals intensify earnings momentum. Hong and Stein (1999) stress that information diffuses gradually among investors and causes a return forecastability (i.e., lead-lag effect). For REITs, Mori (2015) find that information demand proxied by Google searches impacts the lead-lag effect. To the best of our knowledge, we are the first who study the effect of unexpected Google search attention on the post-earnings drift of REITs. In this paper, we thus seek to answer the research question: 'Does Investor Attention Intensify Earnings Momentum?'

We conduct our analysis on a diverse sample of 368 property-holding companies globally, drawn from twelve countries represented in the FTSE EPRA/NAREIT Global Real Estate Index. Our study is based on creating low, medium, and high earnings and online attention portfolios using past standardized unexpected earnings (SUE) or standardized Google search volume (SGSV). The returns of the portfolios are analyzed over a holding period of one to twelve months after their formation. To test the effectiveness of strategies that combine these two investment approaches, we employ a two-way sort, constructing portfolios that are ranked by both earnings and attention-based momentum. The performance of the portfolios is evaluated using the Carhart four-factor model, and we aim to answer the question 'What moves first?' through a Granger causality test.

This paper contributes to the existing literature in three ways. Firstly, we analyze the efficiency of both earnings momentum and attention-based momentum in the context of real estate stocks. Consistent with previous literature (Bron et al. (2018); Yung and Nafar (2017)), we find that both strategies lead to outperformance in the subsequent month, but there is no evidence for the earnings momentum for investment horizons longer than one month. This contradicts existing real estate literature that find evidence for the effectiveness of the earnings momentum for holding periods up to twelve month (see e.g.: Bron et al. (2018)). Our result shows that financial markets strive over time for ever greater efficiency.

Secondly, we examine the intensification of earnings momentum that is driven by

Google search attention and analyze their interactions. Previous studies (Curtis et al. (2014); Hou et al. (2009); Li et al. (2019); Moniz et al. (2011); Peress (2008)) show a relationship between attention and earnings momentum, using various proxies for investor attention. We find evidence that Google search attention intensifies earnings momentum.

Thirdly, we answer the question of what moves first - the post-earnings-drift or the post-attention-drift. We hypothesize that investors' attention is partly related to foreseeable earnings, meaning that the post-attention-drift should lead the post-earnings-drift. Our results support this hypothesis, showing that the post-attention-drift leads the post-earnings-drift.

The organization of this paper is as follows: In Section 4.2, we review relevant literature and formulate our hypotheses. Section 4.3 outlines the data used in the analysis and provides a summary of its characteristics. The portfolio construction and econometric models are explained in Section 4.4. The empirical findings are presented and discussed in Section 4.5. Finally, we provide a conclusion in Section 4.6.

4.2 Literature Review

For decades the efficient market hypothesis (EMH) has been debated in the literature. The EMH states that the price of a stock always reflects all available information. Therefore, earnings surprises should immediately be incorporated into stock prices. However, numerous studies document a simple strategy of buying stocks with positive earnings surprises can generate abnormal returns in the months after the earnings reports. The literature denotes this phenomenon related to earnings momentum or post-earnings-announcement drift (see, for example, Bernard (1992); Chan et al. (1996); Feng et al. (2014); Price et al. (2012); Bron et al. (2018)).

Moreover, according to the EMH, markets incorporate new information without delay and provide always the best possible estimate of all asset values. Therefore, each piece of information available on the internet should immediately be priced into stock prices. The price adjustment to earnings surprises requires investors to incorporate new information into their valuation process. In this regard it is important to note that investors' knowledge is linked to the information they dedicate attention to

(Peng and Xiong (2006)). Numerous studies provide evidence that a simple strategy of buying stocks with a high degree of Google search attention outperforms the market (see, for example, Da et al. (2011); Yung and Nafar (2017)). In this chapter we discuss the rationale behind earnings momentum and attention-based momentum.

Earnings Momentum

A popular view held by many researchers is that earnings momentum is related to investors underreaction to past earning news Chan et al. (1996); Hong and Stein (1999). In the case of real estate assets, a rational explanation for the efficiency of earnings momentum strategies is that real estate returns and rental income growth show a strong serial correlation (Case and Shiller (1988); An et al. (2016)). Over the past decades, several studies examining momentum strategies in REITs have been published. Feng et al. (2014); Price et al. (2012); Bron et al. (2018) provide cogent rationale for the effectiveness of momentum strategies. Bernard and Thomas (1990) show the existence of short-term stock price predictability after earnings announcements. Following this argumentation, arbitrage trading would be possible after a positive earnings announcement. Feng et al. (2014) find evidence that the earnings momentum is significantly stronger than the price momentum in terms of economic relevance and statistical significance. Furthermore, they provide evidence that price momentum is dominated by post-earnings-announcement drift. In addition, Zhang and Deng (2010) find that past earnings surprises forecast future hotel real estate stock returns. We expect a strategy of purchasing stocks with high positive earnings outperforms the market.

Attention-Based Momentum

Kahneman (1973) stress that attention is a scarce cognitive resource. Numerous psychological studies show that the central cognitive-processing capacity of the human brain is limited (Johnston and Pashler (1998)).

A series of studies examine the impact of investor attention on future returns. Merton et al. (1987) is an early economic study showing that investors' attention impacts stock prices. Sprenger et al. (2014) find a relationship between tweet sentiment and stock returns. Engelberg et al. (2012) find that stocks mentioned by Jim Cramer on his popular CNBC television show Mad Money show significantly positive overnight returns. Chordia and Swaminathan (2000) find evidence that trading volume is an important determinant of stock return patterns. Da et al. (2011) show that an attention increase due to IPOs leads to an outperformance in the first two weeks while the effect reverses within a year. Tetlock (2011) find evidence that outdated news causes a temporary price movement in stocks dominated by retail investors.

Previous studies use distinct proxies to measure investor attention including financial tweets (see, for example, Bhagwat and Burch (2016); Wu (2019)), media coverage (see, for example, Barber and Odean (2008); Peress (2008); Fang and Peress (2009)), advertisement expenses (see, for example, Chemmanur and Yan (2019); Grullon et al. (2004); Lou (2014)) trading volume (see, for example, Barber and Odean (2008); Gervais et al. (2001); Hou et al. (2009)) and past returns (see, for example, Barber and Odean (2008)). However, these proxies are indirect measures of investor attention (Da et al. (2011)). Investor attention is not guaranteed when a company appears in the media (Huberman and Regev (2001)). However, googling a company's name is undeniably associated with investor attention (Da et al. (2011)).

When buying a stock, an investor's scarce cognitive resource attention is faced with a large amount of information. Barber and Odean (2008) hypothesize that investors are net buyers of attention grabbling-stocks. Therefore, investors can only buy the stocks to which they dedicate sufficient attention. When they are selling, they can only sell the stocks they already own. Therefore, attention-grabbling stocks should outperform the market in the short-run, followed by long-run reversals.

Several articles discuss the impact of online search attention. Overall, there are mixed results regarding the impact of Google search volume (GSV) on stock returns. Da et al. (2011), Joseph et al. (2011), and Bank et al. (2011) find that stocks with high levels of unexpected Google search attention short-run outperform the market. In the long-run, high returns are followed by a reversal. Furthermore, in a study on Japanese startups Adachi et al. (2017) find a positive relationship between GSV and stock returns. Remarkably, they find no neutralization in the long run. Using a panel model on Norwegian stocks, Kim et al. (2019) test the predictive power of

GSV on future returns. They find that GSV predicts trading volume and volatility, but not returns. On the other hand, Bijl et al. (2016) find a negative impact of GSV on future returns of S&P 500 stocks. Nguyen et al. (2019) state that in the case of the Philippines, Thailand, and Vietnam Google search volume significantly lowers stock returns. However, they find no proof for a negative impact in case of Indonesia and Malaysia. Hervé et al. (2019) study the influence of noise traders, as approximated by GSV, and smart investors, as approximated by Wikipedia Page Traffic. The authors find that only GSV influences stock returns. Moreover, they find that GSV increases price volatility while Wikipedia Page Traffic decreases price volatility. Yung and Nafar (2017) test the attention hypothesis of Barber and Odean (2008) on REITs using GSV. They find that attention-grabbling US REITs, short-run outperform REITs with lower levels of GSV.

The influence of investor attention on future stock returns has been extensively studied in the literature. Overall, several researchers find evidence for a positive impact, while others find a negative or an insignificant relationship. We assume investors being net buyers of attention grabbling-stocks and investor attention having a positive impact on future stock returns Barber and Odean (2008). However, DellaVigna and Pollet (2009); Hirshleifer et al. (2009) find proof for a relationship between investor attention (or inattention) and market reactions to earnings announcements. We suspect that investor attention might only intensify future stock returns in the case that the attention is related to good news. For this reason, we question: 'Does Investor Attention Intensify Earnings Momentum?'

Does Investor Attention Intensify Earnings Momentum?

