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Pricing Efficiency and Bounded Rationality: Evidence Based on the Responses Surrounding GICS Real Estate Category Creation

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We use the reclassification of the real estate stocks in the S&P 500 from the Financials sector as a natural experiment to test the co-existence of both market force and behavioural biases. By performing event studies on real estate investment trusts (REITs) included in the S&P 400, S&P 500, and S&P 600 indices on both the announcement and implementation dates, we investigate the impact of the reclassification of the real estate stocks in the S&P 500 from the Financials sector to the newly created Real Estate sector under the Global Industry Classification Standard (GICS) system. We set up four hypotheses to test if the identified reclassification effect is due to improved pricing efficiency or bounded rationality. The event studies confirm the presence of abnormal returns during the announcement of the new sector and the S&P implementation. The reclassification effect is the largest for large-cap real estate stocks that are included in the S&P 500 index. These abnormal returns are robust to various measures of statistical significance and variation of event windows. The creation of a real estate category in the GICS improves the pricing efficiency of real estate stocks, but also triggers framing effects among investors. The market is under the influence of both rational and irrational forces.

Keywords

Behavioural Bias, Framing, Sector Reclassification, Securitised Real Estate, REITs

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1. Introduction

Real estate is emerging as a distinct investment sector in the eyes of regulators, index companies and investors. Across markets, real estate is becoming its own sector as it is separated from the financials sector with which real estate has been historically classified by index companies and investors. Sector taxonomies with specific real estate categories will likely increase the visibility of the asset class. Additionally, rules-based exchange-traded fund (ETF) products and active managers that use sectors to determine asset allocations will be impacted.

However, it is less clear how the reclassification will impact perceptions of investors of real estate securities from a behavioural perspective. Theoretically, there should be no behavioural impact on security pricing as nothing will fundamentally change as stocks are reclassified. As shown by the recent growth of the field of behavioural finance, theory often does not match reality, which results in the following research question raised: does classifying securities as real estate have a behavioural impact on price and if so, what is this impact?

We use the creation of a new Real Estate sector by Standard & Poor's Dow Jones (S&P DJ) and Morgan Stanley Capital International (MSCI) in 2016 to explore how the categorization of real estate impacts security pricing. An event study is employed to determine whether classifying groups of securities in S&P indices as real estate rather than financials causes abnormal returns during two event windows related to the introduction of the new sector.

A behavioural insight into abnormal returns is derived with "the framing effect" theory, as originally outlined by Tversky and Kahneman (1981), and extended to reference dependent framing in which the evaluation of gains and losses is relative to a reference point. We draw on reference dependence to explain that sector reclassification shifts reference points and these reference points are used to frame investment decisions. More specifically, the frame of the Real Estate sector impacts security pricing by changing the reference point from which securities are evaluated.

This paper adds to several strands of the literature on event studies in finance, psychology of choice and behavioural finance. This work relates to Fuller et al. (2019), who also perform an event study on the S&P implementation of the new Real Estate sector (September 19, 2016) to examine the abnormal returns for a group of real estate investment trusts (REITs), and find significantly negative abnormal returns before the event and positive abnormal returns after the event, altogether resulting in a positive cumulative abnormal return over an 11-day window. The authors apply an empirical perspective to their study in that they test for abnormal returns but do not seek to explain why their results occurred.

In this paper, we adopt a behavioural perspective to address this question. The abnormal returns observed may come from two possible sources. First, reclassification of real estate stocks has actually improved the pricing efficiency in the sector. As pointed out by Aguilar et al. (2018), index inclusion will benefit mid-cap REITs mainly because large-cap REITs have been already priced efficiently and small-cap REITs simply cannot attract enough attention. Applying this theory to index reclassification, we would expect that large-cap REITs will benefit from the reclassification because of their relatively small market capitalisation (both individually and collectively) in the large-cap stock price index system (i.e., S&P 500). In other words, large-cap REITs will enjoy the largest enhancement in visibility due to legal implications of the change, subsequently benefiting from the increased volume of automated or mandated trades in this category (Pavlov et al., 2018). This market efficiency effect should be significant on the implementation date because the automated or mandated fund flows were not present on the announcement date.

Second, there may be a psychological effect from the reclassification, which would make investors view the real estate stocks differently, and hence trade them differently. Under this theory, there will be similar effects observed across REITs of all capitalization sizes, and on both the announcement and implementation dates. Finally, both of the abovementioned effects can be in action at the same time. If this is true, we would observe significant changes of the REIT returns on both dates, with large-cap REITs showing the greatest effects. By examining the abnormal returns of REITs included in the S&P 400 (mid-cap), S&P 500 (large cap), and S&P 600 (small-cap) indices on both the announcement and the implementation dates, our analytical framework is capable of isolating the net effect of behavioural bias (i.e., framing effect) in the creation of a real estate category in the Global Industry Classification Standard (GICS).

This paper is structured as follows: Section 2 outlines the details on the events examined, Section 3 reviews the relevant behavioural literature and Section 4 outlines the method and data. Section 5 presents the empirical results. Section 6 concludes.

2. The New Real Estate Sector

Real estate investments are attractive as they are backed by the security of tangible collateral, offer low correlations to stocks and provide excellent inflation hedging due to their lease structures. Over the past 25 years, the market capitalization of US REITs has grown by an average of more than 20% per year and the sector is now estimated to be a US$1 trillion equity market with gross assets of over US$3 trillion (NAREIT, 2017). After the first REIT was launched in 1960, real estate securities have been considered part of the financials sector by major index providers such as S&P DJ, the MSCI, and Financials Times

Stock Exchange Russell (FTSE), as well as by data companies such as Bloomberg and Morningstar. Since (and perhaps even owing to) the global financial crisis of 2008/2009, this attitude has changed; real estate is emerging as a distinct asset class in the eyes of regulators, index providers and investors. Morningstar was the first to adopt a dedicated real estate sector for their analytical tools and ranking systems in 2010.

As the first international stock classification system, the GICS system was developed jointly by the MSCI and S&P DJ (two competing index providers) in 1999. The GICS system is a trademarked product that is sold to asset managers, institutional clients, stock exchanges, researchers and other industry professionals. Clients primarily use the system to benchmark their performance but the rise of exchange-traded fund (ETF) products has created a new business, in which the GICS sectors are used to drive allocations of rules-based investment products. Through the widespread use of MSCI products, GICS is the most widely used industry taxonomy in the world, with over US$13.9 trillion of benchmarked assets and more than 1030 ETFs driven by its associated products (MSCI, 2018).

