DOCTORAL THESIS

The impact of rise and decline in brand equity on firm performance and the moderating role of organizational efficiency
A comparative assessment of consumer and firm based brand equity (CBBE & FBBE)

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Impact of rise and decline in consumer-based and firm-based brand equity on firm performance: The moderating role of organizational efficiency

By

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ABSTRACT

While extant body of marketing-finance research advocates that strong brands significantly enhance firm performance, very little is known about whether this relationship is sustainable over long term. Brand equity is prone to rise or decline over time and without investigating the firm performance impact of such unanticipated directional shifts, brand's true value relevance can be over or under-estimated. Adopting stock returns as firm performance measure and through a longitudinal approach (2010 to 2019), this study provides novel insights that, in long term, firm value erosion due to declining brand equity is significantly higher than the value accrued during positive changes. A further comparative analysis between consumer and firm based brand equity measures reveals two interesting findings. First, the evolution of these brand equity dimensions over time is mutually exclusive and second, the directional firm performance impact of rising and declining CBBE is much stronger as compared to changes in FBBE.

These novel findings are further complemented by identifying potential mechanisms by which superior organizational efficiency can moderate this marketing-finance interface. Anchored to Resource Based Theory (RBT) of sustainable competitive advantage, two key organizational efficiency measures are proposed; core business efficiency (CBEF) and marketing capability (MCAP). Both these multi input-output efficiencies are operationalized using Malmquist DEA benchmarking approach. The findings uncover that CBEF optimizes the financial benefits of rising FBBE and mitigate the negative effects of declining CBBE. In contrary, while MCAP complements the value contributions of growing CBBE, it worsens the firm value erosion due to declining FBBE. Overall, the research not only contribute to existing marketing literature from multiple fronts but also have several managerial and investor related implications.

Dedication

To my late Grandmother

(I miss you everyday Amma)

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The research for this project was submitted for ethics consideration under the reference BUS 19/ 061 in the UR Business School and was approved under the procedures of the University of Roehampton's Ethics Committee on 11.06.19.

Chapter 1: INTRODUCTION

A brand is a distinctive name for which the consumers are willing to pay higher than they would have otherwise spent on similar products (Keller, 2012). Brand equity therefore represents an incremental intangible value attached to a branded product which is over and above a similar offering without that brand name (Aaker 1991, Ailawadi et al., 2003; Veloutsou et al., 2013). Branding theorists have proposed several determinants of brand equity amongst which the most researched are consumer based brand equity (CBBE) and firm based brand equity (FBBE) (Christodoulides et al., 2015). CBBE captures the consumer's cognitive association of awareness, perceived quality and liking towards a brand to estimate its brand strength (Keller, 2016). On the other hand, FBBE estimates incremental value generated directly at brand-level either from accounting outcomes such as revenue premiums and market share, earnings through proprietary assets such as patents and trademarks or derived from brand's financial market valuation (Dutta et al., 2017). Irrespective of its measurement perspective, brand equity is widely acknowledged as a key intangible marketing asset and a source of competitive advantage, that acts as a growth engine for a lasting business success (Christodoulides et al., 2015; Kim & Yoon, 2018). Marketing academics document that brand equity has a significant positive impact on both current-period accounting performance (Fischer & Himme, 2017; Stahl et al., 2012) and performance in long-term measured through stock returns (Bharadwaj et al., 2011; Dutordoir et al., 2015; Johansson et al., 2012; ; Mizik & Jacobson, 2008). However, due its gradually evolving nature, brand equity has lasting effects (Datta et al., 2017) and therefore majority of its financial contributions are realized over longer time periods (Mizik, 2014).

Although current marketing-finance literature have established strong brand equity as a reliable predictor of long-term firm performance, such relationship may not be guaranteed eternally because even strong brands can experience a sudden decline in their equity due to many market factors. This dynamics can be further understood from some real world evidence. A most recent example is the negative market sentiments towards the Pepsi brand after it released a controversial commercial in 2017 during the "Black Lives Matters" protests in the USA (Victor, 2017). The brand invited huge social media backlash, where consumers blamed the firm for agitating communal harmony. Another such example is the famous case of Coca Cola in 1985 where the firm lost a significant amount of market share because of jettisoning their original flavour with a new branding campaign (Gourman & Gould, 2015). Such unanticipated shifts in brand reputation in the marketplace can have significant impact on firm value. For example, Apple's stock price fell steeply after it was reported that their newly launched iPhone 5 is experiencing a weaker-than-expected consumer demand (Osawa, 2013; Reuters, 2013). Another example is of B2B giant General Electric which lost more than 100 billion US dollars' worth of its market value within one year (2017 to 2018) because of weakening investor and consumer confidence towards brand's future growth, following the retirement of CEO Jeff Immelt (Colvin, 2018). Collectively, these examples suggest that unfavourable shifts in brand equity are not uncommon and even prominent brands are prone to such changes. Therefore, it becomes important to understand the long term financial consequences of such directional shifts in brand's market strength to unfold its true value relevance. This study takes this challenge and explores this relatively new dimension of marketing-finance interface. Additionally, the empirical investigation is conducted separately for changes in brand's consumer and firm based equity measures to understand this dynamics from a holistic perspective.

Along with exploring the financial implications of unanticipated rise and decline in brand equity, this research also examines the role of brand owning organization in moderating these effects. This is vital because simply knowing the directional brand equity-firm performance relationship holds limited significance if the brand owning firm is not structurally organized to exploit this information to their benefit. A real world example to better understand such transitional role of organizational competence in brand equity restoration is the case of globally renowned toy brand "Lego". Founded in 1932, the brand experienced a significant decline in demand amongst their most targeted customer-base (i.e. children) in the early 20th century. The firm reported a significant loss of 217 million dollars in 2003, principally due to declining consumer interest in their obsolete product designs (Delingpole, 2009). As a response to the depleting brand strength and its consequences on firm's profitability, the management swiftly acclimatized to the consumer needs and expectations by re-configuring their business model form "pre-built" toys to "building block" approach. This demonstration of splendid marketing intelligence led the incredible comeback of Lego, which today is unequivocally the world's most valuable toy brand with a brand value of 6 billion US dollars (Tighe, 2022). This example suggests that although strategic marketing assets like brand equity have value relevance, but its true contributions are inconclusive without considering the intervening role of organizational competence. In order to theoretically support these arguments, this study leans on the propositions of resource based theory (RBT) of strategic resource management which asserts that firms need to leverage their resources with their capabilities to gain sustained competitive advantage (SCA) (Barney, 1991). Since brand equity is a key intangible marketing resource (Davick et al., 2015; Keller, 2016, Kozlenkova et al., 2014), this study contends that firms with superior organizational efficiency can exploit the information contained in unanticipated rise and decline in its magnitude to gain SCA in the marketplace. Investigating the intervening role of possible moderators in brand equity-firm performance relationship is also undertaken because it helps in understanding the boundary conditions under which existing theory holds (Dutordoir et al., 2015:35; Kimbrough & McAlister, 2009).

The following sections elaborate on the overall research objective and the motivations behind taking this initiative. The underlying aim is segregated into three sub-categories to give a systematic direction to the research. All the objectives are individually overviewed from the context of their relevance to existing marketing literature and the realized potential gaps. The chapter then provides a brief overview of the investigative tools and techniques adopted to empirically examine all the proposed research objectives. The further sections then highlight the significance of this study from the theoretical, managerial and investor's perspectives. The chapter finally concludes with an overview of the entire thesis structure visualized through a sequential flow diagram.

1.1 Motivation of the study and the research objectives

1.1.1 The first research objective

The commercial examples discussed earlier emphasize on why establishing a directional link between brand equity and firm performance is necessary and important. However, the mainstream research on branding prevails around the positive aspects of brand equity. Researchers have established long term contributions of several consumer and firm based brand attributes such as revenue premium (Ailawadi et al., 2003; Yang et al., 2015), perceived quality (Aaker & Jacobson, 2001) and consumer's brand perceptions (Datta et al, 2017; Mizik, 2014; Mizik & Jacobson, 2008; Nam & Kannan, 2014). Along with its value relevance, studies have also endorsed positive brand sentiments such as brand love (Batra et al., 2012; Kaufmann et al., 2016; Zarantonello et al., 2016b), brand personality (Ong et al., 2017; Sung & Kim, 2010); brand trust (Alwi et al., 2016; Becerra & Badrinarayanan, 2013; Li et al., 2015), brand romance (Patwardhan & Balasubramanian, 2011) and brand loyalty (Lu & Xu, 2015). In contrary, marketing research on negative brand consequences is still in its infancy. Recent times have however witnessed a rise of attention towards understanding the importance of negative side of branding (see Veloutsou et al., 2020). For example, Zarantonello et al. (2016a) studied the possible consequences of "brand hate" and found that such extreme negative emotions can trigger several consumer behavioural responses such negative word of mouth (NWOM), protests and reduce patronising. Similarly, Ullrich & Brunner (2015) report that online NWOM significantly downgrades consumer purchase intentions towards strong brands. Apart from NWOM, this limited body of literature has also analysed other negative brand phenomenon such as brand crisis (Jeon & Baeck, 2016), brand rejection (Veloutsou et al., 2020) and brand avoidance (Rindell et al., 2014). In addition to understanding its competing effects, current research also advocates how such brand negativity opens possible opportunities for managers to exploit this information by implementing better brand management strategies (Ramirez et al., 2019). All these studies suggest that firms need to effectively manage these increasingly popular negative brand outcomes (Japutra et al., 2018; Odoom et al., 2019; Veloutsou et al., 2020; Veloutsou & Guzman, 2017).

In parallel to exploring the negative consumer-brand relationships, there exists a small body of marketing-finance literature understanding the long-term financial consequences of such unfavourable brand-related outcomes. For example, Luo (2007) explores the impact of negative consumer brand experience on firm performance and documents that higher level of consumer complaints significantly erodes firm value. Later, the authors also established that brand belittlement through NWOM have a similar effect on firm's long-term growth prospects (Luo, 2009). Luo et al. (2013), on the other hand, examined the financial consequences of positive and negative consumer brand ratings and report that negative brand ratings have a stronger impact on firm performance as compared to positive consumer response. Along with these studies, current marketing research has also investigated the long-term firm performance effects of positive and negative: brand feelings (Marticotte et al., 2016); user chat content (Tirunillai & Tellis, 2013) and news (Xiong & Bharadwaj, 2013) and found similar asymmetrical effects.

This increasing research attention towards the consequences of negatively valanced brand response on both the brand performance and firm value highlight the importance of further examination of these effects (Veloutsou & Guzman, 2017). Zarantonello et al. (2016a:23) also recommends that future research should investigate the antecedents and outcomes of such negative brand phenomenon adopting a wider view and with a longitudinal perspective. These recommendations along with the limited existing evidence motivates this study for its first objective i.e. to explore the long-term financial implications of rise and decline in brand equity. This is achieved by differentiating the positive brand equity changes over time from the negative changes and examining their individual impact on firm performance.

1.1.2 The second research objective

Another goal of this study is to conduct a comparative assessment of the two key brand equity measurement perspectives, i.e., consumer based brand equity (CBBE) and firm based brand equity (FBBE). Although there exists a vast and burgeoning research identifying several brand equity dimensions (Ferjani et al., 2009; Keller & Lehmann, 2006), CBBE and FBBE are the most popular and extensively researched amongst them (Baalbaki & Guzman, 2016; King & Grace, 2009; Nguyen et al., 2015; Srinivasan et al., 2009; Veloutsou et al., 2020). Despite a wide acceptance as key determinants of brand equity, very little is known about their relationship with each other or their unique contributions to firm's future growth prospects. Identifying the interconnection between consumer and firm oriented brand equity is important because although they belong to a common theoretical foundation, they are conceptually different. For example, CBBE centres around capturing consumer's awareness, association, and loyalty towards a brand (Aaker, 1991; Christodoulides et al., 2015), whereas FBBE represents incremental value gained directly from strong brand name (Ailawadi et al., 2003). Therefore, consumer's cognitive assessment of a brand is a *subjective* emotional phenomenon whereas equity gained at brand-level, i.e. through brand earnings such as price premiums and royalties, are *objective* based measures. Due to these mutually exclusive characteristics, CBBE and FBBE reflect unique dimensions of brand equity that capture specific aspects of brand's measurable value (Nguyen et al, 2015:555). Another distinguishable feature between CBBE and FBBE is that the former is a *backward looking* perspective while the latter relies on *forward looking* measures (especially when estimated through projected brand earnings or stock market valuations) (Nguyen et al., 2015:56). Consequently, CBBE and FBBE assess brand equity manifestation at different levels of the Brand Value Chain (Huang & Sarigollu, 2014:786; Keller & Lehmann, 2006).

All these differences among consumer and firm based brand equity measurement perspectives are likely to play a crucial role in determining the level of their intimacy. Surprisingly, the handful of studies that have focussed on understanding this relationship have reported conflicting results. Where one set of studies advocate a strong association between different components of CBBE and FBBE (Bagna et al., 2017; Datta et al., 2017; Stahl et al., 2012), the opposing view suggest that although these measures emanate from a common concept, they are mutually exclusive (Johansson et al., 2012; Nguyen et al., 2015; Tasci, 2020). This lack of consensus amongst researchers calls for a need to further explore the CBBE-FBBE interlinkage (Tasci, 2020). Motivated by this critical gap in the existing branding literature, this research conducts a comprehensive comparative assessment between consumer and firm based brand equity dimensions. Adopting a bi-dimensional approach, focus is not only laid on investigating their inter-relationship but also comparing their individual impact on firm performance. This is important because "brand equity is a complex and multi-faceted concept and, as such, it needs to be captured through a set of measures rather than a single measure" (Christodoulides and de Chernatony, 2010:24). Therefore, without understanding as to how these two distinct measures of brand equity contributes to firm's future growth, anticipating holistic value relevance of brand seems ambiguous. Comparing their individual firm value impacts is also critical to better understand the return on investment from brand building expenditures. Marketing related investments are expected to be recompensed by marketing outputs (Madden et al, 2006; Sheth & Sisodia, 2002). Therefore, without knowing the individual financial contributions of these two "theoretically related but conceptually different" intangible marketing measures, actual brand performance cannot be adequately estimated.

1.1.3 The third research objective

Investigating the first and second research objectives does provide critical information about the favourable or unfavourable "consequences" of brand equity, but this information is incomplete without knowing the potential "remedies" to these effects. Motivated by this notion, the third objective of this study is to explore the role of organizational efficiency in moderating the firm performance impact of upside and downside shifts in brand equity. In doing so, the study relies on the assumptions of Resource Based Theory (RBT) which asserts that a firm is a compendium of heterogenic competitive resources and to enjoy sustainable competitive advantage (SCA), they must exploit these specialized resources with exceptional organizational actions and strategies (Barney, 1991; Wernerfelt, 1984). Another corollary of RBT is that not all the firm resources impart SCA, but only those which are valuable, rare, inimitable, and efficiently organized (VRIO) (Barney et al., 2001). Brand equity fits precisely into the first three constraints. Firstly, extant body of research has established that brand equity is a *valuable* marketing resource which not only contributes towards short-term profitability (Fisher & Himme, 2017; Kim et al., 2003; Srinivasan et al., 2010; Stahl et al., 2012; Wang et al., 2015) but also enhance long term firm performance (Aaker, 1991; Datta et al., 2017; Katsikeas et al., 2016; Lim & Brooks, 2011; Mizik, 2014; Mizik & Jacobson, 2004, Mizik & Jacobson, 2008). Secondly, building strong brands is not a straightforward process (Aaker, 1991) and it requires substantial initial investments (Mizik, 2014). Due to high incurred costs and structural complexity, strong brands are relatively *rare* (Aaker & Joachimsthaler, 2000;

Kozlenkova et al, 2014). Thirdly, because of its complementarity, rarity, ambiguity, and inherent intangibility, it is extremely challenging for the competitors to *intimate* a strategic marketing resource like brand equity.

However, simply owning a valuable, rare, and inimitable resource does not guarantee SCA if the firm is not *organized* to exploit it to its full competitive potential (Barney & Hesterly, 2012). From brand perspective, this suggests that although brand equity is a strategic marketing asset which contributes to firm performance, this relationship is not conclusive without considering the intervening role of the organizational competence (Rahman et al., 2018). Even strong brands fail as a result of incompetent management practices (Golder, 2000). It can therefore be argued that although brand equity is a VRI resource, it cannot lead to sustained long term success if the brand owning organization is incompetent in effectively managing the financial consequences of its rise and decline over time. Despite the importance of the "organization" component of the RBT's VRIO framework, it has been broadly overlooked by the existing marketing research (Kozlenkva et al., 2014). Identifying this potential research gap, the current study argues that until the brand owning firm is efficient in enhancing (mitigating) the positive (negative) firm value impact of rising (declining) brand's strength, brand equity cannot be perceived as source of SCA.

In generic terms, efficiency refers to an output-to-input ratio, therefore an efficient firm is the one which minimizes its available resource allocation to achieve optimum levels of output (Keh et al., 2006; Priem & Butler, 2001). However, in practical terms, firms possess a complex set of resources which they merge together to maximize their desired outcomes (Sun et al., 2019). Therefore, rather than relying on a single input, integration of multiple resources as inputs to measure organizational efficiency is warranted.

Therefore, this study adopts a multi input-output approach and propose two key organizational efficiency measures, namely, core business efficiency (CBEF) and marketing capability (MCAP). CBEF represents the ability of an organization to exploit its core tangible resources like plant, equipment, and employees to generate higher productivity levels (Nath et al.,2010). MCAP, on the other hand, depicts a firm's capability to utilize its marketing assets and expenditures to position their brand exclusively in the marketplace so as to gain consumer interest and retention (Morgan et al., 2018). Both these efficiency measures are well documented as key contributors of long term business success (Feng et al., 2017; Nath et al., 2010; Rahman, 2020; Sun et al., 2019; Yang et al., 2015; Zhu, 2000). However, their intermediary effects in the brand equity-firm performance relationship, especially during unanticipated upside or downside shifts, are still unknown. Therefore, extending the existing knowledge, this research contends that superior levels of CBEF and MCAP can mitigate (enhance) the negative (positive) effects of declining (rising) brand equity on firm performance. Furthermore, to gain richer understanding of how these efficiency measures aid in maximizing holistic brand potential, their moderating roles are examined explicitly for positive and negative changes in CBBE and FBBE.

1.2 Investigative approach

This research investigates the long term firm performance effects of unanticipated positive and negative changes in consumer and firm based brand equity and the sensitivity of this relationship to organizational efficiency levels. Therefore, a longitudinal approach is adopted where the performance of same firm-brands is tracked consecutively for 10 years from 2010 till 2019. This approach aligns well with the propositions of current marketing research that brands have lasting effects and therefore, its total financial impact cannot be realized in short-term (Datta et al., 2017; Mizik, 2014). Additionally, adopting a panel data structure instead of cross-sectional setting offers more variability and greater efficiency because it accounts for unobserved heterogeneity across individuals (e.g. firms) and eliminate biases due to aggregation (Mizik & Pavlov, 2018). The chosen metric to represent long term firm performance is stock returns which is the ultimate measure of shareholder's wealth and firm's expected future discounted cashflows (Mizik & Jacobson, 2004, Srinivasan et al., 2009; Xiong & Bhardwaj, 2013). Furthermore, the time period of the study is intentionally selected immediately after the 2008 financial crisis so that the obtained evidence is not influenced by "black swan events" wherein the markets are generally not in equilibrium (Johannsson et al., 2012).

From the methodological perspective, the econometric model employed for the statistical examination of all the proposed relationships is stock return response modelling (SRRM) (Mizik & Jacobson, 2004). SRRM is a widely popular model in the current marketing-finance literature which establishes whether unanticipated change in any marketing based information contribute to the change in the firm's stock market valuation (Mizik, 2014; Nam & Kannan, 2014; Tuli & Dekimpe, 2012; Yang et al., 2015). One of the vital aspect of SRRM is that it assesses the explanatory power of the underlying marketing asset as an "incremental information content" to that of standard accounting information (e.g. sales and earnings) and economy wide risk factors (Mizik & Jacobson, 2008). Including accounting and risk characteristics along with the "variable of interest" as the determinant of stock returns therefore significantly enhance the quality of the obtained empirical evidence by reducing the omitted variable bias.

Along with SRRM, the benchmarking method employed to operationalize the proposed efficiency measures of CBEF and MCAP is Data Envelopment Analysis (DEA), which is a non-parametric based linear programming tool (Charnes et al., 1978). DEA allocates efficiency by comparing the input-output transformation process of all the entities under investigation (also called as decision making units, DMUs) and identify the best performers amongst them (Dutta et al., 2005). Jointly, all these efficient units form an efficiency frontier and the inefficient DMUs are enveloped under it (Ruiz et al., 2014). Instead of employing standard DEA model, the study takes advantage of its longitudinal structure and estimate CBEF and MCAP through an advanced time-series version of DEA i.e. Malmquist Total Factor Productivity Change (TFPCh) (Fare et al.,1994). Malmquist TFPCh provides a dynamic and comprehensive view of firm's overall productivity by incorporating the effects of changes in firm's internal efficiency and technology over time. Due to these time-series characteristics, TFPCh based efficiencies account for the carry-over effects of previous period employed resources in the subsequent year's efficiency (Luo & Donthu, 2006), thus providing richer theoretical and statistical inferences.

From the data acquisition perspective, all the required marketing, accounting and financial data are obtained from multiple secondary sources. The yearly consumer and firm based brand equity valuations are retrieved from two prominent commercial brand consultants namely, Millward Brown BrandZ and Brand Finance, respectively. The brand value estimates provided by these two institutions have been extensively employed in the current literature to explore various aspects of the marketing-finance interface (some recent examples are Bagna et al. 2017; Chang & Young, 2016; Dorfleitner et al., 2019; Gerekan et al., 2019; Yildiz & Camgoz, 2019). The secondary sources approached to acquire all the required accounting and stock market related data include Kenneth French online data library and Eikon DataStream database. The statistical software package utilized for conducting the overall empirical analysis is Stata (Park, 2011), and the DEA linear programming tool used to operationalize Malmquist TFPCh based efficiency measures of CBEF and MCAP is DEAP (Coelli, 1996).

1.3 Contributions of the study

This research offers several contributions not only to the existing theoretical knowledge but also for the managers and investment community. First and foremost, by adopting a directional approach, the study provides novel insights about the potential imbalance in the firm performance impact of positive and negative changes in brand equity. Current literature is predominantly limited to analyse the overall brand equity-firm value relationship neglecting the possible asymmetry in these effects during upside and downside shifts in brand strength. This is important because brands are prone to grow or decline over time (Veloutsou & Guzman, 2017), therefore ignoring the financial consequences of such unexpected variations can significantly jeopardize firm's future growth prospects. This research fills in this lacuna by desegregating the overall changes in brand equity into its negative and positive components and assess their individual link with firm performance. Adopting such a magnified approach not only informs about long term contributions of brand equity but provide novel insights about the potential financial consequences due to its unexpected decline, which until now is largely overlooked.

Along with exploring the directional brand equity-firm performance interface, this study also contributes to current branding scholarship by providing a comparative view of consumer and firm based brand equity measurement perspectives. Existing research has mainly explored the value relevance of either CBBE or FBBE (e.g. Oliveira et al, 2018; Rahman et al., 2019; Vomberg et al., 2015; Yildiz & Camgoz, 2019), with very few including both these dimensions under a single research framework (e.g. Bagna et al., 2017; Johansson et al., 2012). Furthermore, there still lacks unanimity amongst marketing academics about the degree of association between CBBE and FBBE (Cristodoulides & De Chernatony, 2010; Tasci, 2020; Veloutsou et al., 2013:247). Realizing these vital gaps, this study adds to the limited knowledge about the true association between consumer and firm based brand equity by systematically answering two vital questions 1) is CBBE closely related to FBBE? and 2) if not, which amongst them is more diagnostic in explaining long term firm performance? Such a simultaneous examination of the "characteristics" and "performance" aspects of both these two brand equity measures is still lacking in the current branding literature (Huang & Sarigollu, 2014).

Besides offering direct contributions to marketing-finance literature, the current study also complements the research validating the theoretical underpinnings of RBT in the marketing context. Firstly, the research refines the theoretical underpinnings of RBT by addressing some of its key limitations such as it being inward-looking (Lavie, 2006), static (Kraaijenbrink et al., 2010), tautological (Priem & Butler, 2001) and lacking generalizability due to construct validity issues (Almarri & Gardiner, 2014; Levitas & Ndofor, 2006). Secondly, by adopting a contingency approach, it provides richer and more nuanced insights of the context influencing the interaction between brand equity and future firm performance. Focus, in particular, is directed to understand how an efficiently organized (O) management can transform a valuable, rare, and inimitable (VRI) marketing resource like brand equity into a source of sustained long term growth. This is achieved by examining the intermediary role of firm's "organizational efficiency" in moderating the effects of positive and negative changes in brand equity on firm value. Although extant body of marketing research has demonstrated the direct and indirect firm value contributions of various organizational functions such as business efficiency (Nath et al, 2010; Zhu, 2000), brand management efficiency (Rahman et al.,2018) and marketing capability (Feng et al., 2017; Mishra & Modi, 2016; Nguyen & Oyotode, 2015), no study until now have explored these interactions during unanticipated upside and downward shifts in brand equity (to the best of researcher's knowledge). This research advances this knowledge and investigate the moderating effects of both the *profitability* and *marketability* based organizational efficiency factors represented through core business efficiency (CBEF) and marketing capability (MCAP), respectively. By simultaneously examining the firm value impact of rise and decline in brand equity and the moderating effects of organizational efficiency, this research advances the existing knowledge from exploring *"**how** brand equity creates value?"* to understanding *"**when** does brand equity create or destroy value?" and "**what** can be done to capitalize on this information?"*.

Apart from the academic significance, the current study also offers several implications for brand and marketing managers. Firstly, it encourages managers not to simply perceive their brand's past success as a signal of competitive advantage, rather maintain objectivity by closely monitoring the unanticipated positive and negative shifts in their brand's equity in future. Subsequent downward shifts or higher volatility may signal brand inconsistency (Luo et al., 2013), which can be a result of either a lapse in firm's internal management efficiency or incapability of acclimatising to the everchanging marketing environment (Rahman et al., 2018). A directional view of brand equity-firm performance relationship can therefore better inform managers about the possible financial implications of unfavourable changes in their brand performance. Secondly, the study also highlights the importance of engaging with brand haters and switching consumers for a more productive brand management. Additionally, it conveys brand owners to constantly monitor their core business competencies and marketing capabilities as any prevailing weaknesses in them may lead to suboptimal brand performance. A cross comparison of the moderating effects of CBEF and MCAP independently for CBBE and FBBE also guides managers to adjust the levels of their implemented strategies and marketing actions based on the brand equity aspect they are dealing with. This can lead to better budget allocation and confidence in explaining the deployed marketing expenditures to the board of directors and shareholders.

Along with managerial relevance, the research is also resourceful for investors and shareholders. Firstly, by adopting a longitudinal approach, the study highlights the importance of investing in brands for long-time horizons so as to attain maximum financial benefit. Furthermore, a comparative assessment of consumer and firm based brand equity within a single research framework provides new mechanisms through which financial community can better understand the holistic brand relevance, rather than relying on their own subjective judgements about it. Focusing simultaneously on the financial impact of unanticipated shifts in consumer brand association (CBBE) and brand related earnings (FBBE) can aid them in better understanding the true strength (or weakness) of a brand and appreciating the brand equity-stock price dynamics in a much profound manner.

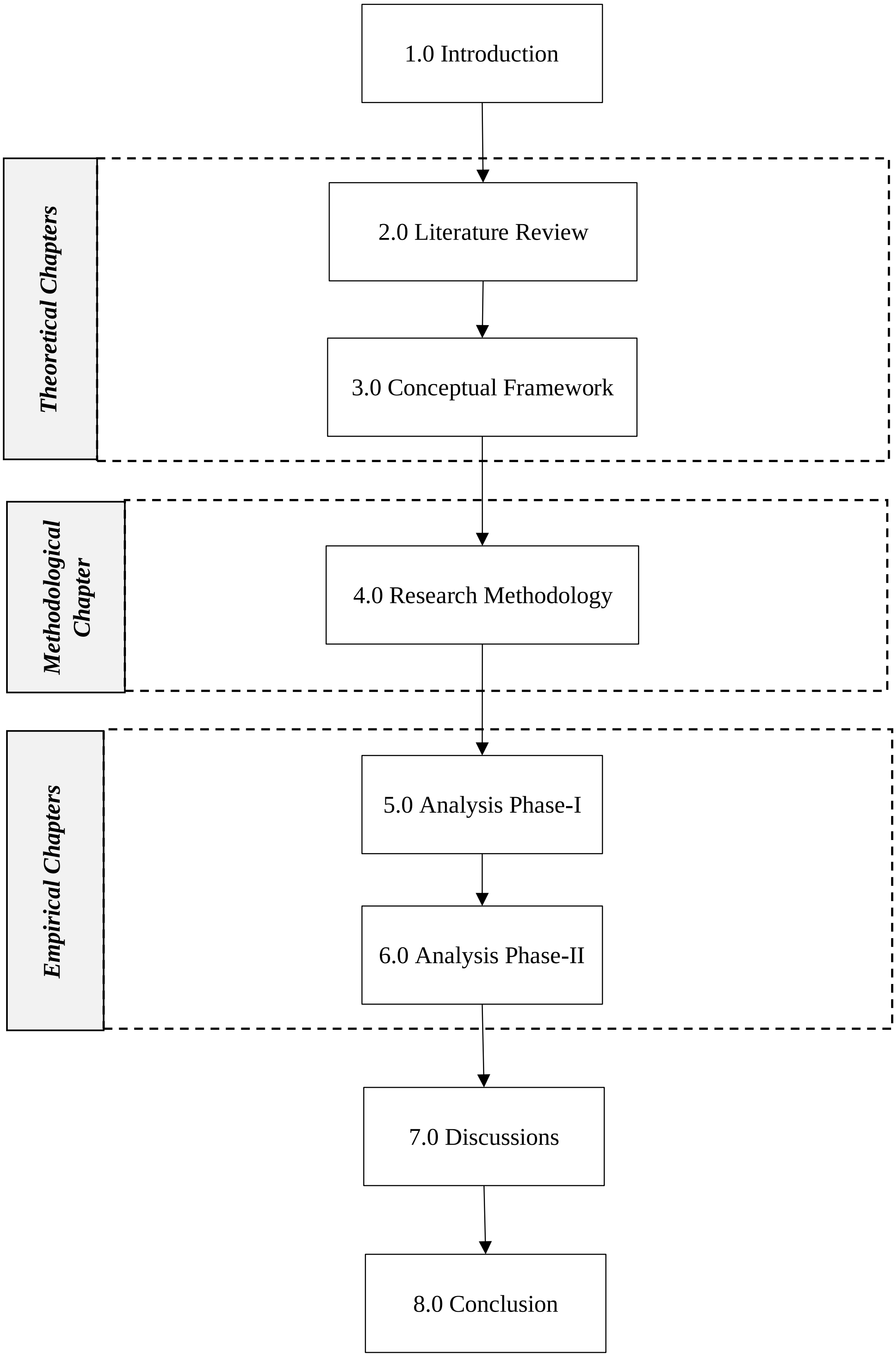
Additionally, by incorporating RBT, the proposed framework determines how investors and shareholders might respond to firm's core business efficiency and marketing capabilities. If an organization has consistently demonstrated an efficient utilization of its core resources like equipment and employees, it can serve as a positive signal in the stock market thus enhancing firm value. Similarly, brand managers with superior marketing capabilities can systematically inform the investors and shareholders as to how their brand value is being created and managed, thus enhancing investor confidence. This can lead to a more informed stock market response towards unanticipated positive and negative changes in brand equity. A simultaneous investigation of the complementary effects of CBEF and MCAP can encourage investment community not to simply rely on changes in brand equity to make investment decisions, rather conduct a more in-depth analysis of the organization's competence for better returns. It also recommends investment institutions and financial analysts to add management's *profitability* and *marketability* skills in in their toolkit when predicting the future performances of brands.

Apart from the key contributions discussed above, this study advances the existing marketing-finance knowledge from several other fronts. The final chapter of this thesis (conclusion) discusses all the research contributions in detail including a recapitulation of the ones which are outlined in this chapter.

1.4 Thesis Structure

Figure 1.1 provides a schematic view of the entire structure of this thesis. The diagram outlines the sequential flow of all the included chapters, highlighting the theoretical, methodological, and empirical segments.

Figure 1.1 Thesis Structure



Source: Author's elaboration

Chapter 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of the existing knowledge surrounding brand equity-firm performance relationship and the translatory role of organizational efficiency in this marketing-finance interface. Firstly, a critical review of the emergence of brand equity concept and its taxonomies is conducted. Focus is concentrated predominantly on consumer and firm based perspectives of brand equity measurement, discussing their individual characteristics, advantages, and potential limitations. These two brand equity dimensions are then more specifically explored in the context of their commercial measurement by identifying several globally known third party brand research institutions. Focus is then directed to understand the unique brand equity estimation methods adopted by Millward Brown BrandZ and Brand Finance, which represents the CBBE and FBBE measures, respectively, for this study. The discussion provides justifications as to how their estimations align with the CBBE and FBBE dimensions and their application in existing marketing literature. The subsequent sections then overview existing marketing-finance research investigating the value relevance of CBBE and FBBE, encompassing both their overall and directional effects. This is followed by a critical review of the current branding research exposing the inter-relationship between CBBE and FBBE, which provide directions for this study to conduct a systematic comparative analysis between them. Finally, the relevant RBT based research in marketing is identified which specifically explores the pivoting role of organization in the "marketing resources to firm performance" translation process. The segment begins with an overview of the emergence of resource based theory and its applicability in marketing research stream. It then overviews several organizational efficiency constructs that contributes to the marketing-finance interface either directly or indirectly. The chapter finally culminates with a short summary of the entire literature overview highlighting existing themes and potential research gaps which this study aims to address.

2.2 Emergence of Brand Equity and its taxonomies

A brand is an entity that endows a product or a service with an intangible additional value which extends beyond their functional capabilities (Farquhar, 1989; Aaker, 1991). Until today, the most common definition of a brand is that of the American Market Association's defining it as "a symbol, name, term or any other feature that identifies the seller's goods or services as distinct from those of other sellers" (AMA, 2020). Gabbot and Jevons (2009) argue that the term "brand" cannot have a single definition as it is a profound contextualized concept which can be approached via multiple aspects and understandings, leading to a continuous development process. This argument is further validated by a recent review of contemporary branding research stating that a brand cannot be recognized as a mere name for a product or service, rather it reflects the manufacturer or supplier's guarantee of quality and reliability which in turn binds customer's interest (Davick et al., 2015:4). This incremental value attached to a brand known as "brand equity" (Kerin & Sethuraman, 1998:261), therefore, is an outcome of continuously developing relationship within a brand and its stakeholders (Brahmbhatt & Shah, 2017). Since its inception in late 70s, brand equity has been identified as a major element of intangible off-balance sheet assets and have attracted considerable academic and managerial attention (Srivastava & Reibstein, 2005; Yang et al., 2015).

Chronologically Srinivasan (1979) is the first to detangle brand equity from the product value by estimating its “brand specific effect". The author argued that even if two products have almost identical attributes, their market share may vary substantially depending on their individual brand strength. Following these propositions, marketing research community explored this newly acknowledged intangible marketing asset in more depth and therefore many definitions of brand equity emerged thereafter. Shocker and Weitz (1988) defined brand equity as “the net present value of the incremental cash flows attributable to a brand name”. Aaker (1991) conceptualized it as a set of assets and liabilities associated with a brand name or symbol which has a potential of either contributing or harming the value of the product or service it provides.

Although brand equity has been recognized as a valuable marketing resource, yet there is no consensus about an appropriate approach to measure it (Datta et al., 2017; Davick et al., 2015). While marketing theorists have conceptualized brand equity from numerous perspectives, existing research in this area have broadly adopted two main approaches i.e. consumer based brand equity (CBBE) and firm based brand equity (FBBE) (Ahmad & Butt, 2012; Christodoulides et al., 2015; Torres et al, 2015). Keller (1993:2) define CBBE as “the differential effect of brand knowledge on consumers’ response to the marketing of the brand”. The proposed paradigm rests on the principle of customer’s psychology and measures their cognitive attachment and behavioural attributes towards a brand (Christodoulides et al., 2015; Yoo & Donthu, 2001). Firm based brand equity measure, on the other hand, captures the incremental value attained at the brand-level e.g. through strong brand name (Feldwick, 1996), product-market based measures (Cobb-Walgren et al, 1995; Dyson & Hollis, 1996; Ailawadi et al., 2003) or its financial market performance (Barth et al., 1998; Simon & Sullivan, 1993).

This brand equity dimension therefore focuses on monetary gains resulting directly from non-consumer based brand attributes such as *brand name* itself. Apart from CBBE and FBBE, there are several other brand equity perspectives emerging in the branding literature such as employees (Tavassoli et al., 2014), suppliers (Wang & Sengupta, 2016), channel members (Nyadzayo et al., 2011) and citizen based brand equity (Teodoro & An, 2018). However, following the popularity and acknowledgement of CBBE and FBBE as two key brand measurement dimensions, the current research embraces them to explore the holistic brand equity-firm performance relationship. The following sections conducts an in-depth review of both these brand equity measures to gain an understanding about their evolution, significance, potential shortcomings, and commercial measurement approaches.

2.2.1 Consumer Based Brand Equity (CBBE)

Consumer based brand equity is defined as "a set of perceptions, attitudes, knowledge, and behaviours on the part of consumers that results in increased utility and allows a brand to earn greater volume or greater margins than it could without the brand name" (Christodoulides & de Chernatony, 2010:48). This brand equity measure is therefore "memory associated" and captures the cognitive association of consumers to a particular brand (Keller, 1993). Of all the existing brand equity dimensions, consumer based brand equity is the most recognized in the existing marketing literature (Christodoulides et al., 2006; Veloutsou et al, 2020:41). This is because consumers are considered to be the main stakeholders in any business around whom the majority of actionable strategies are designed (Chatzipanagiotou et al., 2019; Keller, 1993). The concept of CBBE emerged in early '90s when Aaker (1991) proposed a conceptual framework incorporating brand awareness, loyalty, perceived quality, and brand association as the key determinants of consumer equity. The author argued that if consumers exhibit all these five attributes towards a brand, then it is very unlikely that they will switch to other alternatives available in the market. Keller (1993:2) also referred brand equity from a cognitive psychology perspective defining it as “the differential effect of brand knowledge on consumer response to the marketing of the brand”. They conceptualized CBBE through a “brand resonance pyramid” structure comprising a network of several ascending steps from bottom to top as: brand salience, brand performance, brand imagery, brand judgements, brand feelings and brand resonance being the peak (Keller, 1996; 2001). Simply by accessing the number of customers at each level, marketers can evaluate the degree to which their brand resonates in consumer’s hearts and minds (Brahmbhatt & Shah, 2017). Creation of strong consumer brand loyalty and association therefore requires maximum consumers at the pinnacle of the CBBE pyramid (Keller, 2013). Both Aaker and Keller’s models are perceived to be the building blocks of consumer focused branding structure and are most popular amongst marketing researchers because of their comprehensiveness and validity (Lehmann et al., 2008; Szocs, 2012). The subsequent literature extended their frameworks in more depth by focusing on individual CBBE subcomponents and their value generation capabilities. For example, Christodoulides and De Chernatony (2010) in their thorough examination of existing CBBE literature, divided it in two broad categories based on the adopted measurement style: *direct* and *indirect* approach. The former captures brand equity by detaching the value of a brand from the total price of the product based solely on consumer preferences. On the other hand, the indirect method adopts a more holistic approach by either adhering to CBBE’s theoretical dimensions (like those of Aaker’s and Keller’s) or via the accounting outcomes of customer equity e.g. price premium for its measurement. The authors support the superiority of the indirect CBBE measurement approach over the direct method as it provides a clearer picture of different drivers and sources of CBBE. For example, Srinivasan and Hanssens (2009) found “brand awareness” to be the main contributing source of customer equity. Fischer et al. (2010) measured brand equity as “brand relevance” and propose that a rise in consumer’s personal preference towards a particular brand impact their buying behaviour resulting in higher levels of CBBE. Profound marketing professor Bryon Sharp in his book *How brands grow* demonstrate the key role of “brand salience” in the creation of consumer based brand equity (Sharp, 2010). Through the lemonade stands example, the author argues that a continuous repetition of any distinctive feature of a brand (brand logo in this case) will have an eternal cognitive impact on consumer’s mindset. This psychological phenomenon leads to a differential customer’s preference towards a specific brand and influencing their response to marketing mix (Datta et al., 2017). In contrast to other traditional CBBE models that focus on holistic brand impact associated with a firm, Wang and Finn (2013) analysed consumer’s perceptions towards different product categories within a single brand. They developed a hybrid model by integrating various existing dimensions of CBBE and implying them to the subcategories of the master brand to facilitate the true sources of brand equity.

Above discussions signify that the existing literature on CBBE is dense and this concept has been approached via multiple aspects for its measurement. But still there is a disagreement within marketing researchers as to which consumer based attributes fully capture CBBE (for a detailed discussion, see Veloutsou et al., 2013). Additionally, despite being the most recognised brand measurement perspective, CBBE has some caveats which makes it incapable of solely capturing brand’s overall strength (Brahmbhatt & Shah, 2017). Firstly, the estimation of CBBE relies predominantly on the consumer's brand perceptions reflected at an individual level making the approach "*subjective*" in nature (Oliveira et al., 2015). Customer's responses gathered through experimental data collection techniques such as surveys and questionnaires lack broader implications as they may account for a specific framework designed by the researcher for a selective marketing mix (Kim et al., 2018). Another limitation of CBBE is its inability in effectively estimating brands pertaining to B2B businesses (Boo et al., 2009). Since B2B sector deals with internal transactions between corporate managers, suppliers, etc and have minimal interaction with the customers, CBBE measurement frameworks may not be able to identify the actual strength of such brands. The psycho cognitive nature of consumer based estimation approach may misinterpret brand's true value since different clusters of individuals in a marketplace have different levels of brand awareness, loyalty, and experience (Morgan, 2000). Also the level of consumer's association with a brand may vary across cultures, geography, and time (Davick et al., 2015). All these arguments suggest that determining brand equity merely through customer's cognitive response has limited significance and therefore relying on a single brand measurement perspective can only provide partial knowledge about holistic brand effects (Christodoulides et al., 2015). Therefore, it is suggested to include alternative dimensions of brand equity and conduct a simultaneous analysis of their value imparting capabilities to gain a complete understanding about the incremental value a brand imparts to a firm (Nguyen et al., 2015; Tasci, 2020; Yang et al., 2015). Following these recommendations, the current study includes another key brand equity measurement perspective i.e. firm based brand equity (FBBE) in order to analyse the holistic value relevance of brand equity.

2.2.2 Firm Based Brand Equity (FBBE)

In contrast to CBBE, firm based brand measurement perspective focusses on organizations rather than consumers for its conceptualization (Yildiz & Camgoz, 2019). FBBE is defined as "the tangible wealth emanated from the incremental capitalized earnings and cash flows achieved by linking a successful established brand name to a product or a service" (Kerin & Sethuraman, 1998:260**).** In generic terms, firm based brand equity reflects incremental value gained directly from a strong brand name rather than consumer's subjective perceptions about it. Its estimation process involves isolating the monetary value of firm's tangible assets like plants, equipment, etc and evaluating the incremental value gained from intangible components i.e. income through goodwill, patents, trademarks, and other intellectual property (Srinivasan et al., 2012). This intangible equity therefore is the outcome of the firm's marketing investments and applied management tools that can augment future cashflows emanated directly from strong brand presence. FBBE can be estimated either from firm's financial market performance such as future discounted cashflows (Amir & Lev, 1996; Kapferer, 1997; Simon & Sullivan, 1993) or product-market based measures such as profits and revenue premiums (Ailawadi et al., 2003; Boulding et al. 1994; Chaudhuri & Holbrook, 2001; Keller & Lehmann, 2006). Simon and Sullivan (1993) were the first to materialize FBBE by developing an econometric framework that can detangle firm's intangible value from its market capitalization and the worth of its tangible assets. They proposed that by doing so, a brand can be assigned with an *objective* monetary value which is a determinant of its brand equity. Similarly, Kapferer (1997:25) defined FBBE as "net cash flow attributable to the brand after paying the cost of capital invested to produce and run the business and the cost of marketing." The main advantage of estimating FBBE from the stock market perspective is its forward looking capabilities (Nguyen et al., 2015). According to the efficient market hypothesis, the current market value of the firm highlights the unbiased estimates of all its future incremental cash flows (Mizik, 2014). Thus it is the best source of predicting long term perspectives of investors, customers, and other stakeholders towards a branded firm. The proposed methodology by Simon and Sullivan (1993) still holds credibility and have been validated by many researchers in the marketing and finance literature (Kim et al., 2018; Nguyen et al., 2015; Schulze et al., 2012).

Adopting a relatively distinct approach, Mahajan et. al (1994) manifested firm based brand equity from a strategic management perspective of merger and acquisitions arguing that brand equity needs to be included in the balance sheet during such occasions. They estimated the value of the brand through a balance-model approach by interviewing key decision makers during such strategic operations including board members and senior executives. From the product-market perspective, Ailawadi et al. (2003) identified “revenue premium” to be the best determinant of firm based brand equity. Their study postulates that the excess income generated through the sales of branded goods as compared to similar unbranded counterparts is a result of the branding intangibles associated with these products. The main advantage of this approach is its ability to generate more reliable interpretations about brand’s actual strength since its measurement is based on actual market data rather than hypothetical consumer assumptions (Kim et al., 2018). Goldfarb et al. (2009) relied on consumer’s willingness to pay more for a branded product as compared to a similar private labelled offering to estimate FBBE. Their brand value estimations were based solely on the additional earnings gained because of a strong brand name excluding other factors such as price and advertising. Apart from the discussed studies, marketing academics have also materialized FBBE through other intermediary brand-based metrics like patents and trademarks (Damodaran, 2009); market share (Chaudhari & Holbrook 2001) and the residual stock market value (Srinivasan & Hanssens, 2009; Ferjani et al., 2009). A key similarity amongst all these constructs is their reliance on information economics context for brand equity valuations (Erdem & Swait, 2016). In sum, the term firm based brand equity represents both the product market and financial market measures such as enhanced revenues, profits, market share and returns, attributable to a firm solely due to its brand name (Yildiz & Camgoz, 2019).