Attention is found to be a key indicator of how investors react to news (DellaVigna and Pollet (2009); Hirshleifer et al. (2009)). DellaVigna and Pollet (2009) compare market responses to earnings announcements on Friday to responses on other weekdays. They find that Friday's market reactions to earnings announcements are less immediate (i.e., more delayed). DellaVigna and Pollet (2009) argue that on Friday, investors are distracted from work-related activities. Their finding shows the impact of underreactions to new information caused by inattention on the post-earnings announcement drift. Hirshleifer et al. (2009) analyze the distracting effect of other industry-unrelated news on investors the impact on the post earnings drift. They find evidence for a less immediate stock market price reaction to a firm's earnings surprises, and a stronger post earnings drift, in case of a greater number of other same-day earnings announcements. Moniz et al. (2011) show that news flow signals intensify the post-earnings-drift. However, Peress (2008) find that higher media coverage lowers profits of earnings momentum. Hou et al. (2009) study the impact of investor attention on price and earnings momentum strategies using stock trading volume as a proxy for investor attention. They find higher profits from earnings momentum among low volume stocks. Curtis et al. (2014) find a linkage between social media activity and the sensitivity of earnings announcement returns. Li et al. (2019) use the SEC's EDGAR daily log files to measure sophisticated investor attention. They find that more sophisticated investor attention before the earnings announcement lowers the post-earnings-drift. In REIT context, Mori (2015) find that information demand proxied by Google searches influences the process of information diffusion and the lead-lag effect among real estate stocks.

Chae et al. (2020); Drake et al. (2012); Fricke et al. (2014) find evidence that stocks with more investor attention captured by abnormal internet search frequency have a weaker post-earnings-drift. If the online search attention would be a proxy for rational investor's attention demand and if this attention would successfully reduce information asymmetries Drake et al. (2012), then online search attention should improve the flow of information and thus increase market efficiency and therefore reduce the post earnings drift.

Curtis et al. (2014) stress that investors' inattention is a main reason for delayed incorporation of foreign information. They proxy media coverage of foreign news using news article counts in the Wall Street Journal. Hong et al. (2000) argue that momentum is caused by gradual information flow and momentum should be stronger in those stocks that incorporate information more slowly.

In this regards, Da et al. (2011) find that online search attention is a proxy for noise trader attention while more sophisticated have access to more sophisticated tools like Reuters or Bloomberg. Moreover, Schiller et al. (2022) find that the mean-reversion speed of NAV-spreads is slower if online search attention is higher. This indicats a slower incorporation speed of financial information into stock prices in case of a higher level of online search attention. Earnings provide a continuous source of information about a company's future prospects Chan et al. (1996). We suspect that online search attention shows noise traders market participation, slows the speed with which earnings-related news is assimilated into stock prices and therefore even intensifies the post-earnings drift. Therefore, we hypothesis that:

Hypothesis 1: *Online Search Attention Intensifies the post-earnings drift.*

The earnings momentum is a well-established market phenomenon and we primarily focus our study on this investment strategy. However, on the other hand it also might be that positive earnings surprises may intensify attention-based momentum. Therefore, we suspect that investors might extraordinarily reward attention-grabbing stocks if these companies achieved extraordinarily high earnings. We hypothesise that:

Hypothesis 1b: *Positive Earnings Surprises Intensify Attention-Based Momentum.*

Earnings or Online Search Attention? What moves first?

We suspect that both investment strategies, the earnings and the attention-based momentum short-run outperform the market. However, positive earnings are undeniably fundamentals that indicate positive news on the company's financial situation. On the other hand, extraordinary high online search attention can variously reasoned. It can be related to good news, or it can be referred to rising levels of noise trader attention or to bad news.

The key question is: What moves first? Do companies with extraordinarily high earnings receive droves of Google search requests? And did stocks grab attention because they achieved extraordinarily high earnings? And noise traders increase the initial underreaction to past earning news Chan et al. (1996); Chae et al. (2020) and slower the speed of information incorporation into stock prices. Or do companies with high levels of Google search requests achieve extraordinarily high earnings? And investors mispredict earning surprises?

It is well known that words in the financial press include otherwise hard-to-quantify news about fundamentals. Tetlock et al. (2008) show that words in stories about firms' fundamentals help predict both returns and earnings. Mayew and Venkatachalam (2012) find evidence for the predictive power of vocal cues from conversations with executives during earnings conference on firms' future profitability and returns. Drake et al. (2012) show that Google search attention increases about two weeks prior to the earnings announcement and find a markedly spike of online search attention at the moment of the announcement. Da et al. (2010) define online search attention as a leading indicator forecasting earnings which originates from the customers. They argue that customers Google before executing their purchases. Moreover, Da et al. (2010) state that in the extreme case where every customer searches for the specific product before purchasing, search volume will perfectly signal a company's future sales. Drake et al. (2012) show that Google search attention increases about two weeks prior to the earnings announcement and find a markedly spike of online search attention at the moment of the announcement.

We suspect that positive earning suprieses are followed by noise trader attention and suspect that noise traders short-run intensify the earnings momentum. Follwing, we expect that the good news related post-earnings drift leads the post-attention drift. Therefore, we hypothesize:

Hypothesis 2: *The Post-Earnings-Drift Granger causes the Attention-Based Momentum and the Post-Attention-Drift has no Impact on the Post-Earnings-Drift*

4.3 Data and Descriptive Statistics

Sample Description

Our sample consists of monthly company-level data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index, which are provided by the European Public Real Estate Association (EPRA) in conjunction with the National Association of Real Estate Investment Trusts (NAREIT) and the Financial Times Stock Exchange (FTSE). The constituents include listed companies with relevant real estate activities. In this regards, EPRA defines real estate related activities as the ownership, trading, and development of income-producing real estate. We merely include countries with a minimum of 100 observations and at least five observations in each specific period. To prevent survivorship bias, we include active as well as deleted FTSE EPRA/NAREIT Global Real Estate Index constituents. Our dataset consists of financial data collected from Thomson Reuters Datastream on earnings per share data (EPS) and on return index (RI). Using Reuters' variable RI we calculate monthly returns as the percentage difference of today's and the previous month's RI.

Measuring Unexpected Earnings

We follow the literature and measure earnings momentum using the standardized unexpected earnings over the last four quarters (SUE) (see for example Bernard and Thomas (1990); Bron et al. (2018)):

$$E_{i,q} = \frac{E_{i,q} - \frac{1}{4}\sum_{j=0}^{3} E_{i,q-j}}{\sigma_{E,i,q}} \tag{4.3.1}$$

where $E_{i,q}$ represents the earnings per share of company i in the current quarter q and $\frac{1}{4}\sum_{j=0}^{3} E_{i,q-j}$ is the average quarterly earnings per share of company i over the last four quarters. The term in the numerator represents the unexpected earnings. The unexpected earnings are standardized by the standard deviation of earnings $\sigma_{E,i,q}$ over the last four quarters.

Measuring Investor Attention

As a proxy for investor attention, we gather data on GSV from Google Trends. We obtain data on monthly worldwide search requests of the respective company name without limiting to a specific filter (e.g., categories such as finance, real estate, etc.). We leave company names as is in the majority of cases, but remove certain endings (such as Inc. and Corp.) where necessary. Google Trends data are only accessible in a weighted form relative to other companies. For the highest search volume across all companies through time, the value is ranked 100. If a company receives no search requests over a particular point in time, the value is set to 0. Moreover, Google Trends only allows downloading of five time series on relative search requests simultaneously. Thus, we develop our own algorithm in order to determine a ranking for each company name relative to other companies' names across time. The algorithm downloads multiple datasheets, with the name of the first company in each one and four other company names as well. Once downloaded, we are able to combine the datasheets.

For the attention-based momentum, we standardize the unexpected Google search volume by the standard deviation over the last twelve months (standardized Google search volume, SGSV). SGSV is calculated as follows:

$$sgsv_{i,t} = \frac{gsv_{i,t} - \frac{1}{12}\sum_{j=0}^{11} gsv_{i,t-j}}{\sigma_{gsv,i,t}} \tag{4.3.2}$$

where $gsv_{i,t}$ represents our monthly Google search volume of a company i in month t and $\frac{1}{12}\sum_{j=0}^{11} gsv_{i,t-j}$ is the average monthly Google search volume of a company i over the last 12 months. The term in the numerator represents the unexpected Google search volume. The unexpected Google search volume is standardized by the standard deviation of Google search volume over the last twelve months $\sigma_{gsv,i,t}$. Uncorrected Google search requests on a specific company's name tend to be error-prone, since a given company may have a specific shareholder structure, size, location, or investment segment that can lead them to receive significantly higher (lower) levels of search requests than others. Our aim is to measure extraordinarily high or low search requests on a specific company as compared to the number of requests it received in the past. We use the standard deviation of the Google search volume to standardize unexpected Google search volume, because variables like market capitalization, stock price, or total assets could themselves be proxy variables for online search attention. Another major advantage of standardizing our monthly Google search volume and the earnings is that both SGSV and SUE have an expected value of zero and a variance of one. Therefore, standardizing the input variables earnings and Google search volume makes it easier to interpret the respective output variables.