The introduction of the Real Estate sector is the only major change that has been made to the GICS since the creation of the Technology sector during the early 2000s (Driebusch, 2016). The introduction of the new sector was motivated by the absolute and relative growth of real estate companies compared to the US stock market. In 2016, real estate was the eighth largest sector (of eleven) and made up for approximately 4% of the S&P 500 (NAREIT, 2017). The creation of the GICS Real Estate sector was announced at market close on March 13, 2015, taking effect at the start of the trading day on March 16, 2015. The official change to the S&P was implemented at market close on September 16, 2016, taking effect when the market opened on September 19, 2016. We include small- medium- and large-cap S&P indices in this study to facilitate the testing of the hypotheses (see research design in Section 4). The securities included in the S&P 400, S&P 500, and S&P600 and selected for this study are listed in Table 1. Some statistics of the real estate sector in the S&P 400, S&P 500, and S&P600 are given in Table 2. Figure 1 provides an initial glimpse of the different return profiles of the main, real estate and financial indices of the S&P 400, S&P 500, and S&P 600 families, respectively.

Table 1 S&P Real Estate Index Constituents

#	S&P 400 Name	S&P 400 Ticker	S&P 500 Name	S&P 500 Ticker	S&P 600 Name	S&P 600 Ticker
1	American Campus Communities	ACC	American Tower Corp	AMT	Acadia Realty Trust	AKR
2	Alexander & Baldwin	ALEX	Apartment Investment & Management Co	AIV	Agree Realty Corp.	ADC
3	Mack-Cali Realty Corporation	CLI	AvalonBay Communities	AVB	American Assets Trust	AAT
4	Camden Property Trust	CPT	Boston Properties	BXP	Apollo Commercial Real Estate Finance, Inc.	ARI
5	CoreCivic	CXW	CBRE Group	CBG	Capstead Mortgage Corp.	CMO
6	Douglas Emmett, Inc.	DEI	Crown Castle International	CCI	CareTrust REIT, Inc.	CTRE
7	EPR Properties	EPR	Digital Realty Trust	DLR	Cedar Realty Trust, Inc.	CDR
8	First Industrial Realty Trust	FR	Equinix	EQIX	Chesapeake Lodging Trust	CHSP
9	Highwoods Properties	HIW	Equity Residential	EQR	DiamondRock Hospitality	DRH
10	Hospitality Properties Trust	HPT	Essex Property Trust	ESS	EastGroup Properties, Inc.	EGP
11	Healthcare Realty Trust	HR	Extra Space Storage	EXR	Franklin Street Properties Corp.	FSP
12	Jones Lang Lasalle Inc	JLL	Federal Realty Investment	FRT	Getty Realty Corp.	GTY
13	Kilroy Realty Corp	KRC	GGP Inc	GGP	Government Properties Income Trust	OPI
14	Lamar Advertising Company	LAMR	HCP Inc	HCP	Kite Realty Group Trust	KRG
15	LaSalle Hotel Properties	LHO	Host Hotels & Resorts	HST	Lexington Realty Trust	LXP
16	Liberty Property Trust	LPT	Iron Mountain	IRM	LTC Properties, Inc.	LTC

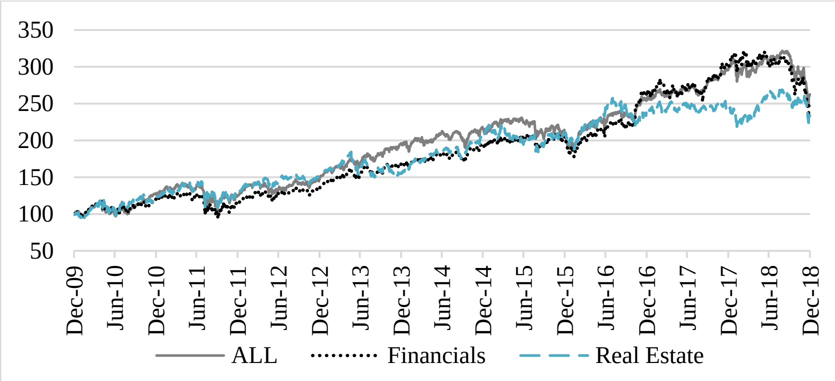
(Continued…)

(Table 1 Continued)

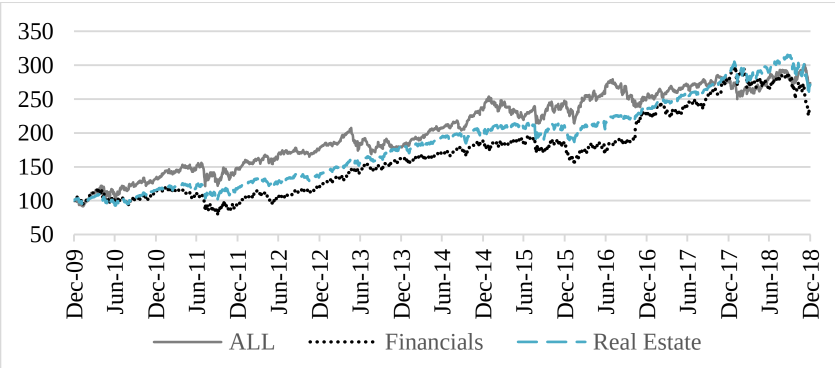
#	S&P 400		S&P 500		S&P 600	
	Name	Ticker	Name	Ticker	Name	Ticker
17	Life Storage Inc	LSI	Kimco Realty Corp	KIM	Pennsylvania Real Estate Investment Trust	PEI
18	Medical Properties Trust Inc	MPW	Macerich Co	MAC	PennyMac Mortgage Investment Trust	PMT
19	National Retail Properties Inc	NNN	Prologis	PLD	PS Business Parks, Inc.	PSB
20	Corporate Office Properties Trust	OFC	Public Storage	PSA	Retail Opportunity Investments, Inc.	ROIC
21	Omega Healthcare Investors	OHI	Realty Income Corp	O	Saul Centers	BFS
22	Potlatch Corp	PCH	Simon Property Group	SPG	Summit Hotel Properties, Inc.	INN
23	Rayonier Inc	RYN	SL Green Realty Corp	SLG	Universal Health Realty Income Trust	UHT
24	Tanger Factory Outlet Centers Inc	SKT	UDR	UDR	Urstadt Biddle Properties	UBA
25	Senior Housing Properties Trust	SNH	Ventas	VTR		
26	Taubman Centers	TCO	Vornado Realty Trust	VNO		
27	Weingarten Realty Investors	WRI	Welltower	HCN		
28			Weyerhaeuser Co	WY		