Although CBBE is the most researched brand equity metric in the current marketing literature (Nguyen et al., 2015; Srinivasan & Hanssens, 2009), there are many factors that makes FBBE as an equally important brand equity dimension. Firstly, being primarily *objective* in nature, FBBE is relatively easy to measure and therefore marketing managers can conveniently gauge the effectiveness of their applied strategies on actual brand performance and compare it to their competitors (Kim et al., 2018). This can enable them to allocate marketing budgets more efficiently by differentiating between good and bad branding policies so as to appreciate long term profitability. FBBE allows firms to consistently evaluate their performance over time due to readily available financial and accounting data. Another advantage of FBBE is its ability to incorporate firm's market size and growth rate in its measurement since they impact future profitability significantly (Oliveira et al., 2015). Defining brand value from consumer's mindset fail to include these vital brand level performance factors as CBBE perspective is limited to capture human psychology through survey or experimental data (Kim et al., 2018).

Additionally, deriving brand equity from firm perspective would be an ideal measure for brands competing in the B2B sector. This is because B2B firms deal with industrial buyers rather than retail customers, therefore measuring brand equity at corporate-level would provide a more realistic view of their actual brand performance. There is an emerging body of marketing literature understanding brand equity from B2B context and have identified CSR (Chi-Shiun et al., 2010), corporate reputation (Van Riel et al., 2005), brand image (Davis et al., 2008) and brand trust (Alwi et al., 2016) as the potential determinants of "industrial brand equity" (Leek & Christodoulides, 2011). Although this study does not focus specifically on industrial brand equity, but these exploratory studies emphasize on the importance of evaluating brand equity at firm level, especially in B2B context. In sum, all these discissions reflects that firm based brand equity captures a completely distinctive dimension of brand's potential and therefore demands a close attendance.

However, as was with CBBE, firm based brand equity measurement perspective also has some caveats. First, it cannot explicitly estimate brand value at an individual brand level especially for the firms that owns cluster of different brands e.g. Unilever, P&G (Davick et al., 2015). Additionally, if FBBE is carved from the firm's stock value alone, the exposure to market noise may perhaps bias the true effect of brand equity on firm performance. Measuring brand equity from sales revenue perspective also has limited relevance due to its inability to foresee firm's future sales performance and thus levels of equity. Forthcoming revenues may vary due to changes in macro-economic and wider market conditions which is beyond the scope of firm's controllability.

The above review of the two key dimensions of brand equity validates the existing argument that no brand equity dimension can single handily capture its overall value relevance (Oliveira et al., 2015). Although consumer and firm based brand equity emanates from a same theoretical concept, they capture two mutually exclusive brand equity dimensions where the former relies on consumer's *subjective* brand judgments while the latter reflects *objective* brand-level incremental value. Additionally, where consumer brand association is more valuable for B2C brands, the performance of industrial brands would better be captured through firm-level brand equity. Both these measurement approaches therefore have limited diagnostic value on their own because of their unique strengths and weaknesses. This is why marketing academics recommend future research to incorporate multiple brand equity measures when exploring this complex and multi-facet construct (Chang & Young, 2016; Nguyen et al., 2015; Tasci, 2020). This would lead to a better understanding of "what actually brand equity is and what is constituent dimensions are?" (Christodoulides et al., 2015:309), the question which still lacks consensus amongst marketing academics (Ambler, 2003; Christodoulides & de Chernatony, 2010; Maio Mackay, 2001; Veloutsou et al., 2013).

2.2.3 Commercial valuations of brand equity

In addition to marketing theorists and academics, commercial research organizations have developed their distinct brand measurement models to quantify brand equity and its distinctive dimensions. These brand consultants transform intangible "brand equity" into a "dollar value or an index score" by integrating traditional theoretical frameworks with their specific financial modelling techniques. These estimations are led by experienced specialists in the fields of marketing, branding and consumer research who provide brand owners not only with brand's financial worth but also guidance for future brand growth (Budac & Baltador, 2013). Founded in 1974, UK based firm *Interbrand* is the first to introduce the concept of brand valuation with a promotional agenda of “brands as key value creators for business and society” (Duguleana & Duguleana, 2014). Interbrand’s methodology evaluates brand value by estimating net present value of brand’s future earnings based on analysts forecast, financial documents and other proprietary quantitative and qualitative information (more information available at www.interbrand.com). Although numerous brand consultants proliferated after the emergence of *Interbrand*, only few of them have been acknowledged globally and their brand estimations embraced by the academic research community. Table 2.1 provide a list of some of the prominent global brand consultants along with their website links, adopted methodological approach and whether their valuations are based on consumer or brand-firm attributes. The table also outlines representative studies which have either discussed their adopted methodologies or examined their value relevance, thereby emphasizing on their popularity amongst the marketing research community.

It is evident from the table that although all these institutions have their unique brand valuation approaches but from the “brand equity measurement focus”, they can be broadly divided into two groups. The first group keeps consumers as the epicentre of their valuation methodology, whereas the other set of consultants focus directly on brand based attributes such as brand earnings, analysts forecasts and royalties for quantifying its strength. For example, Young and Rubicam Brand Asset Valuator (Y&R BAV) conducts annual survey of more than 6000 US consumers to track five brand pillars of differentiation, relevance, esteem, knowledge, and energy to impart a score to each of these components (Mizik, 2014; Stahl et al., 2012). These five pillars represent consumer perceptions towards the fundamental brand attributes[1].

[1] See Stahl et al. (2012) for a detailed description about Y&R BAV model and its elements.

Table 2.1 List of prominent commercial brand consultants

Brand Consultant	Website Link	Methodology	Key Focus	Representative Studies
Brand Finance	www.brandfinance.com	Royalty Relief Methodology	Brand-Firm	Bagna et al. (2017); Yildiz & Camgoz, (2019); Gerekan et al. (2019)
Equitrend	www.theharrispoll.com	Brand Equity Index of three factors – Familiarity, Quality and Purchase Consideration	Consumers	Bhardwaj et al. (2011); Johansson et al. (2012); Nguyen & Feng (2021)
Interbrand	www.interbrand.com	Analyst Forecast and Projected brand earnings	Brand-Firm	Bagna et al. (2017); Dutordior et al. (2015); Johansson et al. (2012); Zampone & Sannino (2021)
Millward Brown BRANDZ	www.kantar.com	Brand Dynamics Pyramid	Consumers	Bagna et al. (2017); Chang & Young (2016); Dorfleitner et al. (2019)
Y&R Brand Asset Valuator	www.bavgroup.com	Five Brand Pillars of Differentiation, Relevance, Esteem, Knowledge, and Energy.	Consumers	Stahl et al. (2012); Mizik & Jacobson (2008, 2009b); Mizik (2014)

On the other hand, Brand Finance value a brand focussing mainly on the future brand income in the form of royalties earned through patents and trademarks that a brand owns (Brand Finance, 2022). Their valuation technique, therefore, does not rely on in-market consumer research but is a result of financial analysis conducted by “panel of experts” and market desktop research (Vasileva, 2016). On the other hand, BrandZ, which is Millward Brown’s brand equity database, captures consumer’s cognitive brand attachment through surveys over 30 countries, spanning over 10,000 brands. The key focus of their brand equity valuation methodology is to assess “the ability of a brand to appeal to relevant customers and potential customers” (Chang & Young, 2016:361). Similar to BrandZ, Equitrend’s brand equity measure is also based on consumer survey and thus represents CBBE (Johansson et al., 2012:235). However, their methodology differs from BrandZ such that their deigned model amalgamates three consumer attributes i.e. brand familiarity, perceived quality, and brand consideration to generate a one-number score (unlike BrandZ dollar valuations). The estimated brand equity score reflects the strength of the brand based on consumer feedback.

From the multitude of representative studies outlined in the last column of table 2.1, it is evident that academic research community have appreciated the brand equity valuations published by these commercial institutions. There are several reasons attracting marketing and branding academics to embrace these quantitative solutions to brand equity measurement provided by commercial brand professionals. Firstly, there is still a lack of literature contending as to which brand equity estimation method has more value relevance and reliability compared to the other (Christodoulides et al., 2015; Bagna et al., 2017). Additionally, it is argued that “consultants, through their daily activities, are in touch with a wide variety of branding problems, thus their knowledge of brands is broad, and their thinking reflects best brand management practice” (De Chernatony & Riley, 1998: 429). Besides this, these third party brand consultants are also viewed as a credible source of standardized brand metrics data since their valuations are not influenced by the brand owning firms (Mizik, 2014). These factors can be one of the driving force behind marketing academics to pursue brand equity estimations provided by third party consultants who are continuously tracking the market performance of commercial brands.

The second motivation is to empirically test the financial relevance of these brand valuations and to what extent they associate with the actual brand performance. For example, Mizik and Jacobson (2008) investigated whether the five perceptual brand attributes proposed by Y&R BAV have value relevance i.e. does they provide any incremental information to that of the firm's balance sheet performance in determining future firm value. Their findings suggest that only brand relevance and energy complements firm performance whereas other three pillars do not. Similarly, Bagna et al. (2017) examined the brand valuations provided by Interbrand, Brand Finance and BrandZ to investigate whether the stock market community respond to these annual publications. Their results show that the monetary estimations reported by all the three agencies are value relevant signalling that any changes in these valuations impact the investors and shareholder's decision making process, thus impacting stock returns.

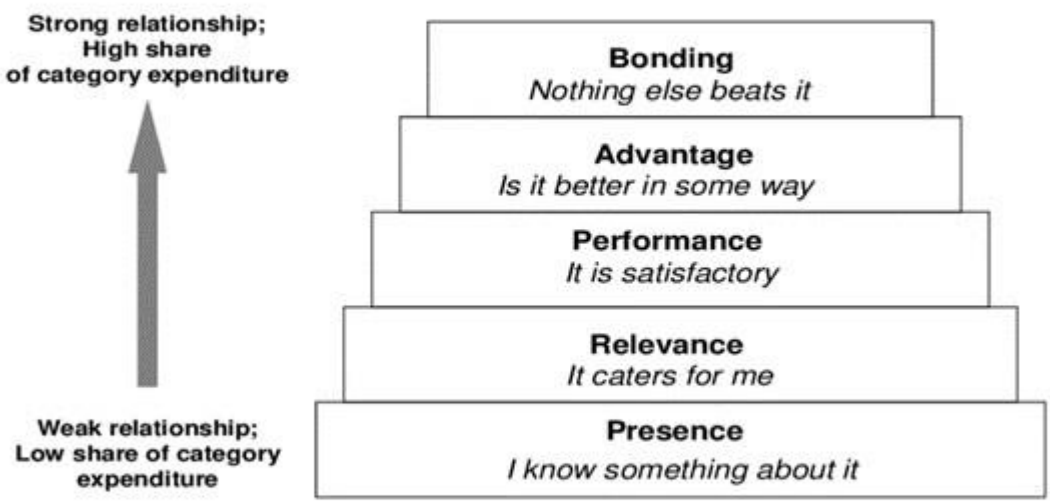
Thirdly and most importantly, the consistent tracking of brand performance and its quantification by these consultancies (e.g. through annual brand values or scores) is very beneficial for research which aims to explore the long-term implications of brand equity. Collecting consumer response data over such long time periods (e.g. monthly or yearly) through primary data collection approach such as surveys, questionnaires or interviews is generally not feasible because of high incurred costs (Chintagunta & Labroo, 2020). For these kind of studies, marketing academics and practitioners rely on brand equity data provided by secondary sources such as specialized commercial brand consultants (Budac & Baltador, 2013).

Since the core objective of this research is to explore the long-term value impact of brand equity on firm performance, the choice of brand equity measures provided by these institutions seems to be viable. After a careful assessment of the brand equity quantification techniques adopted by each of the consultants outlined in the table 2.1, estimations provided by Millward Brown BrandZ and Brand Finance are selected to represent CBBE and FBBE, respectively. The choice of these brand consultants is driven by many factors, the main and foremost of which is their adopted brand equity estimation techniques. BrandZ focuses primarily on consumer brand response for evaluating brand's strength, whereas Brand Finance rely on royalties earned from brand-level proprietary assets such as patents and trademarks (a detailed discussion about their methodologies is conducted in the next sections). The second driving force behind relying exclusively on these commercial institutions among others is the similarity in their unit of measurement. Both BrandZ and Brand Finance publish their brand equity estimations in monetary values (US dollars) and not through a score (e.g. Equitrend) or an index (e.g. Y&R BAV). Similar units of CBBE and FBBE estimations are crucial for this study as it also aims to conduct a comparative assessment between these brand equity perspectives, which otherwise would not have been possible. Finally, the choice is also driven by data accessibility where the brand valuations published by both the consultants are publicly available as compared to other institutions such as Equitrend and Y&R BAV which charge a significant fee for the data access.

2.2.3.1 Millward Brown BrandZ Valuation Methodology

In 1998, Millward Brown BrandZ and its subsidiary WPP developed a unique model to convert the firm's brand strength into financial value. The prime objective of BrandZ methodology is to detangle the monetary value generated by consumer association with a brand from its total financial worth. The first step involves determining the portion of current and future earnings that can directly be associated with the brand asset. Millward Brown scrutinizes firm's financial reports, Bloomberg database and data from their parent company Kantar Worldpanel to estimate these brand revenues (Financial Times, 2013). This so called "financial value" which the consultants perceive as "important but incomplete" is then augmented with the "brand contribution" element which is purely derived from the consumer research. Brand contribution is measured through a survey based approach covering more than 3.7 million consumers in over 50 market segments. The survey framework includes sequential series of five different levels, designed to estimate brand's abilities at each stage as compared to its competitors. These five steps constitute to make "brand dynamics pyramid" with stages identified as presence, relevance, performance, advantage, and bonding (shown in fig. 2.1).

Figure 2.1 Millard Brown BrandZ brand dynamics pyramid



Source: Vasileva, 2016

Each stage signifies the magnitude of relationship consumers have with a brand. The number of consumers at each stage determines the level of brand equity a firm enjoys. Brand presence is the base of the pyramid and captures consumer awareness towards a brand. The questions asked at this stage focus on assessing whether the consumers think of their brand when making a purchase in the product category which the brand offers (e.g. coca cola for soft drinks). If consumers are aware of the brand, then the next step enquires about its relevance to them e.g. “is it worth it? or “does it fits to your lifestyle?”. At the third step of the brand dynamics pyramid, consumers are asked to gauge the performance of the brand as compared to its competitors. A higher number of positive responses at this stage signal that customers perceive the brand with a specific identity. The next phase of the pyramid captures if the brand has outperformed the market by offering high quality products and services reflected through enhanced consumer experience. The consumers exhibit higher levels of emotional attachment with the brand at this stage. The final and the most crucial phase of the consumer-brand relationship is “bonding” which reflects brand loyalty. Consumer responses recorded at this stage are about the level of commitment they have with the brand and if the brand share their values. Positive feedback at this stage signifies a strong bond between the brand and the consumers. The full questionnaire designed by Millward Brown to estimate “brand contribution” is outlined in table 2.2. The respondents are asked to rank each question on a five point scale with 1 being “totally disagree” and a score of 5 signifying strong agreement. It can also be noticed in fig. 1 that the width of each level keeps on decreasing as we ascend towards the top of the pyramid. This signifies that not all consumers that show brand awareness and relevance would end up being bonded and loyal. The higher the number of consumers in upper levels of pyramid, the stronger is their relationship with the brand, thus higher the brand contribution score. Research have also reported that the slice width at each level also vary according to the type of product offered by the brand (Dyson & Hollis:1). The brand contribution score gained from the brand dynamics survey model is then multiplied with the previously calculated "intangible financial value" to impart a dollar value to a brand.

Table 2.2 Millward Brown "Brand dynamics Pyramid" survey questionnaire

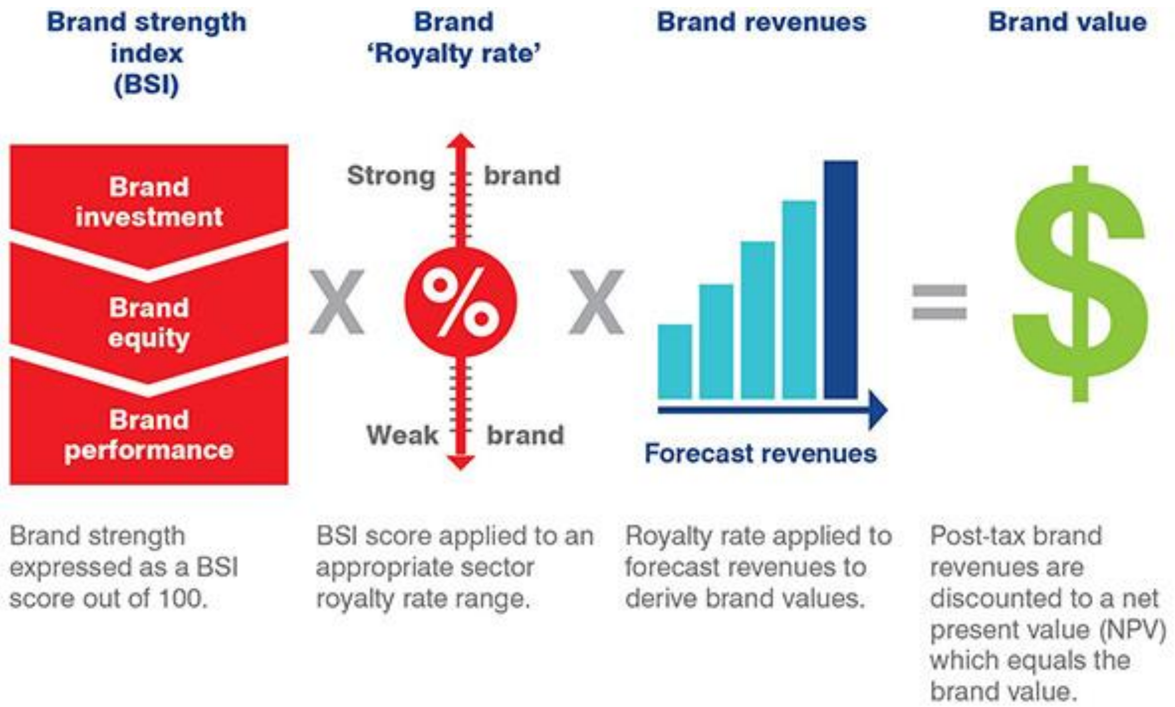
CBBE Attributes	Questions
Presence	I often encounter this brand. There are a lot of ads and other information about this brand. When you think of "add similar branded product", do these brands come to mind? This brand is easy to find.
Relevance	The brand is relevant to me. The brand is relevant to my family and/or close friends. This brand is a good one for me. This brand fits my lifestyle.
Performance	The brand performs well. The brand is effective. This brand lives up to its promises. This brand has served me well.
Advantage	This brand is better than others. This brand offers a clear advantage vs. the competition. In terms of the important attributes of "add similar branded product name" is this brand is better.
Bonding	I am strongly committed to this brand. This brand shares my values. This brand has earned my confidence.

Source: Lehmann et al. (2008)

2.2.3.2 Brand Finance Valuation Methodology

The brand valuation source which is approached to operationalize firm based brand equity is UK based consultancy firm "Brand Finance". Brand Finance utilize "royalty relief methodology" to estimate the exchange value of the brand based on pre-existing market transactions such as royalty rates and forecast future brand revenues through complex financial modelling. The first step is to calculate a brand strength index score (BSI) for each brand ranging between 0 to 100 using a balance scorecard approach. The balance scorecard includes key performance indicators (KPIs) measuring the financial performance and sustainability of the brand owning firm. The next step is to calculate an appropriate royalty rate that a brand under evaluation would charge its hypothetical new acquirer based on its current worth. In simple terms, it is the percentage share of brand specific revenues that a licensee would pay to the brand owning firm (the licensor). In order to estimate the brand specific royalty rate, firstly, the range of previously paid royalties within the same industry sector is determined. Brand Finance use their exclusive database of historical licensing agreements and other credible sources to access this information. They then scale this range to the calculated BSI score to impart a proportional royalty rate to the brand. For example, if the royalty rate in a comparable previous licensing transactions within the brand sector ranges from 0 to 5% and the calculated BSI score is 80, the applicable royalty rate is 4%. After determining the royalty rate, the third step is to apply it to the projected future revenues derived solely from the brand asset. Brand Finance have a team of experienced financial analysts and market experts who use complex financial modelling techniques to forecast these brand derived earnings. These predicted future brand royalties are adjusted for tax and then discounted at an appropriate rate of return to calculate its net present value which corresponds the brand's dollar value. The discount rate is obtained by running a competitive analysis against the competing brands and estimating the brand specific risk coefficient (beta estimation). Figure 2.2 summarizes the Brand Finance royalty relief methodology.

Figure 2.2 Brand Finance Methodology



Source: www.brandfinance.com

The royalty relief methodology is a widely acknowledged evaluative practise which is in accordance with the international accounting standards (Rubio et al., 2016). In the year 2010, International Organization for Standardization (ISO) introduced BSI ISO 10668 *Brand Valuation standard* which outlined the procedures to value a brand efficiently. The core of this financial analysis standard is to estimate the brand value by evaluating the royalty payments received by comparable brands for licensing their patents and trademarks in the existing transactions. Since the brand is not actually being bought or sold, these royalty rates are termed as a "relief from royalty" which a firm is entitled to, based on its current and future brand earnings (Duguleana & Duguleana, 2014). This is why this approach is named as a royalty relief methodology and is considered as the most important evaluation tool both by international finance reporting standards (IFRS) and accounting researchers (Rubio et al., 2016). Infact, David Haigh who is the current CEO of Brand Finance was the member of the committee which introduced BSI ISO 10668 financial brand evaluation standards. His contribution in standardizing the monetary brand measurement using financial modelling techniques has made Brand Finance one of the leading accounting based brand valuation agencies in the world.

An insight of BrandZ and Brand Finance methodologies clearly indicates that although both of them capture the current and future brand earnings to monetize brand equity, their core measurement metrics are entirely different. Millward Brown place consumer perception and association as an epicentre of the brand measurement framework. Since the “brand contribution score” attained from quantitative consumer research is the sole multiplier to the brand revenues, its magnitude directly impacts the estimated brand value. The higher the number of consumers in the top levels of “brand dynamics pyramid”, higher is their emotional bonding with the brand, thus higher will be brand value. Millward brown claims that BrandZ methodology is unique to other approaches because of their main focus on customer viewpoint rather than expert’s opinion in valuing brands. The brand valuations estimated from a large database of over 3.5 million consumers in more than 30 countries and 50 market segments validates its use as a proxy of consumer based brand equity for this research. On the other hand, the methodology adopted by Brand Finance relies on brand based accounting and financial aspects in determining its monetary value. Their estimated brand values reflect three brand measurement aspects; a) transactional value if a same brand is to be bought or sold; b) cost involved in recreating that brand and c) the net present value based on future income generated solely through the brand name (Abratt & Bick, 2003). The use of royalty rate as a key multiplier to these brand measures make the final brand values a function of licencing fees earned from firm's intangibles such as patents and trademarks. This adherence of their methodology to the ISO accounting brand measurement standards makes the brand values published by Brand Finance as an optimal choice to represent firm based brand equity.

2.3 Brand equity and firm performance

Irrespective of the measurement perspective, marketing literature is conclusive that brand equity is one of the most significant strategic marketing assets that imparts an incremental value to a firm (Hsu et al., 2013; Keller, 2012; Vomberg et al., 2015). Existing marketing-finance research seeking to investigate brand equity-firm performance interface can be segregated into two broad categories, based on the observed time horizon. The first group of studies focus on short-term profitability metrics and are termed as "predictive ability studies" while the second set of research embrace long-term firm performance measures and are categorized as "value relevance studies" (Verbeeten & Vijn, 2010:649). *Predictive ability* based research links brand equity to firm's current period accounting-based performance measures. For example, Kim et al. (2003) employs sales revenue as the firm performance metric to investigate the financial contributions of Aaker's (1991) CBBE components of brand awareness, image, loyalty, and quality in the Korean luxury hotel industry. Their results show that apart from brand awareness, all other consumer based brand equity elements are positively related to the current period profitability measure. On similar grounds, Srinivasan et al. (2010) found that the sales performance outcome of consumer brand liking accounts for almost one-third of the total generated revenue. Verbeeten and Vijn

(2010) identifies ROI as a determinant of current accounting measure claiming that brand differentiation i.e. the ability of a brand to “stand out in the crowd” is its main driver. Stahl et al. (2012) provided further supportive evidence that brand differentiation also has a positive relation with immediate financial performance measure of profit margins. Fischer and Himme (2017) adopted a relatively different approach and propose a brand value chain framework linking brand equity to various balance-sheet measures simultaneously. They argue that by doing so, potential interconnections can be made within these accounting metrics and strategic marketing asset, without which their collective informative value is limited for management (Fischer & Himme, 2017:138). Their model shows that marketing investment like advertisements elevates brand equity which in turn enhances firm’s financial resources and capital structure which consequently reduces debt, thus improving credit ratings. Products and services offered by well established brands also enjoy higher customer loyalty and low switching probability leading to a strong balance-sheet performance due to streamlined cashflows and sustainable price premiums (Steenkamp, 2014; Wang et al., 2015).

The short-term financial implications of brand equity have also been explored in an international setting. For example, Oliveira-Castro et al. (2008) studied the relationship between CBBE and firms’ accounting performance measures of market share and revenue across 15 supermarket product categories in Brazil and the UK. The research outcomes signify that CBBE has a significant positive impact on short-term brand performance measures in both the countries, however their inter-relationship level varies based on the product category type. Extending the knowledge about “international CBBE” (Christodoulides et al., 2015), and differentiating global and local brands, Zarantonello et al. (2020) analysed whether CBBE components of brand awareness, perceived quality, brand associations, perceived value, and brand loyalty drives short-term firm performance measured by firm's market share. The findings indicate that although all the identified CBBE components are positively related to firm performance, the strength of their association for global versus local brands depend on country's economic development. The comparative assessment reveals that in developed countries, local brands perform much better than global brands through a stronger association of all their CBBE elements with firm performance (except brand association). Conversely, in emerging countries, global brands are favoured by consumers over local brands with their market share linked to all the investigated CBBE components. Collectively, these studies signal that the positive impact of brand equity on short-term firm performance does not alter significantly based on the country's macro-economic status, thus providing cross-nation validity of this relationship.

Having a contrary view, the second category of research, i.e., "value relevance studies" follow a macro approach and capture long-term financial implications of brand equity through stock market performance (Verbeeten & Vijn, 2010:649). The choice of financial market valuations as an adequate measure of long-term firm performance is driven by the theoretical underpinnings of efficient market hypothesis (EMT) (Fama 1970, 1991). According to EMT, current stock price reflects the net present value of the total future cashflows associated with the firm (Lim & Brooks, 2011). Therefore, the market value of the firm signifies investors and shareholder's sentiments about its future prospects based on publicly available information such as brand likeability (Kirk et al., 2013). Any changes in the levels of firm's brand equity would alter their expectations about firm's future cashflows, thus moving the stock price. This *forward looking* characteristics of stock markets therefore makes them an ideal candidate to measure the true value relevance of “gradually evolving” intangible marketing assets like brand equity (Srinivasan et al., 2012; Mizik & Jacobson, 2009a; Yeung & Ramasamy, 2008). In contrary, having a myopic view, current-term profitability measures such as profits and price premium can only explain brand equity-firm performance relationship partially, missing its true value relevance (Srinivasan & Hanssens, 2009). This is why Aaker and Jacbson (2001:485) argue that “accounting measures alone cannot adequately explain firm value, because they fail to capture the benefits of investing in intangible assets such as brands”. These arguments are further supported by the longitudinal study by Mizik (2014) which assesses the total financial impact of Y&R BAV brand equity dimensions from 2000 to 2010. The findings indicate that the contribution of brand equity on the current year performance is mere 3% whereas the rest 97% of its impact is realized in the future performance measure of stock returns. The author asserts that “building strong brands require significant initial investments which might take several years to recoup, therefore understanding its impact on future earnings is necessary for allocating appropriate resources for marketing activities” (Mizik, 2014:94). Even a recent meta-analysis reports a significant rise in the deployment of stock market based indicators as a measure of firm performance in the top three marketing journals (Katsikeas et al., 2016).

The evaluation of two distinctive lines of research focusing on brand equity-firm performance nexus makes it clear that the stock market based metrics are efficient in predicting firm’s future prospects instead of immediate accounting measures. Since, the core objective of this study is to explore the long-term financial consequences of brand equity, the current research falls into the “value relevance studies” category. Emphasis can therefore now be shifted on the relevant marketing-finance literature exploring the brand equity-firm performance relationship from the capital markets perspective. Table 2.3 provides an overview of prior empirical research in the fields of marketing, branding, management, and finance that have examined the impact of brand equity on different stock market measures. Focus has predominantly been laid on identifying studies involving consumer and/or firm-based brand equity measures in their investigations. The second, third and fourth columns specifically tabulate these aspects outlining the adopted brand equity dimension, type of brand equity measure and source of the acquired data. The subsequent columns contain other vital information about these studies and will be cross referred at the various stages of the thesis. All the representative studies are arranged in a reverse chronological order such that the most recent studies lead the preceding research.

Perhaps the most iconic research exploring the value relevance of branding is of Aaker and Jacobson (1994) where they explore whether perceived quality of branded products provide any incremental information to the stock market community. Using Equitrend's consumer response data as perceived quality measure and stock price as a predictor of firm performance, they found that financial markets respond to unanticipated changes in perceive brand quality and its impact on market value is beyond the effects of accounting performance measures such as earnings. The novel work of Aaker and Jacobson (1994) has gained widespread recognition "as an evidence of brand's ability to create shareholder value" (Madden et al., 2006:5). Aaker and Jacobson (2001) further advanced their research and assessed whether another key component of CBBE i.e. consumer brand attitude has a similar relationship with firm's long term performance. Using consumer survey data in computer related industries, they tested whether investors and shareholders perceive changes in brand attitude as a source of information which is incremental to that reflected in current-term balance sheet metrics. Their findings suggest that, similar to perceived quality, brand attitude leads accounting performance measures in explaining stock returns and therefore is a reliable predictor of future financial performance.

Table 2.3 Representative research in marketing linking brand equity to long-term firm performance

Author(s)	**B.E Dimension(s)**	**B.E Measure Type**	**B.E Measurement Source**	**B.E *at Levels* or *in Changes***	**Industrial Sector**	**Country(s)**	**Firm Performance Metric**	**Study Time period**
Rahman et al. (2019)	FBBE	Brand Valuations	Interbrand	At levels	Diversified	US	Market Share & Tobin's Q	2000-2013
Yildiz & Camgoz (2019)	FBBE	Brand Valuations	Brand Finance	At levels	Diversified	Turkey	Stock Returns	2009-2014
Oliveira et al. (2018)	CBBE	Brand Valuations	Millward Brown BrandZ	N/A	Diversified	Latin America	Stock Returns (Portfolio based)	2004-2013
Chang & Young (2016)	FBBE	Brand Valuations	Brand Finance	At levels	Diversified	US	ROA & Tobin's Q	2009 & 2011
Wang & Sengupta (2016)	FBBE	Brand values	Interbrand	At levels	Diversified	Multi-National	Tobin's Q	2005-2008
Vomberg et al. (2015)	CBBE	Brand Index Score	Equitrend Database		Services & Manufacturing	US	Tobin's Q & Cash flow	2002-2009
Yang et al. (2015)	FBBE	Revenue Premium	COMPUSTAT Database	In Changes	Semiconductor	US	Stock Returns	1990-2006
Dutordoir et al. (2015)	FBBE	Brand Valuations	Interbrand	In Changes	Diversified	US	Stock Returns	2001-2012
Himme & Fischer (2014)	CBBE	Customer Satisfaction	ACSI Scores	At levels	Diversified	US	Stock Market Beta	1991-2006

Table 2.3 *(continued)*

Author(s)	**B.E Dimension(s)**	**B.E Measure Type**	**B.E Measurement Source**	**B.E *at Levels* or *in Changes***	**Industrial Sector**	**Country(s)**	**Firm Performance Metric**	**Study Time period**
Mizik (2014)	CBBE	Consumer brand perceptions					Mizik (2014)	CBBE
Nam & Kannan (2014)	CBBE	Users Social Tags	Social tagging website: *Delicious*	In Changes	Diversified	US	Stock Returns	2006-2010
Feng et. Al (2013)	FBBE	Brand Valuations	Interbrand	N/A	Diversified	Multi-National	Stock Returns (Portfolio based)	2001-2010
Kirk et al. (2013)	FBBE	Brand Valuations	Interbrand	At levels	Consumer vs Industrial	US	Market Capitalization	2001-2008
Johansson et al. (2012)	CBBE & FBBE	Brand Valuations	*CBBE:* Equitrend Database *FBBE:* Interbrand	At levels	Diversified	Multi-National	Stock Returns	2008 Financial Crisis *(01-09-2008 till 31-12-2008)*
Bhardwaj et al. (2011)	CBBE	Consumer brand quality	Equitrend Database	In Changes	Diversified	US	Stock Returns	2000-2005
Rego et al. (2009)	CBBE	CBBE Index	Equitrend Database	At Levels	Diversified	US	Stock return volatility	2000-2006
Mizik & Jacobson (2009)	CBBE	Consumer brand metrics	Y&R Brand Asset Valuator	At Levels	Diversified	US	Stock Returns	2000-2006

Table 2.3 *(continued)*

Author(s)	**B.E Dimension(s)**	**B.E Measure Type**	**B.E Measurement Source**	**B.E *at Levels* or *in Changes***	**Industrial Sector**	**Country(s)**	**Firm Performance Metric**	**Study Time period**
Mizik & Jacobson (2008)	CBBE	Consumer brand perceptions	Y&R Brand Asset Index	In Changes	Diversified	US	Stock Returns	8 Years (unequally spaced)
Yeung & Ramasamy (2008)	FBBE	Brand Valuations	Interbrand	At Levels	Diversified	US	Market Capitalization and Stock Returns	2000-2005
Madden et al. (2006)	FBBE	Brand Valuations	Interbrand	N/A	Diversified	US	Stock Returns (Portfolio based)	1994-2000
Mortanges & Riel (2003)	CBBE	Consumer brand perceptions	Y&R Brand Asset Index	In Changes	Diversified	Netherlands	Stock return, EPS & MTBV	1993-1997
Aaker & Jacobson (2001)	CBBE	Consumer Brand Attitude	Survey data by *Techtel Corporation*	In Changes	Computer Technology	US	Stock Returns	9 Years (unequally spaced)
Aaker & Jacobson (1994)	CBBE	Perceived Brand Quality	Equitrend Database	In Changes	Diversified	US	Stock Returns	1991-1993

Notes: B.E: Brand Equity; CBBE: Consumer based brand equity; FBBE: Firm based brand equity; ASCI: American Customer Satisfaction Index; ROA: Return on Assets; EBIT: Earnings before interest and taxes; EPS: Earnings per share; MTBV: Market to book value N/A: Not Applicable

Marketing-finance research has flourished since the evolutionary studies of Aaker and Jacobson (1994, 2001) and academics from diverse research streams especially from marketing, management, and finance, have further explored several brand equity dimensions and their contributions to firm's future performance. For instance, Mortanges and Riel (2003) explored the firm value relevance of brand strength and brand stature modelled from Y&R BAV consumer brand attributes of knowledge, esteem, relevance, and differentiation[2]. The results demonstrate that changes in brand strength results a similar change in firm's market-to-book value and brand stature is positively associated with stock returns. These findings advocate that consumer based brand equity has a significant positive relationship both with firm's current market value and its future growth prospects. Providing further evidence, Mizik and Jacobson (2008) assesses the value relevance of each of the five brand pillars of the updated Y&R BAV model (i.e. differentiation, relevance, esteem, knowledge, and energy). The results reveal that of these consumer perceptual brand attributes, brand relevance and energy explain long-term firm performance through their positive impact on stock returns. The effects of brand esteem and brand knowledge, however, are reflected in the current period accounting performance. Overall, these findings suggest that information contained in Y&R BAV brand metrics is value relevant. Bhardwaj et al. (2011), on the other hand, retrieved CBBE data from Harris Interactive's Equitrend database to examine its effects on shareholder's wealth. Their findings indicate that consumer's perception of branded product quality is a key determinant of firm's future-term growth and any unanticipated changes in consumer brand response drives stock prices in the

[2] The authors grouped brand relevance and differentiation scores to formulate *brand strength* and components of knowledge and esteem to operationalize *brand stature*.

same direction. Kirk et al. (2013) used FBBE oriented Interbrand's brand valuations to access whether changes in brand strength over time attracts market attention and therefore impact stock returns. The study reports a strong association between movement in brand valuations and firm value signifying that enhancement in brand equity levels have a concrete and measurable effect on firm's long term performance. Infact, an event study conducted by Dutordoir et al. (2015) find that the annual Interbrand brand valuations generate significant abnormal returns on the announcement day with a brand equity-firm value conversion rate of nearly 4 percent[3].

Adopting a relatively different approach, Mizik and Jacobson (2009b) employed conditional multiplier analysis to investigate whether brand equity can improve the predictive accuracy of evaluating firm's market value. The authors accomplish this by deriving a "sales multiplier" which can be applied to the actual revenue figures to attain best estimates of future firm value. Using Y&R BAV database, the designed brand valuation model demonstrates that brand equity significantly improves firm value estimation power through its direct effects on the sales multiplier (Mizik & Jacobson,2009b:151). These findings suggest that apart from enhancing firm value, brand equity is also a significant predictor of firm's future growth. Besides its direct contributions, brand equity has also been established as a potential moderator, complementing the positive effects of stakeholder's relationships on firm performance (Wang & Sengupta, 2016).

[3] Although in the first instance, 4% conversion rate may look negligible, however brands included in the Interbrand list are large firms with market capitalization in billions of dollars. A 4% change in market value within a single day is therefore phenomenal.

Along with generating shareholder's wealth through enhanced returns, academics have also advocated the risk mitigating capabilities of brand equity. For example, Madden et al (2006) created a portfolio of stocks including US brand-firms from Interbrand's list of "most valued brands" from 1994 till 2000 and gauged its performance against the broader market index (e.g. NYSE). The seven year portfolio performance asserted that brands with strong equity tend to yield higher returns with reduced risk as compared to the overall market, thus creating value for their shareholders. Oliveira et al. (2018) ran a similar empirical analysis but in a different geographical setting covering developing Latin American countries (in contrast to developed US). The portfolio comprising of "Most Valuable Latin American Brands" published by Milward Brown BrandZ experienced lower stock price volatility (i.e. risk) as compared to the benchmark companies signifying that brand equity has risk mitigating capabilities even in highly volatile emerging economies[4]. These findings are further supported by Yildiz and Camgoz (2019) demonstrating that strong brands in other emerging markets such as Turkey exhibit similar performance by averting risk during unstable stock market environments. Voss and Mohan (2016) provide further evidence that brands with strong consumer association not only outperform broader markets in market downturns but exhibit similar performance during uptrends as well. Himme and Fischer (2014) focused not only on the stock market-based risk factors but also included debt holder's risk (through credit ratings) to examine the risk averting capabilities of customer satisfaction measured through "American Customer Satisfaction Index" database. The research outcomes affirm that higher consumer brand satisfaction (which is a CBBE component)

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[4] The term "Risk" in financial markets correspond to volatility in stock price movement over time. Higher the volatility, higher is the market risk.

reduce both the default risk (i.e. credit spread) and systematic risk (i.e. stock market beta). Adopting a relatively distinct approach, Chang and Young (2016) analysed how US brands faired during the tough economic times of the late 2000s as compared to their non-branded rivals. Including the top global brands published by Brand Finance, the results document that branded firms performed relatively better than their unbranded counterparts during these unprecedented economic times. These findings further affirms that brand equity is perceived as a valuable intangible marketing asset by stock market participants even during tough market environments.

Based on the overview of the existing literature exploring the brand equity-firm performance linkage, it can be concluded that both consumer and firm based measures of brand equity are value relevant both from the performance enhancement and risk mitigation perspectives. Almost all the studies outlined in table 2.3 have reported a significant relationship of CBBE and FBBE with long term firm performance measured through capital market valuations. One exception is the study by Yang et al., (2015) which reports an insignificant link between FBBE measure of revenue premium and abnormal stock returns. The authors suggest that such anomaly can be due to the reliance on a single aspect of brand equity, therefore recommend future investigations to embrace multiple brand equity measurement perspectives. Table 2.3 also validates these arguments since most studies (except Johansson et al., 2012) have included a single brand measurement construct in exploring brand equity-firm value nexus. Incorporating multiple brand equity measures and conducting a comparative assessment of their individual value imparting capabilities can provide robust inferences about its holistic value relevance which is still lacking in the existing literature (Huang & Sarigöllü, 2014; Tasci 2020).

Another striking feature of the prevailing research is that the academics have adopted brand equity measures both in static (in levels) and dynamic (in changes) state when exploring its long-term financial relevance (refer to column 5 of table 2.3). However, it is strongly recommended that marketing academics should avoid linking firm performance metrics directly to the levels of marketing variables especially when analysing their long term relationship through stock market indicators (Srinivasan & Hanssens, 2018:9). Investors (especially big institutional) are closely and constantly scanning the marketing environment for any brand related updated information (McAlister et al., 2012). It is only the change in the brand's strength (favourable or unfavourable), that would attract their attention thereby triggering a stock price movement (Luo et al., 2013). For these reasons, linking contemporaneous levels of brand equity with stock returns hold limited significance because it is the "change in brand equity" that explains the true firm value translation capabilities of brand rather than its absolute values (Christodoulides et al, 2015). This anomaly can be realized in the empirical study by Yeung and Ramasamy (2008) in which they attempted to link contemporaneous measure of brand equity (Interbrand brand valuations) to firm performance both through stock price and return models. They found a strong association between brand equity and stock prices however reported insignificant results for the market returns model. These results indicate that firm based brand values estimated by Interbrand are closely related to firm's market value but does not explain future returns. This contradiction arises possibly due to temporal aggregation of data where static brand equity estimations are linked directly to the stock returns, which is in-fact a measure of "change in stock price". Marketing academics therefore suggest that future studies should focus on changes in brand equity so as to analyse its impact on long-term firm performance (Huang & Sarigöllü 2014).

2.3.1 Linking brand equity and firm performance: A directional approach

Until now, it is clear that changes in both consumer and firm based brand equity are associated with long term firm performance. However, the incremental value that a brand enjoys either from consumer cognitive attachment or directly from strong brand name is susceptible to increase or decrease over time and such deviations happen in real time (Veloutsou & Guzman, 2017). There can be several favourable and unfavourable market factors driving these changes such as enhanced stakeholder relationship (Wang & Sengupta, 2016), marketing and network capability (Zhang et al., 2015), social media communication (Schivinski & Dąbrowski, 2013), sales promotion (Valette-Florence et al., 2011), negative word of mouth (Sachse & Mangold, 2011), complaints (Japutra et al., 2014), negative product reviews (Ullrich & Bruner, 2015) and brand evangelism (Marticotte et al., 2016). Either way the brand strength is prone to grow or decline over time depending on the severity of these market response elements. Management therefore needs to continuously monitor their brand performance and pay close attention to such unexpected positive or negative shifts in their brand's equity. Without realizing the financial consequences of these directional changes, marketing managers can over- or underestimate their brand's true value relevance leading to suboptimal future performance (Luo et al., 2013, Veloutsou & Guzman, 2017). Despite its importance, research examining the firm value effects of positive and negative changes in brand associated attributes is relatively rare. Table 2.4 organizes these handful of studies, listing the investigated brand response measure, acquired firm performance metric, data collection interval and key findings. Luo et al. (2013) inspects the effect of brand dispersion i.e. the upside and downside variance in consumer brand ratings on firm value measured through stock returns. Their findings report a heterogeneity in brand rating-firm value dynamics where the impact of downside dispersion is significantly higher as compared to the upside dispersion. The authors suggest that a higher volatility in consumer brand perceptions signals *brand inconsistency* (Luo et al. 2013:400). Due to this, brand loses credibility amongst investors which then pursue it to be unreliable, thereby weakening firm's future cash flows.

Apart from brand dispersion, the scholarship in this area have also focussed on the directional firm value effects of few other consumer based attributes. For example, through an event study analysis, Tellis and Johnson (2007) explore the stock market reactions to product quality reviews published by *The Wall Street journal* on and around the information release day. The authors particularly focus their interest in evaluating whether there is a discrepancy in how negative product reviews impact stock returns as compared to a positive reviews. The findings indicate that there is an asymmetry in the stock market response of negative versus positive reviews such that the former outweighs the latter by a significant margin. In other words, investor react more aggressively towards information pertaining to unfavourable consumer response is more aggressive as compared to favourable product quality feedback, resulting in significant deterioration of firm value. Ho-Dac et al. (2013), on the other hand, investigate the effect of positive and negative online consumer reviews acquired from Amazon.com across Blu-ray and DVD player category. The resulting empirical evidence reveal that positive OCRs enhance firm's sales levels for strong brands and negative OCRs deteriorates the sales revenue for weak brands[5]. Tirunillai and Tellis (2013) examines whether user generated content (UGC) through online consumer chatter about product reviews and ratings have any relationship with stock market performance. The findings unveil an asymmetry in the impact of positive and negative UGC such that the firm value erosion due to negative consumer sentiments is significantly higher as compared to positive feedback. Additionally, negative consumer ratings and reviews also increase the stock price volatility (risk) signalling uncertainty amongst investors about firm's future growth prospects.

[5] The strong and weak brands were differentiated based on Interbrand's yearly brand valuations and rankings.

Table 2.4 Empirical studies exploring directional effects of consumer brand response

Author(s)	Investigated Measure	Firm Performance Metric	Data collection frequency	Key Findings
Ho-Dac et al. (2013)	Online consumer reviews (OCR)	Sales	Weekly	Positive OCR has a significant positive relationship with sales whereas negative OCR does not. Negative OCR weakens sales for weak brands.
Luo et al. (2013)	Brand rating dispersion	Stock returns	Daily	Downside dispersion has a greater effect on stock returns as compared to the upside dispersion.
Tirunillai & Tellis (2013)	User Generated Content (UGC) through online chatter	Stock returns	Daily	Negative UGC has significant negative effect on abnormal returns than positive UGC. Negative UGC also increases risk.
Sun (2012)	Consumer product rating dispersion	Sales	Not defined	In the presence of higher variance in consumer ratings, products with lower ratings enjoys higher sales as compared to high ranked products.
Luo (2009)	Negative word of mouth	Stock Returns	Monthly	Consumer complaints towards a brand have both short-term and long-term consequences gauged through firm's cash flows and stock prices, respectively.
Tellis & Johnson (2007)	Product quality reviews	Stock returns	Unequally spaced	Inferior product quality reviews lead to significantly lower abnormal returns and this negative effect is larger than the return response of positive effects of good reviews.
Luo (2007)	Negative consumer experience	Stock returns	Monthly	Higher levels of consumer negative voice have a significant negative impact on stock returns.

