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Title: Pricing Efficiency vs. Bounded Rationality: The Responses Surrounding GICS Real Estate Category Creation

Authors: Helen X. H. Bao[a], Adam Brady[b] and Ziyou Wang[c]

Affiliation: Dept of Land Economy, University of Cambridge[a,b&C]

Contact corresponding author: Helen X H Bao, hxb20@cam.ac.uk

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Helen X. H. Bao[1], Adam Brady and Ziyou Wang

Department of Land Economy, University of Cambridge, CB39EP, UK

Abstract

By performing event studies on REITs included in S&P 400, S&P 500, and S&P 600 indices on both the announcement and the 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 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 the 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 the real estate category in GICS both improve the pricing efficiency of real estate stocks, but also triggered framing effects among investors. The market is under the influence of both the rational and the irrational forces.

Keywords: Behavioural bias, framing, sector reclassification, securitised real estate, REITs

JEL classifications: G14, G41, R30

[1] Corresponding author (hxb20@cam.ac.uk).

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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 it has historically been 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 investors' perceptions 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 is indicated by the recent growth of the field of behavioural finance, theory often does not match reality, and the resulting research question raises: 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 analyse that classifying groups of securities in S&P indices as Real Estate rather than Financials caused 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 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 altering the reference point from which securities are evaluated.

This paper adds to several strands of 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 new Real Estate sector (Sep 19^{th}, 2016) to examine abnormal returns for a group of REITs, and find significant 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 employ an empirical angle 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 the real estate stocks 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 already been 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 visibility improvement effect due to legal implications of the change, subsequently benefit from the increased amount of automated or mandated trades in this category (Pavlov, Steiner and Wachter, 2018). This market efficiency effects 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 made 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 will observe significant changes of REITs returns on both dates, with large-cap REITs showing the greatest effects. By examining abnormal returns of REITs included in 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 GICS real estate category creation.

This paper is structured as follows: Section 2 outlines details on the events examined, Section 3 reviews 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 growth by an average of more than 20% per year and the sector is now estimated to be a $1 trillion equity market with gross assets of over $3 trillion (NAREIT, 2017). Since the first REIT was launched in 1960, Real Estate securities have been considered part of the Financials sector by major index providers such as Standard & Poor's Dow Jones (S&P DJ), Morgan Stanley Capital International (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 Great Financials 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.

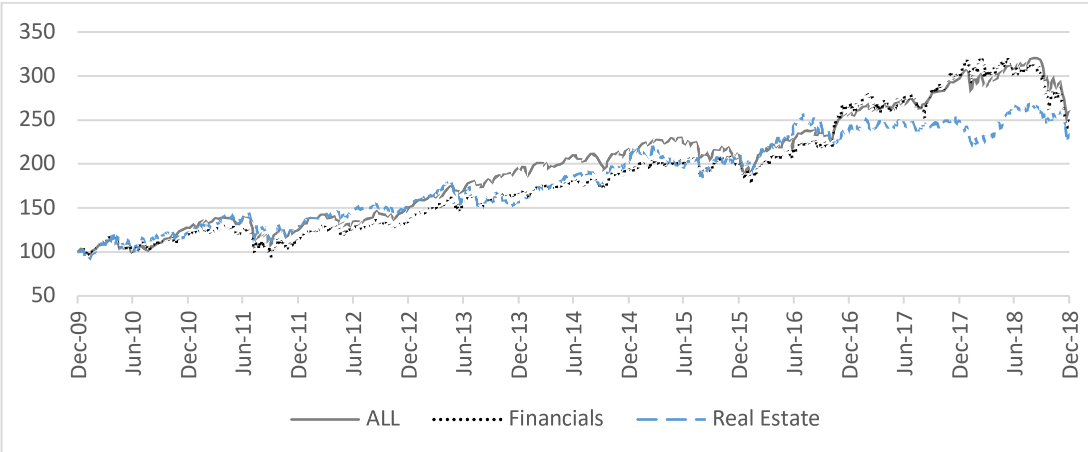
As the first international stock classification system, the GICS classification system was developed jointly by MSCI and S&P DJ (two competing index providers) in 1999. The GICS system is a trademarked product that is sold to asset managers, institutional clients, stock exchanges, researchers and other industry professionals. Clients primarily use the system to benchmark their performance but the rise of 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 the MSCI products, GICS is the most widely used industry taxonomy in the world, with over $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 GICS since the creation of a technology sector during the early 2000's (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 11) 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 Mar 13th, 2015, taking effect at the start of the trading day on Mar 16th, 2015. The official change to S&P was implemented at market close on Sep 16th, 2016, taking effect when the market opened on Sep 19th, 2016. We include small- medium- and large-cap S&P indices in this study to facilitate the test of hypotheses (see the research design in Section 4). The securities included in S&P 400, S&P 500, and S&P600 and selected for this study are listed in Tables 1. Some statistics of the real estate sector in 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 index, the real estate index and the financial index of S&P 400, S&P 500, and S&P 600 families respectively.