Figure 1 Time Series of S&P Indices

Panel A: S&P 400



Panel B: S&P 500



Panel C: S&P 600

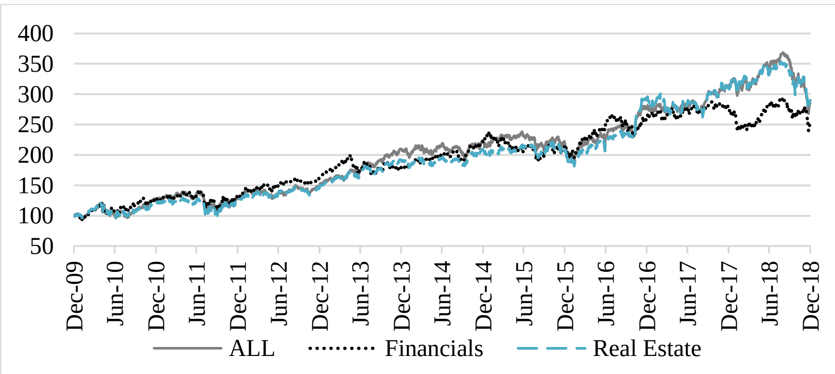


Table 2 S&P 400, 500, and 600 Indices (as of Mar 29, 2019)

Category	S&P 400	S&P 500	S&P 600
All			
No. of securities	400	505	601
Launch date	Jun 19, 1991	Mar 4, 1957	Oct 28, 1994
Median constituent market cap (US$ billion)	4.04	21.17	1.14
Financial			
No. of securities	61	68	95
Launch date	Jun 19, 1991	Jun 28, 1996	Oct 28, 1994
Median constituent market cap (US$ billion)	3.92	22.66	1.24
The % for this sector of the index	16%	12.7%	17.2%
Real Estate			
No. of securities	37	32	41
Launch date	Sep 19, 2016	Sep 19, 2016	Sep 19, 2016
Median constituent market cap (US$ billion)	4.08	17.80	1.20
The % for this sector of the index	10.1%	3.1%	7.5%

***Sources**:* S&P Dow Jones Indices

Although the real estate sector had experienced strong growth preceding the sector introduction, the GICS gave no indication that a new sector would be created before the change was announced. Theoretically, stock that is being reclassified should have no immediate impact on company fundamentals, as their financial position will remain unchanged (Mase, 2008). As such, the presence of abnormal returns during the announcement of the sector reflects the market behavioural reaction to perceiving the impacted stocks as real estate rather than financials.

The S&P implementation had complex legal and financial ramifications that likely caused non-behavioural price movements, as has been outlined by various industry professionals. Coghlan et al. (2016) predict positive inflows from mutual funds and active investors, which would be both exposed as underweights in the sector as a result of the new taxonomy. Many commentators have predicted further inflows as a result of an increase in the visibility of the asset class, thus improving investor education on the perception of the impacted stocks (Blitzer, 2016; Driebusch, 2016; Wotapka, 2016). However, Saunders (2016) notes that financial sector ETFs would be forced to sell their REIT holdings, which would cause excess supply and capital gain taxes. Additionally, Badkar (2016) predicts a negative price impact from US$4 bn of outflows during the implementation. While these various effects may have occurred as the new sector was implemented, abnormal returns identified during the implementation event are assumed to reflect a blend of behavioural and non-behavioural effects.

3. Framing Effect

The framing effect was first outlined in the Asian disease problem in Tversky and Kahneman (1981). The problem presented two versions of the same choice between a risky anti-disease program with a higher expected value and a less risky program with a lower expected value. However, in one version, the outcomes were presented in a positive frame as “lives saved” and in the other, in a negative frame as “lives lost”. Survey participants were overwhelmingly risk averse when it came to lives saved, and risk seeking when it came to lives lost. Tversky and Kahneman (1981) attribute this to “framing”, which is outlined as the impact of “the decision maker’s conception of the acts, outcomes and contingencies associated with a particular choice”. In order to explain the impact of framing choices as gains or losses, Tversky and Kahneman (1981) propose the “prospect theory”, which is outlined as a modified expected utility function with asymmetrical weighting of the gains and losses, where low probability negative events are overweighed. The prospect theory implies that when faced with risky decisions, how choices are framed can create a divergence between empirically observed decisions and those predicted by using classical utility functions. In practical terms, the theory implies that people are more likely to take risks when they believe that they have the chance to avoid losses (negative framing) than to attain gains (positive framing).

Today, framing is generally accepted, but with certain reservations. Early critics were quick to point out that framing is not universally observed. Levin and Chapman (1990) change the wording of the original Asian disease problem to highlight how the same outcome is not observed when the characteristics of the victims are changed to be less socially acceptable. Kuhberger (1995) demonstrates that framing effects can also be eliminated by increasing the amount of information available to subjects or changing the wording of the question while maintaining the same valence of the choices. Furthermore, framing effects are shown to be mitigated, and in some cases, eliminated, by asking decision-makers for the rationale behind their choices or asking them to think about the decision for at least three minutes (Miller and Fagley, 1991; Takemura, 1994). Kahneman (2003) later champions the theory that framing is only impactful when decisions are made intuitively rather than analytically. Despite these reservations, framing remains a relevant theory across the fields of psychology, management science and finance.

The literature has demonstrated that framing is a well-established and empirically robust theory in psychology but has been also examined from limited viewpoints in the sphere of behavioural finance. The understanding of the framing effect depends on how gains and losses are viewed relative to a reference point rather than on an absolute basis. The first and crucial step in framing effect studies is to determine reference points, based on which gain and loss domains can be defined. Only when gains and losses are clearly defined can options be framed in different domains to influence decisions.

Kahneman and Tversky (1979) propose the concept with "reference dependence", which suggests that gains and losses are defined relative to reference points rather than on an absolute basis. Extending the prospect theory based on this premise implies that gains and losses are experienced with diminishing sensitivity relative to this reference point and that negative departures impact utility more than positive departures (Tversky and Kahneman, 1991, 1992). Reference dependence has since been shown to be empirically observable and has become a mainstay of theory on choice across multiple disciplines (see, for example, Fornell et al., 1996; Higgins, 1997; Kahneman et al., 1990; Kristof, 1996; Teece, 2007). However, there is still no dominant theory on exactly how these reference points are formed in psychology or in finance.