Apart from investigating the polarized view of consumer brand response, few other studies have focused solely on the negative side of consumer experience and its long-term impact on firm performance. These include empirical work of Luo (2007) and Luo (2009) where they quantify the financial impact of negative consumer response in the US airline industry. The results however are directionally in-line with the previous discussed studies, conveying that negative consumer experience have both short and long-term impact on cashflows (only Luo, 2009) and stock returns, respectively.

Several research gaps can be realized based on the review of the existing literature exploring the directional firm performance impact of positive and negative consumer brand response. Firstly, as evident in table 2.4, the subject about the polarized brand equity-firm value relationship has not been sufficiently addressed by the current marketing-finance research stream with only handful of studies. It is therefore crucial to extend this knowledge further by exploring the asymmetrical firm performance effects of rising and declining brand equity so as to understand its true value dynamics.

Secondly, existing studies have concentrated solely on the consumer side of brand equity, ignoring other brand measurement perspectives. The only exception is the study by Xiong and Bharadwaj (2013), which examines the stock market impact of positive and negative news related to a brand[6]. A news release about a brand can contain negative or positive information of any nature e.g., change in consumer sentiments, brand earnings or competitor's response. Therefore, this study can be perceived as providing a more generalized view of the directional relationship between any brand

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[6] The study is not included in the table intentionally since it belongs to a more generalized genre i.e. positive and negative news.

related information and firm performance. Since brands are typically complex and multifaceted in nature (De Chernatony & Riley, 1998), it is critical to understand whether such asymmetrical relationship exists for positive and negative changes in other brand equity dimensions such as FBBE.

Thirdly, a common feature in majority of existing studies is their reliance on high frequency marketing data i.e., the acquired information is collected either on daily, weekly, or monthly basis (refer to column 4 of table 2.4). Changes in brand ratings within such rapid time intervals can be due to several short-term factors such as consumer complaints, speculatory news and word of mouth which are not conclusive in determining the brand's long term effects. Therefore, linking changes in consumer response to stock price movement within such short intervals can provide unreliable results due to noise caused by sampling variation (Luo et al., 2013) and/or non-synchronous trading (Lo & MacKinlay, 1988). Brand equity takes years to exhibit its complete value enhancing (or deteriorating) abilities, therefore gauging short-term financial consequences in its growth and decline hold little relevance (Datta et al., 2017). Therefore it is recommended that future research should understand these directional effects over long-term horizons (Luo et al., 2013:411).

2.4 Relationship between CBBE and FBBE

As mentioned earlier, being a complex multi-dimensional construct, marketing research is not yet conclusive about which dimension of brand equity measurement captures its best estimates (Oliveira et al., 2015). Also, it will be inappropriate to state that these measures are independent of each other since they evolve from a common epicentre i.e. brand. For example, if consumers value a brand (CBBE) they will exhibit interest and purchase intentions towards it, boosting its sales and profits (product-market equity i.e. proxy of FBBE) which in turn will be reflected in the firm's earnings, creating a positive investor response (capital market equity i.e. proxy of FBBE). Table 2.5 lists the prevailing empirical studies understanding the degree to which these two vital brand equity measures are related to each other. As evident in the column 5 of the table, marketing academics have adopted two distinctive approaches while linking CBBE with FBBE. The first set of studies focus on examining the inter-relationship between different aspects of CBBE and FBBE, whereas the second stream of research link them individually with firm performance. For example, Lehmann et al., (2008) found a significant positive correlation between consumer attributes such as satisfaction and brand attitude with firm's financial based brand equity. This is because strong brands tend to enhance customers and investor expectations about the firm's future cashflows thus strengthening the bond between CBBE and brand's financial value. Similarly, Huang and Sarigöllü (2014) linked consumer's brand knowledge to product-market based brand equity measure of revenue premium (which is a subset of FBBE) and found a positive association between them. Stahl et al. (2012) compared Y&R BAV consumer perceptual brand attributes with firm based equity measured through profit margins and found a significant positive relation between them. Datta et al. (2017) also attained consumer brand attributes of relevance, esteem, knowledge, and differentiation through Y&R BAV database and compared it with "sales based brand equity" measure (SBBE)". They referred SBBE as the "residual" market based approach of measuring brand equity and operationalized it through aggregated IRI sales scanner data. Their findings uncover relatively similar results to that of Stahl et al. (2012) that besides differentiation which corresponds "brand's ability to stands out from competitors", all other Y&R BAV pillars are strongly associated with SBBE.

In contrast to these findings, other set of studies exploring the association between CBBE and FBBE have reported fairly contradictory results. For example, Nguyen et al., (2015) found that amongst the CBBE elements of brand awareness, loyalty, sustainability, and experience, only brand experience exhibits a positive association with FBBE. These results are further validated by a recent study arguing that even other CBBE components such as brand image, loyalty, familiarity, and quality does not have any significant relationship with FBBE (Tasci, 2020). This deviation of exploratory studies by Nguyen et al. (2015) and Tasci (2020) from the mainstream literature can potentially be due to the data gathering techniques or research design limitations. For instance, CBBE estimates for both the studies come from primary data collection source i.e. online consumer surveys. More specifically, CBBE sample of Nguyen et al. (2015) consists of 348 university students in a single region (Southwest USA), responding their preference towards specific product categories and not the overall brand. Furthermore, the authors compared this relatively micro level CBBE data (small respondent group) directly to *Interbrand* brand valuations which represents firm based brand equity from a much broader spectrum[7]. It is highly likely that due to this significant disparity in the acquired CBBE and FBBE measures, the outcomes were conflicting to the main body of related research. Tasci (2020), on the other hand, collected consumer survey data in US focusing specifically on destination brands and compared it to short-term firm based brand performance metrics such as market share and profits. A major caveat of study by

[7] See Bagna et al. (2017) for a detailed discussion about *Interbrand's* brand valuation methodology.

Tasci (2020) is the lack of any statistical approach to test CBBE-FBBE relationship due to a mismatch in the fundamental characteristics of the acquired CBBE and FBBE measures[8]. The representative population and nature of data of both these studies therefore make their implications limited in terms of scope (only relevant to product categories or a particular industry) and geography (only applicable in US region). Another common feature in both these studies is their cross-sectional research design focusing on a single time period (year) thus lacking the long-term association between consumer and firm based brand equity. Tasci (2020:53) therefore recommends future research to "measure percentage change in CBBE and FBBE in different times and compare these changes to see if there is a link between them".

[8] The unit of analysis of acquired CBBE data pertain to 5-point scale response of stakeholders, residents, etc whereas FBBE data represents yearly dollar brand values.

Table 2.5 Marketing literature linking consumer and firm based brand equity

Author(s)	CBBE Metric	FBBE Metric	B.E Metrics in levels or in change	Comparative Analysis type	Findings
Tasci (2020)	Consumer brand familiarity, image, quality, and loyalty	Market share and income	In levels	Between each other	The CBBE and FBBE rankings based on acquired consumer and firm based measures are uncorrelated to each other.
Bagna et al. (2017)	BrandZ brand valuations	Interbrand and Brand Finance brand valuations	In levels	With firm performance (Market Capitalization)	Between the brand equity dollar measures provided by the three consultancies, Brand Finance has an incremental explanatory power in explaining firm's market value as compared to Interbrand and BrandZ.
Datta et. Al (2017)	Y&R BAV consumer brand attributes	Sales based brand equity	In levels	Between each other	Sales based brand equity is positively associated with Y&R BAV pillars of relevance, esteem and knowledge but have a negative relationship with differentiation.
Nguyen et al. (2015)	Online consumer Survey[**]	Interbrand brand valuations	In levels	Between each other	None of the adopted CBBE scales are positively related to FBBE except brand experience.
Johansson et al. (2012)	Equitrend Database	Interbrand brand valuations	In levels	With firm performance (Stock Returns)	Strong CBBE brands outperform the overall market in 2008 financial crisis, but no such effects were realized for FBBE brand measure.

Table 2.5 *(continued)*

Author(s)	**CBBE Metric**	**FBBE Metric**	**B.E Metrics in levels or in change**	**Comparative Analysis type**	**Findings**
Stahl et al. (2012)	Y&R BAV consumer brand attributes	Profit margins	In levels	Between each other	Y&R BAV consumer perceptual brand attributes relate significantly to profit margins.
Lehmann et al. (2008)	Consumer satisfaction and brand attitude		In levels	Between each other	There is a positive relationship of acquired FBBE measure with consumer satisfaction and attitude towards a brand.
Kamakura & Russel (1993)	Perceived brand quality	Incremental value due to brand name	In levels	Between each other	The derived CBBE and FBBE measures exhibit close association.

*** Four different CBBE scales were implemented adapted by Baalbaki (2012), Brakus et al. (2009), Malar et al. (2011); Netemeyer et al. (2004) & Yoo & Donthu (2001)*

The second research group associating CBBE and FBBE focuses on exploring their unique effects on firm performance rather than their relationship to each other. This literature stream is relatively smaller than its counterpart with limited empirical evidence. Infact only two relevant studies could be identified based on this research theme. The first is of Johansson et al. (2012) where they compared the stock market performance of consumer based brand valuations provided by Equitrend with the Interbrand's monetary measure of FBBE during the 2008 financial crisis. The results indicate that the consumer based brand valuations for the acquired firms have a significant incremental impact on stock returns whereas no such effect is witnessed for the FBBE measure. These findings indicate that CBBE has an additional explanatory power beyond that of economy-wide risk factors and firm's fundamentals in explaining firm's future growth while FBBE does not. According to the authors, these differing performance dynamics can potentially be due to the way CBBE and FBBE are fundamentally captured (Johansson et al., 2012:243). Since firm based brand measures predominantly rely on specific assumptions about brand's projected earnings, it is likely that the incremental information residing in this measure have already been absorbed by the financial community e.g. through analyst forecasts. In contrast, consumer centric brand information is "largely exogeneous to the stock market" because of its *subjectivity* (Johansson et al., 2012: 243). These findings suggest that although CBBE and FBBE dimensions are interdependent, but they are not closely associated from the value relevance perspective. This is the primary reason why researchers advocate that there is no single dimension which can capture the depth and breadth of brand performance holistically (Molinillo et al., 2019).

Another study falling into this research category compares the CBBE valuations published by Millward Brown BrandZ and FBBE dollar estimations of Interbrand and Brand Finance (Bagna et al., 2017). The authors investigate whether brand equity estimations provided by these third party institutions are value relevant and if yes, then which amongst them reflects the stock market response in a better way. Their initial results affirm that brand estimations published by all the three brand consultants are value relevant i.e. investors consider these valuations as an important information in their decision making process, thus impacting stock returns. Furthermore, their empirical findings signify that monetary brand values provided by Brand Finance (which is a FBBE measure) have a much higher impact on firm's future discounted cashflows as compared to other measures. The authors argue that such superiority in Brand Finance measures is due to their "royalty relief methodology". Since Brand Finance determine the royalty rates based on the previously negotiated licence fees concessions of comparable brands, it reduces the *subjectivity* to a greater extent (Bagna et al., 2017:5875)[9].

Although the empirical findings by Bagna et al. (2017) are exactly opposite to that of Johansson et al. (2012), both have their own limitations and therefore a direct comparison between them cannot be made. Firstly, Johansson et al. (2012) compared CBBE versus FBBE performance during the period of market distress and for short time window (4 months following the 2008 stock market crash). Therefore the results cannot be generalized over long-term when markets are largely in equilibrium. In contrary,

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[9] Refer to section 2.2.3 of this chapter for a detailed discussion about Brand Finance brand valuation methodology.

although Bagna et al. (2017) examined the brand equity-firm performance impact for longer time horizons (2013 till 2015), a major limitation in their work is the inclusion of the stock market indicator in its “steady state” form (i.e. market capitalization). Researchers argue that using stock market based metrics “at levels” not only have limited theoretical implications (Srinivasan & Hannsens, 2009:300) but such models also suffer from methodological issues such as autocorrelation (Wooldrige, 2010), thus providing spurious statistical inferences (Mizik & Jacobson, 2009a:321).

It is evident from above discussions that previous research tends to exhibit a mix response about how closely CBBE is associated with FBBE. Surprisingly, all the studies linking consumer based brand equity directly to firm based equity have focused on their contemporaneous relationship rather than their evolution over time (refer to fourth column of table 2.5). Researchers argue that FBBE tends to capture the future cashflows associated with a brand and therefore is a *forward-looking* measurement perspective whereas brand equity based on consumer cognitive attachment is more of a *backward-looking* phenomenon (Nguyen et al., 2015). Based on these mutually exclusive characteristics, one can expect that the way they individually respond to continuously changing business environment would differ significantly. Furthermore, FBBE measures such as brand income from sales, patents and other proprietary assets can be easily monitored by the marketing managers due to readily available financial and accounting data. Due to this *objectivity*, any changes in FBBE levels will be flagged immediately and therefore can be interpreted more precisely. On the other hand, consumer’s cognitive attachment with a brand is *subjective* and therefore is not as straightforward to apprehend (Christodoulides et al., 2015). This is why marketing academics suggest that understanding consumer mind set metrics such as brand knowledge, attitude, perception, and behaviour takes time until a considerable shift in their levels can be recognized (Edeling & Fischer, 2016). Future research is therefore advised to measure the degree of changes in the levels of CBBE and FBBE over long-term and compare these changes to investigate their true inter-relationship (Tasci, 2020).

Furthermore, as novel work by Johansson et al. (2012) and Bagna et al. (2017) suggest, despite increasing focus on CBBE and FBBE, their unique relationship with firm performance is also not substantiated with enough empirical evidence. Similar to the research exploring CBBE-FBBE interrelationship, marketing researchers are also uncertain as to which brand equity dimension, amongst them, is more value relevant. This lack of overall consensus about the true CBBE-FBBE association has led marketing scholars to merge these two brand measurement perspectives and device a brand equity metric which possess both these characteristics (for examples of such conjoint analysis, see Ferjaani et al., 2009 and Oliveira et al., 2015)[10]. But still, there are questions that remain unanswered and call for further investigation: i) is CBBE closely related to FBBE? ii) to what extent did CBBE and FBBE explain long-term firm performance and iii) which measure, amongst them, better predicts firm's future growth prospects? To the best of researcher's knowledge, no empirical study to date has systematically investigated these issues simultaneously following a unified approach. Lehmann et al. (2008:49) emphasize that in order to gain a full understanding of brand's holistic value relevance, multiple sets of brand equity dimensions must be employed

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[10] These studies are not discussed further as the objective of the current research is to provide overview of CBBE-FBBE inter-linkage and compare their individual relationship with firm performance.

together. Such comprehensive frameworks are paramount for extending the richness of existing brand equity literature as the future of brand management and wealth creation relies on such efforts (Nguyen et al., 2015:564).

2.5 Brand equity and firm performance: The moderating role of organization

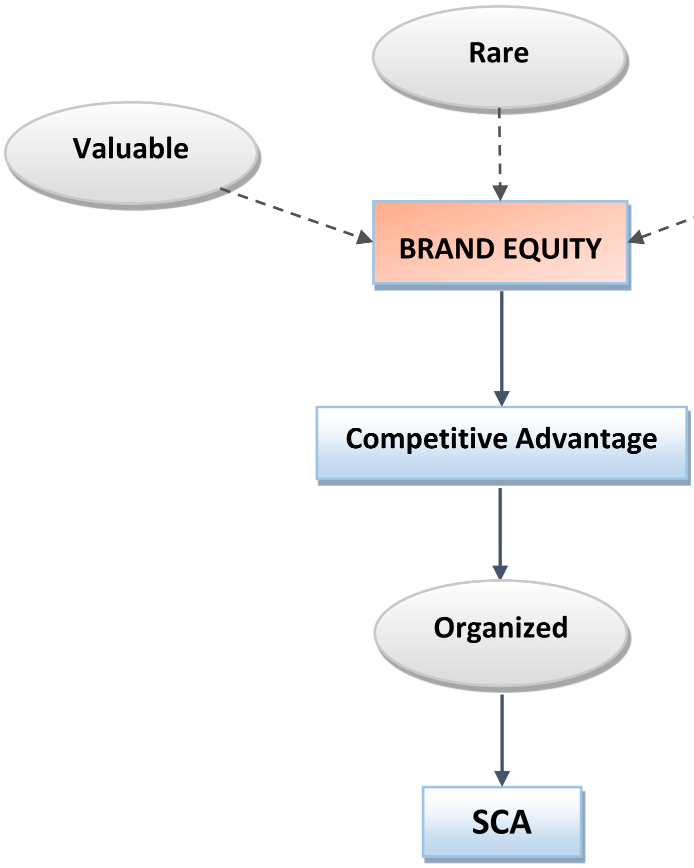
Exploring the directional changes in consumer and firm based brand equity does provide a magnified image of brand equity- firm value dynamics but it holds little significance if the management is incapable of exploiting this information to their firm’s benefit. As mentioned earlier, fluctuation in brand equity levels is a real world phenomenon caused by several market factors which are generally out of the management’s direct reach. Therefore, if organization lacks capabilities to structure themselves and exploit this information to their benefit, then knowing polarized brand equity-firm value relationship has minimal practical significance. The current research therefore aims to provide a holistic view of brand equity-firm performance translation process by not only focusing on the directional value impact of brand equity (including both CBBE and FBBE) but also unfolding how organizational efficiency can moderate this relationship. In order to achieve this, the study leans to the theoretical underpinnings of resource based theory (RBT) of sustainable competitive advantage (SCA) proposed by Barney (1991). RBT asserts that each firm has a unique set of resources and capabilities and if the management can exploit them coherently in a way that the applied strategy becomes “immobile and inimitable”, it can enjoy SCA (Barney et al., 2011). Brand equity has been recognized as a key intangible marketing resource which provides competitive edge to the brand owning firm over its competitors (Kozlenkova et al., 2014). However, based on RBT propositions, it can be argued that such strategic marketing resource can only generate SCA if it is complemented with superior organizational capabilities, otherwise it can only be perceived as a source of competitive advantage. Narrating this from current research perspective postulates that to gain SCA, corporate management should be able to strategize their policies and actions to complement the positive firm value impact of rising brand equity and mitigate the adverse effects of its decline. The study therefore pays close attention on the role of organizational efficiency in moderating the financial consequences of brand equity of firm’s future growth prospects. The following sections build on this narrative by first providing a brief overview of RBT including its emergence, prerequisite assumptions, and relevance in the marketing research stream. This is then followed by identifying empirical studies in the current marketing-finance literature that have focused on investigating the financial implications of different organizational efficiency measures.

2.5.1 Resource-based theory (RBT) – *A Synopsis*

Till the ‘80s, businesses were solely focused on the industry level factors to gauge their performance potential and strategies were developed based on Michael Porter’s (Porter, 1985) analysis of the external market environment (Kozlenkova et al., 2014). Later, academics contradicted this performance valuation approach and argued that it is firm’s internal resources and capabilities which decides its profitability (Barney et al., 2011; Wernerfelt, 1984). Although it makes sense to gauge firm growth by its market share but what if the organization is incapable of exploiting their available resources to its fullest potential. This can lead to suboptimal resource utilization resulting in wastage, extra costs, and finally poor efficiency. In order to link firm resources with performance, Barney (1991) proposed resource based theoretical framework (RBT) identifying firms as “bundles of resources and capabilities which are configured to create competitive advantage in the marketplace” (Rahman et al., 2018:114). Resource based perspective therefore adopts an internally driven approach focusing on firm’s resources and capabilities as a source of competitive advantage rather than its external market position (Kull et al., 2016). Resources can either be *tangible* like plant, equipment and work force or *intangible* such as corporate knowledge, stakeholder relationships and brand equity. Capabilities are subset of resources defined as a complex set of skills and knowledge which are channelized via organizational processes to enhance the productivity of firm’s other resources (Makadok, 2001). A further corollary of RBT is that not all the acquired resources are credible sources of sustainable competitive advantage (SCA) (Vomberg et al., 2015). Only those which fulfil the stringent requirements of being valuable, rare, inimitable, and organized (VRIO) possess strategic importance (Barney et al., 2011). A resource is *valuable* if it has unique characteristics that can enable the firm to develop strategies which can enhance the profits and reduce the overall costs, thus providing a competitive advantage (Barney & Hesterly, 2012). A *rare* resource is the one which cannot be attained easily and therefore is controlled by very few competing firms within an industry (Kozlenkova et al., 2014). Similarly, if a firm has a potential to exploit its resources in a unique and innovative manner such that it imparts additional value, then that firm possess a *rare capability* (Acquaah, 2003). A resource is perceived as *inimitable* if it cannot be easily replicated by the competitors or new market entrants either due to higher acquiring costs or its embedded complexity (Barney & Hesterly, 2012). Possessing an asset which fulfils these three RBT criterion enable the firm to gain a competitive edge over its competitors. However, just attaining a valuable, rare, and inimitable resource does not guarantee SCA if the management lacks the organizational processes to exploit its full competitive potential (Corte et al, 2017). Thus, the *organization* component of the VRIO acronym is the most critical and acts as an “adjustment factor” which can either enable or deter a firm from extracting the maximum performance ability of a VRI asset (Kozlenlkova et al., 2014).

Evolved primarily in the strategic management stream as a nascent view, RBT has gained wide recognition in the field of marketing management (Barney et al., 2012). Infact marketing literature has witnessed a whopping 500% rise in the studies linking RBT with market-based firm resources from the period of 2000 till 2010 (Kozlenkova et al., 2014). Contemporary literature suggest that the intangible firm resources have larger effects on firm performance as compared to the tangible assets (Corte et al., 2017). This can be the prime reason for such an explosive rise of RBT studies in marketing as majority of the market-based resources and functions are intangible and complementary such as customer relationships, innovation, and brand equity. Amongst them, brand equity has been identified as a key strategic marketing asset that can impart a competitive edge to its owner (Kozlenkova et al, 2014; Merrilees et al., 2011; Orr et al., 2011). As discussed in-detail in the previous sections of this chapter, brand equity is a *valuable* resource due to its ability to positively impact both current and future firm performance. Even by its definition, brand equity represents an added value which a product or a service possess due to its brand name (Keller, 2016). A branded product possesses two set of values: the *tangible* value of the product itself and the complementary *intangible effect* of brand name attached to it. This synergetic effect makes it challenging for the competitors to *imitate* as they cannot easily identify which product attribute (tangible or intangible) is responsible for generating the competitive advantage. Even if they are successful in detangling the branding effect from the product value, it is still extremely difficult to replicate it as creating a strong brand is a socially complex and casually ambiguous process (Kotler & Keller, 2011). This makes brand equity a *rare* resource as the cost of building it is prohibitive and the researchers are still striving to understand it completely (Kozlenkova et al., 2014). Additionally consumer brand attributes such as brand awareness, loyalty, and perceived quality lead to superior brand performance through consumer retention, repeat purchase and low switching probability (Keller, 2016). Similarly, firm based brand equity factors such as brand logo, trademarks and other proprietary assets are the key branding resources that engender strategic benefits which are difficult to *imitate* (Park et al., 2013; Glynn, 2012). In sum, brand equity, irrespective of its dimensions, is a strategic marketing resource which fulfils the RBT criteria of being valuable, rare, and inimitable. However, as mentioned earlier, being a VRI resource cannot impart sustainable performance if the firm is not structurally organized to exploit its full competitive potential (Barney & Hesterly, 2012). Therefore following a resource based perspective, this study argues that although brand equity provides competitive edge to a firm but if unanticipated changes in its magnitude are not managed efficiently, it cannot impart a sustained long term performance. This makes the "organization" aspect of VRIO acronym most critical as it enables firms to leverage their key strategic resources like brand equity with their superior management capabilities to gain SCA (Rahman et al., 2018). The proposed narrative is also represented graphically in figure 2.3. RBT proponents outline that the researchers have largely focused on the V, R, and I characteristics in examining the brand equity-firm value relationship whereas the role of "organization" is still under-researched (Kozlenkova et al., 2014; Vomberg et al., 2015). Therefore it is crucial to investigate the moderating role organizational competence in this relationship especially when brand equity is prone to grow and decline over time and these changes are beyond management's direct control.

Figure 2.3 Brand equity as a source of SCA



Source: Author's elaboration

Despite being one of the most recognized strategic management theories in the marketing research, RBT prompts some criticisms which demands refinement. The most telling critique amongst them is its inward-looking perspective advocating that firm's internal resources are the ultimate source of competitive advantage (Lavie, 2006). This reductionist assumption seems logical at first, since RBT emerged explicitly to challenge Michal Porter's (1985) view that business success is determined by external factors such as firm's industrial structure. However, businesses do not operate in isolation and therefore external market forces play a vital role in deciding its ultimate success or failure. For example, there is mounting research indicating that industry type (Adetunji & Owolabi, 2016; Fazlzadeh et al., 2011; Hawawini et al., 2003) and competitive intensity (Bayighomog et al., 2020; Mathur et al., 2021; Ramaswamy, 2001) are the key determinants of firm performance. Furthermore, "externally driven" intangible marketing resources like brands and brand equity are also widely acknowledged for their lasting value contributions (Aaker & Jacobson, 2001; Fischer & Himme, 2017; Keller, 2012; Kozlenkova et al., 2014; Mizik, 2014). As such, resource based theory is not a replacement of Porter's outward-looking perspective, rather it should complement it (Barney, 2002; Mahoney & Pandian, 1992; Peteraf & Barney, 2003). Therefore, to improve the validity of RBT, it is viable to advance a more comprehensive approach and understand how firm's internal assets and capabilities interact with external resources and environments to attain SCA (Lavie, 2006).

Along with being inward-looking, RBT also suffers from issues such as "lack of dynamism" and "construct validity". Firstly, the standard propositions of resource based theory are only applicable to static set of VRI resources and therefore cannot explain how firms can attain SCA in dynamic market conditions (Kraaijenbrink et al., 2010). This is a major drawback because business environments are continuously evolving and therefore understanding the resource-performance translation mechanism in such turbulent conditions is crucial (Day, 2011). But still majority of existing RBT marketing research rely on "steady-state" resource-performance relationship while overlooking "how resources and capabilities are developed or maintained in a dynamic setting"

(Kozlenkova et al., 2014:12). This calls for a dire need to extend the conventional RBT further to better understand its potential to explain SCA, especially in unpredictable and unstable market environments. The "construct validity" issue, on the other hand, emerges from RBT's resource heterogeneity assumption that firms, despite competing within a same industry, possess unique bundles of resources and capabilities (Peteraf & Barney, 2003). RBT critics argue that due to this uniqueness, the resource-performance transformation capabilities across different organizations are not directly comparable, therefore any empirical outcomes of such examination cannot be generalized (Almarri & Gardiner, 2014). Even RBT proponents agree that construct validity issue cannot be fully eliminated (Almarri & Gardiner, 2014; Cronbach, 1975), however recommend some advanced statistical estimation techniques to minimize its effects (Levitas & Ndofor, 2006).

Finally, RBT has been criticized to be tautological i.e. it is true by logic, but it cannot be tested empirically (Priem & Butler, 2001). This issue mainly emerged from its equivocal definition of "value" which appears both in *explanans* (i.e. valuable resource leads to an efficient strategy) and *explanandum* (i.e. competitive advantage is a result of value creating strategy) (Barney, 1991). Priem and Butler (2001:58,60) argue that since "value" (predictor) and competitive advantage (outcome) are both defined in same terms, such a theory lacks an empirical content. To overcome this issue, researchers recommend avoid linking a VRI resource directly to SCA, rather focus on understanding the intermediary role of organizational processes (O) in exploiting such resources (Barney & Clark, 2007; Peteraf & Barney, 2003; Kozlenkova et al., 2014).

All these limitations have motivated this research to not only apply the conventional tenets of resource based theory in explaining how brand equity can generate SCA, rather work towards its refinement by embracing the best proposed recommendations. A detailed discussion about these enhancements is provided later in the concluding section of this thesis.

2.5.2 Brand equity, Organizational Efficiency and Firm Performance: An RBT perspective

RBT suggests that each firm has distinctive set of resources and capabilities and the organization need to implement them cohesively to attain SCA (Sun et al., 2019). The businesses with higher resource management capabilities are thus more efficient in converting their VRI assets into financial gains especially when they are exposed to unexpected market volatilities. This is why researchers acknowledge that brand equity explains firm performance but only to some extent as this relationship is prone to other intermediary “organizational” factors such as management’s intellectuality and efficiency (Aguinins & Glavas, 2012). For example, firms with higher levels of corporate social responsibility (CSR) tend to enhance the positive impact of brand equity on firm performance (Rahman et al., 2019). Similarly the firms which are capable of maintaining strong relationships with their stakeholder groups such as customers, employees and suppliers can exploit a brand to its maximum potential leading to a superior performance (Wang & Sengupta, 2016). Marketing actions like advertisements and R&D have also proven to be a vital factor in strengthening the brand equity firm performance relationship through brand awareness and innovation (Joshi & Hanssens, 2010; Fischer & Himme, 2017; Kim et al, 2018).

A major limitation of these studies is their inclusion of a single management dimension (e.g. CSR, R&D, etc) when exploring the decisive role of organizational architecture in the brand equity-firm value nexus. Organizational process is a complex phenomenon and therefore its overall role cannot be characterized satisfactorily by capturing a single management function (Nath et al., 2010). Utilizing comprehensive models can therefore unfold the role of management efficiency in moderating the marketing-finance relationship in a more profound manner (Rahman et al., 2018). Another advantage of using a multi-factor configuration is its precise fit to the theoretical foundations of RBT which advocates that firm must utilize its resources and capabilities cohesively to gain SCA (Sun et al., 2019). Following the footprints of RBT, the current research focus on integrating multiple input and output resources concurrently to model efficiency measures which best represent the overall organizational influence. The list of representative studies in RBT centric marketing research that have focused on exploring the contributory role of organizational efficiency in enhancing firm performance is presented in table 2.6. The table outlines the adopted management efficiency measure, the implied inputs, and outputs for its operationalization and whether it has been investigated as an intermediary or directly linked to firm performance. The table also presents if the sample firms belong to a particular industry, or a multi-sector approach is adopted.

Table 2.6 Summary of empirical marketing studies on multi-output based organizational efficiency measures

Author(s)	Organizational Efficiency Measure	Input(s)	Output(s)	Moderation	Firm Performance	Industry
Rahman (2020)	Dynamic Marketing Productivity	Advertisement expenditure, account receivables, no. of departures and seat miles	Customer satisfaction, sales and market share	No	Tobin's Q	Airline
Sun et al. (2019)	Marketing Capability	SG&A, Intangible assets, accounts receivables, sales, working capital and earnings	Market share and gross profit margin	Yes	ROA	Diversified
Angulo-Ruiz et al. (2018)	Marketing Capability	Advertisement and promotion expenditures	Customer satisfaction, sales, and sales growth	No	Stock Returns	Diversified
Rahman et al. (2018)	Brand Management Efficiency	Advertisement expenditure, R&D expenditure, accounts receivable	Brand value	No	Tobin's Q	Information Technology
Feng et al. (2017)	Marketing Capability	SG&A, advertisement expenditure and no. of trademarks	Sales	Yes	Profit and Revenue Growth	Diversified
Mishra & Modi (2016)	Marketing Capability	SG&A, accounts receivables and patent stock	Sales	Yes	Stock Returns	Diversified

Table 2.6 *(continued)*

Author(s)	**Organizational Efficiency Measure**	**Input(s)**	**Output(s)**	**Moderation**	**Firm Performance**	**Industry**
Nguyen & Oyotode (2015)	Marketing Capability	SG&A, advertisement expenditure and accounts receivables	Sales	Yes	Not included	Diversified
Yang et al. (2015)	Intellectual capital management capability	R&D expenditure and no. of employees	Sales growth per employee and no. of patents	No	Stock Returns	Semiconductor
Angulo-Ruiz et al. (2014)	Consumer Oriented Marketing Capability	Advertisement and promotion expenditures	Sales, brand equity and customer satisfaction	No	Tobin's Q	Diversified
Wiles et al. (2012)	Marketing Capability	SG&A, advertisement expenditure and no. of trademarks	Tobin's Q adjusted for R&D expenditure and management quality	Yes	Stock Returns	Diversified
Nath et al. (2010)	Business Efficiency (BE) and Marketing Capability (MCAP)	*For BE*: Total assets and working capital *For MCAP:* SG&A, Intangible assets, accounts receivables and sales growth	*For BE*: ROA and ROCE *For MCAP*: Sales	No	Operating Profit	Logistics

Table 2.6 *(continued)*

Author(s)	**Organizational Efficiency Measure**	**Input(s)**	**Output(s)**	**Moderation**	**Firm Performance**	**Industry**
Zhu (2000) **	Profitability	No. of employees, total assets, and shareholder's equity	Profits and Sales	No	No	Diversified
Dutta et al. (1999)	Marketing Capability	Technical base, installed consumer base, account receivables, advertisement, and marketing expenditures	Sales	Yes	Tobin's Q	Technology

Notes: SG&A: Sales, General and Administrative Expenses; ROA: Return on Assets; B2B: Business to Business; ROCE: Return on Capital Employed
***The study by Zhu (2000) does not belongs to marketing research stream, nor it relies on RBT perspective. However its inclusion in the table is crucial for the operationalization of core business efficiency (CBEF) variable defined later in this study.*

The most researched organizational function amongst the listed studies is the firm's marketing capability (MCAP). This comes as no surprise since the focus was laid on identifying RBT studies which centres around marketing based resources in operationalizing organizational efficiency measures. Researchers have defined marketing capability from multiple perspectives depending on the implied inputs and outputs. However, they all revolve around its basic conceptualization by Day (1994) as "the capability of an enterprise to utilize its knowledge, technology and resource to satisfy the needs of market or its customers" (Lee & Hsieh, 2010:110). MCAP therefore involves the integrative processes in which management utilizes its tangible and intangible marketing resources to satisfy consumer specific needs, achieve product differentiation and higher levels of brand equity (Afriyie et al, 2018). As column 5 of table 2.6 reports, the contributory role of marketing capability in business performance has been studied from both the direct and moderating perspectives. Marketing academics exploring its direct effects have linked MCAP to both short-term and long-term firm performance measures. For instance, Nath et al. (2010) model marketing capability as a function of marketing expenditure, intangible resources, customer relationship and installed customer base as inputs and sales as output to examine its effects on overall business performance. Their findings report that MCAP significantly impacts firm's operating profits which captures short-term financial performance. Similarly, Feng et al. (2017) empirically examines how marketing capabilities of 612 US firms have interacted to impact their profit and revenue growth over a time span of 16 years. The results indicate that marketing capability has a positive relationship with both the current-period firm growth metrics included in the study. In contrast to these studies, Angulo-Ruiz et al. (2014) examines the long-term financial contribution of marketing capability through its relationship with stock market indicators of Tobin's Q and analyst's recommendations. Their MCAP conceptualization differs from Nath et al. (2010) and Feng et al. (2017) such that rather than deploying sales as the sole output, they have networked it through customer satisfaction and brand equity, thus calling it as customer-oriented marketing capability (COMC). The choice of adopting such approach is driven by the notion that both brand equity and customer satisfaction are key drivers of sales and therefore their effects need to be accounted for Angulo-Ruiz et al. (2014:4). The empirical outcomes reveal that COMC has long-term value relevance from two fronts: i) directly from its positive impact on Tobin's Q and ii) indirectly through positive analysist revisions about firm's future cashflows based on superior COMC. The second study exploring the future growth implications of marketing capabilities is of Rahman (2020) which coincides with the work of Angulo-Ruiz et al. (2014) in two ways. Firstly, they also linked marketing efficiency to Tobin's Q thus providing a long-term view of firm performance and secondly, the output is not restricted to sales but also includes customer satisfaction. However, they rely on dynamics capabilities theory proposed by Teece et al., (1997) along with RBT for MCAP operationalization and therefore termed it as "dynamic marketing productivity" (DMP). Their research findings reveal that firms with higher DMP experience steeper financial growth (through their positive impact on Tobin's Q) as compared to firms with lower DMP levels. These results further suggests that superior levels of marketing capability can be a valuable source of sustained competitive advantage (SCA), thereby leading to enhanced firm future growth. Collectively, the empirical findings of all the discussed studies signify that MCAP positively impacts firm growth both in short and long run. Additionally, it is evident that the choice of marketing resources as inputs and outputs for its operationalization does not alter its overall value relevance.

In parallel to analysing the direct effects, researchers have also directed their attention towards understanding the moderating role of MCAP in the translation of marketing assets and practices to financial performance. Initially, Dutta et al. (1999) examined whether the link between innovation and firm performance is complemented by superior marketing capabilities in high technology markets. They report a significant interaction effect of MCAP in innovativeness-firm value relationship asserting that marketing capability play a pivotal role in enhancing performance of firms which are engaged in continuous R&D activities. Mishra and Modi (2016) examined the moderating role of MCAP in the relationship between corporate social responsibility (CSR) and shareholder’s wealth. They conclude that CSR is not directly related to firm value, rather it can only translate into superior performance in the presence of strong marketing capabilities. In other words, firm’s discretionary practices to improve societal well-being is only appreciated by shareholders if the management has a strong hold over its consumer-base through effective market communication capabilities. Extending this knowledge further and taking a directional view, Nguyen and Oyotode (2015) report that firms with superior MCAP magnify the impact of positive changes in CSR perceptions on brand equity and mitigate the adverse effects of its negative changes. These research outcomes suggests that apart from positive interactions, MCAP can also be used as a strategic tool to buffer the negative consequences of poor management strategies on firm performance. Strong marketing capabilities have also been found to enhance the brand equity-firm value relationship during brand acquisitions (Wiles et al., 2012). Along with CSR and branding, superior marketing capabilities have also proven to be playing a decisive role in moderating the impact of international expansion on firm performance (Sun et al., 2019).

Apart from marketing capability, a small body of research has also focused on identifying other organizational efficiency measures driven by RBT's multi-resource amalgamation theory. The first study is of Zhu (2000) which explores the role of "business efficiency" in the performance of top 500 brands published by *Fortune Magazine* in 1995. Two-stage multi input-output configuration approach is adopted to estimate the efficiency of the acquired firms. The first stage defines profitability which measures organization's capability to transform its core resources such as physical assets, employees and capital stock into revenue and profits. The second stage evaluates firm's stock market performance based on its business efficiency (i.e. profitability). The research outcomes convey that the Fortune 500 rankings do not coincide with the employed multi-factor business performance analysis where only 3% of the total firms were actually technically efficient. These findings emphasize that business performance is a complex phenomenon which cannot be characterized through a single performance metric such as sales revenues[11]. Therefore a multi factor performance measurement model need to be utilized in order to estimate actual business efficiency (Bagozzi & Phillips, 1982; Chakravarthy, 1986; Zhu, 2000). Following these footprints, Nath et al. (2010) combined various firm inputs and outputs to estimate firm's "resource-performance efficiency" and examined the impact of marketing efforts on firm performance of high versus low efficient firms. The findings suggest that if a firm is

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[11] Note that Fortune 500 companies are ranked based on their annual revenue figures.

efficient in exploiting its available core resources such as total assets and working capital to maximize business output, then the brand it owns leads to exceptional financial performance. Both these studies signify that if the management is knowledgeable in efficiently transforming their fundamental assets to boost productivity, they can enjoy sustained competitive advantage. This organizational knowledge is therefore a vital *intellectual asset*, which plays a pivotal role in driving firm performance (Youndt et al., 2004). This is further validated by Yang et al. (2015) where they develop another multi resource based intellectual asset termed as "Intellectual capital management capability" (ICMC) and link it directly to firm future performance, measured through stock returns. ICMC gauges how effectively management transforms its work force (employees) and innovativeness (R&D) into higher revenues and intellectual property growth (patents). The empirical findings report that ICMC is value relevant i.e. organizations with superior ICMC levels tend to enhance shareholder's wealth by generating better than expected returns. Beside managing fundamental business operations, marketing academics have also focused on exploring the extent to which firm's brand managing capabilities impact long-term firm performance. For example, Rahman et al., (2018) integrated multiple marketing resources such as advertisement, R&D, customer relationships and brand equity to formulate "brand management efficiency". The research outcomes suggest that the firms which are capable of minimizing their brand management resource allocation to attain optimal levels of brand equity enjoy higher level of firm value measured by Tobin's Q.

The above review of the literature exploring the role of multi input-output based organizational efficiency in marketing-finance interface reveal several themes which guide the conceptual framework proposed in this research. Firstly, MCAP dominates as the most studied organizational function in the current literature signifying the importance of efficient marketing resource management for sustainable business growth. Irrespective of the acquired input-output combination, MCAP has demonstrated its value relevance and therefore is a key component of the organizational architecture. Additionally, majority of studies have explored the moderating role of MCAP in marketing-finance interface rather than linking it directly to firm performance. Apart from MCAP, marketing academics have also shown their interest in examining the translation role of other organizational functions but the research in this area is still scarce. From the firm performance perspective, researchers have linked the modelled organizational efficiency to both short and long-term measures, however capturing future performance through stock market indicators have been a preferred choice. No study until now (to the best of researcher's knowledge) has provided insights about the interfering role of organizational competence in brand equity-firm performance relationship especially during positive and negative changes. Since brand is one of the most valuable assets a firm possess (Keller, 2016), it is vital that management is capable of nurturing the intangible value attached to it to its fullest potential. This is only possible if they are organized to deploy strategies that are capable of enhancing (mitigating) the positive (negative) effects of rising (declining) brand equity on firm performance. Only then can brand equity completely fit into the RBT's criteria of being a VRIO resource that can provide sustainable long-term firm growth. In the case where firm is exhibiting poor or deteriorating management competence, the competitive advantage which their brand possess may not be sustainable over long-term.

Additionally, none of the studies (except Nath et al., 2010) have included core business resource management (business efficiency) and marketing resource management (MCAP) based organizational efficiency measures cohesively into a single research framework. This is crucial because in practice, both these organizational capabilities co-exist within firms (Feng et al., 2017) and a simultaneous assessment of their complementary role in brand equity-firm performance interface is warranted. Essentially, CBEF and MCAP capture two entirely different aspects of management competence. Business operating efficiency focus mainly on firm's capability to transform its available fundamental tangible resources such as raw material, workforce, plants, and equipment optimally to produce high quality products and maximize profits (bdc, 2021). Marketing capability on the other hand, gauges management's ability to enhance its customer-base through strategic deployment of the available marketing resources which are mainly intangible in nature (e.g. consumer relations and brand equity) (Day, 1994; Keller and Lehmann, 2003; Rust et al., 2004; Vorhies & Morgan, 2005). Therefore, the way these *profitability* and *marketability* based organizational efficiency measures are weighed by investment community during a sudden rise or decline in the brand equity will be relatively different. A simultaneous examination of the unique moderating effects of CBEF and MCAP in brand equity to firm value translation process also complements the existing RBT based marketing literature where the role of "organized" component of VRIO acronym is largely over-looked (Kozlenkova et al., 2014:14).

2.6 Summary

The purpose of this chapter was to provide a critical review of the existing marketing-finance literature linking brand equity, more specifically CBBE and FBBE, to long term firm performance and the intervening role of organizational efficiency. The conducted overview unfolds several research gaps which lays the foundation for this study to further advance the current knowledge from multiple fronts. Firstly, although a significant positive relationship between brand equity and firm performance has been established with ample empirical evidence, the directional consequences of these unanticipated changes are largely neglected. Even the small body of research exploring the firm value impact of such positive and negative shifts have adopted significantly narrow data collection waves such as daily or weekly intervals. Embracing such a high frequency response data cannot unfold long-term brand performance as brand equity is known to evolve gradually over time (Datta et al., 2017). Secondly, despite the significance of brand equity in marketing theory and practice, existing research is still not able to establish a clear understanding about the relationship between consumer and firm based brand equity perspectives. Marketing academics have attempted to compare CBBE and FBBE both from their “inter-relationship” and “value relevance” perspectives but the research outcomes are broadly conflicting. Addressing these potential voids, this study attempts to fill in small but emerging body of literature from two fronts. Firstly, following recommendations of Luo et al. (2013) and through a longitudinal setting, the study explores the long-term financial implications of unanticipated growth and decline in brand equity. Additionally, it incorporates two key brand equity dimensions i.e. CBBE and FBBE within a single research framework to understand the extent to which they are inter-linked to each other and their individual impact on firm future performance. Adopting such a comprehensive approach enables this research to provide a holistic view of brand equity and its financial connotations, which is still not clearly known.

Along with scrutinizing literature linking brand equity directly to firm performance, the chapter also explores RBT based studies exploring the complementary role of organizational efficiency in this marketing-finance interface. Although, no study was identified which precisely assess interactive role of management competence in brand equity-firm performance linkage, a thematic analysis of the most relevant studies provides valuable directions for this study to address this potential research gap. Existing scholarship suggests that organizational efficiency not only drives firm performance directly but some of its measures (especially MCAP) also plays an intermediary role in enhancing the financial impact of marketing assets and strategies. Driven by these findings, this study aims to expand this knowledge further and understand as to how superior organizational efficiency can transform brand equity from a source of "competitive advantage" to a provider of SCA. All the identified research gaps lead to the formulation of an integrated conceptual framework comprising of several path relationships linking CBBE, FBBE and organizational efficiency measures directly and indirectly to firm performance. The following chapter discusses the proposed conceptual model in detail incorporating several research hypotheses which collectively aid this study to accomplish its overall research objective.