Descriptive Statistics

Table 9 shows the summary statistics for the worldwide sample on monthly returns, GSV, SGSV and SUE. In the overall sample the average Google search volume is 9.05 in the overall sample. As expected, after standardizing both SUE and SGSV have in the overall sample average values close to zero (0.14 and -0.02) and standard deviations close to one (0.96 and 0.90). This result shows the effectiveness of standardizing the input variables earnings and Google search volume. The monthly returns are on average 1.06% with a standard deviation of 9.04%. Moreover, the table shows the summary statistics for the different geographical regions. We summarize the data for the regions Europe, US only, and Asia Pacific. The average Google search volume is highest in North America with 10.05 it is lowest in the Asia Pacific region with 7.21. Both SUE and SGSV indicate in each region values close to zero and standard deviations close to one. The values in each region are similar. The monthly returns are on average highest in the Asia Pacific region (1.13 with a standard deviation of 9.18) and lowest in Europe (0.94 with a standard deviation of 8.43).

Investment Portfolios

For the purpose of our empirical tests, we construct distinct portfolios based on past values of SUE or SGSV. First, we sort the portfolios one-way either on past SUE or SGSV. Second, we construct bidirectional sorting portfolios. Third, we form one-way portfolios on past SUE or SGSV for different geographical and cultural regions.

One-Way Sorted Portfolios

Using past values of SUE and SGSV we construct distinct equally weighted portfolios. Firstly, we independently construct three decile portfolios based on past SGSV or past

Table 9: Summary Statistics for Different Regions

Variable	mean	sd.	min.	max.	obs.
Panel A					
Overall					
Standardized Unexpected Earnings	0.14	0.96	-1.51	1.51	35,447
Google Search Volume	9.05	15.75	0.00	266.21	35,447
Standardized Google Search Volume	-0.02	0.90	-3.18	3.18	35,447
Monthly Return	1.06	9.04	-72.32	192.96	35,447
Panel B					
Europe					
Standardized Unexpected Earnings	0.14	0.95	-1.51	1.50	7,496
Google Search Volume	9.64	14.85	0.00	162.15	7,496
Standardized Google Search Volume	-0.02	0.91	-3.18	3.18	7,496
Monthly Return	0.94	8.43	-72.32	158.89	7,496
North America					
Standardized Unexpected Earnigns	0.08	0.96	-1.51	1.51	16,554
Google Search Volume	10.05	17.77	0.00	266.21	16.555
Standardized Google Search Volume	-0.03	0.91	-3.18	3.18	16,555
Monthly Return	1.07	9.20	-66.70	192.96	16,555
US only					
Standardized Unexpected Earnings	0.08	0.95	-1.51	1.51	14,221
Google Search Volume	9.64	17.77	0.00	266.21	14,222
Standardized Google Search Volume	-0.03	0.91	-3.18	3.18	14,222
Monthly Return	1.07	9.63	-66.70	192.96	14,222
Asia Pacific					
Standardized Unexpected Earnings	0.24	0.96	-1.50	1.51	11,396
Google Search Volume	7.21	12.76	0.00	182.10	11,396
Standardized Google Search Volume	0.00	0.88	-3.18	3.18	11,396
Monthly Return	1.13	9.18	-59.66	125.54	11,396

Our sample consists of monthly company-level data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index. This table summarizes data on mean, standard deviation, minimum, maximum of the variables standardized unexpected earnings, Google search volume and standardized Google search volume and monthly returns. We summarize our data for the regions Europe, North America, US only and Asia Pacific.

SUE. Generating a low (lower 10%), a medium (medium 80%) and a high (top 10%) SUE (*SUE1, SUE2, SUE3*) and SGSV portfolios (*SGSV1, SGSV2, SGSV3*). The returns on these portfolios are computed for different holding periods one to twelve months following the formation applying the buy-and-hold strategy following (Chan et al. (1996)). Moreover, we form long-short portfolios defined as the return difference between highest and the lowest decile. In case of SUE, it is denoted PMN (positive minus negative unexpected earnings) and AMI (attention minus inattention) in case of SGSV.

Earnings Momentum Portfolios

Table 10 shows the summary statistics of the worldwide sample of the monthly returns for different holding periods, i.e. one to twelve months after sorting into different deciles according to the previous month SUE rank. The portfolio returns increase monotonically from low to high SUE until the two-month holding period. The highly significant one-month holding period monthly SUE3 portfolio return equals 1.208% (or 15,499% p.a.). In the one- and two-month holding period the earnings effect is much higher as compared to the subsequent periods. The long-short portfolio return PME equals 0.273% (or 3,326% p.a.) in the one-month holding period and 0.216% (or 2,623% p.a.) in the two-month holding period. However, both the one-month and the two-month PME parameter are both statistically insignificant. In the three-month holding period, the medium SUE return is higher compared to the high SUE portfolio return. However, the top SUE portfolio outperforms the low SUE portfolio and PME equals 0.0208% (or 0,250% p.a.). Until the eight-month holding period top SUE stocks outperform low SUE stocks. The initial outperformance is followed by no clear structure in the subsequent holding periods. For each holding period the lower, medium and higher SUE portfolio returns are at least at the 10% significance level statisically significant. However, in no holding period PME is statistically significant. Figure 6 shows the chain index of the low, the medium, and the high SUE portfolios for the one-month holding period. We find that high SUE stocks outperform low SUE stocks.

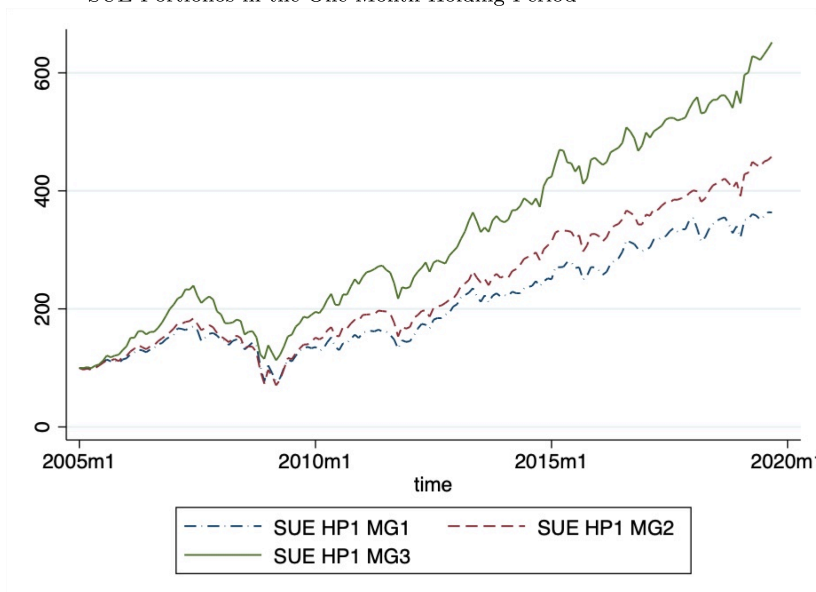
Table 10: Monthly SUE Portfolio Returns for Distinct Holding Periods

	Deciles			
HP	SUE1	SUE2	SUE3	PMN
1	0.935**	1.056**	1.208***	0.273
2	0.909**	1.044**	1.125***	0.216
3	0.812*	1.097**	0.833**	0.0208
4	0.735	1.078**	1.015**	0.280
5	0.871**	1.031**	1.009**	0.139
6	0.875*	1.053**	1.001**	0.127
7	1.023**	1.001**	1.106**	0.0832
8	0.800	1.037**	0.933**	0.133
9	1.125**	0.984**	0.949**	-0.176
10	0.883**	1.034**	0.877**	-0.00607
11	1.034**	0.977**	1.086**	0.0524
12	0.884*	1.032**	1.156**	0.272

The table summarizes the monthly portfolio returns for a 1 to 12 months holding period (hp) for the top and button decile and the medium 80% based on the previous month standardized unexpected earnings (SUE). Our sample consists of monthly data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index. SUE1 is the low, SUE2 the medium and SUE3 the high earnings portfolio. We define SUE by subtracting the past year's average earnings from the quarterly earnings and dividing it by its standard deviation within the past year. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Figure 6: Impact of the Standardized Unexpected Earnings on Stock Returns

SUE Portfolios in the One-Month Holding Period



This figure plots different lines for different levels of the previous month standardized unexpected earnings (SUE). We define SUE by subtracting the past year's average earnings from the quarterly earnings and dividing it by its standard deviation within the past year. The figure shows the chain index for the one-month holding period after sorting into different deciles of the previous month SUE. The dash-dotted blue lines represent the low SUE portfolio, the dashed red lines represent the mid portfolio, and the solid green lines represent the high SUE portfolio.