Initial research on reference points has evolved from references based on the status quo to those driven by less quantifiable concepts such as goals and expectations. Status quo theories focus on the use of current endowments as reference points, such as Knetsch (1992), who show that in simple trading experiments, reference points depend on current wealth. Bowman et al. (1999) generalize this concept to suggest that current wealth is used to create a reference point for gains and losses under conditions of sufficient income uncertainty. However, recent research has noted that in many economic circumstances, there is a divergence of what people expect and the status quo (their current endowments). For example, reference outcomes are not fair gambles with an expected value of zero in the stock market but investors expect positive returns. Economics applications like these have led to a focus on goals and expectations as reference points. Research on goals has claimed that they can alter the valance of outcomes from gains to losses (Heath et al., 1999; Lopes and Oden, 1999). Goal based reference dependence has been tested by Markle et al. (2018), who demonstrate that the satisfaction of marathon runners is described by the prospect theory style diminishing sensitivity to performance relative to pre-set goals. Research on expectations as reference points is still in its preliminary stages but may prove to be even more applicable. Koszegi and Rabin (2009) propose that reference points are formed to match expectations held in the recent past about probabilistic beliefs of future outcomes. The authors have made promising headway in testing this theory in the areas of monetary risk and temporal consumption patterns, but more research is needed to substantiate and empirically test these ideas (Koszegi and Rabin, 2006, 2009).

In the case of the stock market, no substantial theory has been drafted on how reference points are formed (or evaluated). Theory on expectations as reference points, as outlined by Koszegi and Rabin (2006), may offer useful insights into this topic. In traditional financial theory, expectations of stock returns are most commonly formed with models that derive an expected return based on correlation to a market portfolio, size, asset values, geography or macro factors of a given stock (Fama and French, 1993).

In reality, expectations are far more complex; investors make decisions based on a blend of qualitative and quantitative metrics, of which sector classification is a key factor. For example, informed financials analysts expect different returns on equity (ROE), a performance metric that reflects returns on equity capital invested for different sectors (Lal and Meador, 1984). When real estate was previously included in the Financials sector, investors and analysts always took the ROE of the Financials sector as the benchmark (NAREIT, 2017). The ROE of the Financials sector could be the reference point for the investors who hold real estate stocks.

Under the new taxonomy system, REITs and REC are viewed separately from the Financials sector. The ROE of the new sector (Real Estate) becomes the reference point for investors. Less educated investors may forgo quantitative models and complex financial metrics, instead forming expectations of stock returns based on the returns of related indices or industry groups. In that case, this research intends to examine whether the creation of the new Real Estate sector is an influential factor in determining the reference points and thus whether framing has impact on stock pricing.

4. Analytical Framework and Testable Hypotheses

We study the responses to the creation of the real estate category in the GCIS system by investigating the abnormal returns that surround the event by adopting the structure for an event study in MacKinlay (1997). There are alternative methods to study the effect of additions to stock indices, such as the regression discontinuity design in Chang et al. (2015). However, the event study method based on MacKinlay (1997) remains the most commonly used method in the literature.

Under the framework in MacKinlay (1997), the abnormal returns are measured as actual ex-post returns over the event period minus the predicted returns. Predicted returns are estimated by using a simple one-factor model following Brown and Warner (1985), and an estimation window that does not overlap with any of the event periods. As pointed out by MacKinlay (1997), other models more complicated than the one-factor market model do not show any extra benefits. The choice of a single-factor market model is consistent with recent leading papers that examine abnormal REIT returns, including Campbell et al. (2001) and Womack (2012). This sentiment has been reflected historically by the academic community, as shown in the review of the REIT return methodologies in Womack (2012). While there have been some attempts to use multi-factor models to estimate normal real estate returns, such as Peng (2016) and Titman and Warga (1986), the limited statistical significance of these models implies that they do not add value over a single-factor model. Fuller et al. (2019) is the only notable paper to use a market model with additional factors, and these models do not yield significantly different results from the single-factor model employed.

We therefore adopt the one-factor model in this analysis, which is:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{1}$$

R_{it} represents the daily return of i-th security and R_{mt} represents the market return at time t. α_i is the "alpha", or the return not related to the market's return. $\varepsilon_{i\tau}$ is an error term, which is assumed to have an expected value of zero and to be uncorrelated with market returns. β_i is a term that relates the return of the security to that of the market. The estimation window contains 120 trading days before the event date.

The calculated abnormal returns are then aggregated across time and securities to test the hypothesis that these returns are normal at a temporal level (across securities at a single point in time) and a panel level (across both securities and time). First, we calculate the abnormal returns $AR_{i\tau}$, for security *i* at time *t* as:

$$AR_{it} = R_{it} - E(R_{it}|X_t), \tag{2}$$

where $E(R_{it}|X_t)$ is the predicted return during that same period. The cumulative abnormal returns, CAR_i , for security *i* across the event window [t, T] is calculated as:

$$CAR_i = \sum_{t=1}^{T} AR_{it} \tag{3}$$

We then calculate the average cumulative abnormal returns, $\overline{CAR}$, across *N* securities for the event window [t, T] as:

$$\overline{CAR} = \frac{1}{N}\sum_{i=1}^{N} CAR_i \tag{4}$$

Therefore, CAR_i and $\overline{CAR}$ are used to measure the response to the creation of the real estate category in the GICS by individual real estate stocks and the real estate sector respectively. To check if the responses are due to improved pricing efficiency and/or behavioural biases, we propose four competing hypotheses as follows.

First, if real estate stocks have been priced efficiently and the market does not have any behavioural bias, the reclassification should not result in any changes. As all real estate stocks have already been priced correctly and efficiently, we will not observe any significant abnormal returns that surround the announcement or implementation date. This holds true across real estate stocks of all different capitalisation sizes, i.e., real estate stocks that are included in the S&P 400, 500, and 600 indices. This give us the first hypothesis as follows.

Hypothesis 1: There are no significant abnormal returns that surround the announcement and implementation dates.

$$\begin{aligned} &\overline{CAR}^{Annc}_{SP400} = \overline{CAR}^{Annc}_{SP500} = \overline{CAR}^{Annc}_{SP600} = 0 \\ &\overline{CAR}^{Imp}_{SP400} = \overline{CAR}^{Imp}_{SP500} = \overline{CAR}^{Imp}_{SP600} = 0, \end{aligned} \tag{5}$$

where $Annc$ and Imp denote the announcement and implementation dates, respectively.

However, if the market is inefficient, but does not have any behavioural bias, large-cap real estate stocks will benefit the most. This is because large-cap REITs are 'small fish' in the S&P 500 pool. In Table 2, the median market capitalisation of real estate stocks is merely 3.1% of the total market capitalisation of the S&P; the corresponding proportion for small- and mid-cap real estate stocks is 10.1% and 7.5% respectively. Therefore, real estate stocks will benefit the most from the enhanced visibility resultant of the reclassification. Before the reclassification, their small size might not attract enough attention from institutional investors. However, because of the legal implications of the reclassification, large-cap stocks will benefit from the increased amount of automated or mandated trades in their own category. This effect will be smaller for mid- and small- cap REITs, because their size is similar to other members in their own index system. This pattern will only hold true for the implementation day, because fund managers might not be able to make adjustments until the re-classification took effect. Hypothesis 2 is formulated accordingly as follows.