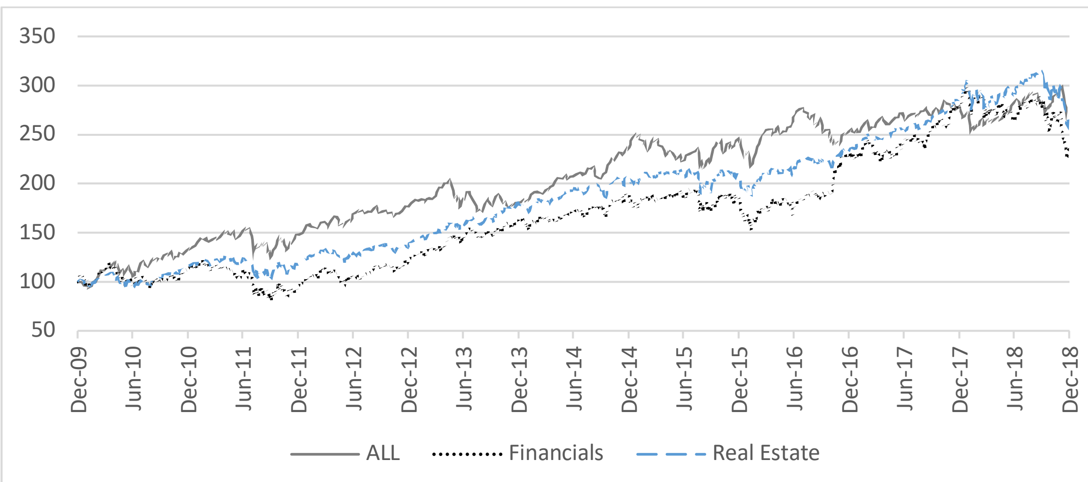
Table 1: S&P Real Estate Index Constituents

	S&P 400		**S&P 500**		**S&P 600**	
#	Name	Ticker	Name	Ticker	Name	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
17	Life Storage Inc	LSI	Kimco Realty Corp	KIM	Pennsylvania Real Estate Investement 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		

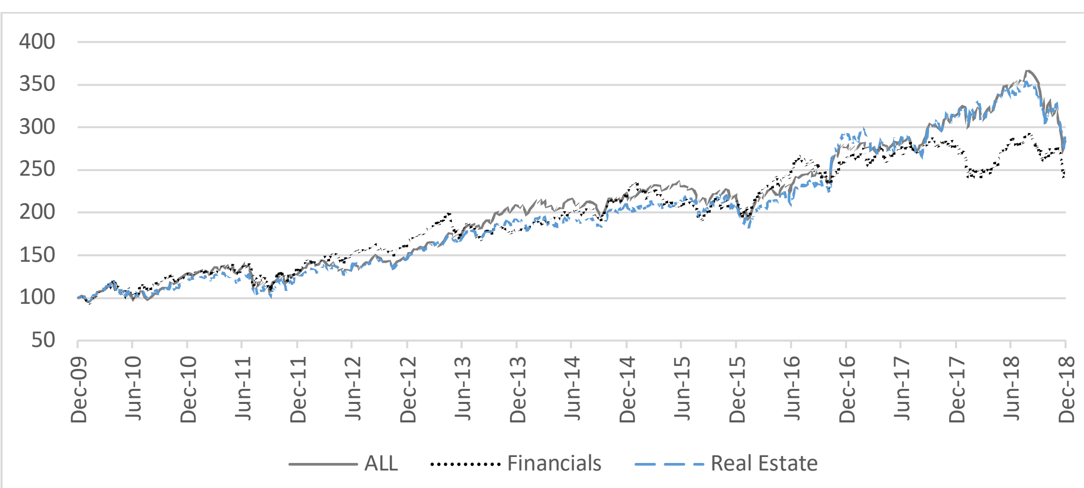
Figure 1: The time series of the S&P indices