Chapter 3: CONCEPTUAL FRAMEWORK

3.1 Introduction

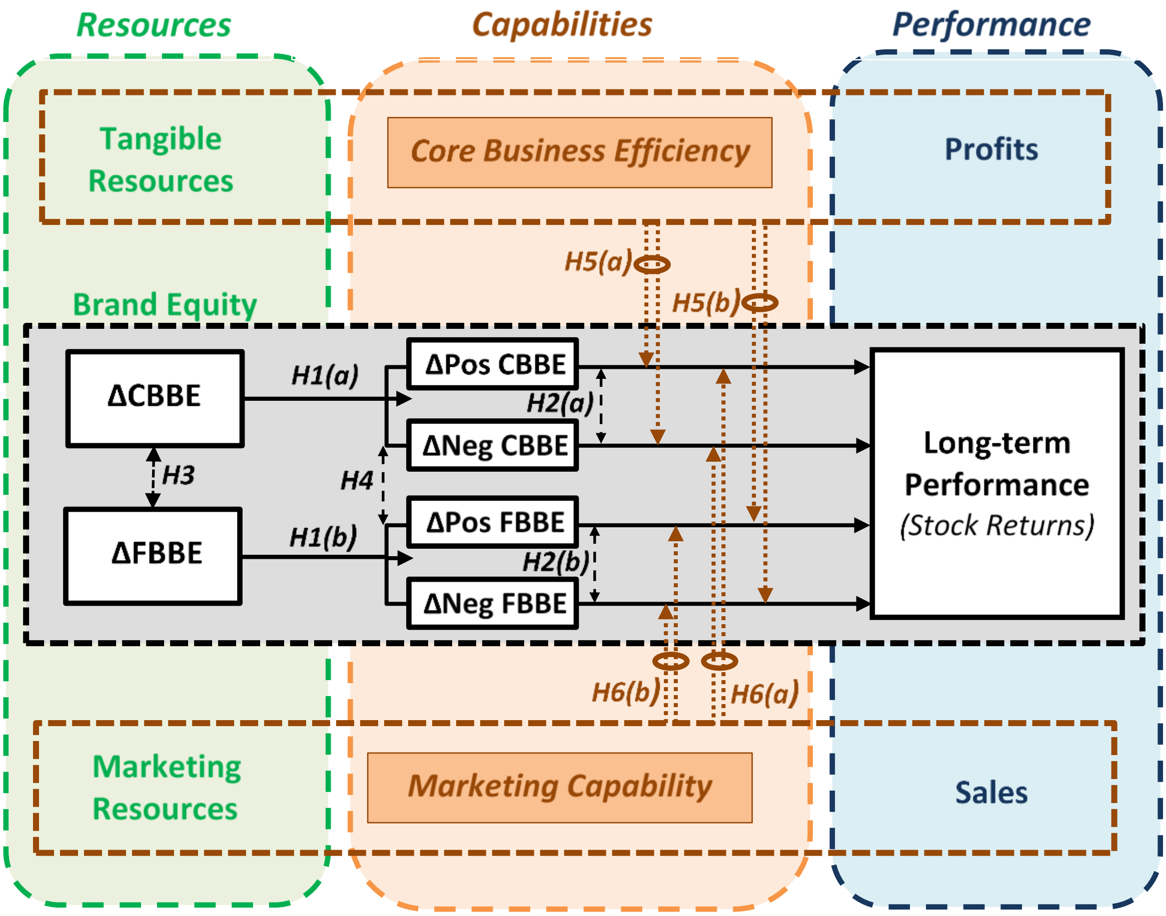
Previous chapter conducted an in-depth review of the existing marketing-finance literature exploring the relationship between brand equity and firm performance and identified some key research gaps. Furthermore, the research applying theoretical conceptualization of resource based theory (RBT) in marketing was critiqued, specifically from the organizational efficiency perspective. This chapter presents the conceptual framework designed to address the identified gaps, including the rationale for their development. Firstly, the proposed conceptual model is visually represented explaining its different constructs and relationships between them, in the context of addressing the outlined research objectives. This is then followed by focusing on each aspect of the conceptual model separately to systematically carve multiple research hypotheses. All the stated hypotheses collectively accomplish the aim of this study i.e. to examine the firm value impact of rise and decline in CBBE and FBBE and the moderating role of organizational efficiency. The chapter finally concludes with a brief summary.

3.2 Conceptual Model

The proposed conceptual model is guided by the gaps identified in existing marketing-finance literature and aim to address three main research objectives: i) examine the impact of positive and negative changes in brand equity on long-term firm performance, ii) compare these dynamics from consumer and firm based brand equity measurement perspectives and iii) explore the role of organizational efficiency in moderating this directional brand equity-firm performance relationship. Figure 3.1 illustrates the designed conceptual framework representing different path relationships connecting the acquired brand equity and organizational efficiency measures directly and indirectly to long-term firm performance. In order to systematically address the outlined research aims, the proposed model is segregated in two sections. The central horizontal block (with grey background) represents model section-I and addresses the first two research objectives i.e. exploring the long-term impact of unanticipated changes in brand equity on firm performance and cross-comparing CBBE and FBBE. More specifically, it provides a polarized view of brand equity-firm value nexus by examining the financial consequences of rising and declining consumer and firm based brand equity. Additionally, the comparative assessment between CBBE and FBBE offer further insights about their true interrelationship and holistic brand relevance, which is still under-researched (Tasci, 2020).

The second section of the proposed conceptual model is represented through three vertical blocks segregating resources, capabilities, and performance. This bifurcation is driven by the theoretical underpinnings of RBT. As discussed in the previous chapter, RBT advocates that firms need to collate their unique set of resources with their superior management capabilities to attain performance which is challenging for the rivals to surpass (Barney, 1991; Kull et al., 2016). Following these propositions, this model section argues that organizations which can efficiently transform their available resources into higher output levels are able to mitigate (enhance) the negative (positive) effects of declining (rising) brand equity on firm value.

Figure 3.1 Proposed Conceptual Model



Hypothesised direct relationships → **Hypothesised moderated effects** ……………▸

Hypothesised comparative relationships

Δ: Change, CBBE: Consumer based brand equity, FBBE: Firm based brand equity, ΔPos: Positive Change, ΔNeg: Negative Change

Source: Author's elaboration

Two key organizational capability factors are identified namely, core business efficiency (CBEF) and marketing capability (MCAP), which have been known to enhance firm performance from multiple fronts (Afriyie et al., 2018; Corte et al., 2017; Nath et al., 2010; Zhu, 2000). As evident in the figure 3.1, CBEF represents the firm's ability to transform its *tangible resources* to higher *profits* whereas MCAP focus on the *sales* outcome of the employed marketing resources. Including both *profitability* and *marketability* aspects, the model therefore provides sound arguments about the holistic role of organizational efficiency in moderating the brand equity-firm performance nexus. It argues that superior management capabilities can augment brand equity from being a source of competitive advantage to a provider of sustainable competitive advantage (SCA). By introducing such a comprehensive framework, the study provides in-depth knowledge about the pivotal role of the "organization" component of the RBT's VRIO framework, which is still under-researched (Kozlenkova, 2014). Both model section I and II collectively guide the development of several research hypotheses to validate all the proposed pathways from CBBE and FBBE to firm performance through the moderating role of CBEF and MCAP. For the sake of simplicity, different types of path relationships are illustrated distinctively such that solid black arrows represent direct relationships, dotted arrows as interaction effects and dashed double-sided arrows as inter-relationships. The following section defines all the key constructs included in the proposed framework along with the explanations about their relationship paths.

3.2.1 Defining model constructs and path relationships

The key outcome variable in addressing the underlying research objectives is "long-term firm performance" and is the main consequence of this study. Since this research examines the long-term value relevance of brand equity, it is desirable that the chosen metric best represents future performance and is not limited to immediate or short-term profitability measures. As discussed in the literature review chapter, existing marketing-finance research has adopted various accounting and financial measures when accessing the performance outcome of branding (for an overview, see Edeling & Fischer, 2016). Amongst them, only stock market based indicators are capable of capturing long-term performance due to their forward looking properties (Levine & Zervos, 1998). However, whether this performance metrics is to be included as "in level" or "in change" is another aspect which needs careful attention. The stock market "level" measures include market capitalization (Kirk et al., 2013; Yeung & Ramasamy, 2008), market-to-book ratio (Mortanges & Riel, 2003) and intangible to tangible ratio (Tobin's Q) (Chang & Young, 2016; Rahman et al., 2019; Vomberg et al., 2015) whereas stock return i.e. "change in stock price in a given period" is by definition a first difference metric (Srinivasan & Hanssen, 2009). Marketing-finance research attempting to examine the financial implications of brand equity have employed both the level and return based measures. However researchers recommend avoiding the "level models", wherever possible, due to "their limited value, both from the theoretical and methodological perspective" (Srinivasan & Hanssens, 2009:300). Efficient market theory postulates that the current market value of the firm represents all the publicly available information about its future growth prospects (Lim & Brooks, 2011). Release of any new information or an update in the existing information (e.g. earnings) would change investors and shareholders perception about firm's future cashflows, thus moving the stock price. This change in market value of the firm (i.e. stock returns) is therefore the accurate predictor of the impact of the "variable of interest" on the firm's long-term performance. Examining the financial outcomes of brand equity (or any other variable) by regressing it directly on the "in level" stock market based metric therefore hold limited explanatory power (Srinivasan & Hannsens, 2009). Additionally, measuring long term performance through market capitalization also pose statistical issues. Stock prices are inherently unpredictable and follow a random walk i.e. they are in a constant state of evolution (Joshi & Hanssens, 2010). This property of stock prices (and all other "in level" measures as they are the function of stock prices) requires the estimation model to be robust to deviations from stationarity otherwise would provide spurious regression issues (Granger & Newbold, 1997; 2014). Ordinary least square (OLS) regressions follow an assumption that the error term is uncorrelated to the independent variables and is identically distributed (Wooldridge, 2010). Therefore, the regression models using autocorrelated "in-level" stock metrics such as market value, market to book ratio or Tobin's Q will return an inflated t-statistic, providing misleading statistical significance (Edeling & Fischer, 2016). In view of these issues, Mizk and Jacobson (2009:321) argue that studies using level metrics without accounting for autocorrelated properties should not even be considered for publication as they are mere artifacts of spurious regression phenomena.

Stock returns, on the other hand, are broadly immune to such theoretical and econometric anomalies due to their mean reversion properties. This metric also fits well within the EMT framework since it reflects stock market reactions to any new firm based information such as unanticipated changes in brand equity (Dutordoir et al., 2015). Additionally, the stationary series obtained by computing the change in the stock prices automatically account for serial correlation and white noise issues to a large extent, thus providing valid statistical outcomes. Following these recommendations, this study includes stock returns as a measure of firm's long term performance. This choice also aligns well with the main objective of the study i.e. to examine the directional brand equity-firm performance relationship. Since the variables under examination (i.e.

CBBE and FBBE) need to be included "in changes" (positive and negative), adopting stock returns in contrast to stock price based performance measure is viable. It has to be noted that since stock returns represent change in investor's expectations about firm's expected future discounted cashflows (Mizik & Jacobson, 2004), the term "long-term firm performance" is interchangeably used as "future performance", "shareholder's wealth", "firm performance", "firm value" or simply "stock returns" throughout the thesis, all of which means the same from this study's perspective.

The main antecedents of this study are positive and negative changes in consumer and firm based brand equity represented by ΔPos CBBE (which corresponds to positive change in consumer based brand equity), ΔNeg CBBE (reflecting negative change in consumer based brand equity), ΔPos FBBE (denoting positive change in firms based brand equity) and ΔNeg FBBE (i.e. negative change in firm based brand equity). These constructs are the disaggregated positive and negative components of overall changes in CBBE and FBBE. Each of the directional elements of CBBE and FBBE are linked individually to firm performance, thereby providing a polarized view of brand equity-firm performance relationship. These relationship paths are represented by four separate horizontal arrows, connected directly to firm-long term performance i.e. stock returns. Along with providing this novel view of brand equity-firm value nexus, model section-I also compares consumer based brand equity and firm based brand equity. The aim of this comparative analysis is to answer two vital questions: i) are these brand equity measures strongly associated with each other and ii) if not (which this study contends), then which amongst them have more power in explaining firm's long-term performance? The first question focuses on the relative evolution of these brand dimensions over time to assess the degree of their mutual association. The path defining this relationship is denoted by a double-sided arrow interconnecting ∆CBBE and ∆FBBE. The model then advances to explore the second objective by contrasting their individual consequences on stock returns (including only common brands in CBBE and FBBE samples). Amalgamating these two comparative approaches simultaneously within a single conceptual framework offer new and in-depth knowledge about the association between these two key brand equity measures, which until now is broadly ambiguous (Nguyen et al., 2015; Tasci, 2020).

As stated earlier, the second section of the proposed model includes two intermediary "organizational efficiency" measures namely core business efficiency (CBEF) and marketing capability (MCAP). These efficiency metrics are expected to moderate the brand equity-firm value relationship such that higher levels of CBEF and MCAP enhance (mitigate) the positive (negative) firm performance effects of rising (declining) brand equity. CBEF represents the ability of a firm to exploit its available *tangible resources* to maximize *profits* (Nath et al., 2010) whereas MCAP captures the management's ability to utilize its *marketing resources* strategically so as to expand its consumer base through enhanced *sales* (Sun et al., 2019). The path relationships emerging from these two efficiency measures connect the model section-I through dotted arrows signifying that they are hypothesized as interacting variables. Following resource based perspective, both CBEF and MCAP are operationalised through multi input-output transformation process. This approach aligns well with RBT advocating that firms must utilize their compendium of resources cohesively to enhance their performance outcomes, thus leading to higher organizational efficiency levels (Sun et al., 2019). The choice of the acquired inputs and outputs to materialize CBEF and

MCAP is guided by the existing literature and is discussed in detail in the subsequent sections of this chapter.

3.2.2 Hypotheses Development in Model Section-I (Direct relationships)

The central part of the proposed conceptual model addresses the first research objective and explore the unique relationship of positive and negative changes in consumer and firm based brand equity with firm performance. However, as evident in figure 3.1, before investigating these directional effects, the model first links overall changes in CBBE and FBBE with firm value (represented through direct paths originating from ∆CBBE and ∆FBBE). Previous marketing-finance research is conclusive that brand equity significantly enhances long-term firm performance, and this incremental value is contributed by both consumer-based (Bhardwaj et al. 2011; Mizik & Jacobson, 2008; Nam & Kannan, 2014) and firm-based brand equity perspectives (Joshi & Hanssesns, 2010; Wang & Sengupta, 2016; Yildiz & Camgoz, 2019). However, it is important to validate if similar firm value association is exhibited by the CBBE and FBBE measures included in this study. Testing and affirming similar association for the acquired brand metrics will therefore lay a solid foundation for this research to advance the knowledge further and examine the value enhancing or deteriorating effects of upward and downward shifts in these two brand equity measures. Although these path relationships are not novel, their inclusion in the model still refines the existing brand equity-firm performance scholarship by embracing best practices recommended. For example, many empirical studies have linked brand equity to short-term firm performance measures such as market share, revenue, and price premium (e.g. Ailawadi et al, 2003; Coleman et al., 2015; Keller & Lehmann, 2006; Luxton et. al, 2015). Marketing academics however emphasize that brands have lasting effects, therefore evaluating its value relevance through current period performance metrics cannot capture its total financial contributions (Goldfarb et al., 2009; Srinivasan et al., 2005). This is in-line with Aaker's (1996) explanation that building strong brands is not a straightforward process because of the pressure to invest elsewhere, thus it challenging to apprehend its value relevance in the short term. Mizik (2014) provides further supporting evidence reporting that immediate accounting performance measure explains only a small portion of the total financial contributions of brand equity as compared to future-term measures. Therefore by linking overall changes in CBBE and FBBE to stock returns, this study provides robust and credible evidence about the lasting financial effects of brand equity.

Secondly, as discussed earlier, it is suggested that in order to evaluate the value relevance of any marketing asset or strategy through stock market based measures, it should preferably be included as "changes over time" rather than "at levels" (Christodoulides et al, 2015). Despite its weak theoretical and practical implications (Srinivasan & Hanssens, 2009), many empirical studies still include these marketing and branding metrics in their absolute form (some recent examples are Chang & Young, 2016; Rahman et al., 2019; Wang & Sengupta, 2016; Yildiz & Camgoz, 2019). This research overcomes these anomalies by analysing the dynamic brand equity-firm performance linkage rather than their contemporaneous relationship.

Thirdly, as reviewed in the previous chapter, almost all the existing brand equity-firm value exploratory research has focussed on a single brand equity measurement metric when evaluating its long term value relevance. Brand equity is a multi-dimensional construct (Veloutsou et al., 2020), and no single brand equity measurement perspective can singularly capture its holistic depth and breadth (Molinillo et al., 2019). Regardless of the complex structure of this intangible marketing construct, current literature still lacks a comprehensive study which evaluates the performance capabilities of brand equity from multiple paradigms (Davick et al., 2015; Nguyen et al., 2015). Bridging this gap and including consumer and firm centric brand equity perspectives cohesively within a single research framework, this exploratory research further contributes to existing scholarship about the "changes in overall brand equity" to firm performance translation mechanism.

In view of above discussions and recommendations, the proposed conceptual model hypothesises the link between brand equity-firm value dynamics considering three main aspects. Firstly, a positive association between brand equity and firm performance is expected (Bhardwaj et al., 2011; Dutordoir et al., 2015; Mizik, 2014; Mizik & Jacobson 2008; Mizik & Jacobson; 2009b; Oliveira et al. 2018) Secondly, the model includes the acquired brand metrics "in changes" to evaluate if it contains any incremental information in explaining firms' future discounted cashflows. And thirdly, the brand equity-firm performance relationship is gauged through both the consumer and firm oriented brand equity measures. Consequently, following two hypotheses are proposed:

H1(a): *Changes in CBBE have a positive relationship with firm performance.*

H1(b): *Changes in FBBE have a positive relationship with firm performance.*

3.2.2.1 Directional relationship of CBBE and FBBE with firm performance

The main objective of section-I of the proposed conceptual model is to provide novel insights about the directional relationship of brand equity, more specifically consumer and firm based brand equity, with firm performance. Nevertheless, multitude of studies have examined the value relevance of brand equity from different measurement perspectives, very few have attempted to isolate their positive and negative components. Existing research is limited to exploring the long-term financial impact of positive and negative: consumer brand ratings (Luo et al., 2013), branded product reviews (Tirunalli & Tellis, 2012) and news release about a brand (Xiong & Bharadwaj, 2013). Other relatable studies to this research stream are that of Luo (2007) and Luo (2009) but they focus solely on the stock market impact of negative consumer complaints and word of mouth, respectively. As discussed earlier, a major limitation of these studies is that they have examined the value relevance of the acquired brand response factors (i.e. ratings, reviews, or news) within very narrow time intervals (daily or monthly). In practical terms, it is highly unlikely that stock market participants can accurately respond to these short-term fluctuations in consumer brand sentiments due to the presence of noise. Changes in brand ratings or reviews on daily (or even monthly) intervals can be due to several short-term factors such as consumer complaints, speculatory news and word of mouth which are not conclusive in determining the brand’s long term value implications. Datta et al., (2017:15) argue that brand equity is an enduring phenomenon, which is “built over years, not weeks or months". It is therefore recommended that future research should examine the dynamics of its change within longer time intervals and its firm value effects over multiple years (Datta et al., 2017; Luo et al., 2013:411). Short-term shifts in brand performance do affect stock prices but such abrupt responses capture only a small share of the true value enhancing (or deteriorating) capabilities of brand equity (Mizik, 2014). Therefore, this study provides novel insights about financial consequences of upward and downward shifts in brand equity over longer time horizons. This is important because an evolving brand equity may translate into enhanced financial growth, but misinterpretation of declining brand equity, especially over prolonged periods can have adverse effects, sometimes beyond recovery (Veloutsou & Guzman, 2017). Therefore, by overlooking these directional brand equity-firm performance dynamics, management can over or undervalue their brand's actual performance (Luo et al., 2013).

Interestingly, all the existing studies examining the directional firm value impact of the acquired consumer brand response metric have reported a stronger impact of negative changes as compared to positive changes (see table 2.4 in the literature review chapter). These findings may seem surprising at the first glance, but it can be explained through negativity bias theory (Tellis & Johnson, 2007) and prospect theory (Kahneman & Tversky, 1979). Negative bias theory asserts that "consumers react more negatively to losses than positively to gains" (Tellis & Johnson, 2007:760). According to prospects theory (also called loss-aversion theory), "a negative, dissatisfying customer experience may matter even more than a positive, satisfying experience because "losses loom larger than gains" (Kahneman & Tversky 1979:263). It is likely that either the stock market community also reacts in a similar manner, or such consumer behavioural trends are foreseen by them (Luo & Homburg, 2007). In any case, it is persuasive that the financial market impact of declining brand equity would be higher as compared to positive changes. Another striking feature of the small body of research providing the polarized view of brand equity is their focus solely on consumer based brand response metrics. To the best of researcher's knowledge, no study until now have focused specifically on examining the stock market response of rising or declining brand equity derived from brand's financial strength (i.e. FBBE). This is important because brand equity is a multifaceted construct (De Chernatony & Riley, 1998; Farjam & Hongyi,

2015) and therefore focusing solely on favourable and unfavourable shifts in consumer brand association would provide incomplete information about overall brand performance. Studies determining the relevance of brand equity in the industrial setting and with a B2B context (e.g. Alwi et al., 2016; Davis et al., 2008) further encourage this research to encompass multiple brand equity perspectives, especially when exploring the value relevance of brands operating in both B2C and B2B sectors[12]. Ignoring the contributory or destructive firm value effects of unanticipated changes in other brand equity dimensions like FBBE can significantly jeopardize firm's future growth.

Based on above discussions, it is clear that not much is known about the directional effects of brand equity on business performance especially over longer time horizons. Additionally, current marketing research has solely focused on the consumer brand association overlooking other brand equity measurement perspectives. Extending this limited body of literature, the current study provides new insights about the directional relationship of rising and declining brand equity with firm future performance focusing on both CBBE and FBBE. Additionally, following the propositions of "negativity bias" and "loss-aversion" theories, it is expected that the negative effects of declining brand equity will be stronger as compared to positive changes. Thus, following two novel hypotheses are proposed:

H2(a): *Negative changes in CBBE have a stronger relationship with firm performance as compared to positive changes.*

[12] As mentioned earlier in section, many of the acquired sample brands in this study are exposed to both B2B and B2C industries.

H2(b): *Negative changes in FBBE have a stronger relationship with firm performance as compared to positive changes.*

3.2.2.2 Comparative assessment of CBBE and FBBE

Apart from exploring the linkage of consumer and firm based brand equity with firm performance, it is also crucial to conduct a comparative analysis of their relative performance dynamics. Despite increasing focus on exploring the value relevance of CBBE and FBBE, their relationship with each other has not been substantiated with enough empirical evidence (Tasci, 2020). As realized while reviewing the existing branding literature, academics have adopted two distinct approaches to link CBBE and FBBE. The first stream of research conducts a direct comparison between these two brand equity measures (e.g. Nguyen et al., 2015; Tasci, 2020) while the others relate them through their association with firm performance (e.g. Johansson et al., 2012). No empirical study to date has integrated both these perspectives into a single research framework to systematically investigate the relationship between CBBE and FBBE. The goal of this section of the conceptual model is therefore to fill this gap by incorporating following two research questions:

1. Are consumer and firm based brand equity measures closely associated with each other?
2. If not, then which brand equity dimension amongst them has stronger association with firm performance?

These questions are worthwhile to pursue because even with limited research linking consumer based brand equity to the firm based measure, their findings are largely inconsistent. One set of studies advocate that brand strength measured through consumer mindset are converging to financial measures of brand equity such as revenue premium (Ailawadi et al., 2003; Huang & Sarigöllü, 2014), profit margin (Stahl et al., 2012) and sales (Datta et al., 2017). These studies claim that both these brand equity dimensions are linked because firm level outcomes i.e. profit, revenue premium and cashflows are the outcomes of consumer based factors such as brand image, awareness, and attitude (Ailawadi et al., 2003:1). The opposing view argues that perpetual brand equity measured through consumer cognitive attachment is not closely linked to the financial measures. For example, Nguyen et al. (2015) investigate the relationship of multiple consumer brand dimensions such as loyalty, perceived value, differentiation, attachment, and experience with financial based measure of brand equity. Their results indicate that apart from brand experience, all other consumer centred brand dimensions are not significantly associated with FBBE. Similarly Tasci (2020) reports no significant relationship between CBBE components of brand image, familiarity, and loyalty with various FBBE measures. Even proponents of strong CBBE-FBBE linkage have found that some financial brand equity measures such as price premium is not associated with consumer mindset measures (Huang & Sarigöllü, 2014). All these contradictory findings suggest that existing marketing research is still inconclusive about the CBBE-FBBE interrelationship. This research therefore aims to further explore this relationship by integrating both the comparative approaches adopted by the existing literature under a single conceptual framework.

Contributing to the ongoing debate, this study takes the stance that although CBBE and FBBE dimensions are interdependent, they are not closely associated. Inclination towards this assumption is driven by several factors. Firstly, majority of existing studies have examined the steady state relationship between CBBE and FBBE rather than their “in change” dynamics. It is priory obvious that the two brand equity measures will concur in terms of their contemporaneous relationship because i) they emerge from a same theoretical concept and ii) they are mechanically interlinked as higher levels of consumer brand loyalty and association (CBBE) will positively impact revenues and cashflows (FBBE) (Rego et al., 2009). However, changes in these brand dimensions over time may not be as closely linked as their “in level” relationship. This is because consumer and firm-level measures assess different stages of brand equity manifestation in the brand value chain (Ailawadi et al., 2003; Huang & Sarigollu, 2014; Keller & Lehmann, 2006). CBBE captures the outcome of perceptual brand attributes and therefore is a backward looking measure (Nguyen et al., 2015). On the other hand, firm centric brand equity represents the brand's current and expected future earnings, therefore is a forward looking measurement concept. Additionally, as discussed in chapter 2, CBBE is *subjective* in nature whereas FBBE is primarily *objective* (Christodoulides et al., 2015). Based on these contradictory facets, it is expected that the dynamics of their change over time will not be closely associated. An assumption of weak CBBE-FBBE linkage is also vital to address the second research objective of this study i.e. to compare how unanticipated changes in CBBE and FBBE are individually linked to firm performance. If CBBE versus FBBE dynamics over time exhibit strong association, then addressing this research aspect will be ambiguous. Considering these arguments, following hypothesis is proposed:

H3: *Changes in CBBE over time are not closely associated with FBBE changes.*

The second research question is whether there is a significant difference in the relationship of CBBE and FBBE with firm value. It is important to address this question since marketing researchers argue that no single dimension of brand equity can fully explain its true value imparting potential (Molinillo et al., 2019). As discussed in the section 2.4 of the literature review chapter, to date, only Johansson et al. (2012) and Bagna et al. (2017) have undertaken a direct empirical comparison between the stock market impact of consumer and firm based estimations of brand equity. However, their empirical outcomes are largely contradicting each other where Johansson et al. (2012) reports no incremental effects of FBBE measure on stock returns whereas Bagna et al. (2017) found both the measures to be value relevant. Although these studies are one of their kind, they have some potential limitations which calls for further investigation. Firstly, the comparative analysis of Johansson et al. (2012) encapsulates a very narrow time window, specifically four months preceding the September 2008 stock market crash (May until August 2008). Empirical results obtained in such a small time frame, especially for a gradually evolving strategic marketing asset like brand equity, cannot be generalized and therefore holds limited value. Secondly, the comparative analysis is conducted during the time when financial markets were undergoing economy-wide distress and were broadly out of equilibrium. A more reliable approach would be to evaluate such performance dynamics in a more conventional macro-economic environment and for longer time horizons, thus reducing the impact of any external noise. Thirdly, both the studies include the acquired CBBE and FBBE measures in their steady-state form which is known to have low statistical and theoretical implications (Srinivasan & Hanssens, 2009).

Realizing these potential limitations, this study extends the existing knowledge by providing a long-term view of CBBE-FBBE relative firm performance dynamics. Since the aim of this research is to analyse the directional effects of rising and declining brand equity, the comparative assessment also follows the same suite. That is to say, it examines if the positive (negative) relationship of rising (declining) CBBE with firm's future profitability is significantly different as compared to changes in FBBE measures for the same firm brands. Although, no study until now has directly contrasted the polarized firm value implications of these two brand equity measures, this research expects these effects to be stronger for CBBE as compared to FBBE. Certain explanations for this assumption can be drawn from the existing marketing-finance literature. Firstly, empirical findings of Johansson et al. (2012) indicate that the stock market participants favoured consumer based brand equity estimations over FBBE when assessing their investment risk during the 2008 financial turmoil. This suggests that investors and shareholders pay more attention to any unexpected changes, positive or negative, in consumer brand response to re-evaluate their investment strategies.

Secondly, despite numerous measurement perspectives, consumers are the foundation and main drivers of the brand equity concept (Stahl et al., 2012). Ultimately it is the consumer's association and loyalty towards a brand that leads them to willingly pay higher prices for its products compared to equivalent unbranded offerings (Aaker,1996; Keller, 2008). Therefore, any rise or decline in consumer brand perceptions will directly impact brand's market performance e.g. sales and profits. This would in-turn alter investors and shareholder's expectations about firm's future growth prospects, resulting in a revaluation of firm's stock price. This is indicative that CBBE is the foremost predictor of long-term firm performance as compared to other brand equity measures.

Thirdly, marketing researchers suggest that changes in CBBE are subjective to consumer psychology and difficult to apprehend (Nguyen et al., 2015). On the other hand, even a minor alteration in the projected brand earnings (i.e. proxy of FBBE) can be easily tracked due to the practicability and ease of its measurement (Huang & Sarigöllü, 2014). This continuous tracking of a brand's financial performance can enable brand managers to address any anomalies effectively in time before it has any long-term consequences. Management can therefore confidently communicate their strategies to counter such positive and negative FBBE changes to the investors and shareholders, thus gaining their confidence and reducing the stock price volatility.

Based on above arguments and conducting a comparative assessment of the polarized firm value effects of consumer versus firm oriented brand equity dimensions, following novel hypothesis is proposed:

H4: *The value enhancing (deteriorating) impact of rising (declining) CBBE is stronger as compared to FBBE changes.*

The first section of the proposed conceptual framework focussed on exploring the direct relationship between brand equity and firm performance leading to the formulation of six distinctive hypotheses. These hypotheses test the brand equity-firm value linkage from multiple perspectives such as their overall and directional effects, their comparative dynamics and individual association with firm value. The following section discusses the arguments presented for the second part of the model which focus on the interacting effects of organizational efficiency in translating brand equity as a source of sustainable future performance.

3.2.3 Hypotheses development in Model Section II (Moderating Relationships)

The three vertical blocks denote the second section of the proposed conceptual model and focus on examining the intermediary role of organizational efficiency in brand equity-firm performance relationship. Anchored to resource based theory (RBT), the blocks segregate firm resources, capabilities, and performance measures to provide a magnified view of the brand equity value translation mechanism. According to RBT, firms need to combine their available resources with their superior capabilities to generate performance which is sustainable over time (Barney & Hesterly, 2012). From this study's perspective, this translates that exploring the directional changes does provide a magnified image of brand equity-firm value dynamics, but it holds little significance if the management is incapable of exploiting this information to their benefit. Therefore it is crucial to evaluate if the adverse (favourable) effects of declining (rising) brand equity are sensitive to organizational efficiency levels. RBT proponents argue that majority of RBT based marketing studies neglect the "organized" aspect of the VRIO acronym despite its importance for the completeness of the resource based perspective (Kozlenkova et al., 2014; Vomberg et al., 2015). This section of the proposed model therefore complements the previous section by paying close attention to the role of organizational efficiency in moderating the directional effects of rising and declining brand equity. The model proposes firm's core business efficiency (CBEF) and marketing capability (MCAP) as two key organizational functions. CBEF represents the ability of a firm to exploit its available tangible resources to maximize profits (Zhu, 2000). MCAP, on the other hand, captures the firm's ability to market its products and services to achieve a desired output e.g. sales revenue (Sun et al., 2019). The following sections elaborate on these two management factors, highlighting their importance in the model and the development of relevant research hypotheses.

3.2.3.1 Core Business Efficiency (CBEF) - Profitability

A “resource efficient” management employs accumulated business knowledge and expertise to convert its distinctive set of resources to produce an output which is valuable and hard to imitate (Modi & Mishra, 2011). Business efficiency therefore pertains to the ability of a firm to utilize its primary resources such as plant, equipment, employees, and capital competitively so as to maximize profitability (Nath et al., 2010). Possessing knowledge and expertise to run the core business is therefore a prerequisite for any firm to thrive in the dynamic and competitive commercial environment. Efficiency is defined as a ratio of output to input; hence firms classified as more resource efficient are capable of maximizing their output with the minimal resource allocation (Nath et al., 2010). They achieve it through competent administration, skilled workforce, and elite operations management (Kozlenkova et al., 2014). Higher level of efficiency therefore is an *intellectual asset* which enables firms to persistently outperform the marginal competitors to achieve sustained competitive advantage (Kharal et al., 2014). A main caveat in majority of existing studies examining the value relevance of the derived *intellectual assets* is their sole focus on linking it directly with firm performance (for list of representative studies, refer to table 2.6). Very few studies have explored its intermediary role especially in brand equity-firm performance translation mechanism. Another shortcoming is that very few academics have operationalised an *intellectual asset* which specifically corresponds to the core business operating efficiency of a firm. Infact, only two relevant studies are identified which have embraced multiple input-output transformation to benchmark firm's fundamental business managing capability. The first study is by Zhu (2000) which employs an input-output approach to measure profitability of top 500 firms published by Fortune magazine. The author defines profitability as firm's ability to minimise the deployment of its available resources of labour, assets, and capital stock to attain similar level of income (Zhu, 2000:107). The second research is by Nath et al. (2010: 321) who define an efficient firm as the one which can "maximize its financial performance with given resource constraints". The two studies however differ in the way they have examined these efficiency metrics. Zhu (2000) evaluates the direct performance implications of the measured efficiency metric whereas Nath et al. (2010) explore its moderating role in enhancing the impact of marketing actions on business performance.

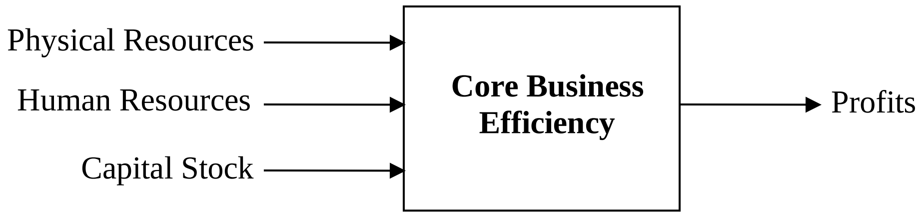
Interestingly, there is still an absence of empirical research that explores the moderating role of business efficiency in brand equity-firm value nexus especially during positive and negative changes (to the best of author's knowledge). This is important because resource based theory asserts that the firm's valuable resources can only lead to sustainable competitive advantage (SCA) if the management is competent enough to nurture them efficiently (Rahmnan et al., 2018). A management that is innovative in processing and managing any new information about their key resources is also likely to apply that knowledge to reconfigure their operating strategies (Barrales-Molina et al., 2014). Therefore, this study argues that if a firm is competent in utilizing its core resources to its maximum potential, it should be able to enhance (mitigate) the positive (negative) effects of rising (declining) brand equity on firm performance. Following the footsteps of RBT and including both consumer and firm based brand equity perspectives, the study contributes to the existing RBT literature in marketing by proposing following two hypotheses:

H5(a): *The impact of rising and declining CBBE on firm performance is positively moderated by firm's core business efficiency.*

H5(b): *The impact of rising and declining FBBE on firm performance is positively moderated by firm's core business efficiency.*

In order to empirically examine the proposed hypotheses, appropriate measures of inputs and outputs need to be identified in order to operationalize CBEF. Since only two studies closely correspond to the proposed efficiency metric, they both were scrutinized to obtain the best possible input and output measures. Nath et al. (2010) define inputs as total assets and working capital while the outputs are represented by ROA and return on capital employed (ROCE). Their research focuses on the logistics industry which makes working capital as a viable input since logistics firms rely mainly on liquid assets to run their day-to-day business operations (Min & Joo, 2006). This is however not applicable to other industries such as banking and finance, where firms do not have typical current assets such as account receivables or inventories, which defines working capital. Additionally, ROA in itself is a measure of efficiency as by definition it represents the amount of profit (output) a firm generates relative to its total assets (input) (Hagel et al., 2012). Similar is the case with ROCE which is the ratio of total profits to working capital. On the other hand, Zhu (2000) has included brands from diversified industrial sectors to quantify business efficiency metric, thus their choice of inputs and outputs is more generalized. They include number of employees, total assets, and shareholder's equity as inputs with profits as the sole output. Since the acquired sample in this study represents brands from diversified industrial sectors including the financial sector, the inputs and outputs proposed by Zhu (2000) are adopted. Figure 3.2 summarizes the input-output combination employed to operationalize core business efficiency. All the adopted inputs represent firm's physical resources; therefore they are collectively defined as tangible resources in the proposed model.

Figure 3.2 CBEF Conceptualization



Source: Author's elaboration

3.2.3.2 Marketing Capabilities (MCAP)- *Marketability*

The second organizational efficiency metric included in the proposed conceptual model is marketing capability (MCAP) which represents "firm's ability to use available resources to perform marketing tasks in ways that achieve desired marketing outcomes" (Morgan et al., 2018:61). This study argues that to accomplish optimum levels of "organizational competence", management need to maintain a consistent brand image and exclusivity in the marketplace to bind customers, along with strong core business efficiency. It is only possible with higher levels of marketing capabilities which reflects management's knowledge, skill, and best practices to understand consumer specific needs and differentiate their offerings from the competitors. Existing research has advocated the long term firm value implications of superior marketing capabilities on two fronts. The first set of studies have established a direct relationship of MCAP with different firm performance measures such as stock returns (Angulo-Ruiz et al., 2018; Yang et al., 2015), Tobin's Q (Rahman, 2020; Rahman et al., 2018; Angulo-Ruiz et al., 2014) and operating profit (Nath et al., 2010). These studies indicate that superior levels of marketing capabilities drive firm performance both in short and long term. The second stream of research have paid attention towards the moderating role of MCAP to understand its multifaceted value imparting abilities (Feng et al., 2017; Mishra & Modi, 2016; Nguyen & Oyotode, 2015; Sun et al., 2019; Wiles et al, 2012). The joint empirical evidence signifies that organizations possessing superior marketing capabilities are able to exploit any favourable or unfavourable outcomes of their employed actions and strategies to their firm's advantage.

In view of above discussions, it is clear that marketing capabilities not only contributes to firm performance directly, but also complements the positive firm value effects of several marketing and management factors. This evidence suggests that firm's marketing capability is a valuable asset which can enhance brand's value-in-use (Amit & Schoemaker, 1993; Bahadir et al., 2008). If marketing management is efficient in strongly communicating their current and future brand building strategies, they can enhance brand demand more effectively (Kapferer, 2004). This will in turn not only generate more cashflows from the brand assets but simultaneously strengthen brand equity (Morgan et al., 2009; Vorhies & Morgan, 2005). Due to these perspectives, stock market participants are likely to view superior marketing capabilities as an indicator of enhanced future cashflows. Conversely, firms with weak or deteriorating MCAP levels are likely to generate sub-optimal future returns due to their inability to communicate their brand's true potential both to consumers and financial community (Wiles et al., 2012). Therefore in an event of a sudden decline in brand equity, firms with stronger marketing capabilities will be favoured by investors and shareholders over the firms with weak MCAP levels**.** Even RBT proponents argue that MCAP in itself is a valuable, rare, and inimitable organizational resource which provides capital markets with supplementary information about firm's future earnings (Morgan et al., 2009; Angulo-Ruiz et al., 2018).

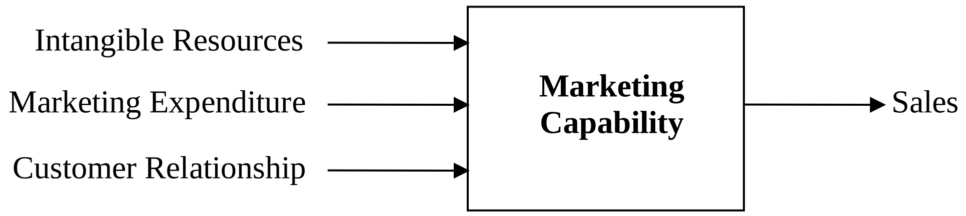
Till now, these is no empirical evidence about the pivotal role of firm's marketability in explaining the firm value implications of unexpected downward or upward shifts in brand equity. The most closely associated study is of Nguyen & Oyotode (2015), however it examines the interaction effects of MCAP in CSR-brand equity relationship, focusing on positive and negative changes in CSR perceptions. Extending this research dimension and drawing upon RBT, this study argues that MCAP is a possible moderating link to brand equity-firm performance such that firms with enhanced marketing capabilities would be able to complement the positive effects of rising brand equity. Similarly, if there is a sudden decline in firm's brand strength, management with stronger MCAP will be able to mitigate its deteriorating effects through effective communication with the stakeholders. These interaction effects are also expected to hold its relevance for directional changes in both consumer and firm based measures of brand equity. Embracing these views, following research hypotheses are suggested:

H6(a): *The relationship between rising (declining) CBBE and firm performance is stronger (weaker) for firms with enhanced marketing capabilities.*

H6(a): *The relationship between rising (declining) FBBE and firm performance is stronger (weaker) for firms with enhanced marketing capabilities.*

Similar to the efficiency framework (Nath et al., 2010; Zhu, 2000), MCAP also integrates multi input-output resource allocation approach for its operationalization and this choice is guided by the existing literature. For example, Sun et al., (2019) include multiple inputs such as SG&A, balance sheet intangibles, receivables, sales growth, working capital and earnings with firm's market share and gross margin as the outcome variables. Angulo-Ruiz et al. (2018), on the other hand, operationalized MCAP with customer satisfaction, sales, and sales growth as outputs while advertisement and promotion expenses to be the input measures. Rahman et al. (2018) conceptualizes marketing capability as the sales outcome of marketing expenditures (advertising and R&D based) and accounts receivables. On a relatively similar note, Mishra and Modi (2016) determine firm's MCAP by measuring the level of sales revenue generated given the available input resources such as SG&A, accounts receivables and patent stock. A common feature of existing studies modelling the marketing capability measure is their inclusion of SG&A and account receivables as inputs and sales as output (to see the full list of applied inputs and outputs, refer to table 2.6 in the literature review chapter). Following this extant body of literature and data availability, this study conceptualizes MCAP as deployment of three vital inputs; i) marketing resources, ii) intangible resources and iii) customer relationship to achieve the desired output of higher sales revenue (Angulo-Ruiz et al., 2014; Nath et al., 2010). Figure 3.3 outlines the configuration of MCAP along with the adopted inputs and output.

Figure 3.3 MCAP Conceptualization



Source: Author's elaboration

All the hypotheses formulated in both the sections of the proposed conceptual model are denoted in figure 3.1 with their respective numbers, positioned close to their defined relationship paths. For further ease of reference, table 3.1 summarizes all these hypotheses by segregating them into groups based on the two sub-sections of the proposed conceptual model defined earlier.

Table 3.1 Summary of all the research hypotheses proposed in this study

Hyp. No.	Theoretical Arguments
	Model Section-I
H1(a)	Changes in CBBE have a positive relationship with firm performance.
H1(b)	Changes in FBBE have a positive relationship with firm performance.
H2(a)	Negative changes in CBBE have a stronger relationship with firm performance as compared to positive changes.
H2(b)	Negative changes in FBBE have a stronger relationship with firm performance as compared to positive changes.
H3	Changes in CBBE over time are not closely associated with FBBE changes.
H4	The value enhancing (deteriorating) impact of rising (declining) CBBE is stronger as compared to FBBE changes.
	Model Section-II
H5(a)	The impact of rising and declining CBBE on firm performance is positively moderated the levels of firm's core business efficiency.
H5(b)	The impact of rising and declining FBBE on firm performance is positively moderated by the levels of firm's core business efficiency.
H6(a)	The relationship between rising (declining) CBBE and firm performance is stronger (weaker) for firms with enhanced marketing capabilities.
H6(b)	The relationship between rising (declining) CBBE and firm performance is stronger (weaker) for firms with enhanced marketing capabilities.

3.3 Summary

Overall, the proposed conceptual framework encapsulates all the research objectives i.e. (1) examining directional firm value impact of rise and decline in CBBE and FBBE; (2) conducting a comparative assessment between CBBE and FBBE and (3) investigating the moderating role of organizational efficiency factors of CBEF and MCAP in brand equity-firm performance translation mechanism. While the model addresses various research gaps in the marketing-finance literature, it also tests whether existing relationships holds true for the acquired constructs. Associating overall changes in CBBE and FBBE with firm performance not only aids this research to re-establish the value relevance of brand equity but also provides a concrete foundation to make further contributions to the existing marketing-finance scholarship. Furthermore, the model also elaborates on the association between consumer and firm based brand equity measures by conducting a comparative assessment on two fronts: their inter-relationship and individual relation to firm performance. While there is still a disagreement in the existing literature about the true relationship between consumer and firm based brand equity measures, empirical evidence is limited to only handful of studies (Davick et al, 2015; Nguyen et al., 2015 Tasci, 2020). This study expects a weak relationship between CBBE and FBBE as they evolve over time and a stronger directional firm value impact of changes as compared to FBBE changes. Finally, the proposed conceptual framework supports the proponents of RBT and expects both CBEF and MCAP to moderate this brand equity-firm performance relationship. Although similar assumptions are made for the interaction effects of CBEF and MCAP, they are operationally different to each other. Core business efficiency is an *inside-out* management function where the firm is expected to employ its internal resources strategically to maximize earnings. On the other hand, MCAP follows an *outside-in* view where organizations need to competently align its resources and capabilities according to the outside market demand to enjoy enhanced consumer-base (Afriyie & Appiah, 2018). Consequently the way they individually moderate the brand equity-firm value interface will have different theoretical and practical implications. Therefore, by including firm's *profitability* through CBEF and *marketability* through MCAP simultaneously, the proposed model provides a holistic view about the interactive role of "organizational efficiency" in the brand equity-firm value link. With new evidence, this study contributes to the RBT literature by building on its underpinnings to investigate how organizations combine their heterogeneous resources with superior CBEF and MCAP to create sustainable competitive advantage.

Chapter 4: RESEARCH METHODOLGY

4.1 Introduction

Previous chapter drafted a comprehensive conceptual framework guided by the potential gaps and defined several research questions to systematically explore the effects of changes in brand equity on firm value and the moderating role of firm's core business efficiency (CBEF) and marketing capability (MCAP). This chapter elaborates on the research methodology employed to empirically test the proposed relationship paths. The chapter starts with a brief discussion about the embraced research philosophy which provides directions to the adopted research design. The following sections scrutinize available methodological options in the existing marketing-finance literature and identify the one which justifies the scope of this research. This is then followed by detailed discussions about the preferred research method i.e. stock return response modelling (SRRM), including its assumptions, applicability in marketing literature and appropriateness for the current research. A step-by-step approach is then followed to formulate the final SRRM model for this study. Along with SRRM, the study also includes a second methodology which is specifically used to operationalize multi-input based moderating variables, CBEF and MCAP, defined in the previous chapter. Advanced version of data envelopment analysis (DEA) known as "Malmquist total factor productivity change (TFPCh)" is implemented to measure these two efficiency variables. A detailed overview of DEA and its basic frameworks is conducted followed by Malmquist TFPCh model development. Finally the chapter provide information about multiple sources approached for retrieving all the required raw data including the sampling plan, representative population, size, and its segmentation across countries and industrial sectors. The chapter finally concludes with a short summary.