Hypothesis 2: Abnormal returns that surround the implementation dates are significant only for real estate stocks included in the S&P 500 index on the implementation day.

$$\begin{aligned} &\overline{CAR}^{Annc}_{SP400} = \overline{CAR}^{Annc}_{SP500} = \overline{CAR}^{Annc}_{SP600} = 0 \\ &\overline{CAR}^{Imp}_{SP400} = \overline{CAR}^{Imp}_{SP600} = 0, \text{ and } \overline{CAR}^{Imp}_{SP500} \neq 0 \end{aligned} \tag{6}$$

If, on the other hand, real estate stocks have been priced efficiently, and there is behavioural bias that affects all of the real estate stocks, the framing effect will be significant across the board. There is no difference among the three indices. This provides the third hypothesis as follows.

Hypothesis 3: Abnormal returns that surround the implementation and announcement dates are significant and of a similar size for all three indices.

$$\begin{aligned} &\overline{CAR}^{Annc}_{SP400} \cong \overline{CAR}^{Annc}_{SP500} \cong \overline{CAR}^{Annc}_{SP600} \neq 0 \\ &\overline{CAR}^{Imp}_{SP400} \cong \overline{CAR}^{Imp}_{SP500} \cong \overline{CAR}^{Imp}_{SP600} \neq 0 \end{aligned} \tag{7}$$

Finally, if the market is inefficient with behavioural bias, the reclassification will affect all three groups on both days, with the largest effect on the S&P 500. We will expect the combined effects that are captured in Hypotheses 2 and 3. Our last hypothesis is formulated as follows.

Hypothesis 4: Abnormal returns that surround the implementation and announcement dates are significant for all three indices, and the largest for the S&P 500 index.

$$\begin{aligned}&\overline{CAR}_{SP400}^{Annc} \cong \overline{CAR}_{SP500}^{Annc} \cong \overline{CAR}_{SP600}^{Annc} \neq 0\\&\left|\overline{CAR}_{SP500}^{Imp}\right| > \left|\overline{CAR}_{SP400}^{Imp}\right| \neq 0, \text{ and } \left|\overline{CAR}_{SP500}^{Imp}\right| > \left|\overline{CAR}_{SP600}^{Imp}\right| \neq 0\end{aligned} \tag{8}$$

5. Empirical Implementations

The daily price data on each of the securities are examined for a sample period which started two years before the announcement date and ended one month after the S&P implementation date (March 15, 2013 – October 19, 2016). This data range is purposefully made larger than required in order to provide flexibility to test various event and estimation windows. The 10-year constant maturity Treasury bills for the same period is used as a proxy for the risk-free rate.

The initial event windows are five-day periods on either side of these event dates (11 days in total) and the securities analysed are only those that are reclassified from the Financials sector to the Real Estate sector. An 11-day window is the most commonly accepted and employed in event studies in finance, which is 76.3% of all studies (Oler et al., 2007).

A gap between the estimation and event windows is placed to ensure that the events do not influence the normal returns models. For the announcement (March 16, 2015), a gap of seven trading days is allowed for variation of the event window size in later robustness checks. This event was unannounced and it is thus assumed that the estimation window was not influenced by any lead-up period fund flows that preceded the event period. However, a larger gap is used for the implementation (September 19, 2016) because the market was aware of both events. This implies that the lead-up periods before the events might have been impacted by fund flows that occurred in advance of the official introduction of the Real Estate sector. To avoid this effect, a conservative 30-day gap is used for the implementation event.

Analysis of actual returns relative to predicted normal returns implicitly assumes that the normal returns model is correct. This assumption implies that there is potential for unexplained variation of abnormal returns due to omitted variable bias. This is a fundamental problem with any empirical research that assumes a model and while it cannot be completely overcome, we mitigate this risk by choosing a model based on the related literature, by using multiple statistical measures for robustness and estimating the sensitivity of the event window .

Statistics tests on abnormal returns at both the temporal and panel levels are conducted for each event window. At the temporal level, the null hypothesis

$\overline{AR_t} = 0$ is tested to examine whether average abnormal returns across securities are significantly different from zero at a given point in the event window[1]. At the panel level, the null hypothesis $\overline{CAR} = 0$ is tested to examine if the average cumulative abnormal returns across both securities and time are significantly different from zero. We adopt three statistical tests including the cross-sectional t-test, Patell test (Patell, 1976) and BMP Z test (Boehmer et al., 1991). Brown and Warner (1985) highlight the need for these additional tests by outlining common problems experienced when performing event studies on daily stock market data. They highlight the issues of: non-normality of excess returns, non-synchronous trading that biases the regression estimates of the market parameters and autocorrelation, and event induced volatility that skews variance estimates (p. 5). The Patell test compensates for the non-normality of returns by using standardized abnormal returns, which assumes a separate standard error for each security and cross-sectional independence. However, the test is still prone to event induced volatility and cross-sectional correlation. The BMP Z test is an alternative standardized cross-sectional statistical measure that compensates for the distribution of abnormal returns, event induced volatility and serial correlation by standardizing returns with the standard deviation of the forecast error correction. As none of the three tests is superior over the others in an absolute term, we adopt all three in our analysis for the sake of robustness.

6. Results and Discussion

The average abnormal returns ($\overline{AR_t}$) and cumulative abnormal returns ($\overline{CAR}$) for the S&P 400, S&P 500, and S&P 600 on the implementation and announcement days are reported in Tables 3 through to 8. Statistical significance based on the cross-sectional T-test, Patell Z-test and BMP Z-test are also reported in these tables.

Our results of implementation echo the findings of REITs in Fuller et al. (2019); before the event date, they are generally negative and after the event date, generally positive. Specifically, the variations of $\overline{AR_t}s$ that surround the two event dates are similar. For the announcement day, most of the $\overline{AR_t}s$ in the event window are positive and the rest are slightly negative. In the implementation event, the securities experienced negative $\overline{AR_t}s$ prior to the event date but positive ARs after the date. The patterns of $\overline{CAR}$ are also similar in the two events respectively. $\overline{CAR}$ is always positive during the announcement but eroded by a negative $\overline{AR_t}s$ at first and becomes positive due to a positive $\overline{AR_t}s$ after the implementation date.

[1] The average abnormal returns AR_t is calculated as $\frac{1}{N}\sum_{i=1}^{N} AR_{it}$.