Attention-Based Momentum Portfolios

Table 11 reports the summary statistics of the global sample of the monthly returns for different holding periods, i.e. one to twelve months after grouping into distinct deciles according to past month SGSV rank. Table 11 shows that high SGSV portfolios with a holding period of one month statistically significantly outperform low SGSV portfolios. In the one-month holding period the portfolio returns increase monotonically from low to high SGSV and the statistically significant AMI equals 0.468% (or 5.763% p.a.). The one-month holding period monthly SGSV3 portfolio return equals 1.408% (or 18,268% p.a.) and is statistically significnatly different from zero at the 1% significance level. In the two-month holding period the top SGSV-portfolio still outperforms the low SGSV-portfolio and AMI equals 0.144% (or 1,742% p.a.). However, the portfolio returns do not increase monotonically from low to high SGSV and the medium SGSV-portfolio outperforms the top SGSV-portfolio. For subsequent holding periods this initial outperformance is followed by reversals. Remarkably, we find that the *SGSV2* portfolio seems to outperform in the holding periods of two to six months. This is followed by no clear structure in the subsequent holding periods. For each holding period the lower, medium and higher SGSV portfolio returns are statisically significant at least at the 10% significance level. However, only in the one-month holding period AMI is statistically significant. Figure 7 shows the chain index of the low, the medium, and the high SGSV portfolio for a holding period of one month. The figure illustrates the outperformance of high SGSV stocks.

Two-Way Sorted Portfolios Secondly, we construct bidirectional sorting portfolios based on tercile portfolios of SGSV or SUE. Stocks within each tercile are categorized into three equal size portfolios, low, mid, and high of the respective other variable. This bidirectional sorting procedure generates nine two-way sorted portfolios. After the formation the returns of these nine portfolios are calculated for different holding periods, i.e. 1, 2, 3, 6, 9, and 12 months applying the buy-and-hold strategy of Chan et al. (1996). Moreover, we construct long-short portfolios defined as the return difference between the highest SUE (or SGSV) and the lowest SUE (or SGSV) portfolio for each sorting sequence.

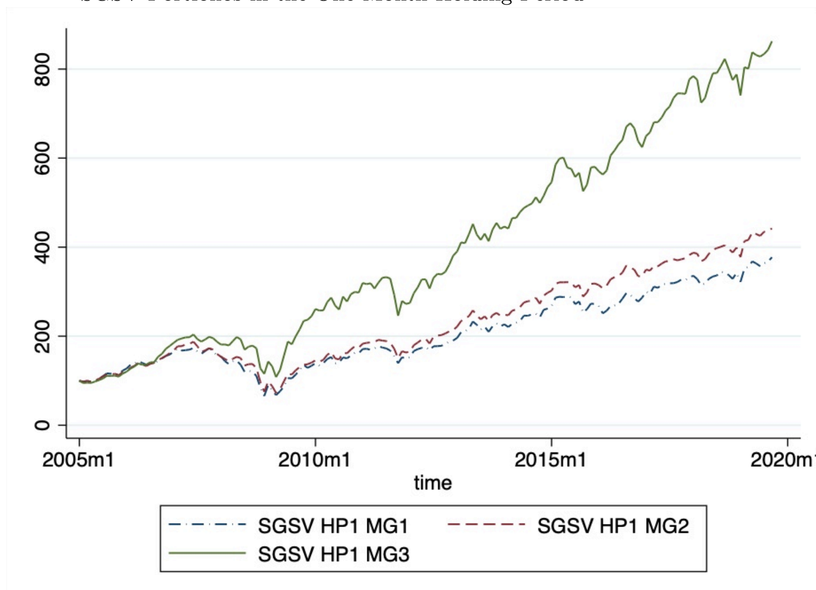
Table 11: Monthly SGSV Portfolio Returns for Distinct Holding Periods

	Deciles			
HP	SGSV1	SGSV2	SGSV3	AMI
1	0.940**	1.030**	1.408***	0.468**
2	0.835*	1.074**	0.979**	0.144
3	0.986**	1.067**	0.868**	-0.117
4	0.825*	1.071**	0.979**	0.154
5	0.817*	1.054**	0.884**	0.0665
6	0.914*	1.056**	0.957**	0.0430
7	1.185**	0.985**	1.077**	-0.108
8	0.837*	1.017**	1.042**	0.205
9	0.996**	1.023**	0.793**	-0.203
10	1.058**	1.000**	0.973**	-0.0856
11	0.854**	1.015**	1.000**	0.146
12	1.090**	1.035**	0.918**	-0.172

The table summarizes the monthly portfolio returns for a 1 to 12 months holding period (hp) for the top and button decile and the medium 80% based on the previous month standardized unexpected Google search volume (SGSV). Our sample consists of monthly company-level data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index. SGSV1 is the low, SGSV2 the medium and SGSV3 the high SGSV portfolio. We define SGSV by subtracting the past year's average Google search volume from the monthly Google search volume and dividing it by its standard deviation within the past year. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Figure 7: Impact of the Google Search Attention on Stock Returns

SGSV Portfolios in the One-Month Holding Period



The figure plots different lines for different levels of the previous month standardized Google search volume (SGSV). We define SGSV by subtracting the past year's average Google search volume from the monthly Google search volume and dividing it by its standard deviation within the past year. The figure shows the chain index for the one-month holding period after sorting into different deciles of the previous month SGSV. The dash-dotted blue lines represent the low SGSV portfolio, the dashed red lines represent the mid portfolio, and the solid green lines represent the high SGSV portfolio.

Table 12 summarizes the monthly returns of the two-way sorted portfolios. The left-hand side of the table uses SUE as the first sorting order while the right-hand side uses SGSV as the first sorting order. Relying on SUE as the first sorting order for the one-month holding period, we find that SGSV statistically significantly intensifies the returns in the SUE3 portfolio. In the SUE1 and SUE3 first-order portfolio the returns increase monotonically from low to high SGSV. Moreover, the AMI in the SUE3 tercile is statistically significant. In case of the SUE2 first-order portfolio the SUE2/SUE3 outperforms. However, the SUE2/SGSV2 portfolio returns are lower compared to the SUE2/SGSV1 portfolio returns. The highly significant one-month holding period monthly SUE3/SGSV3 portfolio return equals 1.271% (or 16,365% p.a.). In the SUE3 portfolio the return intensifying effect of rising SGSV in the one month holding period is followed by a reversal in the two months period. When we rely on SGSV as first sorting order we also find a tendency that SUE also intensifies the *SGSV2* and the *SGSV3* portfolio returns. In both cases the SUE3 portfolio outperforms. However, in no case PMN is statistically significantly different from zero. Moreover, neither in the *SGSV2* nor in the the *SGSV3* case the returns increase monotonically. The highly significant one-month holding period monthly SUE3/SGSV3 portfolio return equals 1.314% (or 16,959% p.a.). The initial intensification in the first holding period is followed by no clear structure. Figure 8 shows the chain indices for our two-way sorted portfolios for the one-month holding period. In the top row of the figure, we examine whether SGSV intensifies SUE in the bottom row we study whether SUE intensifies SGSV. The figure may add to the suspicion that both strategies intensify each other. Consistent with our initial assumption, which can be derived from the values in Table 12, we find further evidence that SGSV intensifies the returns in each SUE portfolio. In each case in the upper part of the figure the top SGSV portfolio outperforms. However, in the SUE2 first-order portfolio the low SGSV portfolio outperforms the medium SGSV portfolio. Moreover, SUE intensifies the SGSV portfolio returns in the SGSV2 and SGSV3 first-order portfolio. However, in both cases the low SUE-portfolio outperforms the medium SUE-portfolio. In case of the SGSV1 first-order portfolio the figure shows no return intensifying effect of SUE.

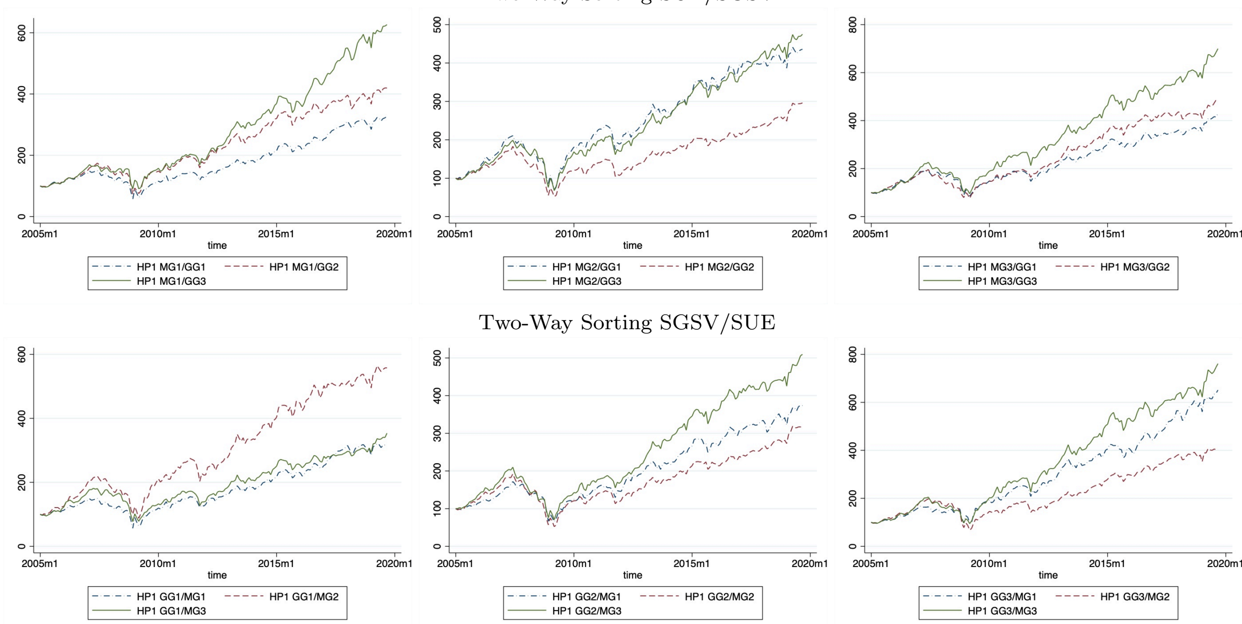
Table 12: Two-Way Sort Portfolios on Standardized Google Search Volume and Standardized Unexpected Earnings