4.2 Research Paradigm

Paradigm which takes its name from the Greek word “paradeigma” meaning “pattern”, was first introduced by Kuhn (1962) in the field of research. The author defined it as “a research culture with a set of beliefs, values, and assumptions that a community of researchers has in common regarding the nature and conduct of research” (Antwi & Hamza, 2015: 218). In simple terms, it reflects researcher’s beliefs about the nature of reality and the philosophical approach about conducting a research. It is crucial to identify and nominate a well-defined research paradigm as it will serve as a clear basis of subsequent decisions pertaining to chosen research design and methodology (Kivunja & Kuyini, 2017). A paradigm which a research scholar adopts is defined from their beliefs and assumptions about three components i.e. ontology, epistemology, and methodology (Creswell, 2014). All these assumptions are interdependent to each other such that the chosen ontological belief dictates the researcher’s epistemological stance which in turn guides the chosen research methodology.

Ontology refers to the researcher’s belief about the “nature of reality”, where the questions to be answered are “how reality exist and “what can be known about it” (Rehman & Alharthi, 2016:51). The current study adopts a positivist ontology believing that a single reality exists which can be determined independent of human senses, rather than multiple subjective realities as interpretivism assumes (Mackenzie & Knipe, 2006). Realizing the empirically validated reality that brand equity holds a strong association with firm value (Davick et al., 2015; Keller, 2016; Mizik, 2014), the current study explores this relationship in more depth and from a new dimension. Driven by positivism, the study is conducted embracing an "objective" epistemological stance which endorses total separateness between the researcher and the research (Scotland, 2012). Adopting an objective approach affirms that the observed reality is not controlled or manipulated in any way by the researcher's personal beliefs. This research therefore relies on secondary data sources to measure and quantify all the dependent and independent variables defined earlier in the conceptual framework chapter. The quantitative nature of this study also aligns well with the adopted time-horizon i.e. longitudinal (10 years). Existing research affirms that brand equity has lasting financial implications which cannot be captured completely in short term (Datta et al., 2017; Mizik, 2014), therefore a long time-series brand equity data would be an ideal choice for a robust analysis. Following these arguments, historical monetary brand values published by professional brand consultants were obtained to quantify this core marketing variable.

The ontological beliefs of positivism further guide this research to adopt a "deductive" reasoning approach where existing theories are consulted to develop multiple hypotheses which are then tested through scientific empirical methods (Gill & Johnson, 2010; Saunders et al., 2015). This ensures that the obtained results are based purely on data and facts and are neutral or unbiased towards researcher's own beliefs (Crotty, 1998). Following this approach, firstly a causal relationship is developed between positive and negative changes in brand equity on firm performance. Afterwards, adopting resource based theory, the moderating role of core business efficiency and marketing capability in translating brand equity-firm value dynamics is tested. The use of quantitative data and econometric analysis to identify patterns and making generalizations appropriately links the adopted methodology with the positivist and objectivist philosophical paradigm (Sobh & Perry, 2006). Table 4.1 summarizes the philosophical stance taken in the current research defining all the sub-components and their respective assumptions.

Table 4.1 Philosophical Stance undertaken in the current study

Term	**Position Adopted**
Research paradigm *(Ideological orientation)*	Realism
Ontology *(Theory of being)*	Positivism
Epistemology *(Theory of knowing)*	Objectivism
Approach to theory development *(Relation to theory)*	Deductive
Methodology *(Theory of discovery)*	Statistical econometric analysis
Time horizon *(Cross-sectional, mid-range, longitudinal)*	Longitudinal
Methods and techniques *(Collection of data)*	Secondary and Quantitative

4.3 Research Method

Since this study adopts stock returns as a representative of long term firm performance in order to examine the "value relevance" of brand equity, the identification of a research methodology that can precisely and robustly analyse this relationship is vital. The "value relevance studies", as termed by Holthausen and Watts (2001:1), firstly emerged in the field of accounting research to investigate the impact of firm's financial information metrics on stock market valuation. The investigated measures include earnings and revenue surprises (Jagadeesh & Livnat, 2006; Nichols & Wahlen, 2004), reaction to analysts' forecasts (Clement et al., 2003; Doyle et al., 2005) and market efficiency tests (Lewellen & Shanken, 2002; Piotroski, 2000). It is generally straightforward to link such financial information directly to stock returns as they are one of its key determinants (see Kothari, 2001). Investors continuously scan the markets for any new information available about firm's current period accounting performance and immediately react to any unexpected changes (e.g. earning release). However, marketing measures especially the intangibles like brand equity are not included in the balance sheet, thus the information contained in them is not readily available. Therefore, analysing the impact of such non-financial metrics on stock market based indicators need more careful modelling. Simply regressing a marketing variable on stock returns without considering firm's accounting performance measures and other economy-wide factors could provide misleading interpretations as it cannot replace these metrics in determining firm future performance (Mizik & Jacobson, 2004). Based on these arguments, existing marketing-finance literature was carefully assessed to identify "value relevance" based research methodologies that can efficiently link marketing strategies, especially brand equity, to stock returns (some recent examples of such studies are Dorflienter et al, 2019; Dutordoir et al, 2015; Mizik, 2014; Sorescu et al., 2017; Skiera et al., 2017; Yang et al., 2015). The literature overview yielded three most widely employed econometric models namely event study analysis, calendar-portfolio approach, and stock return response modelling (SRRM). Amongst them, SRRM fits precisely to the current research's objectives in contrast to the other two econometric methods. The following sections justify this choice by first briefly discussing event study analysis and calendar portfolio approach and explaining their unsuitability as an appropriate methodology for this research. This is then led by an in-depth understanding of SRRM modelling technique, focusing on its relevance to the current study, application in existing literature and the modelling procedure.

4.3.1 Event-Study Methodology

The first approach is the “event study method” that develops direct inferences between a well-defined discreet information and the investors and shareholders reactions to it (Kimbrough et al., 2009). The methodology rests on the principle that markets are efficient and the current stock price reflects all the available information about the underlying firm (Fama, 1970). Any event with new information will therefore result in an instantaneous change in stock prices that would have not occurred in the absence of this event. Event study methodology is designed to capture these short term excess returns attributed to particular event of interest (Skiera et al., 2017). These abnormal returns are estimated either for the same day or summed across immediate time horizons surrounding the event to obtain cumulative abnormal returns (CARs) (Srinivasan & Hanssens, 2009). This extended time-frame is known as “event window” which can last till 5 to 30 trading days around the event date (Mizik & Jacobson, 2004). Researchers recommend this window to be as narrow as possible to eliminate the chance of any confounding information affecting the excess returns (McWilliams & Siegel,1997). Primarily developed by finance researchers to examine stock price reactions to corporate announcements (e.g. earnings release), event studies have gained wide importance in the marketing stream (Collins & Kothari, 1989; Francis & Ke, 2006; Kimbrough et al., 2009). Scholars have applied this approach to access the extent to which investor and shareholder respond to any information publicized concerning various marketing actions and strategies (see meta-analysis by Sorescu et al., 2017). For example, Dutordior et al. (2015) report that brand value announcements by third party brand consultants generate positive abnormal returns on the day of the information release. Gao et al. (2015) find that the immediate negative stock price reaction to critical marketing announcement such as product recall can be mitigated through boosting advertisement spending. Other prominent marketing events that have been investigated through event studies include brand acquisitions (Wiles et al., 2012), brand name changes (Kalaignanam & Bahdir, 2013), new product announcements (Borah & Tellis, 2014) and chief marketing officer appointments (Boyd et al., 2010). A key benefit of this quasi-experimental approach is its ability to capture discrete marketing information at known time stamps and provide a clear rationale about its magnitude of impact (Dutordoir et al., 2015). Furthermore, due to examination of immediate investor reactions to an event, there is minimal chance of inclusion of any noise caused by other external market factors in the stock price.

Irrespective of its popularity in the marketing research, event studies are not without limitations. Firstly, event study approach is not appropriate for examining a dynamic processes that occur over periods of time (Sorescu et al., 2017:204). Its main objective is to determine whether an event has succeeded or failed to meet investor expectations rather than affirming whether this information did actually materialise in future (Sorescu et al., 2017). Besides this, event study methodology can even sometimes inaccurately examine the short term effects of marketing actions (Pauwels et al., 2004). For example, a marketing announcement such as “significant increase in advertisement expenses for the next year” could have mixed short-term investor response due to discrepancy in their quick judgements. One group of investors may see it as additional costs while others may appreciate it as an investment to strengthen future brand equity. These conflicting reactions could drag the stock price in either direction in short term. The event study capturing such marketing event could therefore provide misleading information and make it problematic to generalize these findings (Geyskens et al., 2002; Johnston, 2007). Even from the statistical point of view, event study methodology is not suitable for measuring long-term abnormal returns especially when the firm events are clustered over time. This is due to the inability of this method to account for cross-sectional dependence across events, thus providing misleading statistical inferences (Kothari & Warner, 2006). All these discussions suggest that although event study has been widely implied in exploring the marketing-finance relationship, its true implications are only valid for short term studies. Since this research aims to examine the longitudinal effects of rising and declining brand equity on firm performance, event study methodology does not seem to be an appropriate choice.

4.3.2 Calendar-time Portfolio Approach

In order to overcome the issues arising due to short-time span of event studies, marketing researchers have adopted yet another methodology emerged in finance stream, specifically the calendar-time portfolio analysis (Jaffe, 1974; Mandelker, 1974; Sorescu et al., 2007).). A calendar-time portfolio approach (CPA) involves constructing a stock portfolio by grouping firms based on "marketing event or asset" as the unit of analysis. The firm stocks are bought on the day of the event and held for the length of measurement window which can last from six months to several years. Monthly portfolio returns are then calculated for the entire period of study and regressed on various market based and economy-wide risk factors (Sorescu et al., 2017). An example of a calendar portfolio model is outlined below:

$$R_{Pt} - R_f = \alpha_P + \beta_P(R_{mt} - R_f) + \beta_1(SMB_{Pt}) + \beta_2(HML_{Pt}) + \varepsilon_{pt} \qquad (4.1)$$

Where, R_{Pt} is the realized monthly portfolio return, R_f is the risk-free rate, R_{mt} is the monthly returns of the overall market index in which the target firms trade (e.g. S&P 500 for the US and FTSE100 for major firms in the UK). SMB_{Pt} and HML_{Pt} are the Fama French (1973) risk factors of size and book-t-market value respectively and ε_{pt} is the error term (an in-depth discussion of these risk factors is conducted in the next section of this thesis). The coefficient of interest in any CPA model is the intercept α_P which represents the portfolio performance (Hoechle & Zimmermann, 2007). A significant positive alpha indicates that the marketing information under investigation is valuable such that it is able to generate returns greater than what were expected during the estimation period. In contrary, if α_P is zero or insignificant, it signifies that all the variation in the portfolio returns have been captured by the coefficients of R_{mt}, SMB and HML. In that case, there are no long-term abnormal returns that can be associated with the marketing information released during the underlying event. A major advantage of CPA approach over event study analysis is its ability to capture long term financial performance of marketing assets and strategies. Additionally, unlike event based studies where stock returns are computed for individual firms, CPA addresses the monthly variation in the returns of a single portfolio with multiple stocks. The standard error of the calendar portfolio regression therefore is not obtained from cross-sectional variance within firms, rather represents serially uncorrelated monthly portfolio returns (Mitchell & Stafford, 2000; Srinivasan & Hanssens, 2009). Due to this, CPA automatically accounts for cross-sectional dependence of returns across firms and therefore provide more accurate statistical inferences. A detailed explanation about this phenomena along with an illustrative example is provided in Appendix A.

However there are some downsides of calendar-time portfolio technique which makes it infeasible to be employed for the current research analysis. Firstly, CPA is incapable of examining firm-specific effects of an underlying event on abnormal returns (Sorescu et al., 2017). Since the stocks are grouped into a single portfolio, the performance outcomes can be associated with the overall effect of a particular marketing event rather than the individual firm response. In simple words, CPA is unable to measure how firm specific marketing information (e.g. unanticipated changes in brand equity) impact long term performance rather it is more of an "event-centred" approach. Secondly, researchers in finance and economics (e.g. Loughran & Ritter, 2000) also caution that abnormal returns captured through portfolio regressions have low statistical power. This is because CPA cannot differentiate the months of heavy event activity from other relatively slower months and simply gauge the overall portfolio performance. This averaging down of performance thus provide incomplete information about the true financial implications of the "hot" event activity period (Srinivasan & Hanssens, 2009:302). Thirdly, by no means it is possible to accommodate positive and negative brand value changes simultaneously into a calendar portfolio to explore their individual effects. Lastly, it is challenging to explore the interaction effects of moderating variables through a portfolio approach. The only feasible way is to divide events into different sub-portfolios based on the "interacting information content" and capture separate regression intercepts for each model. The main disadvantage of this technique is the survivorship bias that occur when the sample data is limited or there are multiple moderating variables. In such cases the number of firms in each portfolio can drop significantly resulting in the loss of power in the empirical analysis (Sorescu et al., 2007). All these anomalies make calendar-portfolio methodology inadequate for addressing the overall objectives of this study.

4.3.3 Stock Return Response Modelling

The third methodology that has been increasingly employed to explore the value relevance of marketing and branding assets on firm performance is stock return response modelling (SRRM). SRRM, as the name suggests, access the stock market response to any new information contained in a measure. More specifically, it establishes whether investors and shareholders perceive information about change in a non-financial measure as a contributing factor to a change in firm’s future cashflows (Mizik & Jacobson, 2004). Stock market participants perceive firm’s current period balance-sheet performance as a key metric to project long term performance (Mizik, 2014). The framework therefore examines the impact of marketing variables on stock returns after considering the effects of current period profitability and other macro-economic factors. The motivation behind this approach is that the financial community project firm’s future valuations not only based on current period earnings but also on other information such as intangible assets and future growth opportunities (Mizik & Jacobson, 2008). SRRM assumes that stock markets are efficient, and investors have access to both financial and non-financial data e.g. sales, earnings, and brand strength. Any unexpected change in these measures alter their expectations about firm’s future cashflows, thus causing a movement in the stock price (i.e. stock returns). Information residing in current period accounting performance measures (e.g. earnings surprises) generally get immediately absorbed whereas impact of intangibles like changes in brand equity take longer to fully reflect in firm value (Datta et al., 2017; Mizik & Jacobson, 2004). Thus, to capture the complete stock return response of such marketing assets, SRRM includes both the accounting and non-accounting measures simultaneously over longer time horizons. This is because non-financial measures such as marketing assets and strategies are not a replacement to standard accounting information in determining future firm value (Mizik, 2014). Therefore, developing marketing response frameworks without the inclusion of accounting and other market-wide factors driving stock prices may produce misleading empirical inferences. This provides the foundation for stock return response modelling. The section below discusses the development of the valuation model in detail showing linkages between marketing assets and stock market metrics.

4.3.3.1 Developing SRRM valuation framework

According to efficient market theory (EMT), the current stock price of a firm reflects all the publicly available information about its future profitability prospects (Fama & French, 1992). Investors and shareholders scan firm's financial statements in order to access the amount, timing, and uncertainty of its future cashflows (FASB, 1978). Therefore, the market capitalization of a firm signifies the investor's evaluation of its net present value discounted at an appropriate risk-adjusted rate of return (Kothari, 2001). This can be expressed through the following discounted cashflow valuation model:

$$MV_{it} = \sum_{T=t}^{\infty} \left(\frac{1}{1 + r_{it}}\right)^{T-t} E(CF_T) \tag{4.2}$$

Where MV_{it} and r_{it} are the market value and discount rate of firm i at time period t, respectively, and CF_T is the net cash flow at period T. EMT postulates that security prices reflect all the available information and only react to any unanticipated events (LeRoy, 1989). Positive information tends to move the stock price higher (positive market sentiment) whereas unfavourable developments push it downwards. Therefore the current market value not only reflects the change in investor sentiments towards firm's future cashflows, but it also contains other information including:

1. Its previous period capitalization.
2. Its expected rate of return based on firm-specific risk and macro-economic conditions.

Therefore, equation 4.2 can be re-expressed as:

$$MV_{it} = (1 + ER_{it})MV_{it-1} + \sum_{T=t}^{\infty} \left(\frac{1}{1 + r_{it}}\right)^{T-t} \Delta E(CF_{iT}) \tag{4.3}$$

Where MV_{it-1} is the previous period market value of the firm "i" and ER_{it} is the returns expected from holding the security "i" for the period "t" considering the firm-specific and economy-wide risk factors.

Dividing both sides of eq. 4.3 by MV_{it-1} and reorganizing the terms yield the following:

$$\frac{MV_{it} - MV_{it-1}}{MV_{it-1}} = ER_{it} + \sum_{T=t}^{\infty} \left(\frac{1}{1 + r_{it}}\right)^{T-t} \frac{\Delta E(CF_{iT})}{MV_{it-1}}$$

The left hand side term $\frac{MV_{it}-MV_{it-1}}{MV_{it-1}}$ is the percentage change in firm i's market value from the period t-1 to t and therefore is replaced by R_{it} which symbolise the actual stock returns of firm i in time t[13].

$$R_{it} = ER_{it} + \sum_{T=t}^{\infty} \left(\frac{1}{1+r_{it}}\right)^{T-t} \frac{\Delta E(CF_{iT})}{MV_{it-1}} \tag{4.4}$$

The term $\frac{\Delta E(CF_{iT})}{MV_{it-1}}$ represents the ratio of "unanticipated change in expected future cashflows" occurred in time T to the firm's previous period market capitalization. Since MV_{it-1} remains constant during this period, it signifies that if there is a positive change in investor expectations for firm's future cashflows between the period t-1 and t, the actual stock returns R_{it} will be higher than the expected returns ER_{it}. On the other hand, if the value of $\Delta E(CF_{iT})$ is negative, R_{it} will be less than the returns expected by the investors and shareholders in that period. These differences (either positive or negative) between actual and expected returns are the "abnormal returns". These abnormal returns are the result of any unanticipated information and events that unfolds during the period t-1 and t which tend to alter investor's expectations for the firm's discounted future cashflows (Mizik & Jacobson, 2004). Existing research in accounting and finance has established a strong association between unanticipated changes in various accounting measures and abnormal returns e.g. earnings (Chen & Tiras, 2015; Keung et al., 2010; Johnson & Zhao, 2012), revenue surprises (Jegadeesh & Livnat, 2006; Kama, 2009) and

[13] Note that the market value of a firm is the product of its stock price and the number of shares outstanding. Therefore for a given period, percentage change in firm's market value is same as percentage change in its stock price, which ultimately represents stock returns.

return on equity (Clubb & Naffi, 2007). However, these effects are contemporaneous and not farsighted. Stock markets are forward looking and therefore the current accounting measures are not capable of completely predicting firm's future performance (Mizik & Jacobson, 2008). Existing research indicates that marketing activities and strategies contain information that take longer to be fully incorporated in firm value (Pauwels et al., 2004; Joshi & Hanssens, 2010). Therefore, strategic marketing assets (like brand equity) are expected to have long term effects on firm's financial valuation, incremental to the short-term returns gained from the balance sheet performance (Srivastava et al., 1998). Although it voids the EMT assumptions of dissemination of all available information immediately in the firm value, this anomaly is infrequent and occur for shorter time periods (Mizik & Jacobson, 2004). For marketing-finance analysis based on longer time horizons (several years), stock market efficiency theory holds its credibility and "is a good approximation for the functioning of the financial markets" (Mizik & Jacobson, 2004: 1). These arguments suggest that investor expectations of firm's long-term profitability depend on unanticipated changes in both; i) current term accounting measures and ii) long-term performance of their strategic marketing assets. This can be mathematically expressed as:

$$\sum_{T=t}^{\infty}\left(\frac{1}{1+r_{it}}\right)^{T-t}\frac{\Delta E(CF_{iT})}{MV_{it-1}} = U\Delta AccPrf_{it} + U\Delta Marketing_{it} + \varepsilon_{it} \tag{4.5}$$

Where, $U\Delta AccPrf_{it}$ captures the unanticipated changes in current accounting performance measures like ROI, sales, and income and $U\Delta Marketing_{it}$ denotes the changes in marketing assets and strategies such as brand equity. The term ε_{it} represents all other information and events that occurred within the time t-1 and t which could possibly generate abnormal returns. Replacing the changes in discounted future cashflows with its functional form defined in eq.4.5 in eq.4.4 yields the following model:

$$\mathbf{R_{it}} = \mathbf{ER_{it}} + \beta_1 \mathbf{U\Delta AccPrf_{it}} + \beta_2 \mathbf{U\Delta Marketing_{it}} + \boldsymbol{\varepsilon}_{\mathbf{it}} \qquad \text{(A)}$$

Equation A is the standard form of stock return response modelling (SRRM). It aims to explore if non-financial measures such as marketing strategies contain any "incremental information" beyond the standard accounting performance, after controlling for economy-wide risk factors through expected returns (Mizik & Jacobson, 2008). It regresses stock returns on changes in accounting and marketing measures to establish whether they have any value relevance that can change market expectations of firm's future cashflows. β_1 is the accounting performance response coefficient and has been extensively validated for its value imparting capabilities in the existing accounting and finance literature (Kothari, 2001; Kothari & Sloan, 1992). The coefficient of interest for researchers exploring the marketing-finance interrelationship is β_2. If β_2 is significantly different from zero, it implies that unanticipated changes in the marketing asset under investigation provides a non-overlapping added information in explaining the abnormal returns (Mizik, 2014). In contrary, if β_2 is zero or statistically insignificant, that would suggest that the stock market participants perceive the implied marketing strategies of no importance in explaining the firm's future profitability beyond what is reflected in the current term performance. Mizik and Jacobson (2004) outline three vital requirements for any marketing measure to be suitable for examination through SRRM. Firstly, its effects on firm value should not be short-lived e.g. a product recall and brand name change (Kalaignanam & Bahdir, 2013). The impact of such marketing information is likely to be reflected in the current accounting performance and can be evaluated through event studies discussed previously. Only those marketing measures which have long-term effects on future cashflows like customer loyalty, association and brand equity should be analysed using SRRM. The second requirement is the public availability of the information about the change in the marketing measure. This is in line with the propositions of efficient market theory which states that market participants react only to new available information (Mizik & Jacobson, 2008). Any marketing strategy or action that is designed or implied without a public disclosure is unlikely to attract attention of the financial community. Including such variables in a stock response model are unlikely to generate any meaningful interpretations. Lastly, the marketing measure under scrutiny should be recurring and vary over time (e.g. brand value changes) as otherwise its impact on future firm value will already be absorbed in the previous period's stock price (Mizik & Jacobson, 2004).

Stock return response modelling has been extensively implemented in leading marketing journals to explore the valuation context of different marketing assets and strategies on firm long term performance. Table 4.2 provides a reverse chronologically ordered list of studies that have adopted SRRM in exploring the marketing-finance relationship, highlighting the studied marketing variable, the industrial focus, and the recipient marketing journal. There are several aspects of stock return response modelling which makes it superior over other methodologies in accessing the long-term value relevance of marketing assets and strategies. Firstly, as explained earlier, it models stock returns as a function of unanticipated changes in accounting profitability measures as well as changes in marketing metric after controlling for economy-wide risk factors. Adopting such an approach treat the standard accounting information as the main determinant of stock returns and non-financial measures as an “incremental signal”. The findings of SRRM therefore establish if the marketing measure has any added explanatory power to the balance sheet performance metrics in explaining stock returns. This makes this model unique in accessing the true performance impact of the measure under investigation by accounting for omitted variable bias, thus enhancing the strength of the analysis (Mizik, 2014). Unlike calendar portfolio approach, SRRM explores the abnormal returns associated with cross-section of firms rather than a clustered portfolio. This provides richer insights about the market expectations of firm’s future cashflows associated with changes in the marketing information and not merely the financial outcomes of marketing events (Mizik & Jacobson, 2004).

The main advantage of SRRM over event studies is that the former assesses the investor response to a dynamic marketing phenomena occurring repetitively over years whereas the later revolves around the event date for its analysis. Stock response method does not require a specific event date to seek value relevance of a new marketing information rather track changes in a series over longer time horizons. This is because SRRM does not assume a strict causal relationship between a measure and stock returns, rather a significant finding signal that investors consider this information as the potential driver of future firm valuation (Sorescu et al, 2007).

Table 4.2 Representative marketing-finance studies adopting SRRM modelling technique

Author(s)	Marketing Variable	Industry focus	Journal Name
Yang et al. (2015)	Brand equity & Management capability	Semiconductor	Journal of Strategic Marketing
Mizik (2014)	Brand equity	Diversified	Journal of Marketing Research
Nam & Kannan (2014)	Brand familiarity and association	Consumer Goods	Journal of Marketing
Raithel et al. (2012)	Customer satisfaction	Automobile	Journal of the Academy of Marketing Science
Tuli & Dekimpe (2012)	Advertisement spending and sales growth	Retail	Journal of Retailing
Bhardwaj et al. (2011)	Brand quality	Diversified	Journal of Marketing
Raithel et al. (2011)	Advertising efficiency	Diversified	Measurement and Research Methods in International Marketing
Srinivasan et al. (2009)	Product Innovation & Advertisement	Automobile	Journal of Marketing
Mizik & Jacobson (2008)	Brand relevance, differentiation, esteem, and knowledge	Diversified	Journal of Marketing Research
Sorescu et al. (2007)	Product Capital (R&D &Sales expenditures)	Pharmaceutical	Journal of Marketing
Mizik & Jacobson (2003)	R&D and Advertisement	Manufacturing	Journal of Marketing
Aaker & Jacobson (2001)	Brand attitude	Computer	Journal of Marketing Research
Barth et al. (1998)	Brand values	Diversified	Review of Accounting Studies
Aaker & Jacobson (1994)	Perceived brand quality	Diversified	Journal of Marketing Research

Apart from the benefits discussed above, there are some additional aspects of stock return response method which makes it an ideal choice for the current research analysis. Firstly, SRRM is designed specifically to examine if a "change" in a particular measure contributes towards long term stock returns measured over one year or longer (Sorescu et al., 2017). Since this study explicitly explores the financial outcomes of changes in brand equity that too for a time period of 10 years, stock return response framework is a suitable approach. Additionally, the marketing variable included in this research fulfil all three criterion outlined by Mizik and Jacobson (2004). Brand value estimates from BrandZ and Brand Finance captures two distinct brand equity dimensions i.e. CBBE and FBBE respectively, both of which are documented to enhance long-term firm performance (refer to table 2.3 in the literature review chapter). Furthermore, the yearly consumer and firm based brand equity estimates of BrandZ and Brand Finance, respectively, are announced publicly thereby attracting global investor attention. And lastly, these yearly monetary brand valuations either rise or decline based on unanticipated changes in consumer brand perceptions (for CBBE) and expert reviews (for FBBE), therefore containing updated information about brand performance. Srinivasan and Hannsens, (2009: 300) suggest that stock return response studies typically work well with such marketing events (especially for globally recognized brands) due to high *signal-to-noise ratio*. Apart from this, SRRM also makes it possible to explore the directional effects of rising and declining brand equity on stock returns, which is one of the core objectives of this research project. This can be achieved by decomposing the overall "brand value changes" into positive and negative sub-components and including them in a single SRRM regression model. By no means, such approach can be applied to calendar-time portfolio analysis. Besides this, SRRM can conveniently accommodate the moderating variables of core business efficiency and marketing capability included in my study (CBEF and MCAP). The only requirement for these variables to be efficiently examined through SRRM regression is to include them as a variable of "change" and not at levels. All these reasons further validate the appropriateness of stock return response modelling as a relevant methodology for this research analysis. But before moving further, appropriate measures for expected returns and accounting performance metrics need to be determined. The following sections elaborate on these instruments and design the appropriate SRRM model for this study.

4.3.3.2 Modelling Expected Returns (ER_{it})

Stock prices are not only influenced by firm's internal developments but also respond to other market based and economy wide factors. Therefore, expected returns of a security need to be carefully modelled by evaluating all the internal and external risks involved. Estimating SRRM without parcelling out these risk characteristics not only cause potential omitted variable bias but also reduces the strength of the analysis (Mizik & Jacobson, 2004). Over the years, researchers in the field of finance have explored several models to estimate the cost of equity by identifying various associated risk attributes. Initially, William Sharpe (1964) introduced "capital asset pricing model" (CAPM) which evaluates the expected return of a stock based on risk premium of the overall equity market in which that particular stock trades. In other words, the expected return of a particular security is dependent on the overall market performance which is also known as its systematic risk. According to CAPM the expected return of a stock is expressed as:

$$ER_{it} = R_f + \beta_i(R_{mt} - R_f) \tag{4.6}$$

Where R_f is the risk free rate and R_{mt} is the returns of the broader market index (e.g. FTSE100 and S&P 500). The coefficient β_i also known as "stock's beta" measures the sensitivity of the stock's return as compared to the return of the market portfolio R_{mt} (Perold, 2004). Stocks with higher beta tend to outperform the broader market index and are potentially riskier, whereas assets with lower values of beta pose lower risk levels but also yield lower returns. This risk-return relationship is in line with the capital market's "high risk - high returns" trade-off characteristics (Shefrin, 2001).

Later in the 90s, prominent finance researchers Eugene Fama and Kenneth French criticised CAPM arguing that broader market risk alone cannot explain the differences in stock price changes across firms (Fama & French, 1993). To explore other risk factors, they constructed multiple portfolios based on firm size (market capitalisation) and book-to-market values (B2M which is the ratio of shareholder's equity to the market value) to compare their performance. Their findings demonstrated that small cap firms and the stocks with low book-to-market ratio (value stocks) generate higher returns as compared to stocks with large market value and high B2M, i.e. growth stocks (Kilsgård & Wittorf, 2011). Therefore, the authors proposed Fama-French 3 factor model (FF3) which include firm's size and book to market value (B2M) as additional risk factors along with broader-market risk to efficiently explain expected returns.

$$ER_{it} = R_f + \beta_i(R_{mt} - R_f) + \beta_S(SMB_t) + \beta_H(HML_t) \tag{4.7}$$

Where, SMB_t and HML_t are the estimates for size and book-to-market risk factors which are computed by subtracting the average returns of the respective portfolios in the time period t. For example, monthly SMB (small minus big) risk factors are estimated by taking the difference between average returns of small cap portfolios and the large cap portfolios in that particular month. Similarly, coefficients of HML (high B2M minus low B2M) are the difference between high and low book-to-market portfolios. It is also to be noted that both SMB and HML factors contain only time series components as these factors are computed from portfolios containing all the stocks within a market in a given time period (e.g. US, Asian and developed markets).

Later, Carhart (1997) further improvised the Fama-French 3 factor model by introducing “momentum” as an additional explanatory factor in modelling the expected returns. The momentum based risk loading capture the tendency of stock price to continue moving in the same direction based on its previous performance (either upwards or downwards). To understand momentum associated risk, Carhart (1997) segmented mutual funds into different portfolios based on their previous period stock market performance and analysed their behaviour in the subsequent time period. The findings report that the portfolios that generated higher returns in the preceding year continued to perform well and those that underperformed previously followed the same suite. This persistence in the stock performance is the momentum risk factor MOM (also termed as UMD meaning up minus down) which is quantified by including previous year’s winning and losing stocks into separate portfolios and calculating the difference in their average returns in the following year (Fama & French, 2012). Adding the momentum factor to eq. 4.7 gives Fama-French and Carhart 4-factor model (FF-C 4) to capture expected returns.

$$\mathrm{ER_{it}} = \mathrm{R_f} + \beta_\mathrm{i}(\mathrm{R_{mt}} - \mathrm{R_f}) + \beta_\mathrm{S}(\mathrm{SMB_t}) + \beta_\mathrm{H}(\mathrm{HML_t}) + \beta_\mathrm{M}(\mathrm{MOM_t}) \qquad (4.8)$$

The Fama-French (1993) and Carhart (1997) four factor model has been extensively employed by marketing researchers to account for economy wide risk factors when examining the value impact of marketing assets (Bhardwaj et al. 2011; Ruiz et al., 2018; Srinivasan & Hanssens, 2009; Srinivasan et al., 2010). Despite its popularity, one of the most prominent critics of Fama-French model are Daniel and Titman (1997) who contend that the risk premia of size (SMB) and value (HML) cannot be simply explained by sorting stocks into separate portfolios based on these characteristics. In order to verify this, the econometricians designed two separate asset pricing models. The first model mimicked that of Fama French (1997) where the expected stock returns are determined by size and book-to-market factor loadings. Since all the stocks are loaded with same factor, these risk premiums are cross-sectionally fixed and vary only over time. The second model represents stocks with similar size and book-to-market (B2M) characteristics but different loadings on FF-C factors. The performance comparison between these two models present evidence that Fama French risk factors provide no additional information in explaining stock returns in the presence of firm specific characteristics of size and B2M ratio.

Although the alternative characteristics based approach proposed by Daniel and Titman (1997) provides new insights about the variation in the expected returns across firms, there is still an ongoing debate within finance community as to which amongst them has better explanatory power (Avramov & Chorida 2006; Brennan et al, 1998). Recently, Chordiya et al. (2017) have attempted to answer this question by including all four FF-C risk factors along with size and B2M characteristics in a single regression model to access their relative contribution in estimating stock returns.[14] The findings report that the FF-C four loading factors explain only 12% cross-sectional variance in stock returns whereas size and value collectively account for 110% variance. Clearly, the characteristic based approach has a higher explanatory power in determining expected returns as compared to factor-based approach. But this does not imply that the risk factors should simply be ignored and dropped from the model as their effects are also significant. Therefore, not opining with "loadings versus characteristics" debate and following Mizik (2014), the current study adopts a modest approach and include FF-C 4 loading factors in conjunction with firm-specific risk characteristics of size and B2M in estimating the differences in the expected returns. Doing so makes the model robust in addressing both the economy wide effects and firm-based risk factors simultaneously. Equation 4.8 can thus be re-written as:

$$\mathrm{ER}_{it} = \mathrm{R}_f + \beta_i(\mathrm{R}_{mt} - \mathrm{R}_f) + \beta_S(\mathrm{SMB}_t) + \beta_H(\mathrm{HML}_t) + \beta_M(\mathrm{MOM}_t) + \eta_t(\mathrm{Size}_{it-1}) + \vartheta_t(\mathrm{B2M}_{it-1}) \qquad (4.9)$$

Where, Size_{it-1} is the log of previous period market value and $\mathrm{B2M}_{it-1}$ is the lagged book-to-market value i.e. the ratio of log of total shareholder's equity to the market value in the period "t-1". It is worth mentioning that unlike the loading factors of size (SMB) and value (HML) which only have time-series components, these characteristics vary both in time and across firms.

[14]The study also develops market-factor based CAPM and Fama-French 3 factor model, but the discussion is limited to FF-C4 factor because of its inclusion in this study.

4.3.3.3 Modelling unanticipated changes in accounting metrics

EMT contends that the present market value reflects all the publicly available information about firm's current and future prospects and the financial community reacts only to new information (Mizik & Jacobson, 2004). Short term abnormal stock returns are the result of surprises in the firm's financial results, the most straightforward of which are the top-line (sales) and bottom-line (earnings) (Srinivasan & Hanssens, 2009). Current period earnings are perceived as the most vital metric of the accounting system both by investors and senior management (Bhardwaj et al., 2011; Graham et al., 2005). A rise in income signifies growth whereas stagnated or declining earnings raise uncertainty about the underlying strength of the firm. Studies in the accounting and finance stream confirm that investors and shareholders react to unanticipated changes in both the sign and magnitude of earnings by re-evaluating firms expected future cashflows (Bartov et al., 2002; Johnson & Zhao, 2012; Kothari, 2001). There are two methods employed by the finance researchers to estimate the unanticipated components of accounting measures. The first approach is based on market survey data, e.g. financial analysts forecast about firm's future growth and profitability (Mizik & Jacobson, 2004). Financial analysts predict firm's future earnings and revenue by conducting intensive market based research focussing on consumers, suppliers, competitors, and broader market conditions. This consensus of analysts' forecasts is typically available on quarterly and annual basis. Researchers model the unanticipated component of these accounting metrics as the difference between analyst forecast and the actual reported figures (Nam & Kannan, 2014). The second method involves time-series extrapolations of accounting performance measures as a proxy of market expectations (Lev, 1989). Stock market participants build future outlook about firm's profitability based on its current term earnings (Sorescu et al., 2007). These accounting metrics therefore tend to exhibit persistence, at least in immediate time periods such as subsequent quarters or years. In such cases, the unanticipated components of these measures can be approximated through a bivariate autoregressive model of the following form, where the variable is regressed upon its own lag:

$$\mathrm{AccPrf}_{\mathrm{it}} = \phi_0 + \phi_1 \mathrm{AccPrf}_{\mathrm{it-1}} + \eta_{\mathrm{it}} \tag{4.10}$$

The residual term η_{it} from this time series regression serves as the unanticipated component i.e. the portion of earnings in time “t” which could not be predicted based on the previous period earnings (Mizik, 2014). The primary assumption in this approach is that these measures does not follow a random walk. That is to say that the previous period earnings and sales have carryover effects in the subsequent period’s performance. These dynamic properties of accounting performance components can be determined through appropriate statistical assessments such as unit root test (this will be discussed further in the analysis chapter). In cases, where there is no evidence of persistence (i.e. series follow a random walk), the unanticipated changes can simply be approximated by calculating first differences (Mizik & Jacobson 2004). Existing research has some disagreement as to whether the analyst or time-series forecast provides better estimates of accounting measures. Some researchers advocate that the analysts forecast provides more accurate predictions as they have an up to date information about firm actions and strategies (Bradshaw, 2011; Brown & Rozeff 1978; Srinivasan & Hanssens, 2009). Therefore it has both “information” and “timing” advantage over time-series models (Brown et al. 1987). In contrary, other group of researchers argue that analyst forecasts can be subjected to anomalies such as bias towards a firm or conflict of interest that can lead to manipulated predictions (Dugar & Nathan, 1995; McNichols & O'Brien 1997; Lin & McNichols, 1998). Broadly, there is an inclination amongst researchers towards analysts estimates but empirical evidence suggests that both approaches perform equally well in capturing earning shocks (Cheng et al., 1992; Mizik & Jacobson, 2008). Infact, Bradshaw et al. (2012) document that analysts forecast exhibits almost similar levels of predictive power as compared to time-series models, when compared over longer time horizons. Furthermore, their empirical study reports that even when the analysts forecast is more accurate, the difference is economically negligible.

Above discussions suggest that both the time series and analyst forecast approaches have their own predictive abilities and are broadly indistinguishable when implied for longer time periods. Additionally, the choice of method also depends on the data availability and the area of research. Due to lack of earnings and sales forecast data for all firms in the acquired sample data, this study adopts time-series autoregression model to estimate the unanticipated changes in these accounting measures. Following existing marketing research, size adjusted earnings i.e. return on assets (ROA) and firm sales revenue are adopted to represent current period accounting performance (Mizik, 2014, Angulo-Ruiz et al., 2018; Xiong & Bharadwaj, 2013). ROA is modelled as the ratio of operating income before depreciation (OIBD) to the total assets:

$$\mathrm{ROA} = \frac{\mathrm{OIBD}}{\mathrm{Total\ Assets}}$$

The unanticipated component of accounting performance in equation A can therefore be represented as:

$$U\Delta AccPrf_{it} = U\Delta ROA_{it} + U\Delta Sales_{it} \quad (4.11)$$

Where, ΔROA_{it} and $\Delta Sales_{it}$ are unanticipated changes in earnings and sales obtained as the residuals from time-series autoregression models represented in equation above (subject to the results of unit root test). A detailed information about the type of autoregressive econometric models employed is discussed in the analysis chapter of the thesis.

Another accounting metric included in the designed empirical model to control for firm specific risk is financial leverage, which is defined as degree to which borrowed funds are utilised for business operations (Johansson et al., 2012). Luo and Bhattacharya (2009) report that higher levels of leverage have negative effects on stock returns as investors perceive it as a high risk factor, especially during the period of financial turmoil. Even in normal economic cycles, stock market participants are cautious about investing in firms with high debt levels because of dilution of its future profitability due to substantial repayment obligations (Fischer & Himme, 2017; Harris & Raviv, 1990). Any unexpected shock in the current or future earnings due to management weakness or competitive stress could trigger an immediate exodus of shareholders due to foreseeable financial stress, causing a rapid decline in firm value. To weather such situations, highly leveraged firms maintain large cash reserves in their balance-sheet, which in-turn reduce their flexibility to exploit potential investment opportunities (Fischer & Himme, 2017). The amount of debt therefore provides valuable information to the investment community about firm's future prospects and could make them reluctant to invest in highly leveraged firms due to higher default probability (Harris & Raviv, 1990). Therefore current study includes firm's leverage as a predictor of future stock returns and expects a negative relationship between them. Following current literature, leverage is defined as the extent to which the firm is debt financed relative to the value of its total equity (Johansson et al., 2012; Luo et al, 2013), i.e.:

$$\mathrm{LEV_{it}} = \frac{\text{Total debt}}{\text{Total Shareholder's Equity}}$$

Where LEV_{it} represents the debt to equity ratio of firm "i" at time "t". A value significantly higher than 1 signals debt levels surpassing the capital stock, posing greater risk of shareholder's wealth recovery in case of liquidation. Conversely, a reasonably low debt to equity ratio is perceived as a protection of the stockholder's capital. Adding LEV_{it} along with the functional forms of ER_{it} and $U\Delta AccPrf_{it}$ from eq. 4.10 and 4.11 in the standard SRRM model defined in equation A yields the following final regression model:

$$\begin{aligned} \mathrm{R_{it}} - \mathrm{R_f} = {} & \beta_1(\mathrm{R_{mt}} - \mathrm{R_f}) + \beta_S(\mathrm{SMB_t}) + \beta_H(\mathrm{HML_t}) + \beta_M(\mathrm{MOM_t}) \\ & + \eta_t(\mathrm{Size_{it-1}}) + \vartheta_t(\mathrm{B2M_{it-1}}) + \beta_2 \mathrm{U\Delta Marketing_{it}} \\ & + \beta_3 \mathrm{U\Delta ROA_{it}} + \beta_4 \mathrm{U\Delta Sales_{it}} + \beta_5 \mathrm{LEV_{it}} + \varepsilon_{it} \end{aligned} \tag{4.12}$$

For the sake of simplicity, the risk factors of market, SMB, HML, MOM, firm size and value are collectively termed as RISK which makes the above model expressed in its compact form as:

$$\begin{aligned} \mathrm{R_{it}} - \mathrm{R_f} = {} & \beta_r \mathrm{RISK} + \beta_2 \mathrm{U\Delta Marketing_{it}} + \beta_3 \mathrm{U\Delta ROA_{it}} + \beta_4 \mathrm{U\Delta Sales_{it}} \\ & + \beta_5 \mathrm{LEV_{it}} + \varepsilon_{it} \end{aligned} \tag{4.13}$$

Equations 4.12 and 4.13 outline the standard stock return response model implemented in the current study. The designed model is however refined further based on the underlying research questions. For example, to explore the hypotheses linking changes in brand equity directly to firm performance, the proposed SRRM models will incorporate overall and directional changes in CBBE and FBBE, exclusively. Similarly, the moderating role of core business efficiency (CBEF) and marketing capability (MCAP) in brand equity-firm value relationship will be separately investigated through "interaction-effects based" stock return response models. But before commencing the empirical analysis, firstly an appropriate methodology to operationalize these multi input-output base organizational efficiency measure (CBEF and MCAP) needs to be realized. The next section of this chapter elaborates on the identified methodology explaining its emergence, underlying assumptions, modelling techniques and relevance to the current research.

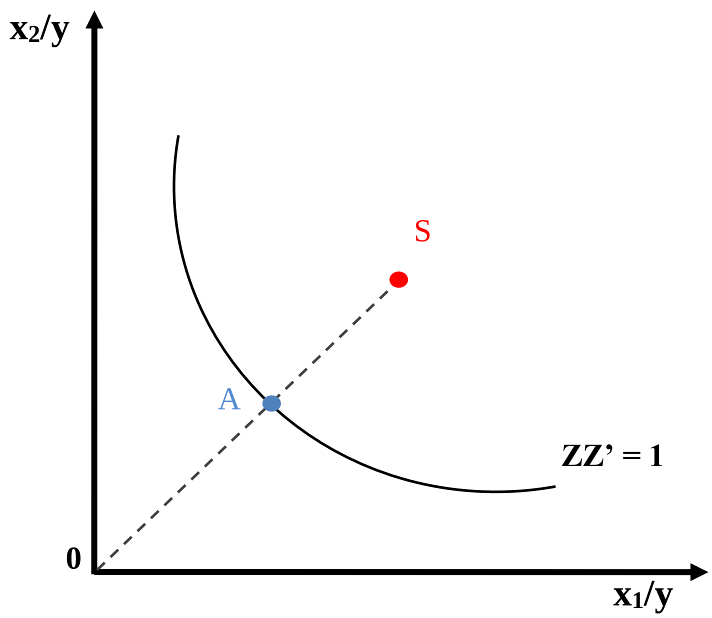
4.4 Methodology for operationalizing moderating variables (MCAP & CBEF)

As discussed earlier, both CBEF and MCAP are efficiency based measures which aim to evaluate firm's ability to exploit its available core business and marketing resources to maximize productivity and attain sustainable competitive advantage. The most simplistic and traditional way of calculating efficiency is through the ratio analysis where an input is divided by an output to obtain the efficiency estimate (Rezaie et al., 2011). This approach however has a stringent condition that there has to be a single output and a single input. However, in real world, business organizations have heterogeneous resources which they utilize collectively to create value in the competitive marketplace. Resource based theory also advocates that firms should strategically exploit its unique set of resources along with best management practices to attain sustainable performance over time (Kozlenkova, 2014). Relying on a single input-output measurement technique is therefore incapable of amalgamating different operational characteristics of a firm, when defining efficiency (Donthu et al., 2005; Roh & Choi, 2010). For example, ROA measures management's efficiency as the ratio of profits to the total assets without considering other vital resources such as labour, capital stock and technological advancements over time. Simply explaining profitability based on the acquired assets could provide incomplete information about firm's true business efficiency. These inherited flaws in conventional ratio analysis have motivated this study to adopt a more rigorous methodological approach which can incorporate multiple inputs and outputs simultaneously to produce an aggregate measure of efficiency. This research therefore embraces the "modern efficiency measurement" concept introduced by Cambridge economist M.J. Farrell in 1957 for operationalizing CBEF and MCAP. Farrell (1957) initially outlined a method to measure efficiency based on multiple inputs and a single output. The model is called "input oriented" as the idea is to minimise the utilised set of inputs to produce similar level of output, thus becoming cost efficient. Fare and Lovell, (1978) later extended this concept by defining an "output oriented" framework which focus on maximising the productivity, given the same input levels. The following section briefly discusses both these multi input-output efficiency estimation models with an illustrative example of each. It is crucial to understand these basic models as it will then lead to the selection of the implemented methodology to operationalize the two efficiency variables adopted in the study.