The abnormal returns of mid-cap real estate stocks are reported in Table 3. Most of the positive $\overline{ARs}$ (at t = -5, -4, -2, +2 and +4) in the announcement event are statistically significant at the 5% level as indicated by all of the test statistics. By contrast, all the negative $\overline{ARs}$ (at t = -3, -1, +3 and +5) in the announcement event are insignificant. The implementation event shows a different pattern in Panel B. The negative $\overline{AR}$ at t = -4 is significant at the 1% level, while at t = -2 is not always significant as suggested by the three tests. $\overline{AR}$ at t = 0, +3 and +4 are positive and significant at the 5% level. Unlike the announcement event, the signs of the statistically significant abnormal returns differ before and after the event date (t = 0). We observe the same patterns for small- and large-cap real estate stocks as can be seen in Tables 4 and 5. Abnormal returns before the event date are generally negative, while those on or after the event date are generally positive. The results for both events are relatively robust to the type of test employed as well as the level of significance used.

Table 3 Average Abnormal Returns ($\overline{AR_t}$) over 11-Day Event Window (S&P 400)

Event day	$\overline{AR_t}$	Cross Sectional T-test	Patell Z-test	BMP Z-test
Panel A: Announcement date - Mar 16, 2015				
-5	0.82%	3.8834***	3.8392***	4.4931***
-4	0.65%	2.7005**	3.0660***	3.6683***
-3	-0.19%	-1.1999	-1.0540	-1.5866
-2	0.67%	4.0489***	3.3256***	5.4609***
-1	-0.04%	-0.2954	-0.0782	-0.1326
0	0.40%	2.7469***	1.7492*	3.2860***
1	0.08%	0.7638	0.4414	1.1789
2	1.26%	9.0479***	6.0418***	10.7876***
3	-0.01%	-0.0785	0.0359	0.0586
4	1.86%	10.2545***	9.0728***	9.8506***
5	-0.20%	-2.3307**	-1.0664	-2.7927***
Panel B: Implementation date - Sep 19, 2016				
-5	0.03%	0.1991	0.3673	0.4812
-4	-1.83%	-6.8403***	-8.9995***	-7.7276***
-3	0.42%	2.2386**	1.8612*	2.5977**
-2	-0.27%	-2.1320**	-1.3109	-2.1954**
-1	0.02%	0.1430	0.0254	0.0459
0	0.52%	2.7826***	2.4000**	2.9945***
1	0.03%	0.0996	0.3416	0.2991
2	0.24%	0.9286	1.3129	1.0931
3	1.24%	8.8989***	5.7024***	9.0394***
4	0.47%	3.1311***	2.1637**	3.6463***
5	0.40%	2.6569**	1.9293*	3.0711***

Notes: ***, ** and * are used to indicate 1%, 5% and 10% levels of significance, respectively.

Table 4 Average Abnormal Returns ($\overline{AR_t}$) over 11-Day Event Window (S&P 500)

Event day	$\overline{AR_t}$	Cross Sectional T-test	Patell Z-test	BMP Z-test
Panel A: Announcement date - Mar 16, 2015				
-5	0.67%	2.276**	2.668***	2.389**
-4	0.45%	2.837***	1.824*	2.751***
-3	0.04%	0.279	0.397	0.618
-2	0.89%	7.169***	3.904***	7.074***
-1	-0.03%	-0.147	-0.320	-0.365
0	0.54%	3.681***	2.332**	3.654***
1	-0.30%	-1.687	-1.280	-1.888*
2	1.34%	9.208***	5.955***	9.955***
3	-0.06%	-0.421	-0.203	-0.362
4	1.55%	4.206***	7.288***	4.909***
5	-0.14%	-0.987	-0.422	-0.704
Panel B: Implementation date - Sep 19, 2016				
-5	0.15%	0.747	1.062	1.291
-4	-1.61%	-7.916***	-7.828***	-9.075***
-3	0.23%	1.527	0.992	1.529
-2	-0.30%	-2.291**	-1.597	-2.576***
-1	0.00%	-0.014	-0.073	-0.139
0	0.91%	8.686***	4.420***	8.176***
1	-0.20%	-1.314	-1.188	-1.543
2	0.28%	1.816*	1.63	2.406**
3	1.19%	5.582***	5.799***	6.308***
4	0.62%	10.906***	2.949***	10.412***
5	0.63%	4.912***	3.023***	5.366***

Notes: ***, ** and * are used to indicate 1%, 5% and 10% levels of significance, respectively.

Following Fuller et al. (2019) and Malic (2016), we estimate the $\overline{CAR}$ for different event windows to investigate how the results are affected by the length of the event window selected. The initial analysis of each event takes place over an 11-day event window, including the event date (five days before and after the event). We follow Fuller et al. (2019) by using event windows that are up to 11-days in length. The following robustness tests vary these event windows from (-0, +0) to (-5, +5), testing from the event date in isolation to an 11-day period around each event. Testing event window variations is necessary as certain investors may respond to new market information at different speeds based on liquidity needs and decision-making process timelines. This sensitivity analysis examines the $\overline{CAR(t_0, t_1)}$ implied by each event, where t_0 and t_1 denote the start and end of the event window in the event time (relative to the event date). The three tests are also used in this part. The results are presented in Tables 6 to 8.

Table 5 Average Abnormal Returns ($\overline{AR_t}$) over 11-Day Event Window (S&P 600)

Event day	$\overline{AR_t}$	Cross Sectional T-test	Patell Z-test	BMP Z-test
Panel A: Announcement date - Mar 16, 2015				
-5	-0.20%	-0.6371	-0.9460	-0.9055
-4	0.51%	3.0281***	2.2441**	2.9689***
-3	-0.03%	-0.1809	-0.1800	-0.2388
-2	1.05%	4.9148***	4.8164***	5.7367***
-1	0.00%	-0.0037	-0.1037	-0.1548
0	0.36%	3.9009***	1.8414*	3.4826***
1	0.00%	-0.0046	0.1438	0.2598
2	1.36%	6.2402***	6.3016***	8.6541***
3	-0.08%	-0.8493	-0.2820	-0.6455
4	1.39%	8.5431***	6.7481***	8.2427***
5	0.32%	2.4700**	1.3144	2.1109**
Panel B: Implementation date - Sep 19, 2016				
-5	-0.06%	-0.2717	0.1617	0.1960
-4	-1.66%	-6.8181***	-7.2773***	-6.9150***
-3	0.24%	1.4745	0.8630	1.3706
-2	-0.37%	-3.7072***	-1.4861	-3.3976***
-1	0.12%	0.7397	0.5759	0.7195
0	0.38%	2.3572**	1.7704*	2.7889***
1	-0.08%	-0.9361	-0.3323	-0.8846
2	0.56%	3.9971***	2.5229**	4.3337***
3	0.93%	5.5478***	4.1525***	6.0416***
4	0.38%	2.7383***	1.4594	2.4783**
5	0.36%	1.6840	1.8088*	2.2462**

Notes: ***, ** and * are used to indicate 1%, 5% and 10% levels of significance, respectively.