HP	SUE/SGSV	SGSV1	SGSV2	SGSV3	AMI	SGSV/SUE	SUE1	SUE2	SUE3	PMN
1	SUE1	0.921*	1.010**	1.216***	0.295	SGSV1	0.907*	1.183***	0.881**	-0.0268
	SUE2	1.055**	0.863*	1.111**	0.0560	SGSV2	0.940**	0.885*	1.121***	0.181
	SUE3	0.985**	1.081***	1.271***	0.286*	SGSV3	1.248***	1.018**	1.314***	0.0664
2	SUE1	0.956*	1.205***	0.975**	0.0188	SGSV1	0.926*	1.026**	1.160***	0.234
	SUE2	0.913*	1.138**	1.023**	0.110	SGSV2	1.174***	1.136**	1.031**	-0.144
	SUE3	1.140***	1.139***	0.875**	-0.265	SGSV3	1.043**	0.891*	0.959**	-0.0841
3	SUE1	1.091**	1.125**	1.028**	-0.0628	SGSV1	1.020*	1.048**	1.022**	0.00190
	SUE2	0.973**	0.986**	1.187**	0.214	SGSV2	1.163**	0.910**	1.120**	-0.0427
	SUE3	1.010**	1.129**	0.856**	-0.154	SGSV3	0.971**	1.210***	0.868**	-0.103
6	SUE1	1.168**	1.021**	0.962**	-0.206	SGSV1	1.195**	0.895*	1.115**	-0.0805
	SUE2	0.914**	1.141**	1.052**	0.138	SGSV2	1.083**	1.121**	1.096***	0.0125
	SUE3	1.057**	1.051**	0.919**	-0.137	SGSV3	0.847**	1.099**	0.791*	-0.0566
9	SUE1	1.090**	1.194**	0.886**	-0.204	SGSV1	1.032**	1.009**	1.166**	0.134
	SUE2	0.874*	0.947**	0.909**	0.0352	SGSV2	1.219**	0.931**	0.919**	-0.300
	SUE3	1.278**	0.828**	0.938**	-0.339	SGSV3	0.906**	0.903**	0.877*	-0.0286
12	SUE1	1.192**	0.826**	0.927**	-0.265	SGSV1	1.253**	1.028**	1.048**	-0.205
	SUE2	1.067**	1.160**	0.847*	-0.220	SGSV2	0.838*	1.160***	1.165***	0.326*
	SUE3	1.037**	1.129***	1.082***	0.0452	SGSV3	0.872**	0.797*	1.063***	0.191

The table summarizes the monthly returns of the two-way sorted portfolios. The left row summarizes the portfolio returns using standardized unexpected earnings (SUE) as the first sorting order and standardized unexpected Google search volume (SGSV)as the second sorting order. The left row summarizes the portfolio returns using SGSV as the first sorting order and SUE as the second sorting order. Our sample consists of monthly data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index. Using past values of SUE and SGSV we construct distinct equally weighted portfolios. Firstly, we independently construct three tercile portfolios based on past SGSV or past SUE values. Generating low, medium and high SUE (*SUE1, SUE2, SUE3*) and the SGSV portfolios (*SGSV1, SGSV2, SGSV3*). Stocks within each tercile are categorized into three portfolios, low, mid, and high of the respective other variable. This bidirectional sorting procedure generates 9 two-way sorted portfolios. Moreover, we construct long-short portfolios defined as the return difference between the highest SUE (or SGSV) and the lowest SUE (or SGSV) portfolio for each sorting sequence. The returns on these portfolios are computed for different holding periods, i.e. 1, 2, 3, 6, 9 and 12 months. Moreover, we form long-short portfolios defined as the return difference between highest tercile (or decile) portfolio and the lowest tercile (or decile) portfolio. In case of SUE, it is denoted PMN (positive minus negative unexpected earnings) and AMI (attention minus inattention) in case of SGSV for each sorting sequence. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Figure 8: Simultaneous Impact of Standardized Unexpected Earnings and Google Search Attention on Stock Returns

Two-Way Sorting SUE/SGSV



The figure plots different chain indices for two-way sort portfolios on different levels of the previous month standardized unexpected earnings (SUE) and standardized Google search volume (SGSV). We define SUE by subtracting the past year's average earnings from the quarterly earnings and dividing it by its standard deviation within the past year. SGSV is calculated by subtracting the past year's average Google search volume from the monthly Google search volume and dividing it by its standard deviation within the past year.

The upper row shows the chain indices for the holding period of 1 month after primarily sorting into different terciles of the previous month SUE and then into different SGSV clusters. The dash-dotted blue lines represent the low SGSV portfolio, the dashed red lines represent the mid portfolio, and the solid green lines represent the high SGSV portfolio.

The bottom row shows the chain indices for the holding period of 1 month after primarily sorting into different terciles of the previous month SGSV and then into different SUE clusters. The dash-dotted blue lines represent the low SUE portfolio, the dashed red lines represent the mid portfolio, and the solid green lines represent the high SUE portfolio.

The Carhart Four-Factor Model We rely our analysis on the Carhart four-factor model to evaluate the performance of our trading strategies (Carhart (1997)). We regress portfolio i's excess return on the benchmark portfolio's excess return, the size (SMB), the book-to-market (HML), and the momentum (WML) factor:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{3,i} WML_t + u_{i,t} \tag{4.3.3}$$

where $r_{i,t}$ is the total return of REIT i in month t, $r_{f,t}$ is respective local currency's one-month risk-free rate, and $r_{m,t}$ is the monthly return of the market portfolio proxy. The term ($r_{i,t}$-$r_{f,t}$) represents the excess return of portfolio i. It is calculated as the equally weighted return of all portfolio constituents minus the respective local currency's one-month risk-free rate. ($r_{m,t}$-$r_{f,t}$) is the excess of the benchmark portfolio. As benchmark portfolio we use the equally weighted portfolio of all stocks in our sample. SMB_t is the difference between the returns on diversified portfolios of small stocks minus the return on a diversified portfolio of big stocks in month t, HML_t is the return on a diversified portfolio of high minus low book-to-market stocks in month t and WML_t is the return difference between the return in the portfolio of the past year‘s winners minus the return in the portfolio of the past year's losers in month t. $u_{i,t}$ represents the zero-mean error term. The data on $r_{f,t}$, $r_{m,t}$, SMB_t, HML_t, and WML_t come from Kenneth French's website.[12] We estimate for each decil portfolio on SUE and SGSV for the holding periods one to twelve months a Carhart four-factor model. Moreover, we run the Carhart four-factor model on each bidirectional sorting portfolio.

Granger Causality Test

In our study, we analyze whether the attention-based momentum forecasts the earnings momentum or whether the earnings momentum predicts the attention-based momentum. We can answer this chicken or egg dilemma by applying a Granger

[12] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

causality test. Granger (1969) argues that causality in an economic context can be analyzed by testing the ability of one time series to forecast another time series. A time series is said to Granger-cause another time series if it can be shown that its past values include statistically significant information to forecast the other time series. Under hypothesis 2 we suspect that the attention-based momentum Granger-causes the earnings momentum. Our empirical analysis is based on the following VAR model:

$$PMN_t = \sum_{i=1}^{6} \alpha_{1,i} PMN_{t-i} + \sum_{j=1}^{6} \beta_{1,j} AMI_{t-j} + e_{1,t} \tag{4.3.4}$$

$$AMI_t = \sum_{t=1}^{6} \alpha_{2,i} PMN_{t-i} + \sum_{j=1}^{6} \beta_{2,j} AMI_{t-j} + e_{2,t} \tag{4.3.5}$$

The upper formula shows the relationship between the long-short portfolio returns of high SUE returns minus low SUE returns and the values of the last six periods of this time series and of the long-short portfolio returns of high SGSV returns minus low SGSV returns. The lower formula shows the relationship between AMI and the values of the last six periods of PMN and AMI. PMN_t represents the time series on monthly returns on the long-short portfolios of SUE. AMI_t is the time series on monthly returns on the long-short portfolios of SGSV. $e_{1,t}$ and $e_{2,t}$ are the error terms. In our specification we allow six lags of each variable. Under Hypothesis 2 we suspect in the global sample $\alpha_{2,1}, \ldots, \alpha_{2,6}$ to be jointly statistically significant and $\beta_{1,1}, \ldots, \beta_{1,6}$ not to be jointly significantly differ from zero.