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 March 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$ M)	4,038.54	21,171.72	1,138.76
Financial				
	No. of securities	61	68	95
	Launch Date	Jun 19, 1991	Jun 28, 1996	Oct 28, 1994
	Median Constituent Market Cap (US$ M)	3,918.47	22,660.68	1,242.88
	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$ M)	4,081.49	17,803.90	1,195.57
	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 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 causes non-behavioural price movements, as was outlined by various industry professionals. Coghlan et al. (2016) predicted positive inflows from mutual funds and active investors, which would both be exposed as underweight in the sector as a result of the new taxonomy. Many commentators predicted further inflows as a result of an increase in the visibility of the asset class, improving investor education on and perception of the impacted stocks (Blitzer, 2016; Driebusch, 2016; Wotapka, 2016). However, Saunders (2016) noted that Financial Sector ETFs would be forced to sell their REIT holdings, causing excess supply and capital gains taxes. Additionally, Badkar (2016) predicted a negative price impact from $4bn 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 outcomes were presented in a positive frame as “lives saved” and in the other they were presented 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 “Prospect Theory”, which is outlined as a modified expected utility function with asymmetrical weighting of gains and losses, where low probability negative events are overweighed. Prospect Theory implies that when faced with risky decisions the way that choices are framed can create a divergence between empirically observed decisions and those predicted by classical utility functions. In practical terms, it implies that people are more likely to take risks when they believe 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) changed the wording of the original Asian Disease Problem to highlight how the same outcome was not observed when the characteristics of the victims were altered to be less socially acceptable. Kuhberger (1995) demonstrated that framing effects could also be eliminated by increasing the amount of information available to subjects or by altering the wording of the question while maintaining the same valence of the choices. Furthermore, framing effects were shown to be mitigated, and in some cases eliminated, by asking decision-makers for the rationale behind their choices or by asking them to think about the decision for at least three minutes (Miller and Fagley, 1991; Larrick et al., 1992; Takemura, 1995). Kahneman (2003) later championed the theory that framing is only impactful when decisions are made intuitively rather the analytically. Despite these reservations, Framing remains a relevant theory across the fields of psychology, management science and finance.

Literature has demonstrated that framing is a well-established and empirically robust theory in psychology but also that it has been examined from limited viewpoints in the sphere of behavioural finance. The understanding of 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) proposed the concept with “Reference Dependence”, which suggested that gains and losses are defined relative to reference points rather than on an absolute basis. Extending Prospect Theory based on this premise implied 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 about 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 focused 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, Minehart and Rabin (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, in the stock market, reference outcomes are not fair gambles with an expected value of zero; investors expect positive returns. Economics applications like these have led to a focus on goals and expectations as reference points. Research on goals has proposed 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 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 (2006) proposed that reference points are formed to match expectations held in the recent past about probabilistic beliefs of future outcomes. The authors have made promising headways 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, 2007, 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 on 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 (Baca et al., 2000). For example, informed Financials analysts expect different Return on Equity (ROE), a performance metric that reflects return on equity capital invested, for different sectors (Meador, 1984). When real estate was previously included in the Financials sector, investors and analysts always took the ROE of 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 the 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 new Real Estate sector is an influential factor in determining the reference points and thus the framing takes 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 surrounding the event by adopting the structure for an event study in MacKinlay (1997). Abnormal returns are measured as actual ex-post return over the event period minus the predicted return. Predicted returns are estimated using a simple one-factor model following Brown & Warner (1985), and using 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 benefit. 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 is shown in the review of 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. (2018) 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

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

R_{it} represents the daily return of i-th security and R_{mt} represents 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.

The calculated abnormal returns are then aggregated across time and across 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

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

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

$$CAR_i = \sum_t^T AR_{it}$$

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

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

Therefore, CAR_i and $\overline{CAR}$ are used to measure the response to GICS Real Estate category creation 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 constructed 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 make any changes. As all real estate stocks have already been priced correctly and efficiently, we will not observe any significant abnormal returns surrounding neither the announcement day nor the implementation day. This holds true across real estate stocks of all different capitalisation sizes, i.e., real estate stocks that are included in S&P 400, 500, and 600 indices. This give us the first hypothesis as follows.

<u>Hypothesis 1</u>: There is no significant abnormal returns surrounding the announcement date and the implementation date.

$$\overline{CAR}^{Annc}_{SP400} = \overline{CAR}^{Annc}_{SP500} = \overline{CAR}^{Annc}_{SP600} = 0$$

$$\overline{CAR}^{Imp}_{SP400} = \overline{CAR}^{Imp}_{SP500} = \overline{CAR}^{Imp}_{SP600} = 0 ,$$

where $Annc$ and $Immp$ denote the announcement date and implemetation date respectively.