4.4.1 Multi Input-Output Efficiency Models

To illustrate Farrell's input optimisation approach, let us assume a hypothetical situation where the isoquant curve ZZ' of an efficient firm Z is known (equal to unity) and the aim is to measure the efficiency of firm Q, relative to firm Z.[15] This is illustrated in the figure 4.1 below.

Figure 4.1 Input oriented isoquant efficiency curve



Source: Author's elaboration

The efficiency curve ZZ' is concave following the law of diminishing returns which states that after a certain point, the effect of increasing the level of an input will have negligible effect on the output (provided there is one fixed input) (Brue, 1993). If firm Q uses the inputs x_1 and x_2 defined by point S, then its inefficiency can be known by calculating the distance AS, which represents the proportion by which both the inputs need to be reduced without impacting the output. This estimate can be converted into percentage by dividing AS by 0S, which basically represents the ratio of "required

[15] An isoquant curve shows different combinations of inputs that can produce same level of output.

inputs reduction" to the "actual proportion of applied inputs". The relative technical efficiency of firm Q can therefore be calculated as:

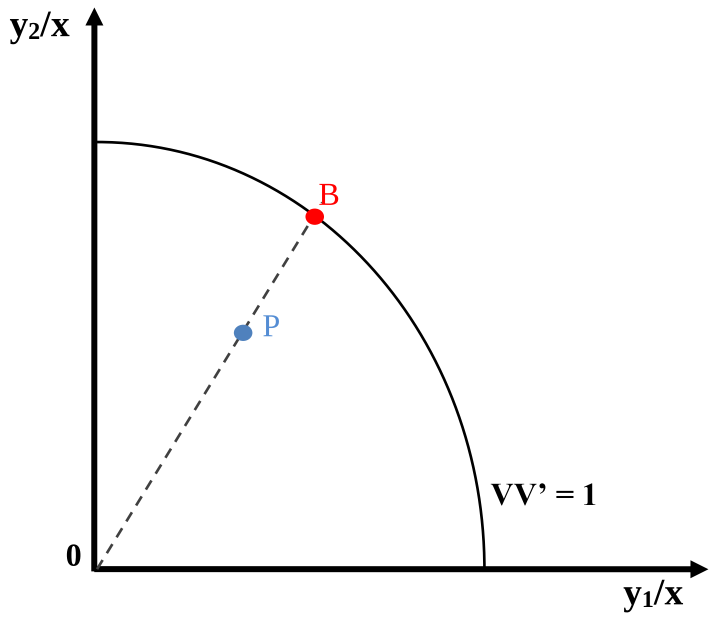
$$\mathrm{TE_i} = \frac{0\mathrm{A}}{0\mathrm{S}} \text{ , which is same as: } 1 - \frac{\mathrm{AS}}{0\mathrm{S}}$$

The computed efficiency value lies within the range of 0 and 1 and is dependent on the distance of the observed unit's input combination point from the efficient isoquant. For example, if the distance SA is zero in figure 4.1, then the efficiency score of firm Q can be computed as:

$$1 - \frac{0}{0\mathrm{S}}, \text{which is equal to 1 (i.e. fully efficient)}$$

The subscript "i" in equation A denotes that it is an input oriented model, which addresses the question "by how much can input quantities be proportionally reduced without changing the output quantities produced?" (Coelli, 1996:7). An alternative approach is an "output oriented measure" where the focus is on maximizing the output without altering the applied input (Fare & Lovell, 1978). The output oriented model is illustrated in figure 4.2 with two outputs y_1 and y_2 and a single input x. One distinguishing feature of this model is the orientation of the assumed production frontier VV' for an efficient firm V. The curve is convex because it represents the maximum level of productivity that can be achieved by utilising two inputs x1 and x2 (unlike ZZ' in fig. 4.1 where minimal inputs were desirable).

Figure 4.2 Output oriented isoquant effcincy curve



Source: Author's elaboration

Here the distance PB denotes the proportion of outputs produced by inefficient firm P relative to firm V and the output-oriented technical efficiency TE_o can thus be computed as:

$$TE_o = \frac{0P}{0B}, OR\ 1 - \frac{PB}{0B}$$

It has to be noted that in an output oriented model, all the inefficient firms lie below the curve as the efficiency frontier in this case corresponds to the upper bound of the production possibilities. Conversely, all inefficient entities lie above the input oriented frontier as it represents the minimum possible combination of inputs that can produce a desired output. A common feature among these models is that both compute the technical efficiencies by measuring the radial distance of the observed production points from the origin. This makes these methods independent of the "units" of implied inputs and outputs, meaning that altering the measurement units does not change the efficiency scores (Coelli, 1996).

In both the efficiency estimation models discussed above, it is assumed that the isoquant and production possibility curves are known, which is not true in the real world. In practice, these efficiency frontiers need to be estimated by examining the input-output transformation process for a sample of firms. The literature provides two distinct approaches of estimating these efficiency frontiers: (1) Data envelopment analysis (DEA) and (2) Stochastic frontier analysis (SFA) (Akdeniz et al. 2010; Dutta et al., 1999; Angulo-Ruiz et al., 2014). Proposed by Charnes et al (1978), DEA is a non-parametric optimization based linear programming model that can estimate relative efficiency based on multiple inputs and outputs. Relative efficiency is determined by clustering a set of similar observations called decision making units (DMUs) and computing their input-output transformation performance relative to each other (Cook & Seiford, 2009; Emrouznejad et al., 2008). By allocating optimal weights to different inputs and outputs for each DMU through a sequence of linear programming, DEA constructs an efficient production frontier (Roh & Choi, 2010). All the DMUs located on the efficiency frontier are deemed as efficient whereas the data points "enveloped" under the frontier are identified as inefficient entities (thereby getting name as date envelopment analysis). In contrary, SFA proposed by Aigner et al. (1977) and Meeusen and Van Den Broeck (1977) is an econometric approach which involves statistical data examination in determining the efficiency of the underlying DMUs (Kumbhakar et al., 2020). Stochastic frontier analysis provides a framework where the efficiency relationship between different DMUs is estimated an OLS based average analysis.

However, a key distinction of SFA to standard OLS models is its ability to decompose the total deviation of the data-points from the regression curve (i.e. idiosyncratic error) into two terms i.e. statistical noise and inefficiency (Kumbhakar et al., 2020:5). Therefore unlike DEA, the deviations of DMUs from the SFA regression frontier can not only be due to their inefficiency but also due to statistical errors.

Both the data envelopment and stochastic frontier based efficiency estimations models have been extensively employed in the current marketing literature (Charles & Zavala, 2017; Corte et al., 2017; Dutta et al., 1999; Feng et al., 2017; Rahman, 2020; Angulo-Ruiz et al., 2018; Sun et al., 2019; Wiles et al., 2012; Xoing & Bhardwaj, 2013). However, the main advantage of DEA over SFA is its greater level of flexibility, since it does not require any explicit functional form imposed on the data (Coelli et al., 2005; Dutta et al., 1999; Angulo-Ruiz et al, 2014). Secondly, unlike regression based SFA which is unable to accommodate multiple outputs, DEA can estimate efficiencies for multi input-out configurations (Ahn & Le, 2014; Banker et al.,1984; Rahman et al., 2018)[16]. Thirdly, DEA constructs an efficiency frontier based on peer analysis, therefore enabling a comparison of inefficient firms to the best performers rather than relying on "mean" comparison approach followed by SFA (Donthu et al., 2005). Based on these qualities, this research embraces DEA framework borrowed from operations research in operationalizing the acquired efficiency variables of CBEF and MCAP. Another reason for adopting DEA over SFA is the researcher's prior knowledge and expertise in mathematical linear programming.

[16] Because standard OLS models can only have one independent variable.

Consistent with Farrell's (1954) definition, DEA treats DMUs constituting the production frontier as fully efficient (having efficiency score of 1) whereas entities with score less than 1 are technically inefficient and enveloped within the frontier surface (that is why it gets the name, data envelopment analysis). For example, a DMU *k* with a score of 0.70 is inefficient and must improve its input-output transformation capabilities by 30%. This can be achieved by either increasing the productivity with the same input levels (output-orientation) or minimizing the allocated inputs to attain same output (input-oriented approach). In the case of an input oriented measure, DEA will run the following set of linear programming equations:

$$\theta_k = \min\left(\sum_{i=1}^{m} v_i\, x_{ik}\right)$$

Subject to:

$$\sum_{i=1}^{m} v_i\, x_{ij} - \sum_{r=1}^{s} u_r\, y_{rj} \geq 0 \quad (j = 1,2,\ldots.,n)$$

$$\sum_{r=1}^{s} u_r\, y_{rk} = 1$$

$$u_r \geq 0;\ (r = 1,\ldots,s) \qquad v_i \geq 0; (i = 1,\ldots,m)$$

Where, Θ_k represents the input oriented technical efficiency of DMU *k* relative to a set of *n* DMUs. All the DMUs have *m* inputs x_{ij} (i=1, 2…, m) and *s* outputs y_{rj} (r=1, 2…, s). x_{ik} and y_{rk} are the total number of inputs and outputs, respectively for DMU *k*. The coefficients u_r and v_i are the non-negative variable weights for each input and output to be determined by solving the linear programming model, subject to the applied restrictions. The first restriction is that the difference between sum of weighted inputs and outputs should be a non-negative number. It has to be noted that in order to restrict the weighted input and outputs requirement for *kth* DMU, DEA will run *n* number of linear programs one per each observation. Therefore, for imposing the same requirement for all other DMUs, DEA will run a total of "*n x n"* linear programming models. The second objective function is the equality constraint which requires the sum of all weighted outputs of each DMU should be equal to unity. It is added to restrict the number of possible input-output combinations generated during the programming (Branda & Kopa, 2014). Without this restriction, there will be infinite number of solutions for the written model, which is not desirable. The constraint is applied to weighted sum of outputs and not inputs because it is an input oriented model which identifies efficient DMUs as the one that can produce same level of output by minimizing input allocation. The final restriction requires all the optimized weights allocated to each input *r* and output *s* should either be zero or greater. This is to ensure that there are no negative values incorporated in any of the equations since standard DEA models can only deal with positive inputs and outputs (Sarkis, 2007:6).

The set of linear programming equations for an output oriented model are slightly different where the focus is on restricting all the weighted inputs to unity and maximizing the outputs. For example, output centred relative efficiency of o^{th} DMU for the same set of n DMUs defined above, with *m* inputs x_{ij} (i=1, 2…, m) and *s* outputs y_{rj} (r=1, 2…, s) can be modelled as:

$$\theta_o = \max\left(\sum_{r=1}^{s} u_r \, y_{ro}\right)$$

Subject to:

$$\sum_{r=1}^{s} u_r \, y_{rj} - \sum_{i=1}^{m} v_i \, x_{ij} \leq 0 \quad (j = 1,2,\ldots.,n)$$

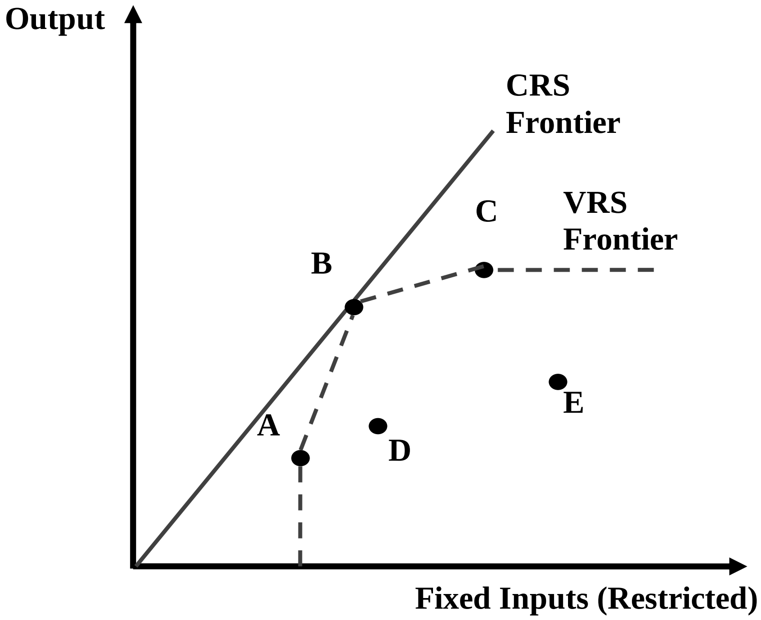
$$\sum_{i=1}^{m} v_i \, x_{io} = 1$$

$$u_r \geq 0; \; (r = 1,\ldots,s) \qquad v_i \geq 0; (i = 1,\ldots,m)$$

The key differences to be noted here are i) maximization of the weighted sum of outputs *r* rather than minimising *i* inputs, ii) the difference between the sum of optimised outputs and inputs is restricted to be zero or less and iii) the unity constraint is applied to the weighted inputs (and not the outputs) to keep them at same level for all the DMUs. Appendix B provides an illustrative example for both type of oriented models with hypothetical inputs and outputs. The choice of the adopted model in a study depends on the research question and the nature of DMUs. For example, if a business has direct control over the outputs (e.g. a production plant), and the researcher aims to distinguish the efficient firms from the inefficient based on productivity maximization, then an output oriented model is desired. Conversely, if the management cannot directly alter their business outcomes such as sales and brand equity, rather can optimize their implied inputs e.g. marketing expenditures, then an input oriented approach is viable (Nath et al., 2010).

Along with input or output orientations, DEA models can also be specified as constant return to scale (CRS) or variable returns to scale (VRS). A CRS model assumes that all DMUs are operating in similar business conditions and therefore the change in applied input(s) would result a proportional change in the output(s) (Charnes et al., 1978; Podinovski, 2004). For example if (X, Y) represents vectors of inputs and outputs for an efficient DMU, under CRS assumptions, the input-output configuration of another efficient DMU will be (aX,aY) where a > 0. VRS model does not assume this type of proportionality and allow different efficient DMUs to have a flexible set of input-output combinations (Banker et al., 1984). A VRS model is applicable where the observed business units are believed to be exposed to imperfect operating environments where an increase in an input may not produce proportional increase in the output (output may also decrease) (Rahman et al., 2018). A CRS model can be converted to a VRS model simply by adding the convexity restriction i.e. the sum of all the inputs should be greater than or equal to zero (Coelli, 1994). Adding this instruction therefore allow only convex input-output combinations resulting in a non-linear efficiency frontier as shown in figure 4.3. As evident in the figure, allowing the frontier to take a non-linear shape also results in more DMUs being efficient as compared to CRS.

Figure 4.3 CRS versus VRS efficiency frontier



Source: Author's elaboration

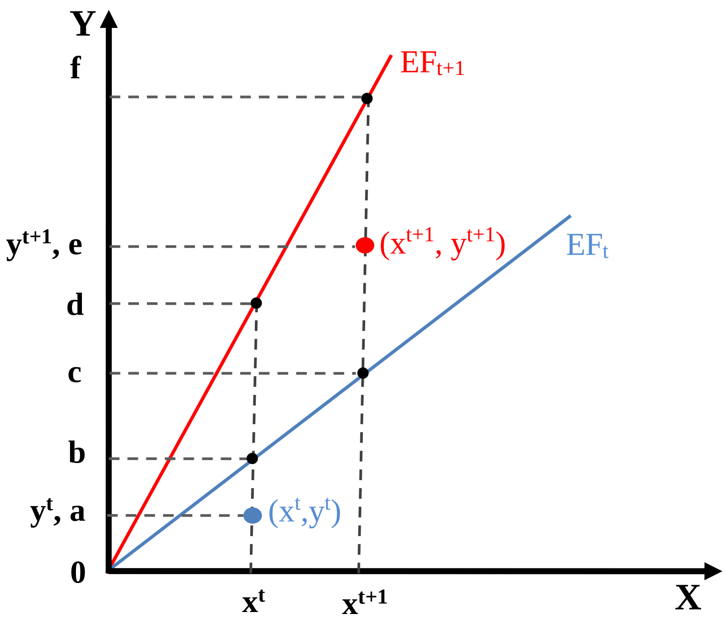
Above discussions provide a clear rationale about the superiority of DEA benchmarking method over traditional ratio analysis both from multi input-output handling, orientation and returns to scale perceptive. Through the best practice frontier approach, DEA i) separates the efficient firms from the inefficient by weighing their performance in the input-output transformation process and ii) identify the "room for improvement" for inefficient firms by comparing their performance to the one which are efficient (Nath et al., 2010). The benchmarking method thus provides a rich diagnostic tool for businesses not only to identify their resource utilisation performance but also improve productivity by allocating available assets more efficiently. Emanated in the field of operations research, DEA has become increasingly popular in other business disciplines such as marketing (Rahman et al., 2018), branding (Charles & Zavala, 2017), finance (Stewart et al., 2016) and production (Seth et al., 2020).

However, utilising standard DEA models is not advised when the production data for the set of observed DMUs is available for multiple time periods (Demerjian, 2018). This is because static DEA framework treats each DMU as an independent observation therefore ignore the effects of time shift on the efficiency dynamics. To address this issue, Malmquist (1953) suggested the concept of measuring total factor productivity change (TFPCh) using the time-series Malmquist productivity index (MPI). Malmquist TFPCh based efficiencies incorporates the effects of both time and firm's internal efficiency and therefore is an advanced version of the basic DEA framework. Since this study is longitudinal in nature (i.e. having panel data structure), MPI based efficiency measurement technique is used to operationalise the acquired efficiency variables. The following section elaborates on this method and derives the Malmquist total factor productivity change through a distance function approach proposed by Fare et al. (1994).

4.4.2 Estimation of Malmquist Total Factor productivity change (TFPCh)

The environment in which a firm operates is susceptible to change over time and therefore these effects need to be factored in when estimating future efficiencies. Resource utilization technologies which firms used a decade ago are expected to be significantly different as compared to what is available today. This variation in technology over time could either increase or decrease the efficiency of a business depending on whether they competently embraced it to improve their productivity or not. Both Malmquist (1953) and Fare et al. (1994) emphasized on the importance of considering temporal shift in technological progress when evaluating multiple time-period performance of a decision making unit (e.g. country or a firm). Ignoring the longitudinal effects of innovation and technical reform could provide incomplete information about firm's true productivity over time (Yang et al., 2015). This can be illustrated through figure 4.4 which outlines a single input-output configuration with constant returns to scale (CRS). DMU X uses x^t amount of input to produce y^t units of output in time "t", therefore denoted by the production point (x^t,y^t). The set of efficient DMUs in time "t" defines the efficiency frontier EF' and DMU X being technically inefficient lies below it. Assuming an output oriented model, DMU X need to increase its output level by the distance "ab" to maximize its efficiency and join the frontier. Using the distance ratios, the technical efficiency of X relative to EF_t can be computed as 0a/0b and is denoted as $D_{o,t}(x^t,y^t)$.The subscript "o,t" signifies that it is an output oriented model, and the efficiency is calculated relative to the production frontier in time "t" (i.e. EF_t).

Figure 4.4 Malmquist Total factor Productivity and Output Distance Functions



Source: Author's elaboration

It is to be noted that here the distance function defined to measure relative efficiency (i.e. 0a/0b) is the reciprocal of Farrell's (1957) output-based technical efficiency of 0b/0a (refer to fig. 4.2). Farrell et al. (1994) have made this transformation to evaluate the ratio of the output produced by DMU X to the maximum feasible output that can be produced based on the technology in time "t" (and not the distance between the production point and the frontier as in fig. 4.2). This makes it possible to examine if the proportion of input-output of DMU X in time "t+1" has increased beyond the maximum possible production in time "t". For example, let's assume this new production point as (x^{t+1}, y^{t+1}) in fig. 4.4. Distance function $D_{o,t}(x^{t+1},y^{t+1})$ measures the maximum output change which the point (x^{t+1},y^{t+1}) need to undergo in order to become feasible in relation to technology in time "t" i.e. 0e/0c. Since 0e>0c, it means that the efficiency of DMU X in period "t+1" relative to the frontier at "t" is greater than 1 (the reason why (x^{t+1}, y^{t+1}) is above EF_t). This violates Farrell (1957) specification of efficiency score to be rangebound between 0 and 1, with observations having unity score operating at the best practise frontier. This anomaly indicates that the efficiency frontier has in-fact shifted over this time in such a way that either the point (x^{t+1}, yt^{+1}) lies on it (i.e. X being efficient relative to it) or below it (still inefficient). Examination of such "technological change" over time is only possible by inverting Farrell"s (1957) standard distance ratios. As shown in fig. 4.4, the production frontier EF_t has moved upwards to a new position EF_{t+1}, signifying that a technological improvement has occurred during this period. Malmquist productivity index defined by Caves et al. (1982) measures the change in the position of the production points of the observed unit from time "t" to "t+1" relative to the technology available at time "t" as:

$$\mathrm{MPI}^{t} = \frac{D_{o,t}(x^{t+1}, y^{t+1})}{D_{o,t}(x^{t}, y^{t})} \text{ i.e. } \frac{0e/0c}{0a/0b} \text{ for DMU X}$$

Similarly, MPI for these two production points relative to technological change in time "t+1" can be calculated as:

$$\mathrm{MPI}^{t+1} = \frac{D_{o,t+1}(x^{t+1}, y^{t+1})}{D_{o,t+1}(x^{t}, y^{t})} \text{ i.e. } \frac{0e/0f}{0a/0d} \text{ for DMU X}$$

Where, $D_{o,\,t+1}$(x^{t+1}, yt^{+1}) and $D_{o,t+1}$(x^t,y^t) are the technical efficiencies of points (x^{t+1},y^{t+1}) and (x^t,y^t) relative to the technology frontier EF_{t+1}. In both the above equations, Malmquist productivity change will be greater than 1, if there is an increase in the productivity of DMU X in period t+1, regardless of the reference frontier (EF_t or EF_{t+1}). Similarly, MPI value less than unity signifies a technological regress occurring within “t” and “t+1”. And $x^t = x^{t+1}$ and $y^t = y^{t+1}$ signals no change in the input-output configuration of DMU X between this period and therefore the productivity index will be equal to 1. These two equations however provide productivity information with only one technological reference at a time. To estimate the total factor productivity growth of DMU X between time “t” and “t+1”, Farrell et al. (1994) took the geometric mean of the MPIs in both the periods as:

$$\mathrm{TFPCh_o}(x^{t+1}, y^{t+1}, x^t, y^t) = \sqrt{\left(\frac{D_{o,t}(x^{t+1}, y^{t+1})}{D_{o,t}(x^t, y^t)}\right)\left(\frac{D_{o,t+1}(x^{t+1}, y^{t+1})}{D_{o,t+1}(x^t, y^t)}\right)} \qquad (4.14)$$

Where, $\mathrm{TFPCh_o}$ is the output-oriented total factor productivity change of any observed DMU between time periods “t” and “t+1”. All the four distance functions are defined below in simple terms:

$D_{o,t}(x^{t+1},y^{t+1})$: *Maximum possible output in next year, relative to current year’s technology.*

$D_{o,\,t+1}(x^{t+1},\, yt^{+1})$: *Maximum possible output in next year, relative to next year’s technology.*

$D_{o,t}(x^t,y^t)$: *Maximum possible output in current year, relative to current year’s technology.*

$D_{o,\,t+1}(x^t,y^t)$: *Maximum possible output in current year, relative to next year’s technology.*

All these component distance functions (efficiencies) can be calculated using DEA linear programming, given any number of inputs and outputs. For example, if x^t and y^t are not single input and output, rather represents a set of *m* inputs x_{ij} (i=1, 2…, m) and *s* outputs y_{rj} (r=1, 2…, s), then the efficiency represented by distance function $D_{o,t}(x^t,y^t)$ can be estimated by the same output-based linear programming model outlined earlier i.e.:

$$[D_{0,t}(x^t, y^t)]^{-1} = \max\left(\sum_{r=1}^{s} u_r\, x_{rxt}\right)$$

Subject to:

$$\sum_{r=1}^{s} u_r\, y_{rjt} - \sum_{i=1}^{m} v_i\, x_{ijt} \leq 0 \quad (j = 1,2,\ldots.,n)$$

$$\sum_{i=1}^{m} v_i\, x_{ixt} = 1$$

$$u_r \geq 0;\ (r = 1,\ldots,s) \qquad v_i \geq 0; (i = 1,\ldots,m)$$

Here, the inverse of $D_{o,t}(x^t,y^t)$ is taken to align it with the Farrell's (1954) efficiency measure (recall that in the TFP estimation, all the efficiencies are inversely proportional to that measured by Farrell). Similarly, other three relative distance functions can be estimated but with special treatment for $D_{o,t}(x^{t+1},y^{t+1})$ and $D_{o,t+1}(x^t,y^t)$, where the distance of the production points are calculated relative to technologies from different time periods (Coelli, 1996). In both these cases, the measured efficiencies can violate Farrell's 0 to 1 efficiency restrictions and go beyond these limits. For example, in fig. 4.2, the distance ratio 0b/0a must always be greater than or equal to 1, which holds true for all other Farrell based DEA efficiencies.[17] However as seen in the case of $D_{o,t}(x^{t+1},y^{t+1})$, the ratio 0d/0c > 1, signifying a technological progress (in actual DEA measurement, it means 0c/0d < 1). Therefore, DEA linear programming models for

[17] This should not be confused with the normal DEA efficiency score being greater than 1. DEA estimates the ratio 0b/0a to measure efficiency i.e. the distance between point "a" and the frontier point "b". If 0a > 0b, then 0b/0a will be less than 1 and point "a" will therefore lie above the frontier, which is not desirable. To restrict this from happening, normal DEA program limits 0b/0a to be always ≥ 1.

estimating distances $D_{o,t}(x^{t+1},y^{t+1})$ and $D_{o,t+1}(x^t,y^t)$ allow these ratios to be less than unity.

In order to decompose total factor productivity growth into efficiency change and technical change, the right hand side of equation 4.14 is divided and multiplied simultaneously by $\sqrt{D_{o,t+1}(x^{t+1},y^{t+1}) \times D_{o,t}(x^t,y^t)}$ as follows:

$$= \frac{\sqrt{D_{o,t+1}(x^{t+1},y^{t+1}) \times D_{o,t}(x^t,y^t)}}{\sqrt{D_{o,t+1}(x^{t+1},y^{t+1}) \times D_{o,t}(x^t,y^t)}} \mathrm{X} \sqrt{\left(\frac{D_{o,t}(x^{t+1},y^{t+1})}{D_{o,t}(x^t,y^t)}\right)\left(\frac{D_{o,t+1}(x^{t+1},y^{t+1})}{D_{o,t+1}(x^t,y^t)}\right)}$$

$$= \sqrt{\left(\frac{D_{o,t+1}(x^{t+1}y^{t+1})}{D_{o,t}(x^t,y^t)}\right)^2 \times \left(\frac{D_{o,t}(x^{t+1},y^{t+1})}{D_{o,t+1}(x^{t+1},y^{t+1})}\right) \times \left(\frac{D_{o,t}(x^t,y^t)}{D_{o,t+1}(x^t,y^t)}\right)}$$

Rearranging the terms by cancelling the radical for the squared items yields the following final equation:

$$\mathrm{TFPCh}_o(x^{t+1},y^{t+1},x^t,y^t)$$

$$= \frac{D_{o,t+1}(x^{t+1}y^{t+1})}{D_{o,t}(x^t,y^t)} \times \sqrt{\left(\frac{D_{o,t}(x^{t+1},y^{t+1})}{D_{o,t+1}(x^{t+1},y^{t+1})}\right) \times \left(\frac{D_{o,t}(x^t,y^t)}{D_{o,t+1}(x^t,y^t)}\right)}$$

Here, the first fraction measures the change in the relative technical efficiency between period “t” and “t+1” and the two fractions inside the radical represents the geometric mean of the shift in the production frontier with respect to x^{t+1} and x^t, respectively. In other words, the first ratio measures the change in the position of the production point (x,y) over this time period relative to the final position of the production frontier, thus representing its efficiency. The geometric mean measures the relative position of the efficiency frontier itself between "t" and "t+1", therefore measuring the change in technology. That is,

$$\text{Efficiency Change} = \frac{D_{o,t+1}(x^{t+1}y^{t+1})}{D_{o,t}(x^{t}, y^{t})}$$

$$\text{Technical Change} = \sqrt{\left(\frac{D_{o,t}(x^{t+1}, y^{t+1})}{D_{o,t+1}(x^{t+1}, y^{t+1})}\right) \times \left(\frac{D_{o,t}(x^{t}, y^{t})}{D_{o,t+1}(x^{t}, y^{t})}\right)} \qquad (4.15)$$

$$\text{i.e. Total Fator Productivity Change} = Efficiency\ Change \times\ Technical\ Change$$

Farrell et al. (1994:72) summed up these two components as "improvements in the efficiency change is the evidence of catching up with the frontier while improvement in technical change is an evidence of innovation". Note that all the mathematical calculations pertaining to TFPCh or its sub-components are ratios of two efficiencies, therefore their values can either be greater (when numerator > denominator) or less than one (numerator < denominator). A value greater than unity is a signal of a positive change and any value less than one signifies decline in productivity or its sub-components. Also, it is worth mentioning that it is not necessary that both the technology and efficiency components need to shift in the same direction within a time period. There can be certain times where the internal efficiency of a DMU may decline (e.g. 0.75 or -25%) but because the technology improved over that period (e.g. 1.50 or +50%), the total factor productivity would essentially rise (1.125 or +0.125%). This property of Malmquist TFPCh index of considering both the external (technology) and internal (efficiency) effects in determining the true productivity change makes it an ideal choice for benchmarking studies dealing with panel data (Demerjian, 2018). This research therefore employs Malmquist total factor productivity to operationalize both the moderating variables i.e. core business efficiency and marketing capability. The linear programming software adopted to calculate these efficiencies is DEAP developed by Coelli (1996) of Centre for Efficiency and Productivity Analysis (CEPA), School of Economics, University of Queensland, Australia. This DOS based computer program is free to download and is compatible with windows using file manager. DEAP is capable of calculating both standard and Malmquist productivity based efficiencies and its user friendliness makes it extremely popular amongst researchers and academicians (Iliyasu et al., 2015).

After realizing the adequate methodologies to empirically examine all the proposed research hypotheses and modelling CBEF and MCAP, focus can now be shifted in overviewing the sample data collected to accomplish these objectives. The following sections provide a detailed view about the data characteristics including their acquisition sources, representative population, and the employed criterion for the final sample selection.

4.5 Data and Measures

Various secondary sources were approached to retrieve all the relevant marketing, financial and accounting data for this study. The main benefit of relying on multiple sources for data collection is the avoidance of common method bias (Dotzel et al., 2013; Mishra & Modi, 2016). The acquired data can be broadly divided into three segments based on their individual characteristics and sources they are acquired from. Firstly, as discussed in section 2.2.3 of chapter 2, the consumer and firm based brand equity estimations are obtained from BrandZ and Brand Finance which are the two globally recognized commercial brand consultants (Bagna et al., 2017). Secondly, the risk loading factors proposed by Fama French (1993) and Carhart (1997) are downloaded from Kenneth French's online data library and finally, all the other accounting and financial data is retrieved from Eikon DataStream database. Sections below focus on each of these segments individually outlining the overall sampling procedure adopted to finalize the raw data for analysis.

4.5.1 CBBE and FBBE measures

Consumer and firm based brand equity measures adopted in this study are represented through the brand valuations provided by BrandZ and Brand Finance, respectively[18]. Both the brand consultancies publish their monetary brand value estimates for all major global brands on an annual basis. Millward brown BrandZ generates an annual list of "Top 100 most valuable global brands" whereas the "Global 500" report released by Brand Finance comprises of the most valuable 500 brands worldwide. To maintain uniformity within CBBE and FBBE samples, only the yearly estimates of top 100 brands were extracted from Brand Finance database. This resulted in an initial sample size of 1000 brand-year observations for each sample from 2010 till 2019. However not all these brands could be included in the final dataset either due to corresponding financial data constraints or unavailability of the brand estimations for the consecutive 10 year study period. For example, the brand-firms which are not publicly listed in any stock exchange (e.g. Ikea) were dropped due to absence of relevant stock market data. Another reason of excluding certain brands was the unavailability of their yearly brand

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[18] For discussions regarding selection of BrandZ and Brand Finance brand valuations to represent CBBE and FBBE, respectively, see section 2.2.3 of the literature review chapter.

estimations for the entire study period i.e. 2010-2019. Not all brands could make it to the top 100 list of Brand Finance and BrandZ every year and therefore were excluded due to inaccessibility of continuous brand value estimations. Additionally, CBBE and FBBE valuations were also required for a year preceding the estimation period i.e. 2009 to calculate brand value changes for the year 2010. Apart from the data constraints, few other restrictions were imposed on the initial sample as guided by the existing marketing-finance research. For example, only those firm brands were included which are originated in the developed countries (Dutordoir et al., 2015). This is to control for any discrepancies that may arise due to cross-cultural and economy-wide differences between developed and developing nations. For example, Zarantonello et al. (2020) demonstrates that the consumer brand association varies significantly based on country's economic status. Their findings reveal that in developed countries, local brands are favoured over global brands whereas in emerging economies, consumers are more inclined towards foreign brands as compared to domestic brands. Other studies validating this inconsistency in relative brand importance in developed versus emerging nations include Demirbag et al. (2010), Guo (2013), Leonidou et al (2007) and Sharma (2011). Apart from the country of domicile, table 4.3 summarizes all other constraints applied to finalize the acquired CBBE and FBBE samples.

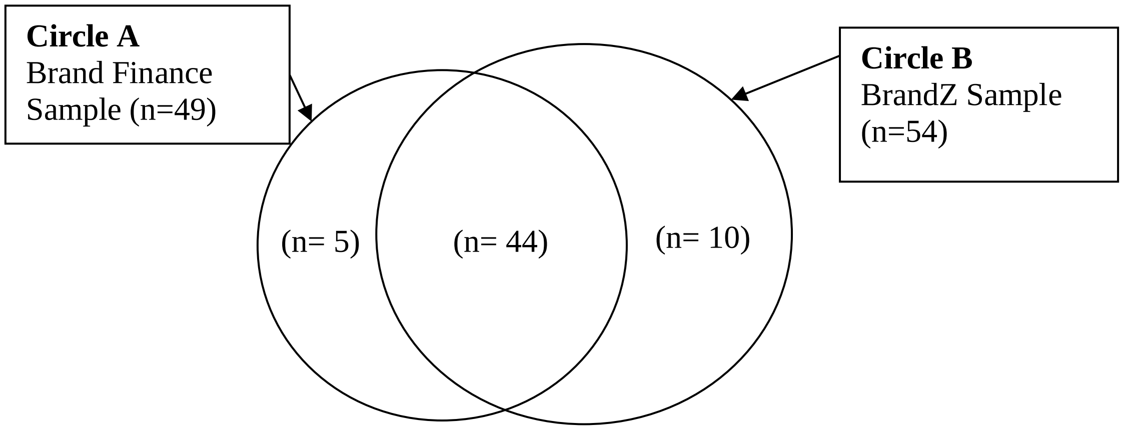
Table 4.3 List of restrictions imposed on raw CBBE and FBBE data

S.No	Imposed requirements
1	The brand must be owned by the firm domiciled in the developed country.
2	The brand-firm must be publicly listed in the country's major stock exchange.
3	The brand owning firm should be listed with the same name as the brand itself. For example, retailer Next plc is Next (NXT.L) on London stock exchange whereas Primark is listed as Associated British Foods (ABF.L).
4	The brand values of BrandZ and Brand Finance database should be available from 2010 till 2019 plus a year prior (i.e. 2009) so as to calculate yearly brand value changes for 2010.
5	The financial and accounting data for the brand owning firm should be available at Eikon DataStream database.

After imposing all the criterion, the resulting CBBE and FBBE samples comprise a total of 54 and 49 brands yielding 594 and 539 firm-year observations, respectively, from the period 2009 till 2019. However, the loss of one year of cross-sectional data (2009) while calculating "changes in brand values" returns a final panel data set of 540 firm-year observations for CBBE and 490 for FBBE. The main advantage of adopting panel data over the cross sectional and time series is its ability to generate more accurate predictions for individual outcomes (Hsiao, 2014). This is because panel data analysis can efficiently segregate the effects "within" a variable (e.g. a brand) over time (10 years) and "between" different variables (all brands) in the same time period (single year) (Wooldridge, 2010). Accounting for cross-sectional heterogeneity across sample firms therefore generate more robust results as compared to simple OLS regression (Rahman et al., 2018).

Since this research also aims to conduct a comparative assessment between the value relevance of CBBE and FBBE, it is desirable to have maximum number of firms common within the two datasets. As shown in the Venn diagram (figure 4.5), 44 firm brands are common in both the consumer and firm based brand equity datasets, resulting in a sample size of 440 firm-year observations for the comparative analysis.

Figure 4.5 Venn Diagram for CBBE and FBBE sample structure, 2009-2019



Source: Author’s elaboration

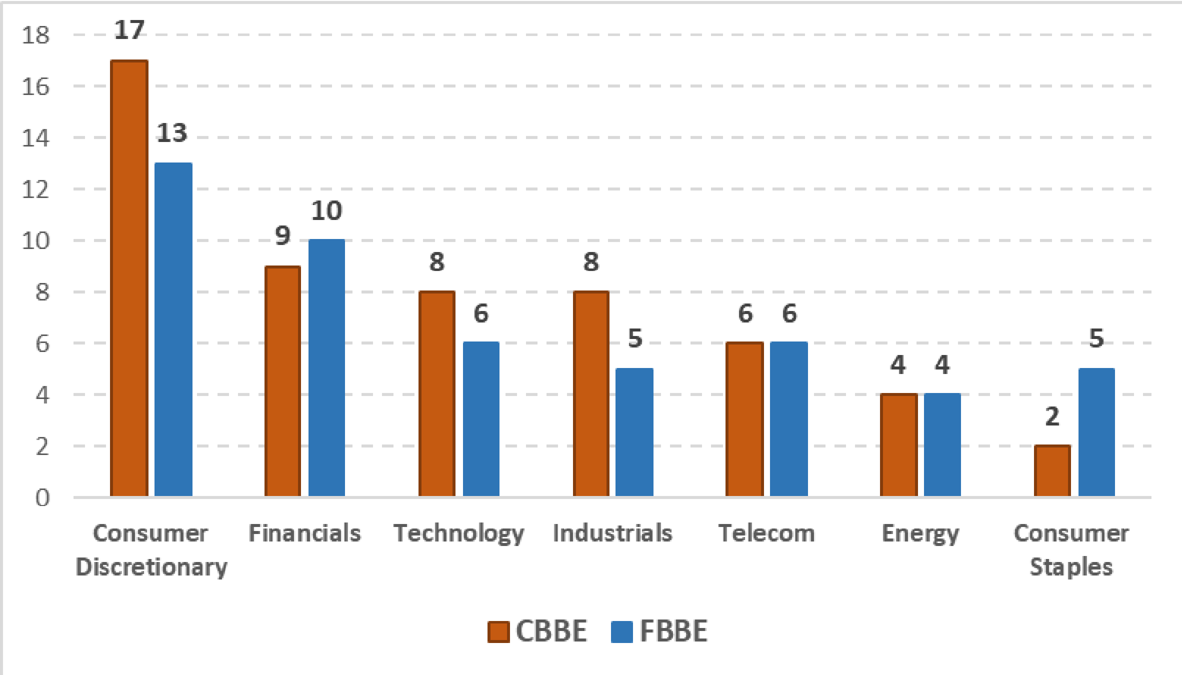
Table 4.4 provides the distribution of the acquired CBBE and FBBE samples by country. The most represented country in both the datasets is the United States with 63% overall share including prominent brands like Amazon, Google, Microsoft, Coca-Cola, and Mc Donald’s. Germany is with the second most firms including globally recognized brands such as Daimler, Volkswagen, and BMW. The BrandZ sample has France as third most represented country including luxury brands like LVMH and Loreal. The only brand domiciled in Switzerland is Nestle which is the part of Brand Finance FBBE sample.

Table 4.4 CBBE and FBBE sample distribution by country

Country	BrandZ		Brand Finance	
	N	% Share	N	% Share
United States	34	63%	31	63%
Germany	6	11%	6	12%
United Kingdom	3	6%	3	6%
Japan	3	6%	3	6%
Canada	2	4%	2	4%
France	4	7%	1	2%
Spain	1	2%	1	2%
Netherlands	1	2%	1	2%
Switzerland	-	-	1	2%
Total	**54**		**49**	

The clustered column chart in figure 4.6 outlines the distribution of the collected sample by different industrial sectors. The industrial categorization of the acquired sample is based on the industry classification benchmark (ICB) code provided by global analytics firm FTSE Russell (Phillips & Ormsby, 2016). An ICB code is allocated to a firm according to the nature of its business and the market sector from which majority of the revenue is generated. More information about FTSE Russell's benchmarking procedure can be obtained from their official website www.ftserussell.com. The table with the ICB codes for all the industrial sectors included in the dataset is included in Appendix C. Consumer discretionary has the highest number of observations in both the datasets with firms from different sub-sectors like automobile, retail, apparel and fast-food. The second most represented industry is the financial sector with banks and insurance companies such as Citi, JP Morgan & Chase, Santander, and Allianz. Both the datasets contain 5 universally known technological firms i.e. Apple, Google, Microsoft, Intel, and Oracle. The two additional names in BrandZ list are German software brand SAP and US based IT firm Hewlett-Packard, commonly known as HP. The industrial brands in both the samples include logistics firms FedEx and UPS, conglomerate like General Electric and commercial payment services such as Visa and American Express (the latter is only the part of FBBE sample). Both the telecom and energy sectors are equally weighted in both datasets and contain iconic brand names like BP, Shell, Vodafone, Orange, and T-Mobile. However, the number of firms belonging to consumer staples sector in BrandZ list are more than twice as compared to Brand Finance sample. This is due to the inclusion of brands like Nestle, CVS Health and Walgreens Boots in the BrandZ dataset.

Figure 4.6 CBBE and FBBE sample segmentation by industry



Source: Author’s elaboration

4.5.2 Fama-French and Carhart risk loading factors

As explained in section 4.3.3.2 of this chapter, to control for economy wide-risk factors, Fama French (1993) and Carhart (1997) risk loading factors of R_m, SMB, HML and

MOM are included in the proposed SRRM model. All the risk loadings are retrieved from the Kenneth French's online data library available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. This open source database publishes weekly, monthly, and annual data for all the risk loading factors and risk-free rates. The data is also provided for different geographical zones including developed markets, Europe, Japan, and Asia pacific. Table 4.5 provides the list of all countries included in different regions. Since this study includes brand-firms domiciled in developed countries, monthly FF-C loading factors are obtained for the "developed market" category of Kenneth French's database. All the countries represented in the acquired datasets are highlighted in grey for a clear interpretations. The database calculates market returns (R_{mt}) for the "developed market" category as average monthly returns of the value-weighted portfolio of major markets in all the 23 countries. The risk-free rate R_f published under this category represents the monthly US treasury bill interest rate (Fama & French, 2012).

Table 4.5 Fama French (1993) and Carhart (1997) risk loading factors by regions

Country	Developed	Developed ex US	Europe	Japan	Asia Pacific ex Japan	North America
Australia	✔	✔			✔	
Austria	✔	✔	✔			
Belgium	✔	✔	✔			
Canada	✔	✔				✔
Switzerland	✔	✔	✔			
Germany	✔	✔	✔			
Denmark	✔	✔	✔			
Spain	✔	✔	✔			
Finland	✔	✔	✔			
France	✔	✔	✔			
Great Britain	✔	✔	✔			
Greece	✔	✔	✔			
Hong Kong	✔	✔			✔	
Ireland	✔	✔	✔			
Italy	✔	✔	✔			
Japan	✔	✔		✔		
Netherlands	✔	✔	✔			
Norway	✔	✔	✔			
New Zealand	✔	✔			✔	
Portugal	✔	✔	✔			
Sweden	✔	✔	✔			
Singapore	✔	✔			✔	
United States	✔					✔

Source: Kenneth French official website

4.5.3 Other accounting and financial data

All the other accounting and stock market based data required for the empirical analysis is acquired from Refinitiv DataStream. DataStream is the world's most comprehensive financial database containing more than 65 years of data pertaining to financial markets in 175 countries (Refinitiv, 2021). University of Roehampton has a paid subscription to the database and all the required data is obtained through the university account. Table 4.6 provides the list of all the retrieved accounting and financial variables in alphabetical order including their DataStream code and description.