4.4 *Empirical Results*

This chapter summarizes the empirical results. The following section shows the performance evaluation of the earnings momentum, chapter 4.2 evaluates the results of the attention-based momentum portfolios. The combined effect of earnings momentum and online search attention on future stock returns is described in chapter 4.3. Chapter 4.4 shows the result of the Granger causality test.

Earnings Momentum

Table 13 provides the global sample results of our Carhart four-factor model on one-way sorted portfolios on SUE. We rely our analysis on decile portfolios and sort the sample based on past values of SUE. After formation we evaluate the performance of our portfolios over a holding period of one to twelve months. Table 13 reports positive and significant alphas for the high earnings portfolio for a holding period of one month. The one-month holding period SUE3 portfolio alpha equals 0.342. Furthermore, in the one-month holding period the alpha of the long-short portfolio is statistically significant and PMN equals 0.406. In line with Feng et al. (2014); Price et al. (2012); Bron et al. (2018) our result provides evidence that stocks with high SUE outperform the market in the short run. However, in our study we only observe an outperformance in the one-month holding period. Bron et al. (2018) find evidence for the effectiveness of the earnings momentum for holding periods up to twelve months. We find that the initial outperformance in the one-month holding period is followed by no clear structure for longer holding periods. This result shows that financial markets strive over time for ever greater efficiency.

Attention-Based Momentum

Table 14 summarizes the results of the Carhart four-factor model on one-way sorted portfolios on Google search attention. Again, we rely our analysis on decile portfolios and sort the sample based on past values of SGSV over a holding period of one to twelve months after formation. Relying on a holding period of one month we find evidence for a positive impact of past Google search attention and future stock returns. This result is in line with Da et al. (2011); Joseph et al. (2011); Bank et al. (2011). The alpha in the high Google search attention portfolio is statistically significant from zero and equals 0.414. Furthermore, in the one-month holding period the respective alpha of the long-short portfolio is positive and statistically significant and equals 0.428. This result is in line with Barber and Odean's (2008) hypothesis that investors are net buyers of attention grabbling stocks and proves that stocks with high levels of Google search attention short run outperform the market. The initial positive effect is followed by a no clear structure for longer holding periods.

Table 13: Alpha Values of the Carhart Four Factor Model on SUE Portfolios for Distinct Holding Period

	Deciles			
PMN	SUE1	SUE2	SUE3	PMN
1	-0.167	-0.0237	0.342**	0.406*
	(0.132)	(0.0220)	(0.151)	(0.230)
2	-0.173	-0.0289	0.196	0.265
	(0.134)	(0.0231)	(0.145)	(0.222)
3	-0.283**	0.0387*	-0.155	0.0245
	(0.128)	(0.0225)	(0.150)	(0.210)
4	-0.397***	0.00433	0.115	0.408
	(0.148)	(0.0284)	(0.169)	(0.250)
5	-0.209	-0.0153	-0.0145	0.0909
	(0.156)	(0.0332)	(0.144)	(0.198)
6	-0.323**	-0.000970	0.0210	0.241
	(0.152)	(0.0396)	(0.187)	(0.270)
7	-0.131	-0.0475	0.0555	0.0829
	(0.126)	(0.0376)	(0.191)	(0.260)
8	-0.415***	-0.00197	-0.0994	0.213
	(0.151)	(0.0303)	(0.149)	(0.228)
9	0.0123	-0.0586*	-0.106	-0.221
	(0.161)	(0.0303)	(0.140)	(0.212)
10	0.0123	-0.0586*	-0.106	-0.221
	(0.161)	(0.0303)	(0.140)	(0.212)
11	-0.134	-0.0632*	0.0445	0.0755
	(0.164)	(0.0322)	(0.133)	(0.227)
12	-0.305**	-0.0290	0.246	0.447
	(0.150)	(0.0450)	(0.223)	(0.293)

The table summarizes the alpha values of our Carhart four factor model for a 1 to 12 months holding period (hp) for the top and button decile and the medium 80% based on the previous month standardized unexpected earnings (SUE). Our sample consists of monthly data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index. SUE1 is the low, SUE2 the medium and SUE3 the high earnings portfolio. We define SUE by subtracting the past year's average earnings from the quarterly earnings and dividing it by its standard deviation within the past year. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Table 14: Alpha Values of the Carhart Four Factor Model on SGSV Portfolios for Distinct holding period

	Deciles			
HP	SGSV1	SGSV2	SGSV3	AMI
1	-0.117	-0.0384*	0.414***	0.428**
	(0.120)	(0.0205)	(0.141)	(0.212)
2	-0.288**	0.0283	-0.102	0.0825
	(0.137)	(0.0239)	(0.128)	(0.213)
3	-0.104	0.0145	-0.149	-0.148
	(0.123)	(0.0271)	(0.137)	(0.193)
4	-0.343***	0.0206	-0.0296	0.210
	(0.122)	(0.0240)	(0.120)	(0.196)
5	-0.301***	0.00796	-0.0977	0.1000
	(0.115)	(0.0249)	(0.123)	(0.182)
6	-0.252**	0.0124	-0.113	0.0360
	(0.121)	(0.0300)	(0.131)	(0.195)
7	0.0437	-0.0670**	0.0644	-0.0825
	(0.123)	(0.0304)	(0.118)	(0.193)
8	-0.309***	-0.0409	0.0882	0.294*
	(0.115)	(0.0249)	(0.113)	(0.177)
9	-0.124	-0.0310	-0.176	-0.155
	(0.114)	(0.0267)	(0.156)	(0.221)
10	-0.124	-0.0310	-0.176	-0.155
	(0.114)	(0.0267)	(0.156)	(0.221)
11	-0.0806	-0.0644**	0.0243	0.00158
	(0.131)	(0.0289)	(0.123)	(0.190)
12	-0.0504	-0.0284	-0.0137	-0.0666
	(0.126)	(0.0328)	(0.139)	(0.209)

The table summarizes the alpha values of our Carhart four factor model for a 1 to 12 months holding period (hp) for the top and button decile and the medium 80% based on the previous month standardized unexpected Google search volume (SGSV). Our sample consists of monthly company-level data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index. SGSV1 is the low, SGSV2 the medium and SGSV3 the high SGSV portfolio. We define SGSV by subtracting the past year's average Google search volume from the monthly Google search volume and dividing it by its standard deviation within the past year. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Our result is in line with the finding of Yung and Nafar (2017). They analyze the impact of Google search attention on the future performance of real estate stocks. They find that a zero-cost strategy that longs stocks with high Google search attention and shorts stocks with no Google search attention results in positive returns. Despite our compelling result, our objective in this study is not to apply investor attention as an investment strategy. Given the inconsistency found in the literature regarding the impact of investor attention on future returns, we suspect that an unexpected Google search attention may rather have a reinforcing effect on earnings momentum than being considered in isolation.

Combined Effect of Earnings Momentum and Investor Attention

In the style of Bron et al. (2018) who analyze the joint effect of earnings and price momentum we evaluate the joint effect of earnings momentum and Google search attention. Firstly, relying either on past earnings or past Google search attention as first sorting order we generate each three tercile portfolios. Secondly, clustering the stocks in these tercile portfolios each into further three terciles we generate nine bidirectional sorting portfolios.

Table 15 summarizes the regression results of the Carhart four-factor model on these bidirectional sorting portfolios. On the left-hand side, we rely on SUE as first sorting order, on the right-hand side we rely on SGSV as the first sorting order.