However, if the market is inefficient, but without 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 RE stocks is merely 3.1% of the S&P total market capitalisation; the corresponding proportion for small- and mid-cap RE stocks is 10.1% and 7.5% respectively. Therefore, RE stocks will benefit the most of the visibility improvement resulted from 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 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 may not be able to make adjustments until the re-classification took effect. Hypothesis 2 is formulated accordingly as follows.

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

$$\overline{CAR}_{SP400}^{Annc} = \overline{CAR}_{SP500}^{Annc} = \overline{CAR}_{SP600}^{Annc} = 0$$

$$\overline{CAR}_{SP400}^{Imp} = \overline{CAR}_{SP600}^{Imp} = 0, \text{ and } \overline{CAR}_{SP500}^{Imp} \neq 0$$

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

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

$$\overline{CAR}_{SP400}^{Annc} \cong \overline{CAR}_{SP500}^{Annc} \cong \overline{CAR}_{SP600}^{Annc} \neq 0$$

$$\overline{CAR}_{SP400}^{Imp} \cong \overline{CAR}_{SP500}^{Imp} \cong \overline{CAR}_{SP600}^{Imp} \neq 0$$

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

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

$$\overline{CAR}_{SP400}^{Annc} \cong \overline{CAR}_{SP500}^{Annc} \cong \overline{CAR}_{SP600}^{Annc} \neq 0$$

$$\left|\overline{CAR}_{SP500}^{Imp}\right| > \left|\overline{CAR}_{SP400}^{Imp}\right| \neq 0, \text{ and } \left|\overline{CAR}_{SP500}^{Imp}\right| > \left|\overline{CAR}_{SP600}^{Imp}\right| \neq 0$$

5. Empirical Implementations

The daily price data on each of the securities examined for a sample period starting two years before the Announcement date and ending one month after the S&P implementation date (Mar 15th, 2013 – Oct 19th, 2016). This data range was 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 were reclassified from the Financials to Real Estate Sector. An 11-day window is the most commonly accepted and employed in event studies in finance, representing 76.3% of all studies (Oler et al., 2007).

A gap between the estimation windows and event windows is placed to ensure that the events do not influence the normal returns models. For the announcement (Mar 16th, 2015), a gap of seven trading days is to allow 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 preceding the event period. However, a larger gap is used for the implementation (Sep 19th, 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 real estate sector introduction. To avoid this effect, a conservative 30-day gap was 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 related literature, by using multiple statistical measures for robustness and by estimating event window sensitivity analysis.

Statistics Tests on abnormal returns at a both a temporal and a panel level 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 event window. At the panel level, the null hypothesis $\overline{CAR} = 0$ is tested to examine if average cumulative abnormal returns across both securities and time are significantly different from zero. We adopted three statistical tests including cross-sectional t-test, Patell test (Patell, 1976) and BMP Z test (Boehmer, et al., 1991). Brown and Warner (1985) highlights the need for these additional tests by outlining common problems experienced when performing event studies on daily stock market data. The authors highlight issues of: non-normality of excess returns, non-synchronous trading biasing regression estimates of market parameters and autocorrelation and event induced volatility skewing variance estimates (p. 5). The Patell Test compensates for non-normality of returns by using standardized abnormal returns, assuming separate standard error for each security and cross-sectional independence. However, the test is still prone to event induced volatility and cross-sectional correlation (Muller, 2018). 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 a forecast error correction standard deviation. As none of the three tests is superior than the others in an absolute term, we adopt all three in our analysis for robustness sake.

6. Results and Discussions

The average abnormal returns ($\overline{AR_t}$) and cumulative abnormal returns ($\overline{CAR}$) for S&P 400, S&P 500, and S&P 600 on the implementation and announcement days are reported in Tables 3 through 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 with the findings of REITs in Fuller et al. (2019); before the event date they are generally negative and after the event date they are generally positive. Specifically, the variations of $\overline{AR_t}s$ surrounding 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 slight negative. In the implementation event, securities experienced negative $\overline{AR_t}s$ prior to the event date while positive ARs after the date. The patterns of $\overline{CAR}$ are also similar in two events respectively. $\overline{CAR}$ are always positive during the announcement but are eroded by negative $\overline{AR_t}s$ at first and become positive due to positive $\overline{AR_t}s$ after the implementation date.

The abnormal returns of mid-cap real estate stocks are reported in Table 3. Most of positive $\overline{AR}$ (at t = -5, -4, -2, +2 and +4) in the announcement event are statistically significant at the 5% level as indicated by all test statistics. By contrast, all the negative $\overline{AR}$ (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 1% level, while at t = -2 is not always significant as suggested by 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.