Table 4.6 List of all the accounting and financial metrics acquired from DataStream Database

Variable	DataStream Code	Description
Accounts Receivables	WC08131	Net Sales or Revenues / Average of Last Year's and Current Year's Receivables-Net
Intangible Assets	WC02649	Total Intangible Other Assets Net (including goodwill, patents, trademarks, etc)
Market capitalization	MV	Market Value (Stock price multiplied by total number of shares outstanding
OIBD	WC18155	Operating Income Before Depreciation & Amortization
Sales, General & Administrative Expenses	WC01101	Selling, General & Administrative Expenses including advertisement and R&D expenditures
Stock Price	P	Market closing stock price
Total Assets	WC02999	Sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.
Total Debt	WC03255	All interest bearing and capitalized lease obligations including long and short term debt
Total Employees	WC07011	The number of both full and part time employees of the company
Total Sales	WC01001	Gross sales and other operating revenue less discounts, returns and allowances.
Total Shareholder's Equity	WC03995	Sum of Preferred Stock and Common Shareholders' Equity

4.6 Summary

This chapter overviewed the methodologies undertaken for this research. Both the acquired methods and data collection techniques synchronise well with the adopted philosophical stance of positivism and objectivism. After scrutinizing the most relevant empirical approaches employed in the existing marketing-finance literature, SRRM is identified as a viable choice over event study or calendar-time portfolio approach. This is because SRRM includes accounting, macro-economic and firm specific factors which are prime drivers of stock returns before introducing any non-financial asset such as brand equity. The model therefore examines if the marketing asset under investigation has value relevance incremental to that of firm's balance sheet metrics and other risk factors. This approach therefore not only addresses the omitted variable bias but also provide robust insights about the true financial implications of marketing based assets and strategies. The chapter also identifies Malmquist DEA total factor productivity change as the most appropriate technique over standard DEA models in operationalizing organizational efficiency variables of CBEF and MCAP. Adopting this advanced benchmarking approach aids this study in taking full advantage of its panel data structure by incorporating the effects of technological changes over time in the estimated efficiencies. Along with the methodologies, the chapter also revealed different secondary sources referred to compile all the required marketing, accounting, and financial data. Not all the acquired CBBE and FBBE sample brands from BrandZ and Brand Finance database, respectively, could be preserved either due to the financial data constraints or the implied requirements guided by current marketing literature. However, the final sample is still large enough and represent wide range of countries and industrial sectors. Therefore a robust analysis can be conducted to empirically test all the proposed hypotheses, which is the main objective of the succeeding chapters.

EMPIRICAL ANALYSIS

The comprehensive analysis conducted in this study strive to extract meaningful information from the collected quantitative data from the marketing, accounting, and financial sources. In order to maintain consistency with the proposed conceptual model and lay a systematic approach to address all the proposed research hypotheses, the empirical analysis is segregated into two chapters. The first chapter, named as "analysis phase-I", encompasses section-I of the conceptual model and delve with testing the direct brand equity-firm performance path relationships, including CBBE-FBBE comparative assessment. As outlined in model section-I, focus is directed in understanding the firm value effects of both the overall and directional (i.e. positive and negative) shifts in CBBE and FBBE. The chapter begins with an outline of the procedures and strategies adopted to organize and reconcile all the retrieved raw data common for sections I and II of the proposed conceptual model (i.e. entire analysis). The applied econometric method to statistically examine all the research questions within this chapter is stock return response modelling (SRRM). The second chapter i.e. analysis phase-II, alternatively, focuses exclusively on the hypotheses proposed in the section-II of the conceptual framework. Anchored to the underpinnings of resource based theory (RBT), this chapter complements the preceding chapter by analysing whether superior organizational efficiency can translate brand equity into a source of sustainable competitive advantage (SCA). In particular, it investigates the role of core business efficiency (CBEF) and marketing capability (MCAP) in moderating brand equity-firm performance interface utilizing both DEA Malmquist TFPCh and SRRM methodologies. Both the chapters commence with an introduction and conclude with a brief summary of key findings.

Chapter 5: ANALYSIS PHASE - I

5.1 Introduction

This chapter is driven by model section-I of the designed conceptual framework and investigates the direct effects of brand equity, specifically CBBE and FBBE, on firm long-term performance. Incapsulating both overall and directional changes (i.e. positive and negative) in these brand equity perspectives, the analysis expects strong empirical support for all the proposed research questions. For the empirical investigation, stock return response modelling (SRRM) is employed which is one of the widely used econometric models in the existing making-finance literature. Along with linking CBBE and FBBE to stock returns, the chapter also conducts a comparative analysis between these two brand equity measures adopting multiple approaches. The statistical software package employed for the empirical examination of all the proposed SRRM models is Stata. The chapter begins with an overview of the process involved in transformation of the raw data into a working dataset for the entire analysis (including phase I and II). This includes, aligning all the gathered time-series data with the BrandZ and Brand Finance brand valuation waves and modelling unanticipated changes in accounting (ROA and sales) and brand equity variables (CBBE and FBBE). Since the current study is longitudinal in nature, the subsequent section overviews the procedure for a systematic analysis of the panel data models, followed by a discussion of the adopted analysis strategy. The next section recalls all the proposed hypotheses under model section-I before empirically analysing them individually in the following sections. To maintain a systematic flow throughout the analysis, the hypotheses are dealt in the same order as outlined in the proposed conceptual framework. Each of the analysed SRRM model is supported with data description, correlation inspection, post-estimation tests and robustness checks. Finally, the chapter concludes with a short summary of the key empirical outcomes.

5.2 Data Preparation and alignment

A number of steps were taken to transform all the data into a meaningful panel dataset that corresponds well with the acquired consumer and firm based brand valuations. As discussed in chapter 4, both BrandZ (proxy of CBBE) and Brand Finance (proxy of FBBE) publish their monetary brand values on annual basis. Therefore, the first step is to annualize all the monthly or quarterly accounting and financial data so as to align them with the acquired CBBE and FBBE metrics. In the second stage, the unanticipated components of current-term accounting performance measures i.e. earnings (ROA) and sales are estimated so as to include them in the designed SRRM models. The final step is to convert the annual brand valuations of BrandZ and Brand Finance into “change per year” to comply with the requirements of stock return response modelling (Mizik & Jacobson, 2008). The subsequent sub-sections elaborate on these procedures for the data initialization.

5.2.1 Annualizing the collected data

5.2.1.1 Stock Returns

Firstly, the outcome variable of the designed SRRM model i.e. stock returns are annualized by compounding the monthly returns over the 12 month period as:

$$\mathrm{R_{iT}} = \prod_{\mathrm{m}=1}^{\mathrm{M}} (1 + \mathrm{ret_{im}}) - 1$$

Where, R_{it} is the yearly stock returns i^{th} firm in year T and ret_{im} is the holding period return of firm "i" in month "m" and T is the year corresponding to months, m = 1…, M[19]. The months, 1 till M, are not simply the financial or calendar year months, rather corresponds specifically to the BrandZ and Brand Finance brand value announcement waves. BrandZ publish their brand valuations in May every year whereas Brand Finance annual announcement month is January. Therefore firm i's stock returns for CBBE and FBBE sample firms are compounded over different 12 month window for the same year T. For example, to calculate cumulative yearly returns for BrandZ firms for the year 2010 (CBBE model), m=1 is the first month following the previous year brand value announcement i.e. June 2009 and M is the last month of the year T before the next valuations were released i.e. May 2010 (Mizik, 2014). The equation for calculating cumulative yearly returns for CBBE based stock return response model can be rewritten as:

$$\mathrm{R}_{\mathrm{i}\mathbf{T}} = \prod_{\mathrm{m}=\mathrm{Jun}_{\mathrm{T}-1}}^{\mathrm{May}_{\mathrm{T}}} (1 + \mathrm{ret}_{\mathrm{im}}) - 1$$

Since Brand Finance releases their valuations in January each year, the annual raw returns are estimated from m=1 i.e. February of previous year (T-1) to January in current year T. The equation can therefore be expressed as:

[19] Month end stock prices for each sample firm were retrieved from DataStream from 2009 till 2019 to calculate monthly returns.

$$R_{i\mathbf{T}} = \prod_{m=\mathrm{Feb}_{T-1}}^{\mathrm{Jan}_T} (1 + \mathrm{ret}_{im}) - 1$$

It has also to be noted that the actual dependant variable of the designed SRRM model is risk-free rate adjusted returns i.e. $R_{it} – R_f$ and not simply the raw returns R_{it} (refer to equations 10 and 11 in section 4.3.3). Therefore monthly risk free rates obtained from Kenneth French online data library were subtracted from the monthly raw returns before compounding them annually.

5.2.1.2 Explanatory variables

Similar to the raw returns calculated above, monthly Fama French (1993) and Carhart (1997) loading factors of R_{mt} - R_f, HML, SMB and MOM are also compounded annually adopting separate monthly windows for CBBE and FBBE models. However, in contrast to Kenneth French's data library which publish data on monthly basis, DataStream provides majority of the accounting data already cumulated annually at the end of each quarter. For example, the figures for total assets for Q4 of 2010 represents the sum of the asset values in Q4 and the previous three calendar quarters (i.e. Q1, Q2 and Q3, 2010). Therefore the total assets figures of Q4 2010 reflects the aggregated total assets from January 2010 till December 2010 (i.e. yearly values). Therefore, in order to compile and align other explanatory variables with the CBBE and FBBE yearly brand estimation waves, quarterly data from DataStream is retrieved. Since BrandZ reports their brand values in second quarter of each calendar year (May), the corresponding financial data is obtained for Q2 each year. For FBBE sample firms (having January as announcement month), annual estimates are captured from the first calendar quarter (Q1) every year. Since Daniel and Titman (1997) firm specific risk characteristics are modelled through lagged firm size (i.e. total assets) and book-to-market value (i.e. shareholder's equity/market capitalization), their yearly values are aligned with CBBE and FBBE models by obtaining their previous year's figures in the same quarters. For all other control variables which are not lagged such as ROA (i.e. OIBD/ total assets), sales and leverage (total debt/shareholder's equity), the data was obtained from the current year quarters. For example, annual sales for CBBE and FBBE sample firms are retrieved using Q2 (current year) and Q1 (current year) sales data, respectively[20].

Using monthly and quarterly data to compile all the outlined variables also overcome the fiscal period disparity issue. The firms included in the sample have different fiscal year end periods and therefore annualizing the data using monthly and quarterly measures align it precisely with the required 12 month brand value announcement waves for CBBE and FBBE models.[21] Additionally, since firms included in these samples belong to different countries, all the pertaining accounting and financial data is converted into US dollars before extracting it from DataStream. This is to eliminate any effects of currency discrepancies on the analysis and findings.

5.2.2 Modelling unanticipated changes in ROA and Sales

Stock return response modelling (SRRM) postulates that financial community reacts only to the unanticipated changes in firm's current period performance and adjust their perceptions about firm's future discounted cashflows accordingly (Mizik, 2014).

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[20] When retrieved all the output data in US dollars, DataStream automatically converts all the non-US currencies to US dollars by applying the respective month end exchange rates.

[21] DataStream divides quarters based on calendar year for all the firms irrespective of their actual fiscal period end months.

Inputting aggregated yearly values of ROA and sales in any SRRM model will therefore provide no incremental information about their value relevance. These balance sheet metrics need to be first transformed into "unanticipated change" components. However, deciding whether to estimate the unanticipated changes in earnings and sales through an autoregressive (AR) model or first differencing depends upon the dynamic properties of their time series. If the time-series has a unit root i.e. it follows a random walk, then taking first differences is a viable choice and if it exhibits stationarity, then an AR model can be deployed (Mizik & Jacobson, 2008). There are several unit root tests designed specifically for panel data models, and their choice depends upon the panel properties such as number of observations N, time periods T and whether it is balanced or unbalanced. For example, one of the widely used panel unit toot test introduced by Levin-Lin-Chu (2002) can only provide reliable results for panels having 25 to 250 observations and where T is significantly larger than N (Baltagi, 2013). For relatively shorter panels (with N>T and T ranging between 10 to 15), Harris-Tzavalis (1999) test for panel data stationarity is a viable alternative. For example, Gumus and Celikay (2015) applied H-T test to inspect sequential stability of their data comprising a panel of 52 countries over 15 years. H-T test is based on unaugment Dicky-Fuller regression with null hypothesis supporting the presence of a unit root and alternative hypothesis indicating stationarity in the panel (Blander & Dhaene, 2012). Since the retrieved sample in the current study comprises of a comparatively short panel data with T < N, H-T test for panel unit root detection is adopted. As a robustness check and reliability of the results, two other tests are also conducted, namely Breitung (2000) and Im–Pesaran–Shin (2003) test. The choice of these tests and practise to implement multiple tests to affirm panel stationarity is guided by the existing empirical literature (Colicev et al., 2018; Gumus & Celikay, 2015; Kang et al., 2016). Similar to H-T test, Breitung and IPS have a null hypothesis that the panel contain unit root. A distinguishing feature of IPS over Breitung and H-T test is its ability to accommodate unbalanced panels and relax the assumption of auto-correlated parameters in the panel.

Yearly ROA is calculated for all the 54 brands in CBBE and 49 brands in FBBE sample from 2009 till 2019 yielding a panel of 594 (54 X 11) and 539 (49 X 11) observations, respectively[22]. Compounded quarterly data of OIBD and total assets were obtained from DataStream to align ROA values with the corresponding brand dimension waves. Annual sales, retrieved as cumulative quarterly sales from DataStream, were converted to logarithmic form to construct panel series for respective CBBE and FBBE waves (Dutordoir et al., 2015; Mizik & Jacobson, 2008). Table 5.1 presents the results for H-T, Breitung and IPS panel unit root for both the accounting variables segregated for CBBE and FBBE models. Each test has three columns representing the z-statistic, its corresponding p-values and affirming whether the series have a unit root or not.

Table 5.1 Panel Unit Root Tests

	H-T Test			**Breitung Test**			**IPS Test**		
	z-statistic	p-value	Unit Root	z-statistic	p-value	Unit Root	z-statistic	p-value	Unit Root
CBBE									
ROA	-3.717	0.000	No	-1.674	0.047	No	-2.059	0.020	No
LogSales	3.4191	0.999	Yes	5.017	1.000	Yes	2.059	0.980	Yes
FBBE									
ROA	-2.952	0.001	No	-1.284	0.099	No	-2.678	0.004	No
LogSales	3.079	0.999	Yes	3.883	0.999	Yes	1.236	0.892	Yes

No. of observations for CBBE sample variables = 594; for FBBE sample variables = 539

[22] The year 2009 is included so that ROA change values can be calculated later for 2010, which is the first year of the analysis. Same logic applies for other accounting and marketing metrics.

All the three tests demonstrates that ROA exhibits stationarity over time for both CBBE and FBBE panels. However, the null hypothesis of panel unit root cannot be rejected in case of LogSales for both the models and therefore the series is in continuous state of evolution. Based on these findings, unanticipated changes in earnings can be modelled through an autoregressive regression whereas sales changes can be attained through first differencing (Mizik & Jacobson, 2004). First order auto-regressive (AR1) fixed effect regression is used to estimate unanticipated changes in ROA which can be represented through the following model (Bhardwaj et al., 2011; Srinivasan & Hanssens, 2009):

$$\mathrm{ROA}_{\mathbf{iT}} = \phi_0 + \phi_1 \mathrm{ROA}_{\mathbf{iT-1}} + \eta_{\mathbf{iT}}$$

Where, ROA_{iT} and ROA_{iT-1} are the current and lagged yearly measures of return on assets. ϕ_1 is the AR1 coefficient of the bivariate dynamic panel series regression. η_{iT} is the obtained residual which represents the unanticipated component $\mathrm{U\Delta ROA}_{iT}$ i.e. portion of ROA that could not have been anticipated for time "t" based on the information available at time "t-1" (Mizik, 2014). The proposed AR1 model has been employed separately for estimated the unanticipated ROA for CBBE and FBBE firms based on their corresponding yearly windows. Including lagged ROA simultaneously with its current period value in the AR1 models reduces the number of cross-sectional observations by one year resulting a total of 540 and 490 firm-year observations for CBBE and FBBE models, respectively.

Since LogSales follow a random walk, unanticipated changes for consumer and financial based SRRM models can simply be calculated as annual sales growth:

$$\Delta \text{Sales}_{\text{i}\mathbf{T}} = \text{LogSales}_{\text{i}\mathbf{T}} - \text{LogSales}_{\text{i}\mathbf{T}-1}$$

Where, LogSales_{iT} and LogSales_{iT-1} are the natural log of current and lagged year sales, respectively, for 54 CBBE and 49 FBBE firms for the period 2010 till 2019. The time T comprises of two separate 12 month-sets each corresponding to BrandZ and Brand Finance brand value announcement waves.

5.2.3 Modelling changes in CBBE and FBBE

Finally, the core marketing variables of the study i.e. changes in CBBE and FBBE are modelled. These are computed as the annual percentage changes in BrandZ (for CBBE) and Brand Finance (for FBBE) brand values by the following equations:

$$\Delta \text{CBBE}_{\text{i}\mathbf{T}} = \frac{\text{CBBE}_{\text{i}\mathbf{T}} - \text{CBBE}_{\text{i}\mathbf{T}-1}}{\text{CBBE}_{\text{i}\mathbf{T}-1}}$$

$$\Delta \text{FBBE}_{\text{i}\mathbf{T}} = \frac{\text{FBBE}_{\text{i}\mathbf{T}} - \text{FBBE}_{\text{i}\mathbf{T}-1}}{\text{FBBE}_{\text{i}\mathbf{T}-1}}$$

Where, CBBE_{iT} and FBBE_{iT} are the current year and CBBE_{iT-1} and FBBE_{iT-1} represents the previous year brand valuations of BrandZ and Brand Finance, respectively. Not to mention that their corresponding time periods “T” depict their respective yearly brand announcement month groups. There can be a possibility that the best estimates of changes in CBBE and FBBE could be attained through an auto-regressive model as is the case with earnings. The main issue adopting AR estimation model is the possibility of obtaining different polarities of yearly brand values changes (positive or negative) as compared to their original dynamics. Autoregressive models provide measure of unanticipated changes as regression residuals, which are the differences between actual and projected values. Due to this reason, whether a change is positive or negative will depend on the underlying regression fit rather than actual brand value changes. This is not desirable as the main aim of the research is to examine the impact of real world rise and decline in CBBE and FBBE on firm performance. Taking AR residuals as "change metrics" will therefore drift the conducted empirical analysis from original sample characteristics. To avoid this discrepancy, percentage changes are computed as measure of CBBE and FBBE changes over time. To further validate the chosen method, all three panel unit root tests defined earlier were conducted on BrandZ and Brand Finance brand value panels from year 2009 till 2019. Table 5.2 reports the test results. All the underlying tests fail to reject the null hypothesis suggesting that both CBBE and FBBE brand values are in constant state of evolution and have a unit root. The results further support the choice of taking the first difference through percentage change rather than AR residuals a measure of brand value changes.

Table 5.2 Panel Unit Root Tests for ΔCBBE and ΔFBBE

	H-T Test			**Breitung Test**			**IPS Test**		
	z-statistic	p-value	Unit Root	z-statistic	p-value	Unit Root	z-statistic	p-value	Unit Root
ΔCBBE	9.375	1.000	Yes	11.250	1.000	Yes	16.269	1.000	Yes
ΔFBBE	7.151	1.000	Yes	6.673	1.000	Yes	9.404	1.000	Yes

No. of observations for CBBE = 594; FBBE = 539

5.3 Panel Data Modelling Process

After compiling and aligning all the required marketing, financial and accounting data, focus can now be directed on the overview of systematic panel data analytical procedures. When the acquired data is in a panel format i.e. it contains both cross-sectional and time-series components, it needs more systematic modelling as compared to standard ordinary least square (OLS) regressions (Wooldridge, 2010). Since same cross-sectional units (e.g. firm, country, etc) are observed repeatedly over multiple time periods, the panel regression model may violate OLS assumptions of exogeneity (error terms are uncorrelated with any regressors) and homoscedasticity (errors have same variance). For example, if a study explores the effects of brand equity on annual sales for 10 firms from 2015 till 2020, there may be several unobserved firm-based factors such as industry sector, country of operation and management policies that would impact annual sales in all these years. Since these factors are fixed over time for a specific firm (which is called *heterogeneity*), independent distribution of observations over time cannot be assumed. In other words, these unobserved factors (which will be the constituents of OLS residuals) will exhibit a strong correlation with the independent variables (brand equity in the example), thus violating the endogeneity assumption. The presence of these individual-specific unobserved factors therefore needs special statistical treatment when dealing with cross-sectional time-series data. If a panel data does not have these individual effects, then the model can simply be interpreted as if independent cross-section units are pooled over time. In such cases, efficient estimates can be obtained through a simple OLS regression, also known as pooled OLS in case of panel regression (Park, 2011). However, majority of cross-sectional time series data have individual-specific effects which can be explained either through a “fixed effects” or “random effects” panel regression model. The core difference between the two models is the manner in which they treat the unobserved effects. To understand this, let’s assume u_i to be an individual-specific variable which captures all the unobserved time-invariant factors that affect the dependant variable y_{it} in the following panel data regression model:

$$y_{it} = \alpha + u_i + \beta x_{it} + \varepsilon_{it}$$

Where, α is the regression intercept, x_{it} is the cross-sectional time-series dependent variable and ε_{it} is the idiosyncratic error term which varies both by individuals and time. In a fixed effect model, all the dependant and independent variables are demeaned over time i.e. subtracting the average of all the individuals within one time period from their actual values. Demeaning above equation yields the following model:

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \qquad (5.1)$$

Note that the intercept α and the unobservable effect u_i are not present in the time-demeaned model. This is because the intercept is constant and unobserved effect u_i is time-fixed, therefore they both get “differenced away” in the demeaning process. Since the observations were demeaned within group over time, the fixed effects model is known as “within fixed effects estimator” (Wooldridge, 2010). Estimating equation 5.1 with pooled OLS can now provide unbiased estimates, as the time invariant unobserved effects i.e. heterogeneity is already eliminated. In its functional form, fixed effects estimator allows the unobserved effect u_i to correlate with the regressors and therefore is absorbed in the intercept of the regression model. This can be specified as:

$$y_{it} = (\alpha + u_i) + \beta x_{it} + \varepsilon_{it}$$

For the brand strength-sales example defined earlier, running a fixed effect model on those 10 firms would eliminate the effects of industry, country, and management through a "within transformation", thus providing unbiased estimates of brand equity effects on sales.

A random effects model, on the other hand, assumes that u_i is uncorrelated with the explanatory variables in all the time periods. The unobserved time fixed effects are also assumed independent of the regression residuals ε_{it}. Therefore modelling panel data models with such properties through a fixed effect within estimator would provide inefficient or biased estimators. A random effects model can be expressed in its functional form as:

$$y_{it} = \alpha + \beta x_{it} + (u_i + \varepsilon_{it})$$

Since u_i is assumed to be independent and identically distributed (which is the property of error term in OLS), it is incorporated within the idiosyncratic error term and collectively defined as a "composite error term" i.e.

$$\text{Composite error}\,;\nu_{it} = u_i + \varepsilon_{it}$$

The addition of u_i in the error term ε_{it} causes the composite error to be serially correlated (as u_i is same every year for a specific individual). This auto-correlation property of the composite error is ignored by the pooled OLS method, making it infeasible for estimating random effects (Wooldridge, 2010:396). To overcome this issue, generalized square (GLS) regression method is employed to estimate random effects model (see Wooldridge 2010, Chapter 10 for explanation about GLS)[23].

After understanding different types of panel data regression models, the next step is to determine as to which model fits best for the acquired panel data sample. This can be established by conducting different statistical tests designed to evaluate the relevance and validity of one estimation model over the other. The first test which examines the appropriateness of fixed effects over pooled OLS is a F-test based on least square dummy variable regression (LSDV). Under this test, "N – 1" dummy variables for each individual are created and an OLS regression is run (where N is total number of individuals). The null hypothesis states that the sample has no individual-specific unobserved components i.e. coefficients for all the dummy variables are zero or insignificant. In this case, the model can simply be estimated through a pooled OLS regression. If at least one of the "N-1" intercepts are significantly distinguishable from zero, null hypothesis is rejected in favour of fixed effects over pooled OLS. It is worth mentioning that this F-test should not be confused with the standard joint significance F-test of linear regression models as it is specifically designed to compare LSDV performance with pooled OLS. The second test is Breusch and Pagan's (1980) Lagrange multiplier (LM) test which examines if random effects model is superior to pooled OLS in explaining the presence of time-fixed unobserved effects. Following a chi-squared distribution, LM test examines if the variance components of unobserved factors is zero. If the null hypothesis of zero variance is rejected, it concludes that there

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[23] GLS can only be applied if the covariance structure of the composite error is known otherwise feasible generalized least square (FGLS) or estimated generalized least square (EGLS) regression models are used to estimate random effects models (Park, 2011: 11).

is a presence of significant random effects in the model and estimating it through pooled OLS is not viable. If both F-test and LM test favours fixed and random effects over pooled OLS, respectively, then Hausman test is applied to determine the most relevant amongst them. Hausman specification test examines the covariance of the unobserved individual effects u_i with all the explanatory variables in the model (Hausman, 1978). The null hypothesis states that u_i is uncorrelated with any of the regressors i.e.

$$H_0: \qquad Cov\,(\mathrm{u_i}\,, \mathrm{X_{it}}) = 0$$

$$H_{alt}: \quad Cov\,(\mathrm{u_i}\,, \mathrm{X_{it}}) \neq 0$$

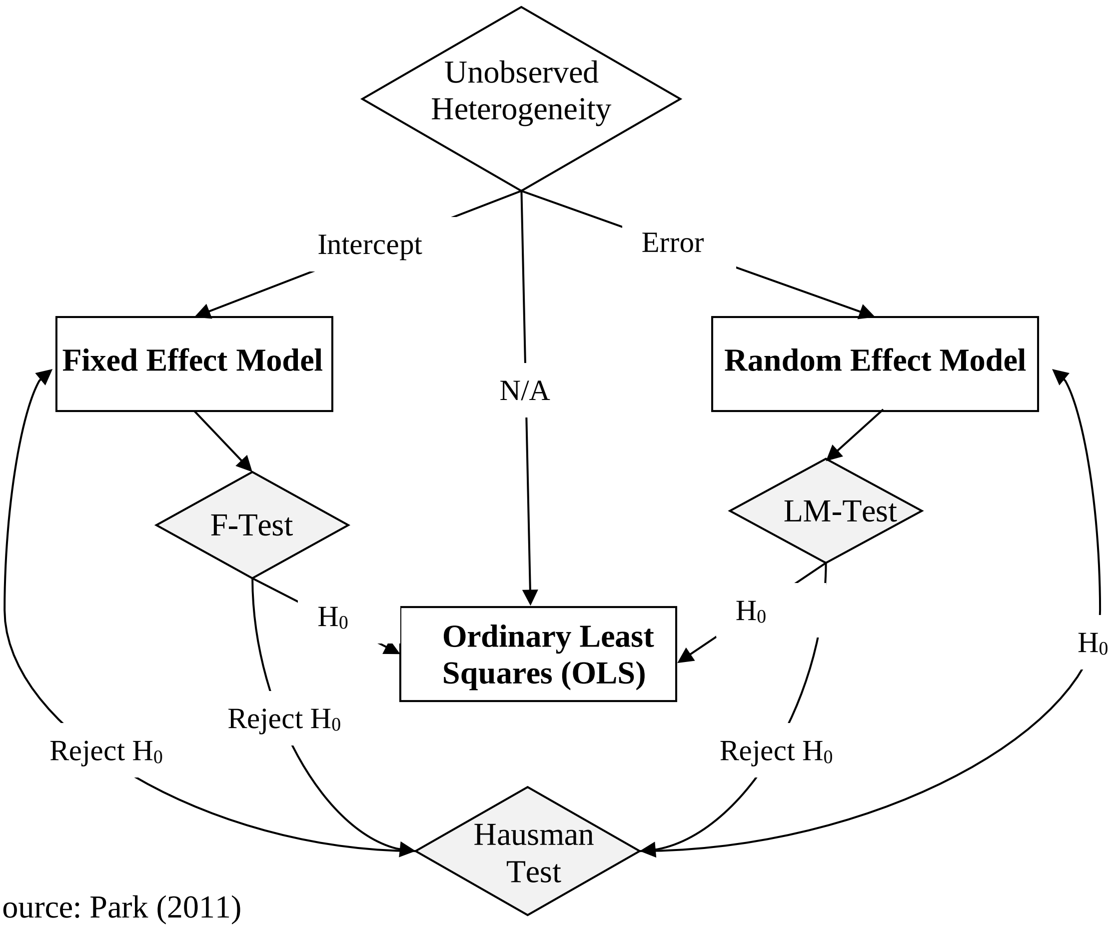
Under the null hypothesis, both fixed and random effects are consistent, however random effect is more efficient due to generation of relatively smaller standard errors as compared to fixed effect estimation (Greene, 2008). If the null hypothesis of no covariance between u_i and X_{it} is rejected, it can be concluded that the unobserved individual effects are corelated with at least one of the explanatory variables and therefore random effects estimation is ambiguous. I this case, only fixed effect estimator is efficient. Hausman test follows a chi squared distribution with *k* degrees of freedom and can be expressed as:

$$\mathrm{W} = \frac{(\beta_{\mathrm{FE}} - \beta_{\mathrm{RE}})^2}{\mathrm{Var}(\beta_{\mathrm{FE}}) - \mathrm{Var}(\beta_{\mathrm{RE}})} \sim \chi^2()$$

Where, β_{FE} and β_{RE} are the coefficient estimates of fixed and random effects models, respectively. $Var(\beta_{FE})$ - $Var(\beta_{RE})$ is the difference between the covariance matrices of fixed and random effects estimation.

The step by step procedure of determining the most relevant panel data estimation model based on the discussed tests is summarised through a logic diagram in figure 5.1**.**

Figure 5.1 Panel Data Modelling Process



Source: Park (2011)

5.4 Analysis Strategy

In order to clearly define the undertaken analysis strategy, firstly all the research hypotheses proposed within section-I of the conceptual model are recalled and tabulated in table 5.3. As evident from the table, there are in total 6 theoretical assumptions encompassing different relationship paths between CBBE, FBBE and firm performance.

In order to systematically address all the proposed research questions, they have been segregated across three themes**.** The first theme examines the overall brand equity-firm performance linkage, thus represents H1(a) and H1(b). The empirical models analysing these path relationships are termed as "*Baseline"* models as they re-examine if the CBBE and FBBE sample brands acquired in this study exhibit similar positive association with firm performance as established by current marketing-finance literature (refer to table 2.3 in the literature review chapter for list of representative studies). Evidence in the favour of H1(a) and H1(b) would therefore lay a strong base to extend the analysis further and explore the stock return response of positive and negative changes in CBBE and FBBE, which corresponds to the "*Main"* SRRM models (thus reflecting hypotheses H2(a) and H2(b)). All the proposed *baseline* and *main* models are grouped by the "brand equity measure under investigation" (CBBE and FBBE) for clearer interpretations[24]. Firstly, the firm value impact of overall and directional changes in consumer based brand equity is analysed through ΔCBBE *baseline* and *main* SRRM models, respectively comprising of 54 sample brands (collectively called Δ*CBBE SRRM Models*). Afterwards similar approach is followed for firm based brand equity estimations for 49 brand-firms, encapsulating both its *baseline* and *main* models under "Δ*FBBE SRRM models"* analysis. Guided by the conceptual framework, the final theme conducts a comparative analysis between CBBE and FBBE focusing exclusively on the 44 common brands in both the samples. The comparative assessment investigates hypotheses H3 and H4, contrasting their dynamics from both their inter-relationship and

[24] Since CBBE *baseline* and *main* models will have equal number of sample firms and all other control variables (even their values will be same in both the models because of CBBE data collection yearly wave), it would provide a clear presentation of the obtained results and the data descriptive. Same holds true for FBBE *baseline* and *main* models.

unique firm performance perspectives. All the proposed SRRM models are validated through post-diagnostics tests for heteroskedasticity and autocorrelation, outlier detection, multicollinearity, and robustness to alternative measure of firm performance.

Table 5.3 Summary of all the hypotheses examined under analysis phase-I

Hyp. No.	**Theoretical Arguments** *(Model Section-I)*
H1(a)	Changes in CBBE have a positive relationship with firm performance.
H1(b)	Changes in FBBE have a positive relationship with firm performance.
H2(a)	Negative changes in CBBE have a stronger relationship with firm performance as compared to positive changes.
H2(b)	Negative changes in FBBE have a stronger relationship with firm performance as compared to positive changes.
H3	Changes in CBBE over time are not closely associated with FBBE changes.
H4	The value enhancing (deteriorating) impact of rising (declining) CBBE will be stronger as compared to FBBE changes.

5.5 Impact of changes in CBBE on firm performance *(ΔCBBE SRRM Models)*

The first objective of analysis phase-I is to examine the effects of directional changes (positive and negative) in brand equity on firm performance. However, in order to re-establish existing brand equity-firm performance relationship, firstly hypotheses H1(a) is empirically examined through ΔCBBE *baseline* stock returns response models. If the preliminary findings are in-line with the existing literature, it would provide a strong base to extend the knowledge further and empirically test the directional effects of CBBE changes through ΔCBBE *main* model. Re-configuring SRRM model defined in equation 4.13 in the methodology chapter, the two CBBE models can be expressed as:

$$R_{i\mathbf{T}} - R_f = \alpha + \beta_2 \Delta CBBE_{i\mathbf{T}} + \beta_r RISK_{\mathbf{T}} + \beta_3 U\Delta ROA_{i\mathbf{T}} + \beta_4 U\Delta Sales_{i\mathbf{T}} + \beta_5 LEV_{i\mathbf{T}} + \varepsilon_{i\mathbf{T}} \quad (5.2)$$

$$R_{i\mathbf{T}} - R_f = \alpha + \beta_2 \Delta Pos\_CBBE_{i\mathbf{T}} + \beta_3 \Delta Neg\_CBBE_{i\mathbf{T}} + \beta_r RISK_{\mathbf{T}} + \beta_4 U\Delta ROA_{i\mathbf{T}} + \beta_5 U\Delta Sales_{i\mathbf{T}} + \beta_6 LEV_{i\mathbf{T}} + \varepsilon_{i\mathbf{T}} \quad (5.3)$$

Equation 5.2 and 5.3 represents the Δ*CBBE baseline* and Δ*CBBE main* models respectively, where:

$R_{iT} – R_f$ =	Annual raw returns of firm "i" in year T after adjusting for yearly risk-free rate;
$\Delta CBBE_{iT}$ =	Percentage change in BrandZ brand values of firm "i" in year T;
ΔPos_CBBE_{iT} =	Continuous variable capturing only the positive changes in BrandZ brand values of firm "i" in year T;
ΔNeg_CBBE_{iT} =	Continuous variable capturing only the negative changes in BrandZ brand values of firm "i" in year T;
$RISK_T$ =	Vector of all the yearly risk factors defined in equation 10 earlier;
$U\Delta ROA_{iT}$ =	Unanticipated component of earnings for firm "i" in year T;
$U\Delta Sales_{iT}$ =	Sales growth of firm "i" in year T;
LEV_{iT} =	Leverage of firm "i" in year T;
ε_{iT} =	idiosyncratic error term;
T =	Year encompassing BrandZ brand value announcement wave (June of previous year T-1 till May in current year T).

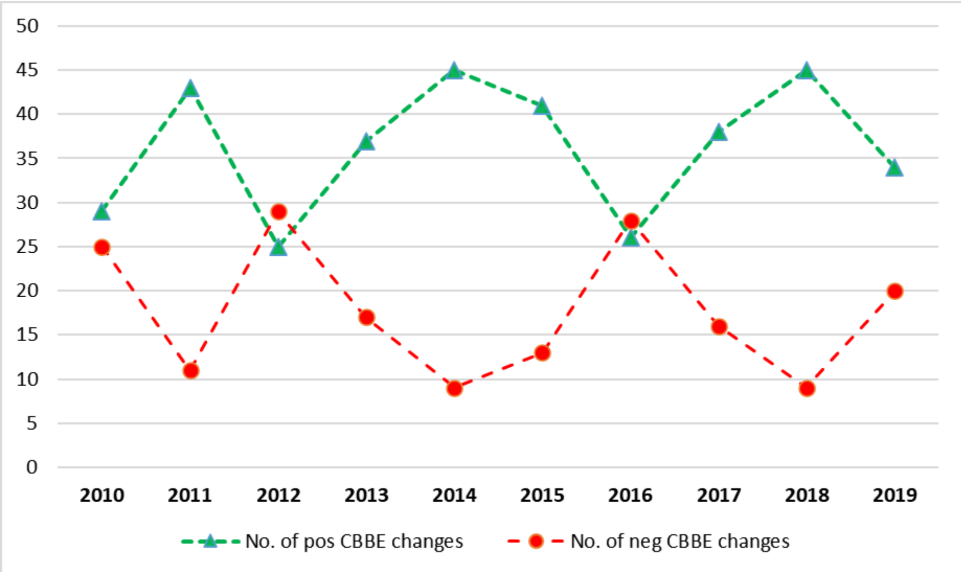
Merging all the data yields a balanced pooled cross-sectional time-series panel data set of 540 observations. A balanced panel data has the same number of cross-sectional observations for all the time periods (Wooldridge, 2010). The model is also free of any missing values as their presence tend to deteriorate the quality of the dataset (Park, 2011). Table 5.4 provides the descriptive statistics for all the variables included in both the models, reporting their frequency, average, standard deviation, minimum and maximum value.

Table 5.4 ΔCBBE SRRM Model Descriptive statistics

	N	Mean	Std. Dev.	Min	Max
Stock return	540	0.12	0.23	-0.60	1.04
ΔCBBE	540	0.08	0.19	-0.45	0.97
ΔPos_CBBE	363	0.17	0.15	0.001	0.97
ΔNeg_CBBE	177	-0.10	0.09	-0.0002	-0.45
R_{mt} - R_f	540	0.11	0.14	-0.12	0.30
SMB	540	0.00	0.05	-0.11	0.10
HML	540	-0.02	0.07	-0.10	0.10
MOM	540	0.06	0.05	-0.04	0.15
Market Cap ($B)	540	127.51	107.99	10.22	909.84
B2M	540	0.54	0.55	0.00	9.36
UΔROA	540	-0.00	0.02	-0.13	0.11
Sales growth	540	0.02	0.05	-0.33	0.22
Leverage	540	1.31	2.92	-16.02	39.69

The average annual change in CBBE brand values is 8% which is positive, signifying that majority of firms have witnessed a growth in consumer brand equity during the 10 year sampling period. Also, the magnitude of extreme positive shift in CBBE (97%) is more than twice as compared to its sharpest annual decline (-45%). These statistics signal that sample firms have generally exhibited high levels of consumer loyalty and association from 2010 till 2019. It is further supported by the fact that in this entire 10 year period, there are only 177 instances of brand value decline as compared to 363 positive CBBE change announcements. This nearly 2:1 ratio of rise vs decline suggests overall stability in brand performance of the sample firms. However as evident in figure 5.2, the frequency distribution of positive and negative changes in CBBE has a wide dispersion in these 10 years. Infact there are certain years such as 2012 and 2016 where there are more firms with declining brand values as compared to positive changes. This suggests that it is extremely challenging to comprehend the changes in consumer's cognitive attachment with a brand as it can be driven by many market factors which are beyond firm's control.

Figure 5.2 Yearly frequency of Negative CBBE changes



Source: Author's elaboration

From the firm performance perspective, the annual raw returns generated by 54 firm brands range from -60% to 104% which is a large variation. It can be partially attributed to wide dispersion in the size of the firms included in the sample. Firms with high market capitalisation are preferred by foreign and institutional investors and are expected to generate stable returns over time (Yildiz & Camgoz, 2019). In contrary, relatively smaller firms tend to be more volatile but are associated with higher returns. As evident in the table, the market value of sample firms has a mean of around 125$B with their size varying from as low as 10$B to a whopping 910$B. The standard deviation of over 100 $B further suggests that there is a significant dispersion in the market value across the acquired sample. This large variation in market capitalisation is therefore expected to cause high level of dispersion in the annual stock returns. The average and standard deviation of book-to-market value are both less than 1 implying that majority of firms in the sample are trading at a premium to their underlying value. Low values of B2M ratio are a good indicator of investor confidence in firm's future cashflow growth and therefore should be associated with higher stock returns (Fama and French, 1992). The average value of earning surprises is close to zero signifying that the annual accounting performance of the sample firms is generally in-line with the market expectations. However, in extreme cases, the magnitude of earnings shock is relatively higher as compared to the positive events of surpassing analyst expectations. Similar dynamics holds true for sales growth but with comparatively higher volatility and dispersion. The leverage figures suggest that generally the sample firms have moderate level of debt with mean and standard deviation of 1.31 and 2.92, respectively. In summary, table shows that the acquired sample represents a wide cross-section of firms with large variations in terms of brand value, size, risk, and profitability.

Table 5.5 reports the pairwise correlation coefficients among the explanatory and response variables along with the significance level. Changes in CBBE has a significantly positive and highest correlation coefficient with stock returns as compared to any other dependant variables included in the model. This signals a strong association between consumer based brand equity and firm value which is well documented in the existing marketing-finance literature (Hsu et al., 2013; Johansson et al., 2012). Similarly balance sheet performance metrics of sales and earnings exhibit positive relationship with firm's future cashflows which coincides with the current accounting literature (Kothari, 2001). The direction and correlation of size, B2M and leverage with stock returns are also as expected. Within the dependant variables, Fama-French risk factors of HML and Mktrf has the highest coefficient of 61% which is statistically significant. HML also shows a relatively strong association with other Fama-French and Carhart risk factors (36 % with SMB and -36% with MOM). High correlation coefficients between these time specific risk factors are not uncommon in existing finance studies (Chordia et al., 2017). Since these loading factors are derived from the returns generated by a set of portfolios, there is a high probability that same stocks are included in portfolios representing different FF-C risk factors. For example, majority of the firms included in the sample are large cap stocks with low B2M ratio. It is highly likely that they are the constituent of portfolios constructed to estimate SMB (i.e. small cap minus large cap returns), HML (i.e. high B2M minus low B2M stock returns). Additionally, MktRf represents cumulative monthly returns of all the stocks which constitutes the broader market index ("developed markets" for this study). Therefore an overlapping of annual raw returns of sample firms with the FF-C portfolio returns is highly likely, especially when they are estimated in the same time period. The issue of high correlation between HML and MktRf however is not ignored, and further checks are conducted in the post estimation diagnostics which include computation of variance inflation factor (VIF) and estimating the model without HML. Unanticipated changes in ROA and sales growth are positively correlated (0.34, $p<0.10$), which is not surprising given that both are indicators of firm's profitability (Artz et al., 2010). Other than the coefficient between HML and Mktrf, all the other correlation coefficients are below 0.40, which indicates no significant collinearity problems (Yildiz & Camgoz, 2019).

Table 5.5 ΔCBBE SRRM Model pairwise correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) R_t - R_f	1.00										
(2) ΔCBBE	0.41*	1.00									
(3) Mktrf	0.39*	0.23*	1.00								
(4) SMB	0.22*	0.08	0.38*	1.00							
(5) HML	0.31*	0.07	0.61*	0.36*	1.00						
(6) MOM	-0.02	0.13*	0.04	0.02	0.36*	1.00					
(7) Log_MV	0.20*	0.00	0.16*	-0.20*	-0.16*	0.03	1.00				
(8) Log_B2M	-0.09	-0.20*	0.09	0.07	0.09	-0.02	-0.12*	1.00			
(9) UΔROA	0.19*	0.12*	0.13*	0.15*	0.08	0.05	-0.04	-0.05	1.00		
(10) UΔSales	0.34*	0.28*	0.21*	0.14*	0.07	0.03	-0.08	-0.17*	0.21*	1.00	
(11) Leverage	-0.16*	-0.08	-0.03	-0.02	-0.02	-0.04	0.02	-0.14*	-0.11*	-0.05	1.00

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.5.1 Results for ΔCBBE baseline SRRM Model

Table 5.6, panel A, presents the results obtained after applying the pooled OLS, fixed and random effects estimators on the baseline model outlined in model equation 5.2. Firstly, the coefficient of the variable of interest i.e. ΔCBBE is positive and statistically significant (p<0.001) in all the models signifying that consumer based brand equity provides stock markets with useful, non-overlapping information to other macro-economic and firm based factors. These findings therefore support the theoretical arguments made in hypothesis H1(a). Secondly, unanticipated changes in ROA also have a significant positive impact on firm's future cashflows in all the estimated models. Infact the magnitude of impact of unanticipated changes in earnings is much higher as compared to changes in CBBE. These findings support the propositions of stock return response modelling that marketing assets and strategies are not the substitute to accounting performance measures in explaining stock returns (Mizik & Jacobson, 2004). Changes in consumer based brand equity contains information about firm's future performance that is incremental to what is provided by firm's current term accounting performance. The coefficients of sales growth and leverage are significant in pooled OLS and random effects (with expected signs) but insignificant in fixed effects model. Therefore, to investigate as to which model amongst them provide most credible estimates, all the tests outlined in figure 5.1 earlier are conducted and the results are reported in panel B of the table.

Table 5.6 Empirical Results for ΔCBBE *Baseline* Model

Panel A: Results for all three panel estimators (baseline model eq. 11a)			
	Pooled OLS	**Fixed Effect**	**Random Effect**
ΔCBBE	.351***	.310***	.351***
	(.047)	(.05)	(.047)
Mktrf	.268***	.276***	.268***
	(.083)	(.082)	(.083)
SMB	.118	-.054	.118
	(.166)	(.169)	(.166)
HML	.482***	.35*	.482***
	(.182)	(.18)	(.182)
MOM	-.1	-.083	-.1
	(.17)	(.167)	(.17)
Loglag_MV	-.101***	-.278***	-.101***
	(.026)	(.067)	(.026)
Loglag_B2M	-.032	.096*	-.032
	(.021)	(.058)	(.021)
UΔROA	.67*	1.12***	.67*
	(.375)	(.384)	(.375)
UΔSales	.764***	.3	.764***
	(.166)	(.183)	(.166)
Leverage	-.009***	-.004	-.009***
	(.003)	(.003)	(.003)
Intercept	1.17***	3.165***	1.17***
	(.288)	(.721)	(.288)
N	540	540	540
F-test (model)	29.11***	5.87***	29.11***
R^2	0.36	0.44	0.36
Adj. R^2	0.34	0.36	0.34
Panel B: Best-Fit Model tests results			
LM chi2(1)	0.00		
F-Test (Fixed effects)	1.31*		
Hausman Test	53.15***		

Clustered robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

The Breusch-Pagan Lagrange Multiplier (LM) test has given a chi-squared value of 0 (p value =1) which signifies that there are no individual-specific error variance component

u_i in the composite error term v_i (refer to eq. C above). In this case, the model can efficiently be estimated with a pooled OLS regression. This is why GLS random effect estimator has provided exactly the same estimates and standard errors as pooled OLS (evident in the table). The results of LSDV based F-test rejects the null hypothesis that all dummy parameters (intercepts) are zero and insignificant ($p<0.10$). In other words, F-test signifies that the panel under investigation contain unobserved effects u_i which are fixed over time and are correlated with the explanatory variables. Hausman test also favours fixed effect over random effect suggesting that u_i is correlated with the regressors, therefore employing random effect would provide biased statistical estimates. Relatively higher R-squared and adjusted R squared values in fixed effect regression further affirms its enhanced explanatory power. All these findings clearly advocate fixed effect to be the best estimator to account for unobserved heterogeneity in the CBBE baseline model. Although econometricians recommend reporting only the "right" model (Park, 2011: 46), the pooled OLS and random effect estimators were included in table 5 solely for demonstration and comparison purposes. All the other empirical results in this study report only the best-fit panel regression model.