On the left-hand side, we observe that the alpha values increase monotonically from low to high SGSV in case of the SUE1 and SUE3 first order portfolio in the one-month holding period. However, relying on the SUE2 as first order portfolio alpha does not monotonically increase from low to high SGSV in the one-month holding period. Nevertheless, the SUE2/SGSV3 alpha is the greatest. The one-month holding period's SUE1/SGSV1 portfolio is negative and equals -0.312, the respective parameter on the SUE1/SGSV3 turns positive and equals 0.156. However, both parameters are statistically insignificant. In the SUE2 first order tercile both portfolio alphas SUE2/SGSV1 and SUE2/SGSV3 are insignificantly negative equaling -0.0507 and -0.0180. The insignificant alpha on the SUE3/SVSV1 portfolio is positive and equals 0.0284, while the alpha on SUE3/SGSV3 equals 0.328 and is highly significant. This

Table 15: Alpha Values of the Carhart Four Factor Model on Two-Way Sort Portfolios

HP	SUE/SGSV	SGSV1	SGSV2	SGSV3	AMI	SGSV/SUE	SUE1	SUE2	SUE3	PMN
1	SUE1	-0.312	-0.00904	0.156	0.365	SGSV1	-0.306	0.132	-0.106	0.0972
		(0.190)	(0.149)	(0.141)	(0.225)		(0.189)	(0.140)	(0.142)	(0.226)
	SUE2	-0.0507	-0.304**	-0.0180	-0.0705	SGSV2	-0.107	-0.247*	0.129	0.133
		(0.145)	(0.146)	(0.122)	(0.171)		(0.129)	(0.141)	(0.154)	(0.210)
	SUE3	0.0284	0.162	0.328**	0.197	SGSV3	0.187	-0.0806	0.373***	0.0821
		(0.127)	(0.158)	(0.148)	(0.178)		(0.157)	(0.138)	(0.135)	(0.209)
2	SUE1	-0.219	0.227	-0.156	-0.0408	SGSV1	-0.238	-0.0491	0.172	0.307
		(0.204)	(0.142)	(0.116)	(0.213)		(0.193)	(0.121)	(0.153)	(0.255)
	SUE2	-0.202	0.0279	-0.153	-0.0544	SGSV2	0.148	0.0309	0.0722	-0.179
		(0.135)	(0.143)	(0.121)	(0.158)		(0.121)	(0.134)	(0.140)	(0.203)
	SUE3	0.200	0.181	-0.0609	-0.364**	SGSV3	-0.0381	-0.264*	-0.00677	-0.0719
		(0.133)	(0.167)	(0.136)	(0.169)		(0.138)	(0.140)	(0.133)	(0.208)
3	SUE1	-0.133	0.106	-0.00506	0.0250	SGSV1	-0.199	-0.00975	-0.0597	0.0364
		(0.194)	(0.132)	(0.123)	(0.213)		(0.192)	(0.122)	(0.123)	(0.233)
	SUE2	-0.0847	-0.123	0.161	0.142	SGSV2	0.129	-0.106	0.0933	-0.139
		(0.115)	(0.150)	(0.129)	(0.166)		(0.154)	(0.141)	(0.154)	(0.245)
	SUE3	-0.0126	0.111	-0.108	-0.198	SGSV3	-0.0463	0.194	-0.126	-0.183
		(0.120)	(0.165)	(0.152)	(0.165)		(0.119)	(0.127)	(0.148)	(0.211)
6	SUE1	-0.0853	-0.0178	-0.0792	-0.0972	SGSV1	-0.0214	-0.237*	0.0660	-0.0158
		(0.224)	(0.125)	(0.131)	(0.236)		(0.223)	(0.141)	(0.0994)	(0.247)
	SUE2	-0.212*	0.108	-0.0717	0.0376	SGSV2	0.0185	0.126	0.130	0.00862
		(0.128)	(0.136)	(0.116)	(0.165)		(0.129)	(0.134)	(0.132)	(0.212)
	SUE3	0.0349	0.0845	-0.0251	-0.163	SGSV3	-0.177	-0.0175	-0.177	-0.103
		(0.107)	(0.130)	(0.158)	(0.177)		(0.127)	(0.118)	(0.159)	(0.234)
9	SUE1	0.0579	0.0472	-0.0509	-0.212	SGSV1	-0.0684	-0.0976	0.0430	0.00814
		(0.112)	(0.133)	(0.127)	(0.146)		(0.126)	(0.124)	(0.151)	(0.204)
	SUE2	-0.245**	-0.0895	-0.133	0.00883	SGSV2	0.119	-0.0384	-0.0729	-0.295
		(0.111)	(0.160)	(0.122)	(0.172)		(0.133)	(0.136)	(0.124)	(0.184)
	SUE3	0.158	-0.108	-0.135	-0.397*	SGSV3	-0.0424	-0.112	-0.204	-0.265
		(0.156)	(0.128)	(0.139)	(0.215)		(0.126)	(0.135)	(0.145)	(0.202)
12	SUE1	-0.108	-0.216**	-0.107	-0.102	SGSV1	-0.00675	-0.0434	-0.0313	-0.128
		(0.224)	(0.105)	(0.131)	(0.225)		(0.220)	(0.121)	(0.0965)	(0.253)
	SUE2	0.00462	0.0605	-0.263**	-0.371**	SGSV2	-0.254**	0.144	0.176	0.327*
		(0.114)	(0.123)	(0.111)	(0.162)		(0.111)	(0.116)	(0.137)	(0.195)
	SUE3	-0.0186	0.161	0.206	0.121	SGSV3	-0.151	-0.342***	0.202	0.249
		(0.107)	(0.129)	(0.157)	(0.179)		(0.135)	(0.114)	(0.160)	(0.246)

The table summarizes the alpha values of our Carhart four factor model of the two-way sorted portfolios. The left row summarizes the portfolio returns using standardized unexpected earnings (SUE) as the first sorting order and standardized unexpected Google search volume (SGSV) as the second sorting order. The left row summarizes the portfolio returns using SGSV as the first sorting order and SUE as the second sorting order. Our sample consists of monthly data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index. Using past values of SUE and SGSV we construct distinct equally weighted portfolios. Firstly, we independently construct three tercile portfolios based on past SGSV or past SUE values. Generating low, medium and high SUE (*SUE1, SUE2, SUE3*) and the SGSV portfolios (*SGSV1, SGSV2, SGSV3*). Stocks within each tercile are categorized into three portfolios, low, mid, and high of the respective other variable. This bidirectional sorting procedure generates 9 two-way sorted portfolios. Moreover, we construct long-short portfolios defined as the return difference between the highest SUE (or SGSV) and the lowest SUE (or SGSV) portfolio for each sorting sequence. The returns on these portfolios are computed for different holding periods, i.e. 1, 2, 3, 6, 9 and 12 months. Moreover, we form long-short portfolios defined as the return difference between highest tercile (or decile) portfolio and the lowest tercile (or decile) portfolio. In case of SUE, it is denoted PMN (positive minus negative unexpected earnings) and AMI (attention minus inattention) in case of SGSV for each sorting sequence. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

result provides evidence for Hypothesis 1a and suggests that online search attention intensifies the post-earnings drift. However, none of the long-short portfolios neither AMI, (i.e., fixed SUE, low minus high online search attention) is statistically significant. Summarizing, we find a tendency that the alpha values increase for rising SGSV and fixed SUE horizontal from left to right. This shows a tendency that SGSV intensifies the SUE portfolio return for a holding period of one month. In the SUE3 portfolio we observe a significantly negative AMI in the two months holding period. Hence, we find evidence of a reversal effect in the two months holding period. We observe no clear structure of an intensifying or weakening impact of SGSV on SUE over the subsequent holding periods. In each portfolio the alpha parameters fluctuate sign over the subsequent holding periods.

On the right-hand side, using SGSV as first sorting order we find for a holding period of one month an intensifying tendency of SUE on SGSV. However, in no case does the alpha values increase monotonically. In the one-month holding period in each first order sorting portfolio relying on SGSV the portfolio alpha on high SUE is greater compared to the low SUE portfolio's alpha. In the SGSV2 and SGSV3 first order tercile the high SUE portfolios achieve the highest alpha. However, in SGSV1 first order tercile the SGSV1/SUE2 portfolio outperforms. The performance parameter on the SGSV1/SUE1 portfolios equals -0.306, the alpha on the SGSV1/SUE3 is -0.106. Both parameters are statistically insignificant. The insignificant alpha values on SGSV2/SUE1 and SGSV2/SUE3 equal -0.107 and 0.129. The SGSV3/SUE1 alpha is 0.187 and statistically insignificant while the SGSV3/SUE3 alpha turns highly significant and equals 0.373. This result provides slight evidence for hypothesis 1b suggesting that positive earnings surprises intensify the attention-based momentum. None of the horizontal long-short PMN portfolios (i.e., fixed SGSV, low minus high earnings) is statistically significant. Relying on a one-month holding period and using SGSV as first order portfolio we find in summary that SUE has a slight intensifying impact on the alpha values. The one-month holding period's intensifying tendency is followed by no clear structure for longer holding periods.

Summarizing we find that both investment strategies intensify each other. However, the intensifying effect of SGSV on SUE is slightly sharper. On the left-hand side, we find in the low and high earnings first-order portfolio monotonically horizontally increasing alpha values from low to high SGSV. This result is in line with Moniz et al. (2011) who find an intensifying effect of news flow signals on earnings momentum. However, Peress (2008) find that higher media coverage lowers post-earnings-drift. Hou et al. (2009) find a higher profits of earnings momentum among low volume stocks. Li et al. (2019) find that attention from more sophisticated investors before the earnings announcement lowers the post-earnings-drift. Mori (2015) stress that Google searches influence the process of information diffusion among real estate stocks. They find evidence for the impact of Google searches on the lead-lag effect. Li et al. (2019) find a lowering effect of sophisticated investor's attention before the earnings announcement on the earnings momentum. We suspect that the post-earnings drift is linked to an underreaction to earning news and assume that short-lived attention from noise traders slowers the incorporation speed of information into stock prices (see: Schiller et al. (2022)), and thereby short run intensifies earnings momentum.