Following Fuller et al. (2019) and Malic (2016), We estimate $\overline{CAR}$ for different event windows to investigate how results are affected by the length of event window selected. The initial analysis of each event took place over an 11-day event window, including the event date (five days before and after the event). We followed Fuller et al. (2019) by using event windows that are up to 11-day long. 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 event time (relative to the event date). The three tests are also employed in this part. The results are presented in Tables 6 to 8.

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.

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 S&P 400 and all the $\overline{CAR}$ are positive in both events. Panel A shows that the $\overline{CAR}$ increases with the window length and the highest $\overline{CAR}$ records 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 $\overline{CAR}$ records 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 is statistically insignificant only within short event windows in the announcement event, while relatively sensitive to the event window chosen in the implementation event.

For real estate stocks in S&P 500, all the $\overline{CAR}$ 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 $\overline{CAR}$ records 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 $\overline{CAR}$ records 2.10% (significant at the 1% level) in the window of (-3, +3).

Table 8 demonstrates a story for S&P 600 similar to S&P 400 and 500, where all the $\overline{CAR}$ are positive in both events. In the announcement event (Panel A), the $\overline{CAR}$ increases with the window length and the highest $\overline{CAR}$ records 4.67% (significant at the 1% level) in the window of (-5, +5) in the. In the implementation event (shown in Panel B), the highest $\overline{CAR}$ records 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 is 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 – Cumulative Average Abnormal Return Sensitivity 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 the $\overline{CARs}$ within a certain event window are significant at the 10% level across all three tests.

Table 7 – Cumulative Average Abnormal Return Sensitivity 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 the $\overline{CARs}$ within a certain event window are significant at the 10% level across all three tests.

Table 8 – Cumulative Average Abnormal Return Sensitivity 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 the $\overline{CARs}$ within a certain event window are significant at the 10% level across all three tests.

An analysis of the two events demonstrates that statistically significant $\overline{CAR}$ occurred during each event window for 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 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 contrary, $\overline{CAR}$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 S&P 500 shows the most significant impacts from the implementation.

To test hypotheses 3 and 4, we conduct a comparative analysis across three indices. First, we summarise the $\overline{CAR}$s reported in Tables 6 through 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. It indicates that behavioural bias plays an important role in the market reactions to the index reclassification.

In addition, the impacts in announcement are more significant than those in implementation, and the magnitude of $\overline{CAR}$s are larger surrounding the announcement date. These are further evidence to support hypotheses 3 and 4, both of which consider behavioural biases. 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 the 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 $\overline{CAR}$s between indices. The results are reported in the 'T-test Statistics' columns in Table 9, where we test 1) if the $\overline{CAR}$s of S&P400 is significantly different from those of the other two indices due to pricing efficiency assumption, and 2) if the $\overline{CAR}$s of S&P500 is significantly different from those of the other two indices due to visibility assumption in the implementation event. We find that the $\overline{CAR}$s of S&P500 is significantly higher than the $\overline{CAR}$s of small-cap (i.e., S&P 600) and mid-cap real estate stocks (i.e., S&P 400) surrounding the implementation date. In addition, the impacts of implementation are found (through Table 6-8) to be more significant in S&P 500.

To conclude, our test results in Tables 3 through 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 GICS both improve the pricing efficiency of real estate stocks, but also triggered framing effects among investors. The market is under the influence of both the rational and the 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	SP400 vs SP500	SP400 vs SP600	SP500 vs SP600
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 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 GICS Real Estate category on stocks that were reclassified from the Financials Sector to the newly created Real Estate Sector. In particular, this paper explores whether reclassifying stocks shows a behavioural effect on security pricing. By performing event studies on REITs included in 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, this paper has examined whether the identified price effects of sector reclassification is due to improved pricing efficiency or framing effect.

The announcement and the implementation events resulted 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. (2018).

Our findings indicate that both rational and irrational factors played a role in the formation of the reclassification effect. On one hand, evidence shows that the creation of the real estate category in GICS improves the pricing efficiency of real estate stocks. In particular, large-cap stocks (i.e. S&P 500) benefit the most. Because of their relatively small size in the S&P universe, the reclassification will enhance large-cap REITs' visibility the most, which will lead to an increase in automated or mandated trades responding to the sector restructuring. On the other hand, the large positive ARs identified during the announcement suggests the presence of behavioural effects. As nothing has changed in economic or financial substance about 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 altered 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 a similar event study on the upcoming creation of a Real Estate sector by FTSE Russel in 2019 or more generally by performing event studies on any stock reclassifications that occur. Finally, the mechanisms with which reference points are formed and evaluated are still unclear and are 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.

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