Table 6 shows the $\overline{CAR}$ for the real estate stocks in the S&P 400 and all of the $\overline{CAR}$s are positive in both events. Panel A shows that the $\overline{CAR}$ increases with the window length and the highest $\overline{CAR}$ is 5.29% (significant at the 1% level) in the window of (-5, +5) in the announcement event. In the implementation event (shown in Panel B), the highest $\overline{CAR}$ is 2.19% (significant at the 1% level) in the window of (-3, +3). The $\overline{CAR}$ is less sensitive to the event window selected and statistically insignificant only within short event windows in the announcement event, while relatively sensitive to the event window chosen in the implementation event.

Table 6 Sensitivity of Cumulative Average Abnormal Returns to Event Window Length (S&P 400)

Event Window	$\overline{CAR}$	Cross Sectional T-test	Patell Z-test	BMP Z-test
Panel A: Announcement Date - Mar 16, 2015				
(-5, +5) #	**5.29%**	11.1229***	7.6504***	11.0092***
(-4, +4) #	4.67%	11.9265***	7.5335***	11.5787***
(-3, +3) #	2.16%	8.8984***	3.9542***	8.8788***
(-2, +2) #	2.37%	9.9376***	5.1339***	9.6817***
(-1, +1)	0.43%	2.4059**	1.2196	2.4484**
(-0, +0) #	0.40%	3.2948***	1.7492*	3.2860***
Panel B: Implementation Date - Sep 19, 2016				
(-5, +5) #	1.27%	5.8893***	1.7468*	2.7752***
(-4, +4)	0.84%	4.2223***	1.1657	1.7977*
(-3, +3) #	**2.19%**	11.3132***	3.9054***	5.6256***
(-2, +2)	0.53%	2.6611**	1.2384	1.4166
(-1, +1)	0.56%	4.3874***	1.5976	2.2089**
(-0, +0) #	0.52%	5.8662***	2.4000**	2.9945***

Notes: ***, ** and * are used to indicate 1%, 5% and 10% levels of significance, respectively. # indicates that the $\overline{CARs}$ within a certain event window are significant at the 10% level across all three tests.

Table 7 Sensitivity of Cumulative Average Abnormal Returns to Event Window Length (S&P 500)

Event Window	$\overline{CAR}$	Cross Sectional T-test	Patell Z-test	BMP Z-test
Panel A: Announcement Date - Mar 16, 2015				
(-5, +5) #	**4.96%**	8.192***	6.677***	8.404***
(-4, +4) #	4.43%	6.376***	6.633***	6.931***
(-3, +3) #	2.43%	6.468***	4.077***	6.586***
(-2, +2) #	2.45%	6.213***	4.737***	6.542***
(-1, +1)	0.21%	0.797	0.423	0.660
(-0, +0) #	0.54%	3.681***	2.332**	3.654***
Panel B: Implementation Date - Sep 19, 2016				
(-5, +5) #	1.89%	8.689***	2.770***	4.255***
(-4, +4) #	1.11%	6.790***	1.701*	3.068***
(-3, +3) #	**2.10%**	11.382***	3.773***	5.592***
(-2, +2)	0.69%	4.401***	1.427	2.252**
(-1, +1) #	0.71%	7.306***	1.824*	3.358***
(-0, +0) #	0.91%	17.982***	4.420***	8.176***

Notes: ***, ** and * are used to indicate 1%, 5% and 10% levels of significance, respectively. # indicates that the $\overline{CARs}$ within a certain event window are significant at the 10% level across all three tests.

For real estate stocks in the S&P 500, all the $\overline{CARs}$ are positive in both events as shown in Table 7. Panel A shows that the $\overline{CAR}$ increases with the window length and the highest $\overline{CAR}$ is 4.96% (significant at the 1% level) in the window of (-5, +5) in the announcement event. Panel B indicates that in the implementation event, the highest $\overline{CAR}$ is 2.10% (significant at the 1% level) in the window of (-3, +3).

Table 8 shows a scenario of the S&P 600 that is similar to that of the S&P 400 and 500, where all of the $\overline{CARs}$ are positive in both events. In the announcement event (Panel A), the $\overline{CAR}$ increases with the window length and the highest $\overline{CAR}$ is 4.67% (significant at the 1% level) in the window of (-5, +5). In the implementation event (shown in Panel B), the highest $\overline{CAR}$ is 1.77% (significant at the 1% level) in the window of (-3, +3). The $\overline{CAR}$ is less sensitive to the event window selected and statistically insignificant only within short event windows in the announcement event, while relatively sensitive to the event window chosen in the implementation event.

Table 8 Sensitivity of Cumulative Average Abnormal Returns to Event Window Length (S&P 600)

Event Window	$\overline{CAR}$	Cross Sectional T-test	Patell Z-test	BMP Z-test
Panel A: Announcement Date - Mar 16, 2015				
(-5, +5) #	**4.67%**	8.9048***	6.6026***	9.3957***
(-4, +4) #	4.56%	13.1965***	7.1766***	13.9801***
(-3, +3) #	2.65%	9.6621***	4.7388***	9.6411***
(-2, +2) #	2.77%	9.9226***	5.8136***	9.7107***
(-1, +1)	0.36%	2.1452**	1.0863	2.2184**
(-0, +0) #	0.36%	3.0746***	1.8414*	3.4826***
Panel B: Implementation Date - Sep 19, 2016				
(-5, +5)	0.79%	3.7220***	1.2720	2.1573**
(-4, +4)	0.49%	3.5713***	0.7494	1.6230
(-3, +3) #	**1.77%**	9.6280***	3.0487***	4.4938***
(-2, +2)	0.60%	3.8724***	1.3643	2.1291**
(-1, +1)	0.42%	3.7790***	1.1627	1.8550*
(-0, +0) #	0.38%	5.3843***	1.7704*	2.7889***

Notes: ***, ** and * are used to indicate 1%, 5% and 10% levels of significance, respectively. # indicates that the $\overline{CARs}$ within a certain event window are significant at the 10% level across all three tests.

An analysis of the two events shows that statistically significant $\overline{CARs}$ occur during each event window for the three indices. For each index, the $\overline{CAR}$s are less sensitive to the event window selected in the announcement event as the tests are statistically significant within almost all of the event windows except for (-1, +1). This robust finding rules out Hypotheses 1 and 2, where responses are expected to be insignificant for the announcement event. By contrast, the

$\overline{CAR}$ s are relatively sensitive to the event windows chosen in the implementation event for each index. The significance of the three tests varies across the indices, and the S&P 500 shows the most significant impacts from the implementation.