Earnings or Online Search Attention? What moves first?

Table 16 shows the results of our Granger causality test as descripted in equation 4 and 5. We test whether the post-earnings-drift Granger-causes the post-attention-drift or whether the post-attention-drift Granger-causes the post-earnings-drift. Table 16 shows that PMN predicts AMI. However, we find that AMI includes no information to forecast PMN. Thus, we find evidence that the returns of the strategy relying on earnings momentum have a forecasting power on the returns of the attention-based investment strategy. Therefore, today's earnings momentum includes information to predict future returns on online search attention. We suspect that earning surprises attract noise traders investors' attention slowing the incorporation of earning news into stock prices, and therefore intensify the earnings momentum. Our result provides evidence for hypothesis 2, and proves that the post-earnings-drift Granger-causes the post-attention-drift.

Table 16: Granger Causality Test

VARIABLES	AMI	PMN
L.AMI	-0.331***	-0.152
	(0.0752)	(0.0947)
L2.AMI	-0.0601	0.0868
	(0.0784)	(0.0987)
L3.AMI	-0.0217	0.0854
	(0.0782)	(0.0984)
L4.AMI	0.0391	-0.0370
	(0.0778)	(0.0980)
L5.AMI	0.177**	-0.0813
	(0.0769)	(0.0968)
L6.AMI	0.153**	0.0354
	(0.0729)	(0.0918)
L.PMN	-0.155**	-0.186**
	(0.0605)	(0.0762)
L2.PMN	-0.130**	-0.156**
	(0.0625)	(0.0787)
L3.PMN	-0.0975	0.00391
	(0.0632)	(0.0796)
L4.PMN	-0.0974	0.0954
	(0.0634)	(0.0799)
L5.PMN	0.0623	-0.0347
	(0.0632)	(0.0795)
L6.PMN	0.0922	-0.0746
	(0.0618)	(0.0778)
Constant	0.607***	0.389
	(0.233)	(0.293)
R-sq	0,1882	0,1075
Observations	171	171
Granger Causality Test		
Xi-Sq Dist. (6 df)		
PMN does not predict AMI	14.916***	
AMI does not predict PMN	2.003	

Our sample consists of monthly company-level data on 368 property-holding companies in 12 countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, United Kingdom, and United States) from January 2005 to September 2019. We chose the sample from the constituents of the FTSE EPRA/NAREIT Global Real Estate Index. We form independently different deciles based on the previous month standardized unexpected earnings (SUE). Then we form long-short portfolios defined as the return difference between highest decile portfolio and the lowest decile portfolio. In case of SUE, it is denoted PMN (positive minus negative unexpected earnings) and AMI (attention minus inattention) in case of SGSV for each sorting sequence. We define SUE by subtracting the past year's average earnings from the quarterly earnings and dividing it by its standard deviation within the past year. SGSV is determined subtracting the past year's average Google search volume from the monthly Google search volume and dividing it by its standard deviation within the past year. This table summarizes in the top part the results of our VAR model on PMN and AMI including three lags on each variable. In the bottom part it summarizes the results of the Granger causality test. Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

4.5 Conclusion

This paper addresses earnings momentum, the impact of online search attention on future REIT returns and the interaction of both investment strategies. Moreover, we analyze the direction of Granger causality of attention-based momentum and earnings momentum. We rely our analysis on the FTSE EPRA/NAREIT Global Real Estate Index from 2005:1 to 2019:9 using a global sample of 368 property-holding companies from twelve countries. We define earnings momentum as the post-earnings drift in the subsequent periods after earnings surprises using standardized unexpected earnings by subtracting the past year's average earnings from the quarterly earnings and dividing it by its standard deviation within the past year. We measure online search attention by standardized Google search volume, given by subtracting the past year's average Google search volume from the monthly Google search volume and dividing it by its standard deviation within the past year.

Using single and bidirectional portfolios sorted on the previous month's earnings surprises and investors' attention we find three major results emerge. First, stocks with positive earnings surprises and stocks with high investors' attention short-run outperform. However, the outperformance is only significant in a one-month holding period followed by long-run reversals. Second, earnings momentum and the attention-based momentum tend to intensify one another. However, investors' attention has a slightly sharper impact on earnings momentum compared to the influence of earnings surprises on the post-earnings drift. Third, we find that the earnings momentum Granger causes the attention-based momentum.

Our study shows the existence and mutual intensification of the post-earnings-drift and the post-attention-drift. Our results have important implications on the success of earnings momentum investment strategies. Bron et al. (2018) find evidence for the success of the earnings momentum strategy for holding periods up to twelve months. However, we find the outperformance only for a one-month holding period. Moreover, in a REIT context we are the first who find that investors' attention proxied by Google search attention intensifies earnings momentum. In advance, we find that the attention-based momentum forecasts the earnings momentum. This shows that investors' attention partly predicts future stock returns related to earnings surprises.

We recommend portfolio managers who rely on the common earnings momentum to monthly reallocate their portfolio and to consider Google search attention to increase their returns.

5 Conclusion

In this dissertation, we aim to understand how investors react to and assimilate financial news. To this end, we explore mutual funds and property holding companies. Chapter 1 provides an overview and identifies the main research questions. Moreover, it provides a rationale for how mutual fund flows and property holding company stock prices react to financial information. Chapter 2 delves into investor behavior by examining the determinants of mutual fund flows. We study fund flow modeling and procedures to manage outliers. For property holding companies, the question is how quickly stock prices incorporate news. Chapter 3 explores the correction speed of stock market mispricings relative to stocks' fundamental values. We also consider how investor attention impacts the adjustment speed of mispricings. Chapter 4 investigates how earnings news is incorporated into stock prices, as well as how investor attention influences earnings momentum.

Our research provides several key insights into mutual fund flows. First, using approximated, rather than exact fund flows, slightly overestimates investors' reactions to strong performance news. Second, winsorizing outlying fund flow values (instead of trimming or excluding) may lead to biased estimates. Third, mutual fund investors do not typically incorporate news immediately. Instead, they react at varying time intervals, which can lead to fund flow persistence. Finally, we find that neglecting persistence when modeling mutual fund flows may lead to biased estimates.

Contradicting previous research that finds no reaction to low returns Chevalier and Ellison (1997); Brown et al. (1996); Sirri and Tufano (1998), we observe fund flow sensitivity to poor performance once we trim outliers and control for persistence. We recommend that researchers on mutual fund flows follow this procedure for robust results.

We also find that stock markets do not correct mispricings of property holding companies' stocks immediately. In our research, we define mispricing using the NAV spread of a property holding company. We find evidence for mean reverting behavior of the NAV spread, with the highest speed for the most undervalued stocks (i.e., stocks with the lowest NAV spreads compared to the other stocks in the same country) and for those with low levels of Google search volume. In this regard, Google search volume is often found to be related to noise trader attention (Da et al. (2011)). Therefore, our results show that noise trader attention slows the correction speed of mispricing.

We also note that the NAV spread is related to other companies' NAV spreads in the respective country. However, a specific company' NAV spreads only depends on that companies with high levels of online search volume. Overall, our results imply a price pressure potential for highly undervalued stocks with low levels of online search volume.

We further observe a post-earnings drift in property holding company stocks. However, the returns only outperform the benchmark significantly for a one-month holding period. Stocks with high levels of online search volume tend to outperform in the short run. Remarkably, we find that Google search volume intensifies the post-earnings drift. Using a Granger causality test, we show that post-earnings drift predicts post-attention drift, and therefore drives the outperformance. Assuming that post-earnings drift is related to investors' incorrect reactions to news (Chan et al. (1996); Hong and Stein (1999)), noise trader attention may intensify those misreactions, and thus intensify earnings momentum.

Our results hold important implications for mutual fund managers and investors of property holding companies. We provide evidence that the flow-performance relationship is not convex, but rather linear. This is important for the moral hazard risk of fund managers that aim to increase their assets under management and their income. We recommend they consider the risk of outflows when making investment decisions.

We also find that certain trading strategies for stocks of property holding companies are advantageous. First, highly undervalued stocks mean-revert rapidly. This suggests a price pressure potential for undervalued stocks. Second, there is evidence of a post-earnings drift for holding periods of one month. Third, attention-based momentum is found for only a one-month holding period. Online search volume slows the incorporation speed of information such as mispricings and earnings. Fourth, on a quarterly basis, there is higher price pressure potential on undervalued stocks with low levels of online search volume. Fifth, during the one-month holding period, online search volume intensifies earnings momentum. We advise portfolio managers that rely on value or earnings momentum strategies to consider Google search volume as a means to increase returns.

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