To test Hypotheses 3 and 4, we conduct a comparative analysis across the three indices. First, we summarise the $\overline{CAR}$s reported in Tables 6 to 8 in the 'Cumulative Abnormal Returns' columns in Table 9. For each event window considered, if the $\overline{CAR}$s are significant at the 10% level in the cross sectional T-test, the Patell Z-test and the BMP Z-test for all three indices, a "#" sign is placed next to the event window label. We take this as an indication of consistency and robustness of the $\overline{CAR}$s for the specific event window. As reported in Table 9, the $\overline{CAR}$s are significant for all event window widths considered for the announcement event except for (-1, +1), whilst the $\overline{CAR}$s are significant for the (-3, +3) and (0,0) event windows for the implementation event. This indicates that behavioural bias plays an important role in the market reactions to the index reclassification.

In addition, the impacts on announcement are more significant than those on implementation, and the magnitude of the $\overline{CAR}$ s is greater around the announcement date. These are further evidence to suggest the presence of behavioural bias. If investors perceive real estate stocks differently due to the reclassification, the resultant framing effect should be significant on both the announcement and the implementation dates, because both events trigger psychological bias. However, due to the 'primacy effect', the initial or the first event will have a larger impact. This is exactly the pattern that we observe from Table 9.

Second, we conduct T-tests to gauge the differences of the $\overline{CAR}$s between indices. The results are reported in the 'T-test Statistics' columns in Table 9, where we test if 1) the $\overline{CAR}$s of the S&P 400 are significantly different from those of the other two indices due to the assumption of pricing efficiency, and 2) the $\overline{CAR}$s of the S&P 500 are significantly different from those of the other two indices due to assumption of visibility in the implementation event. We find that the $\overline{CAR}$s of the S&P 500 is significantly higher than the $\overline{CAR}$s of the small-cap (i.e., S&P 600) and mid-cap (i.e., S&P 400) real estate stocks around the implementation date. In addition, the impacts of implementation are found (in Tables 6 to 8) to be more significant in the S&P 500.

To conclude, our test results in Tables 3 to 9 suggest that the reclassification effect is significant for both the announcement and the implementation dates, and the effect is the largest for the large-cap real estate stocks that are included in the S&P 500 index. The creation of the real estate category in the GICS improves the pricing efficiency of real estate stocks, but also triggers framing effects among investors. The market is under the influence of both rational and irrational forces.

Table 9 Comparison of $\overline{CAR}$s across Three Indices

Event Window	Cumulative Abnormal Returns			T-test Statistics		
	S&P 400	S&P 500	S&P 600	S&P 400 vs S&P 500	S&P 400 vs S&P 600	S&P 500 vs S&P 600
Panel A: Announcement Date – Mar 16, 2015						
(-5, +5) #	5.29%	4.96%	4.67%	0.4285	0.8751	0.3618
(-4, +4) #	4.67%	4.43%	4.56%	0.3010	0.2108	-0.1676
(-3, +3) #	2.16%	2.43%	2.65%	-0.6029	-1.3362	-0.4722
(-2, +2) #	2.37%	2.45%	2.77%	-0.1738	-1.0898	-0.6631
(-1, +1)	0.43%	0.21%	0.36%	0.6910	0.2852	-0.4829
(-0, +0) #	0.40%	0.54%	0.36%	-0.7407	0.2391	0.9639
Panel B: Implementation Date – Sep 19, 2016						
(-5, +5)	1.27%	1.89%	0.79%	-2.0247***	1.5876	3.6281***
(-4, +4)	0.84%	1.11%	0.49%	-1.0487	1.4537	2.9060***
(-3, +3) #	2.19%	2.10%	1.77%	0.3360	1.5734	1.2665
(-2, +2)	0.53%	0.69%	0.60%	-0.6284	-0.2764	0.4084
(-1, +1)	0.56%	0.71%	0.42%	-0.9359	0.8309	1.9782**
(-0, +0) #	0.52%	0.91%	0.38%	-3.8264***	1.2403	6.1276***

Notes: ***, ** and * indicate 1%, 5% and 10% levels of significance, respectively. # indicates that the $\overline{CARs}$ within a certain event window are significant at the 10% level across all three indices.

7. Conclusion

This paper investigates the impact of the introduction of the Real Estate category in the GICS on stocks that have been reclassified from the Financials sector to the newly created Real Estate sector. In particular, this paper explores whether reclassifying stocks has a behavioural effect on security pricing. By performing event studies on REITs included in the S&P 400 (mid-cap), S&P 500 (large cap), and S&P 600 (small-cap) indices on both the announcement and implementation dates, this paper has examined whether the identified price effects of sector reclassification is due to improved pricing efficiency or a framing effect.

The announcement and the implementation events result in positive CARs respectively during 11-day timeframes among three indices. These CARs are robust to different measures of statistical significance and variations in the chosen event windows in the announcement while relatively sensitive in the implementation. The findings for the latter event echoes with the positive impact identified by Fuller et al. (2019).

Our findings indicate that both rational and irrational factors play a role in the formation of the reclassification effect. On the one hand, evidence shows that the creation of the real estate category in the GICS enhances the pricing efficiency of real estate stocks. In particular, large-cap stocks (i.e. S&P 500) benefit the most. Due to their relatively small size in the S&P universe, the reclassification will enhance the visibility of the large-cap REITs the most, which will lead to an increase in automated or mandated trades that respond to the sector restructuring. On the other hand, the large positive accumulative returns identified during the announcement suggests the presence of behavioural effects. As nothing has changed in economic or financial substance in the securities during this period, the statistically significant CARs indicate a behavioural effect on market response to the announcement. The positive abnormal returns can be explained by reference dependent framing. That is, the categorization of real estate rather than financials may have changed the reference point from which the stocks were evaluated.

The link between the empirical results and the behavioural focus of the paper could be strengthened with further research. The strongest link could be made by quantifying the investment products that use GICS taxonomy in either their benchmarks or as rules-based investment drivers. However, this would require extensive analysis of private and proprietary data from multiple companies. Furthermore, the link could be strengthened by performing similar event studies on stock reclassifications in the future. Also, the mechanisms through which reference points are formed and evaluated are still unclear and an excellent area for further study in both psychology and behavioural finance. These mechanisms are undoubtedly powerful and would make a behavioural explanation for the empirical results compelling.

Finally, one important aspect of behavioural biases is that they do not always average out, and are unlikely to be practiced away either. For example, it is well established that an equity premium puzzle exists, for decades. Yet investment in the stock market is still not enough to eliminate the premium. Further studies are needed to verify whether it is possible to ameliorate or even eliminate the framing effect in the real estate market. This type of research usually requires experimental data instead of field evidence as used in this paper.

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