Based on empirical findings from fixed effect estimation, it is now confirmed that the effect of sales growth is in fact insignificant but marginally ($p = 0.105$). The elasticity estimate of firm's leverage has the expected sign but is not significant. Parameter estimates for Fama-French (1993) and Carhart (1997) risk loading factors and Daniel and Titman (1997) firm characteristics are in line with prior literature. Consistent with Bhardwaj et al. (2011), excess broader market index returns (MktRf) and growth vs value portfolio returns (HML) have a positive impact on sample firm's stock performance ($MktRf=0.27$, $p<0.01$; $HML=0.48$, $p<0.01$). The estimated coefficients of risk loading factors of size and momentum are however insignificant. Daniel and Titman (1997) firm-specific risk characteristics of size and book-to-market value are both statistically significant in the expected directions. Firms with relatively smaller size and higher book-to-market ratio tend to outperform the wider stock markets. This superiority of firm size and B2M over FF-C loading factors in explaining expected returns is in-line with the findings of Chordia et al. (2017:17) stating that "it is mainly the characteristics that contribute to the cross-sectional variation in expected stock returns". The obtained results therefore contribute to the ongoing debate between "loading vs characteristics" controversy suggesting that the latter has more explanatory power compared to the former. Overall, the main findings of the baseline CBBE model supports the existing marketing-finance literature that consumer-based brand equity is a key contributor to firm's long term performance (Katsikeas et al, 2016). The analysis can therefore be extended further to complement the existing knowledge by empirically testing the directional effects of positive and negative changes in CBBE on firm value.

5.5.2 Results for ΔCBBE Main SRRM Model

One of the man objectives of this study is to examine the polarized effects of rising and declining brand equity on firm's future performance measured through stock returns. This section focusses on the value relevance of positive and negative changes in consumer based brand equity. Table 5.7 provides the empirical results for the CBBE main stock return response model outlined in the SRRM model equation 5.3.

Table 5.7 Empirical Results for ΔCBBE *Main* Model

	R_t - R_f *(Fixed-Effect)*
ΔPos_CBBE	.192**
	(.066)
ΔNeg_CBBE	.644***
	(.133)
Mktrf	.241***
	(.083)
SMB	.036
	(.168)
HML	.397**
	(.18)
MOM	-.55
	(.167)
Loglag_MV	-.294***
	(.067)
Loglag_B2M	.100*
	(.058)
UΔROA	1.23***
	(.384)
Sales Growth	.325*
	(.182)
Leverage	-.004
	(.003)
Intercept	3.371***
	(.721)
N	540
F-test (Model)	5.97***
R^2	0.45
Adj. R^2	0.37
LM Test	0.00
F-Test (Fixed effects)	1.43**
Hausman Test	63.13***

Clustered robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

The effects of both positive and negative changes in consumer based brand equity measure are statistically significant in the expected directions. The interesting finding is that the response coefficient of declining CBBE is 0.64 (P<0.001) which is three times higher than that of rising CBBE (0.19, p<0.05). These novel findings are in-line with the assumptions of hypothesis H2(a) that the magnitude of impact of negative changes in CBBE on firm value is higher as compared to the positive changes. In other words, unfavourable shifts in consumer’s association and loyalty towards a brand have severe effects on firm's future discounted cashflows. Even though the frequency of negative CBBE changes is relatively less, investors perceive it as a vital information source reflecting uncertainty in firm's future growth prospects. These findings further validate the importance of examining the polarized effects of brand equity on firm performance rather than simply evaluating its overall value relevance. From the statistical point of view, one may wonder as to why declining CBBE is reported to have a "negative" impact on stock returns when in fact its obtained coefficient is positive. This is because the polarity of all the observations for ΔNeg CBBE, which captures only the decline in CBBE, is inherently negative. Therefore any positive values of β_3 will magnify its negative effects on the response variable ($R_t - R_f$) and the severity of these effects will depend on the magnitude of β_3. To understand this relationship statistically, an illustrative example is provided in Appendix D.

Similar to the baseline model, CBBE main model is also best estimated through a fixed effect estimator suggesting the presence of unobserved heterogeneity across sample firms. The earning response coefficient of 1.23 is statistically significant ($p<0.001$) which is in close correspondence with the CBBE baseline model results. Sales growth, in contrary, has a significant positive impact on stock returns, but its elasticity is far less than that of unanticipated changes in ROA. This suggests that stock market participants give much higher weight to earnings performance than sales figures when revaluating their expectations about firm's future profitability. In terms of explaining cross-sectional variance in expected returns, the significance, direction, and magnitude of risk loading factors and firm characteristics is relatively same as the baseline model. Slight increase in adj. R-squared and F-test statistic in the main model signifies an improvement in the explanatory power after segregating overall CBBE changes into positive and negative components.

5.5.3 Post-estimation Diagnostics Tests

Various diagnostics tests were conducted to validate if the designed models comply with the underlying OLS assumptions and are robust to multicollinearity or presence of any influential observations. Firstly, checks for the presence of autocorrelation and heteroskedasticity in the error terms are investigated. If the idiosyncratic error term is positively autocorrelated with the independent variables, any OLS estimate, either simple pooled, fixed, or random estimator, would generate spurious regression results (Mizik & Jacobson, 2009a). To examine this anomaly in the designed CBBE *baseline* and *main* models, Wooldridge (2002) test for panel data serial correlation is employed. Wooldridge's auto-correlation method involves obtaining the regression residuals by first-differencing the original sample and then comparing the estimates with the original panel regression residuals. If the correlation coefficient between the two error terms is -0.5, then the null hypothesis of non-existence of autocorrelation in the panel data is confirmed (Drukker, 2003). Wooldridge (2012) test results for CBBE *baseline* and *main* models fail to accept the null hypothesis suggesting the presence of serial correlation in both the models (*Baseline:* $F = 2.81$, $p<0.10$; *Main*: $F = 3.95$, $p<0.05$). The second step is to examine if the estimated models follow the OLS assumption of homoskedasticity i.e. the error term is independently and identically distributed (Wooldridge, 2012). In case the residuals violate these assumptions, the model is said to be heteroskedastic. Modified Wald test for groupwise heteroscedasticity proposed by Greene (2000: 598) is employed to examine if the residuals obtained in the two CBBE models follow any pattern or are independently distributed. The test is based on the chi-square distribution where the null hypothesis states that the model is homoscedastic with evenly distributed error variance. The test results for both the models reject the null hypothesis indicating the presence of heteroscedastic error terms. The chi-square statistic for the baseline and main FBBE models are reported in the table 5.8 along with the Wooldridge (2012) serial-correlation test results.

Table 5.8 Wooldridge and Wald test results for CBBE baseline and main models

CBBE Model	Wooldridge Test (F-Statistic)	Wald-Test (Chi-Sq.)	Autocorrelation	Heteroscedasticity
Baseline	2.81*	4980.22***	Yes	Yes
Main	3.95**	4786.14***	Yes	Yes

*** *p<.01, *** ** *p<.05, *** * *p<.1*

In order to obtain unbiased estimates from panel data regressions with heteroscedastic and autocorrelated residuals, use of cluster-robust standard errors is recommended (Gow et al., 2010; Peterson, 2009). Clustering the idiosyncratic error term at the panel level (i.e. observations pertaining to same firm in different years) relaxes the OLS assumption of error independence allowing errors to correlate within the cluster (Mizik & Jacobson, 2009a: 321). Following these recommendations, clustered robust standard errors are obtained (and reported in table 5.6 and 5.7) to account for autocorrelation and heteroskedasticity in both the main and baseline models.

The next step is to examine whether the proposed models suffer from multicollinearity issues. Although it is evident from table 5.5 that there is no major pairwise correlation issue between the independent variables (except HML), further checks are conducted to affirm this assumption. Firstly, widely implied diagnostic of multicollinearity i.e. variance inflation factors (VIF) are calculated for each explanatory variable. VIF score for a predictor “X” is the ratio of the error variance of the overall model to the variance of the model including only “X” as the explanatory variable (Heiberger & Holland, 2015). Generally VIF value above 5 for a particular independent variable is considered as an evidence of collinearity (Heiberger & Holland, 2015:291). Table 5.9 reports VIF scores for each explanatory variables included in equations 2(a) and 2(b)**.** Since all the estimated scores are below the threshold of 5, no multicollinearity issues are detected in both the baseline and main CBBE models.

Table 5.9 ∆CBBE Models VIF Scores

Variable	**VIF-Score (Baseline Model)**	**VIF-Score (Main Model)**
∆ FBBE	1.10	
∆ Pos FBBE		1.23
∆ Neg FBBE		1.14
MktRf	2.29	2.30
SMB	2.23	2.26
HML	1.58	1.58
MOM	1.27	1.27
LogLag_MV	1.20	1.20
LogLag_B2M	1.20	1.20
U∆ROA	1.19	1.19
Sales Growth	1.35	1.35
Leverage	1.07	1.07
Mean VIF	**1.45**	**1.44**

However, to further affirm that the high pairwise collinearity coefficient of HML does not impact the precision of the estimated models, equations 5.2 and 5.3 are re-estimated after dropping this variable. The results obtained after the exclusion of HML are consistent with the original findings suggesting no abnormalities due to multicollinearity (results are presented in Appendix E). The final step is to identify if the empirical results obtained from the designed models are influenced by the presence of any outlying observations. Outliers are the observations which are significantly deviated from all other observations in a random sample and their existence can impact multivariate normality by causing a significant shift in mean and standard deviation of the designed regression model (Byrne, 2016). Researchers have further expressed their concerns specifically about outliers in panel data arguing that their presence could contaminate the model and not treating them appropriately could produce biased parameter estimates (Bakar & Midi, 2019). Outliers can broadly be segregated as univariate and multivariate types. A univariate outlier is an extreme value (or values) within a single variable (either dependent or independent) and multi-variate outliers occur within joint combination of two or more variables (either between dependent-dependent or independent – dependent variables) (Kline, 2016). The following sections investigate if the proposed CBBE models are contaminated due to the presence of univariate or multivariate outliers and if yes, adequate treatment is conducted as per literature recommendations.

5.5.3.1 Univariate outliers

Whilst univariate outliers can be easily identified through a visual inspection of the data e.g. scatter or box plots (Ben-Gal, 2015; Kampstra, 2008), a higher level of accuracy can be obtained by adopting a statistical approach. This study examines the presence of univariate outliers within all the variables included in the model through the standardized z-score approach (Kannan et al., 2015). Z-scores for each dependent and explanatory variable can be calculated using their mean and standard deviation as:

$$\mathrm{Z_{score}}(\,\mathrm{x_{it}}) = \frac{\mathrm{x_{it}} - \mu_t(\mathrm{x_{it}})}{\sigma_t(\mathrm{x_{it}})}$$

Where, x_{it} is the actual value of the variable (dependent or independent) of firm "x" in time "t". μ_t and σ_t are the "within" mean and standard deviation of the cross-section of firms in time period “t”. It is worth emphasizing that the “within” mean and standard deviation are calculated instead of full-sample mean and standard deviation because the model is estimated through “fixed effect”. As explained earlier, fixed effect estimator transforms the data by “mean-centring” it before running the OLS regression. Therefore a variable can only be identified as an outlier in a fixed effect regression if its “within” Z-score lie outside the prescribed threshold. The Z scores with an absolute value greater than 3 are generally identified as outliers (Kannan et al., 2015).

Table 5.10 provides the minimum and maximum values of the standardized z-scores for all the variables included in the model. Leverage has the highest minimum and maximum Z scores of -2.8 and +2.8 signifying high dispersion in its frequency distribution. Infact, the calculation of overall Z-scores for “leverage” reveal that it has two extreme outliers with values of 9.4 and 15.97. However, since the obtained “within” Z-scores does not exceed the acceptable limits, they are identified as inliers in the estimated model. Given the positive and negative extremes of the computed “within” Z-scores for all other variables did not exceed the accepted threshold of 3, non-existence of any univariate outliers can be confirmed.

Table 5.10 Univariate Outliers detection in CBBE Models

Variable	Obs	Minimum Z-Score	Maximum Z-Score
Stock Return	540	-2.326	2.463
ΔCBBE	540	-2.377	2.669
MktRf	540	-1.600	1.337
SMB	540	-2.011	1.760
HML	540	-1.199	1.633
MOM	540	-1.723	1.552
Loglag MV	540	-2.674	2.057
Loglag B2M	540	-2.518	2.668
UΔROA	540	-2.756	2.443
Sales Growth	540	-2.747	2.726
Leverage	540	-2.822	2.836

5.5.3.2 Multivariate Outliers

Identifying multivariate outliers in a regression model is not as straight forward as spotting univariate outliers due to its multidimensional nature. Bakar and Midi (2019:341) argue that identification and treatment of multivariate outliers in a fixed effect panel data model is even more crucial due to the possibility of presence of multiple x-outliers concentrated in the time series. Since fixed effect estimator performs a within transformation of the data (by time demeaning), the presence of any extreme value in a particular time period can adversely affect its computed mean[25]. A simple fixed effect regression applied to such contaminated panel data would therefore provide biased and unreliable estimates of the model parameters (Chatterjee & Hadi, 2006). To address this issue, the study adopts robust fixed effects estimation procedure proposed by Veradi and Wanger (2011). Under this procedure, firstly, the original panel sample is centred in a similar way to that of "within fixed effects" estimator but instead of demeaning, median centring is performed. The transformed explanatory and response variables can therefore be defined as:

$$\mathrm{y_{it}} = \mathrm{y_{it}} - \mathrm{median_t(y_{it})} \text{ and } \mathrm{x_{it}} = \mathrm{x_{it}} - \mathrm{median_t(x_{it})}$$

Where y_{it} is the dependent variable parameter of firm "i" at time "t" and $x_{it}^{(j)}$ for (j=1…K) is the j^{th} independent variable measured for firm "i" at time "t". Unlike mean which is distorted by the presence of atypical observations, the median remains unaffected since it is the actual middle value between higher and lower half of the sample distribution (Bramati & Croux, 2007). The next step is to run a S-estimator

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[25] The calculated mean will tend to shift towards the extreme values.

regression on the transformed panel data, which is known to be robust to outliers. Unlike simple OLS regression which measures slope and intercept by minimizing the variance of residuals, S-estimator search for regression betas and intercept by minimizing some other reliable measure of scale associated with the error term (Verardi & McCathie, 2012). The measurement scale adopted in Veradi & Wanger (2011) robust fixed effect estimation is M-estimator of scale (for further details about this scale, see Verardi & Croux, 2009). After running the S-estimation regression, the standardized residuals are obtained and the observations with values larger than 2 are identified as multivariate outliers. Finally, a standard fixed-effect regression is employed to the original panel data with outliers given a zero weight. This procedure has proved to provide unbiased and robust parameter estimates which are comparable to a fixed effect regression model with no outliers (Veradi & Wanger, 2011).

Table 5.11 reports the results of robust fixed effects regression for both the main and baseline CBBE models. As evident in the table, N has dropped from 540 to 500 in both the models signifying the existence of 40 outlying observations in each model. This accounts for 7% contamination of the original panel data sample. The estimated fixed regression coefficients, however, are in close correspondence with the results obtained from the original models. The coefficient of interest i.e. changes in consumer based brand values is still significant (0.33, $p<0.001$) and almost similar to the original baseline model (0.31, $p<0.001$). Similarly the magnitude of positive and negative changes in CBBE are both statistically significant and consistent with those in the main model with outliers (Δ Pos: 0.22 vs 0.19 and Δ Neg: 0.61 vs 0.64). The response coefficients of unanticipated changes in ROA also follow the same suite but with comparatively lower values. Notably, the impact of sales growth is significant in the robust regression main model (β = 0.47, p<0.001) suggesting that its insignificance in the original model may be due to the presence of influential observations in the sample. The adjusted R-squared for both the robust fixed effect regression models have shown a considerable improvement (*Baseline*: 0.45 vs 0.36; *Main:* 0.46 vs 0.37) proving their relatively higher explanatory power. In summary, these findings affirm that although there is presence of multivariate outliers in the designed models, their impact on estimated parameters is insignificant.

Table 5.11 Robust fixed effect regressions for CBBE *baseline* and *main* models

	Rt - Rf Baseline Model	Rt - Rf Main Model
ΔCBBE	.325***	
	(.042)	
ΔPos CBBE		.221***
		(.064)
ΔNeg CBBE		.605***
		(.096)
Mktrf	.287***	.254***
	(.065)	(.063)
SMB	.106	.118
	(.146)	(.141)
HML	.067	.121
	(.141)	(.145)
MOM	.023	.055
	(.133)	(.125)
Loglag_MV	-.147**	-.157**
	(.07)	(.069)
Loglag_B2M	.053	.059
	(.041)	(.04)
UΔROA	.622*	.699*
	(.367)	(.378)
Sales Growth	.473***	.486***
	(.174)	(.178)
Leverage	-.001	-.001
	(.002)	(.002)
Intercept	1.675**	1.809**
	(.76)	(.756)
N	500	500
F-Test (Model)	7.51***	7.61***
R-squared	0.52	0.53
Adj. R-squared	0.45	0.46

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

5.5.4 Robustness Check: The abnormal stock return approach

In order to test the sensitivity and stability of the designed CBBE models, the abnormal stock return SRRM approach is adopted (see Mizik, 2014). Under this investigation, instead of regressing the explanatory variables directly on the annual raw returns, firstly the abnormal stock returns are estimated. Abnormal returns represent the portion of actual returns generated by a stock within a particular period, which are over or below the returns expected from it in that period based on economy wide risk factors. Anormal returns can therefore be mathematically expressed as:

$$\text{Abnornal Returns} = \text{Actual Returns} - \text{Expected Returns}$$

Rearranging the terms in the above equation:

$$\text{Actual Returns} = \text{Expected Returns} + \text{Abnormal Returns} \qquad (5.4)$$

As discussed in the methodology chapter, expected returns can be modelled with Fama-French (1996) and Carhart (1997) loading factors and Daniel and Titman (1997) firm specific risk characteristics as:

$$\begin{aligned} \mathrm{ER_{it}} = {} & \alpha + \beta_{\mathrm{i}}(\mathrm{R_{mt}} - \mathrm{R_f}) + \beta_{\mathrm{S}}(\mathrm{SMB_t}) + \beta_{\mathrm{H}}(\mathrm{HML_t}) + \beta_{\mathrm{M}}(\mathrm{MOM_t}) \qquad (5.5) \\ & + \eta_{\mathrm{t}}(\mathrm{Size_{it-1}}) + \vartheta_{\mathrm{t}}(\mathrm{B2M_{it-1}}) + \epsilon_{\mathrm{it}} \end{aligned}$$

Where, R_{mt}-R_f, SMB, HML and MOM represents the annual FF-C loading factors. The firm based risk factors of $Size_{it-1}$ is the log of previous period market value and $B2M_{it-1}$ is the lagged book-to-market value. Inputting equation 4 in equation 3 yields the following:

$$R_{it} - R_f = \alpha + \beta_i(R_{mt} - R_f) + \beta_S(SMB_t) + \beta_H(HML_t) + \beta_M(MOM_t) \quad (5.6)$$
$$+ \eta_t(Size_{it-1}) + \vartheta_t(B2M_{it-1}) + \epsilon_{it} \; [Abnr_{Ret_{it}}]$$

R_{it}-R_f is the annual raw returns adjusted for risk free rate and $Abnr\_Ret_{it}$ is the abnormal return generated by firm "i" in year "t". Since abnormal returns are unknown (raw returns are available and expected returns can be estimated through FF-C model), they are actually the constituent of the residual ε_{it} from the above regression model. In other words, the idiosyncratic error term ε_{it} represents the portion of the raw returns which are in excess (or less) to the expected returns explained by other economy wide and firm based risk factors. Model equation 5.6 is estimated through fixed effect panel regression to account for unobserved cross-sectional heterogeneity in the sample firms[26]. The obtained annual excess returns are then introduced as a response variable in the main stock return response model defined as:

$$Abnr\_Ret_{it} = \alpha + \beta_1 U\Delta Marketing_{it} + \beta_2 U\Delta ROA_{it} + \beta_3 U\Delta Sales_{it} \quad (5.7)$$
$$+ \beta_4 LEV_{it} + \varepsilon_{it}$$

Reforming equation 5.7 into CBBE baseline and main models yields the following two SRRM models:

$$Abnr\_Ret_{i\mathbf{T}} = \alpha + \beta_1 \Delta CBBE_{i\mathbf{T}} + \beta_2 U\Delta ROA_{i\mathbf{T}} + \beta_3 U\Delta Sales_{i\mathbf{T}} + \beta_4 LEV_{i\mathbf{T}} \quad (5.8)$$
$$+ \varepsilon_{i\mathbf{T}}$$

$$Abnr\_Ret_{i\mathbf{T}} = \alpha + \beta_1 \Delta Pos\_CBBE_{i\mathbf{T}} + \beta_2 \Delta Neg\_CBBE_{i\mathbf{T}} + \beta_3 U\Delta ROA_{i\mathbf{T}} \quad (5.9)$$
$$+ \beta_4 U\Delta Sales_{i\mathbf{T}} + \beta_5 LEV_{i\mathbf{T}} + \varepsilon_{i\mathbf{T}}$$

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[26] All the diagnostics tests were carried to identify the best fit model and the results favoured fixed effect regression over other available panel estimators.

The time “T” corresponds to the yearly time window adopted to compile the dependant and independent variables corresponds to the BrandZ brand valuation release waves. Adopting abnormal stock return based estimation model also addresses the multicollinearity issues amongst Fama-French (1993) and Carhart (1997) risk factors. Table 5.12 presents the pairwise correlation matrix for all the variables included in the models defined in eq. 5.8 and 5.9. Both the marketing and accounting performance metrics are positively associated with abnormal returns signifying their value generating abilities. In contrary, firms with higher levels of debt are considered to be risky especially during the times of financial turmoil. The negative correlation coefficient of leverage with abnormal returns is therefore expected. Overall, all the correlation coefficients within the explanatory variables are below 30% and thus the models do not pose any multicollinearity issues.

Table 5.12 Pairwise correlation coefficients for Abnormal stock return models

Variables	(1)	(2)	(3)	(4)	(5)
(1) Abr_Rt	1.00				
(2) ΔCBBE	0.39*	1.00			
(3) UΔROA	0.15*	0.12	1.00		
(4) Sales Growth	0.29*	0.28*	0.21*	1.00	
(5) Leverage	-0.12	-0.08	-0.11	-0.05	1.00

**** p<0.01, ** p<0.05, * p<0.1*

Table 5.13 reports the results of estimating equation 5.8 and 5.9. Consistent with the CBBE baseline model, the coefficient of ΔCBBE is positive (0.28) and statistically significant. Similarly the effects of rising and declining CBBE on alternate measure of firm performance are both significant and their estimated elasticities show analogous dispersion. The earnings response coefficients of UΔROA in both the models are also significant in the expected direction and are closely aligned with the main and baseline

CBBE models. Both the model equations are estimated through fixed effect regression as guided by the results of LM, F-Test and Hausman test reported in panel B of table 5.13. Clustered-robust standard errors are obtained to account for autocorrelation and heteroskedasticity. The results confirms that the findings of ΔCBBE *baseline* and *main* models are robust to abnormal stock returns measure of firm performance and are not sensitive to the specification of the models in equations 5.2 and 5.3.

Table 5.13 Robustness check with abnormal stock returns models

Panel: A	Model Equation 7(a) (Fixed-Effect)	Model Equation 7(b) (Fixed-Effect)
ΔCBBE	.277***	
	(.051)	
ΔPos CBBE		.166**
		(.076)
ΔNeg CBBE		.572***
		(.135)
UΔROA	1.034**	1.134**
	(.459)	(.479)
Sales growth	.214	.237
	(.242)	(.246)
Leverage	-.004	-.004
	(.006)	(.006)
Intercept	-.021**	.001
	(.009)	(.015)
N	540	540
F-Test (Model)	5.63***	5.69***
R-squared	0.40	0.41
Adj. R-squared	0.33	0.34
Panel: B		
LM Test	49.58***	52.75***
F-Test (Fixed Effects)	3.11***	3.19***
Hausman Test	39.17***	41.29***

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

5.6 Impact of changes in FBBE on firm performance *(ΔFBBE SRRM Models)*

To assess the information content of firm based brand equity, firm’s annual stock returns are regressed on unanticipated changes in earnings, sales growth, firm size, book-to-market value, leverage, and annual changes in FBBE, controlling for expected return with Fama-French and Carhart risk factors. The Δ*FBBE Baseline* model therefore can be expressed as:

$$\begin{aligned} R_{i\mathbf{T}} - R_f = \alpha &+ \beta_1 \Delta FBBE_{i\mathbf{T}} + \beta_{mkt}(R_{m\mathbf{T}} - R_f) + \beta_S SMB_{\mathbf{T}} + \beta_H HML_{\mathbf{T}} \\ &+ \beta_M MOM_{\mathbf{T}} + \eta_t Size_{i\mathbf{T}-1} + \vartheta_t B2M_{i\mathbf{T}-1} + \beta_3 U\Delta ROA_{i\mathbf{T}} \\ &+ \beta_4 U\Delta Sales_{i\mathbf{T}} + \beta_5 LEV_{i\mathbf{T}} + \varepsilon_{i\mathbf{T}} \end{aligned} \tag{5.10}$$

To address the central question of the study i.e. whether the firm value effects of positive FBBE changes are disproportionate to the negative changes, the Δ*FBBE Main* model is proposed as:

$$\begin{aligned} R_{i\mathbf{T}} - R_f = \alpha &+ \beta_2 \Delta Pos\_FBBE_{i\mathbf{T}} + \beta_3 \Delta Neg\_FBBE_{i\mathbf{T}} + \beta_{mkt}(R_{m\mathbf{T}} \\ &- R_f) + \beta_S SMB_{\mathbf{T}} + \beta_H HML_{\mathbf{T}} + \beta_M MOM_{\mathbf{T}} + \eta_t Size_{i\mathbf{T}-1} \\ &+ \vartheta_t B2M_{i\mathbf{T}-1} + \beta_4 U\Delta ROA_{i\mathbf{T}} + \beta_5 U\Delta Sales_{i\mathbf{T}} + \beta_6 LEV_{i\mathbf{T}} \\ &+ \varepsilon_{i\mathbf{T}} \end{aligned} \tag{5.11}$$

Where:

$R_{iT} - R_f$ =	Annual raw returns of firm "i" in year T after adjusting for yearly risk-free rate R_f;
$\Delta FBBE_{iT}$ =	Percentage change in Brand Finance brand values of firm "i" in year T;
ΔPos_FBBE_{iT} =	Continuous variable capturing only the positive changes in Brand Finance brand values of firm "i" in year T;
ΔNeg_FBBE_{iT} =	Continuous variable capturing only the negative changes in Brand Finance brand values of firm "i" in year T;
$R_{mT} - R_f$ =	Broader market index returns in year T (risk free rate adjusted);
SMB_T =	Fama and French (1993) size portfolio returns in year T;
HML_T =	Fama and French (1993) book-to-market value portfolio returns in year T;
MOM_T =	Carhart (1997) momentum based portfolio returns in year T;
$Size_{iT-1}$ =	Firm size measured by log of market capitalisation of firm "i" in the previous year T-1;

$B2M_{iT-1}$ = Log of book-to-market value of firm "i" in the previous year T-1;

$U\Delta ROA_{iT}$ = Unanticipated component of earnings for firm "i" in year T;

$U\Delta Sales_{iT}$ = Sales growth of firm "i" in year T;

LEV_{iT} = Leverage of firm "i" in year T;

ε_{iT} = idiosyncratic error term;

T = Year encompassing Brand Finance brand value announcement wave (February till December in year T).

Merging all the required data pertaining to 49 firm brands included in the FBBE sample for a 10 year period ranging from 2010 till 2019 formulates a panel dataset of 490 firm-year observations. The panel structure is balanced and does not contain any missing values. Table 5.14 provides the summary statistics for the response variable and all the explanatory variables included in baseline and main models.

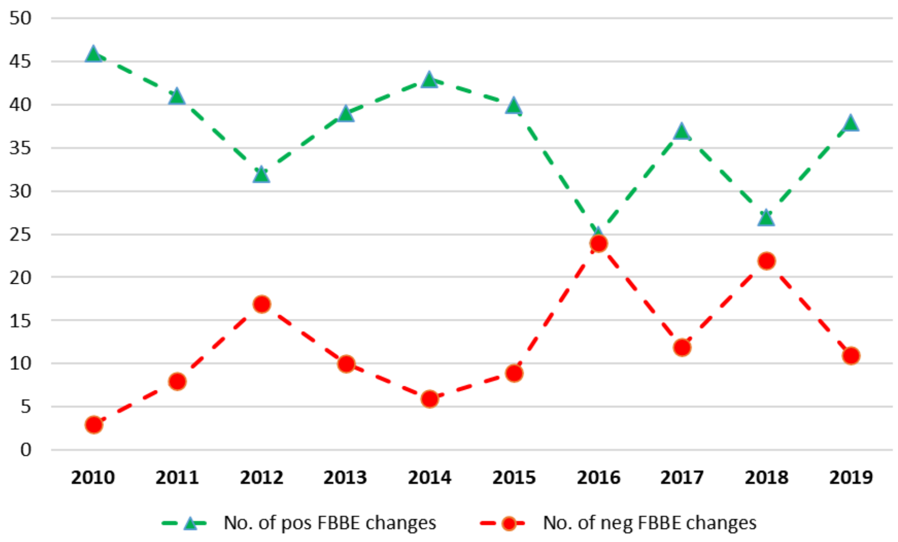
Table 5.14 FBBE Model descriptive statistics

	N	Mean	Std. Dev.	Min	Max
Stock return	490	0.13	0.33	-0.48	4.80
ΔFBBE	490	0.12	0.20	-0.53	1.39
ΔPos_FBBE	368	0.19	0.18	0.001	1.39
ΔNeg_FBBE	122	-0.10	0.10	-0.0003	-0.53
R_{mt} - R_f	490	0.13	0.15	-0.09	0.39
SMB	490	0.01	0.05	-0.08	0.09
HML	490	-0.01	0.07	-0.08	0.13
MOM	490	0.02	0.16	-0.41	0.19
Market Cap ($B)	490	137.40	107.91	6.12	851.32
B2M	490	0.65	0.69	0.00	10.95
UΔROA	490	0.00	0.02	-0.13	0.15
Sales growth	490	0.02	0.05	-0.23	0.22
Leverage	490	1.49	2.95	-16.02	39.69

The average annual stock performance of FBBE sample firms is closely related to the CBBE model which is logical since majority of firms are common in both CBBE and FBBE samples (although with different yearly time windows). However, the stock return volatility and dispersion for FBBE firms is on the higher side. The maximum annual return is 480% which is phenomenal compared to 104% in the CBBE sample. The average market value is around 140$B with a standard deviation of 108$B and the largest firm worth 851$B. These figures clearly show that the sample firms tend to be very large companies, and this should not be surprising given that Brand Finance annual brand publications focus on the world's top 100 brands. The average earnings surprise and sales growth figures of 0 and 0.02 signifies that majority of firms exhibit streamlined annual accounting performance which meets the analyst expectations. Also, overall low B2M ratio of 0.65 suggests the sample firms have higher future growth potential.

As evident in the figure 5.3 below, in the entire 10 year period, there are more firms experiencing a rise in their financial based brand values as compared to decline. But the gap between them seems to be closing in the recent years as 2016 and 2018 has almost equal numbers of firms with positive and negative changes. This trend suggests that increased global competition due to technological advancements in the recent decade has possibly affected brand related earnings i.e. income from royalties, trademarks, and patents. Whether this increasing frequency of firms with declining FBBE brand valuations will have a similar impact on firm's future cashflows will be interesting to examine.

Figure 5.3 Yearly frequency of Positive and Negative FBBE changes



Source: Author's elaboration

Table 5.15 presents the bivariate correlation matrix for dependent and independent variables included in the ΔFBBE models. Changes in brand measure and accounting performance metrics of earnings and sales growth tend to move in the same direction as stock returns. This indicates that both branding and accounting measures are perceived as key drivers of firm's future growth prospects. Similar to CBBE model, Fama-French (1993) and Carhart (1997) risk loading factors exhibit higher levels of correlation within each other. Since these factors are based on portfolio returns probably consisting of common stocks within them and vary only over time (fixed for each firm in a single year), high collinearity is expected. Firm specific risk characteristics of size and B2M proposed by Daniel and Titman (1997) however have no multicollinearity issues with the other explanatory variables.

Table 5.15 FBBE SRRM Model pairwise correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) R_t - R_f	1.00										
(2) ΔFBBE	0.29*	1.00									
(3) Mktrf	0.46*	0.19*	1.00								
(4) SMB	0.33*	0.16*	0.69*	1.00							
(5) HML	0.24*	0.11	0.54*	0.52*	1.00						
(6) MOM	0.28*	-0.17*	-0.40*	-0.38*	-0.27*	1.00					
(7) Log_MV	-0.29*	-0.12	-0.23*	-0.22*	-0.11	0.24*	1.00				
(8) Log_B2M	0.04	0.03	0.10	0.09	0.05	-0.12*	-0.28*	1.00			
(9) UΔROA	0.27*	0.03	0.24*	0.19*	0.11	-0.11	-0.10	-0.11	1.00		
(10) UΔSales	0.24*	0.22*	0.25*	0.30*	0.00	-0.08	-0.07	0.14*	0.32*	1.00	
(11) Leverage	0.22*	0.00	-0.06	0.00	0.02	0.04	-0.05	0.17*	-0.10	-0.05	1.00

*** *p<0.01, ** p<0.05, * p<0.1*

5.6.1 Results for Δ FBBE *Baseline* and *Main* Models

The first column of the table 5.16, panel A, reports the estimation results for the ΔFBBE *baseline* model. The estimated coefficient of ROA is significant indicating that stock markets react favourably to information contained in this measure. The information content of earning surprise induces investors and shareholders to update their expectations about firm's future profitability prospects, resulting in movement in stock price. The variable of interest i.e. changes in FBBE has a positive sign and is statistically significant. These findings are in support with hypothesis H1(b) and are consistent with the existing marketing-finance literature exploring the valuation effects of firm based brand equity measured through Brand Finance yearly estimates (Bagna et al., 2017; Chang & Young, 2016; Gerekan et al., 2019; Yildiz & Camgoz, 2019). As such, stock market participants do not restrict their expectations about firm's future profitability to accounting metrics rather perceive fluctuations in FBBE as vital signals of financial sustainability. In terms of relative explanatory power, estimated coefficient of current period profitability (β_4 = 1.75) is significantly higher than the ΔFBBE coefficient (β_2 = 0.21). This indicates that although investors perceive information contained in FBBE measure crucial in gauging future cashflows, it is not a substitute to firm's balance-sheet performance. In fact, changes in brand's financial strength provides information which is non-overlapping to current period earnings in anticipating firm's long term performance.

The main question of the analysis is which direction, either a rise or a decline in financial based brand valuation attracts more stock market attention. The Column 2, panel A, of table 5.16 reports the empirical results of ΔFBBE *main* model to answer this vital question. The estimated coefficient of positive changes in FBBE is in the expected direction but statistically insignificant ($b=0.09$, $p>0.10$). In contrary, the declining FBBE response coefficient of declining financial based brand values is positive and statistically significant ($b=.70$, $p<0.001$). Even though the elasticity of positive FBBE change is insignificant, its magnitude is much lower as compared to the negative change. Additionally, the effect size of declining financial brand equity is significantly higher than its overall impact (0.70 vs 0.21). These results therefore affirm that the deteriorating effect of negative changes in FBBE are much higher than positive change, which reinforces the theoretical assumptions made in H2(b). In practical terms, this indicates that stock market participants give much higher weight to a sudden decline in brand's financial earnings when updating their expectations about firm's future growth. Other significant variables which have positive impact on stock returns are broader market returns ($\beta=0.59$, $p<0.001$) and unanticipated changes in annual ROA ($\beta=1.8$, $p<0.10$). Similar to the baseline model, the main model is best estimated through a fixed effect panel regression guided by the F-test, LM and Hausman tests. The results of these tests are reported in the panel B of table 5.16.

Table 5.16 Empirical Results for ΔFBBE *Baseline* and *Main* Models

Panel: A	Baseline Model (Fixed-Effect)	Main Model (Fixed-Effect)
ΔFBBE	.209***	
	(.051)	
ΔPos_FBBE		.086
		(.053)
ΔNeg_FBBE		.70***
		(.188)
R_{mt} - R_f	.586***	.565***
	(.105)	(.103)
SMB	-.259	-.175
	(.248)	(.249)
HML	.165	.169
	(.165)	(.16)
MOM	.011	.01
	(.068)	(.069)
Loglag_MV	-.79**	-.795**
	(.345)	(.343)
Loglag_B2M	-.212	-.196
	(.191)	(.186)
UΔROA	1.75*	1.84*
	(.918)	(.926)
Sales Growth	-.058	-.016
	(.298)	(.298)
Leverage	-.03	-.031
	(.027)	(.027)
Intercept	8.733**	8.823**
	(3.789)	(3.773)
N	490	490
F-Test (Model)	6.79***	6.87***
R^2	0.48	0.49
Adj. R^2	0.41	0.41
Panel: B		
LM Test	0.00	0.00
F-Test (Fixed effects)	2.08***	2.19***
Hausman Test	68.72***	99.03***

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of Observations

5.6.2 Post estimation diagnostics tests

To maintain consistency throughout the analysis, all the post estimation tests outlined in the ΔCBBE SRRM models are conducted for FBBE *baseline* and *main* models. Firstly, to examine the prevalence of serial correlation and heteroscedasticity in the developed Δ

FBBE SRRM models defined in equations 5.10 and 5.11, Wooldridge (2012) test and Wald test (Greene, 2000) are conducted. Table 5.17 reports the test results suggesting that both the models suffer from autocorrelation and heteroscedasticity. To account for these issues, clustered robust standard errors are obtained and reported in table 5.17.

Table 5.17 Wooldridge and Wald test results for FBBE baseline and main models.

FBBE Model	Wooldridge Test (F-Statistic)	Wald-Test (Chi-Sq.)	Autocorrelation	Heteroscedasticity
Baseline	17.776***	4980.22***	Yes	Yes
Main	17.311***	4786.14***	Yes	Yes

*** *p<.01*, ** *p<.05*, * *p<.1*

Table 5.18 presents the variance inflation factor scores for the baseline and main FBBE models. The average VIF score for the baseline and main model is 1.45 and 1.44, respectively, with all the individual scores below 5, implying that both models are free from multicollinearity (Heiberger & Holland, 2015).

Table 5.18 VIF scores for ∆FBBE SRRM Models

Variable	VIF-Score (Baseline Model)	VIF-Score (Main Model)
∆ FBBE	1.10	
∆ Pos FBBE		1.23
∆ Neg FBBE		1.14
MktRf	2.29	2.30
SMB	2.23	2.26
HML	1.58	1.58
MOM	1.27	1.27
LogLag_MV	1.20	1.20
LogLag_B2M	1.20	1.20
U∆ROA	1.19	1.19
Sales Growth	1.35	1.35
Leverage	1.07	1.07
Mean VIF	**1.45**	**1.44**

To further check for any possible effects of high correlation between FF-C risk factors, both the models are re-estimated with capital asset pricing model proposed by Sharpe (1964) (i.e. dropping SMB, HML and MOM). The results (reported in Appendix F) are consistent further affirming no effects of multicollinearity amongst FF-C risk factors on the estimated SRRM models.

5.6.2.1 Univariate Outliers

Table 5.19 reports the minimum and maximum Z-scores for all the variables in included in the FBBE baseline and main models. In the downside, leverage has the highest Z-score i.e. -2.8 standard deviations below the mean and the highest upside volatility are identified in risk adjusted raw returns $R_{it} – R_f$ with SD of 2.819. Similar to CBBE models, the lowest dispersion is exhibited by the Fama-French and Carhart loading factors but the risk variables being HML (-0.99) and MOM (0.98). None of the computed Z-scores for FBBE baseline and main models surpass the absolute value of 3 thereby suggesting both models to be free of any univariate outliers.

Table 5.19 Univariate Outliers Detection in FBBE Model

Variable	Obs	Minimum Z-Score	Maximum Z-Score
Stock Return	490	-2.258	2.819
ΔFBBE	490	-2.665	2.794
Mktrf	490	-1.422	1.691
SMB	490	-1.545	1.426
HML	490	-0.990	1.937
MOM	490	-2.503	0.982
Loglag_MV	490	-2.787	2.018
Loglag B2M	490	-2.509	2.775
Leverage	490	-2.822	2.499
UΔROA	490	-2.749	2.632
Sales Growth	490	-2.371	2.505

5.6.2.2 Multivariate Outliers

Since both the FBBE *baseline* and *main* models are estimated through fixed-effects, the method proposed by Verardi and Wanger (2011) can efficiently detect multivariate outliers and provide robust statistical results. Firstly, the panel models are median-centred and then the standardized residuals are obtained by regressing the transformed data through a S-estimator. The error terms that are above or below the threshold value of 2 are flagged as multivariate outliers and allocated zero weight in the final robust fixed effect regression. Table 5.20 presents the multivariate outliers-free robust fixed-effect regression results for both the models. The FBBE baseline and main models contains 55 and 51 multivariate outliers, respectively, which accounts for nearly 10% sample contamination. Omitting these atypical observations have significantly improved the explanatory power of both the models as reflected in the increased adjusted R-squared values. Noticeably, unlike the original model, the effect of positive change in FBBE is statistically significant but with relatively lower elasticity as compared to overall and negative change. This further affirms that the impact of declining brand specific earnings reflected through Brand Finance valuations has a much higher impact on firm future performance as compared to its rising effects. The coefficient of unanticipated change in ROA is still significant and higher in magnitude than those of ∆FBBE and ∆Pos FBBE in the baseline and main model, respectively. This further affirms the superiority of firm's current-term accounting performance in explaining future returns over any other non-financial asset.

Table 5.20 Robust fixed effect regressions for FBBE *baseline* and *main* models.

	R_t - R_f *(Baseline Model)*	R_t - R_f *(Main Model)*
ΔFBBE	.136***	
	(.035)	
ΔPos FBBE		.113**
		(.043)
ΔNeg FBBE		.484***
		(.104)
Mktrf	.615***	.635***
	(.069)	(.067)
SMB	-.537***	-.499***
	(.164)	(.169)
HML	.258**	.311***
	(.102)	(.099)
MOM	-.036	.024
	(.046)	(.048)
Loglag_MV	-.311***	-.200**
	(.077)	(.09)
Loglag_B2M	-.041	.142*
	(.044)	(.073)
UΔROA	1.466***	1.313***
	(.496)	(.439)
Sales Growth	.254	.45**
	(.182)	(.209)
Leverage	-.005	.002
	(.004)	(.002)
Intercept	3.44***	2.258**
	(.845)	(.984)
N	435	439
F-Test (Model)	9.66***	9.98***
R-squared	0.60	0.61
Adj, R-squared	0.54	0.55

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N=No. of observations

5.6.3 Robustness Check with abnormal stock returns

Consistent with the CBBE model robustness check, abnormal stock returns approach is adopted to test the stability of the FBBE baseline and main models. Firstly abnormal returns are computed as the residuals obtained from the following regression model.

$$R_{iT} - R_f = \alpha + \beta_i(R_{mT} - R_f) + \beta_S(SMB_T) + \beta_H(HML_T) + \beta_M(MOM_T) + \eta_T(Size_{iT-1}) + \vartheta_T(B2M_{iT-1}) + \epsilon_{iT} \quad (5.12)$$

Where, R_i-R_f is the annual raw returns adjusted for risk free rate generated by firm "i" in year "T". R_{mT}-R_f, SMB, HML and MOM are Fama-French and Carhart risk loading factors for year "T". $Size_{iT-1}$ and $B2M_{iT-1}$ are the firm specific risk characteristics of size and book-to-market value respectively, lagged for one year. Idiosyncratic error ε_{it} represents the abnormal stock returns generated by firm "i" in the year "T" (denoted by $Abnr\_Ret_{it}$). Year "T" corresponds to the 12 months encompassing the Brand Finance brand valuation announcement wave. The abnormal return regression model defined above is estimated through fixed effect estimator to account for unobserved heterogeneity across the sample firms[27].

The main and baseline FBBE models defined in equation 8(a) and 8(b) are transformed into abnormal stock return based models as:

$$Abnr\_Ret_{iT} = \alpha + \beta_1 \Delta FBBE_{iT} + \beta_2 U\Delta ROA_{iT} + \beta_3 U\Delta Sales_{iT} + \beta_4 LEV_{iT} + \varepsilon_{iT} \quad (5.13)$$

$$Abnr\_Ret_{iT} = \alpha + \beta_1 \Delta Pos\_FBBE_{iT} + \beta_2 \Delta Neg\_FBBE_{iT} + \beta_3 U\Delta ROA_{iT} + \beta_4 U\Delta Sales_{iT} + \beta_5 LEV_{iT} + \varepsilon_{iT} \quad (5.14)$$

Equation 5.13 examines the firm value impact of overall changes in FBBE and therefore empirically test ΔFBBE *baseline* model. Equation 5.14, on the other hand, focus on

[27] The choice of fixed-effect over pooled OLS and random effect is supported by the diagnostics tests outlined in the figure 1.

analysing the statistical outcomes of the *main* ΔFBBE SRRM model. All the independent variables and yearly time wave "T" are same as defined in equation 5.10 and 5.11 earlier. Table 5.21 reports the pairwise correlation coefficients of the explanatory variables with abnormal returns and between each other. Both FBBE and accounting performance metrics of unanticipated earnings and sales growth tend to have a positive association with abnormal returns suggesting their value imparting relevance. Leverage, however, tend to move in the opposite direction to that of excess returns which is expected as stock market participants are cautious investing in firms with higher debt levels. The correlation levels between the explanatory variables are within the acceptable range, thus not posing any major concerns.

Table 5.21 Pairwise correlation coefficients for Abnormal stock return models

Variables	(1)	(2)	(3)	(4)	(5)
(1) Abr_Rt	1.00				
(2) ΔFBBE	0.15	1.00			
(3) UΔROA	0.11	0.03	1.00		
(4) Sales Growth	0.11	0.22*	0.32*	1.00	
(5) Leverage	-0.26*	0.00	-0.10	-0.05	1.00

**** p<0.01, ** p<0.05, * p<0.1*

Table 5.22 presents the empirical results of the abnormal return models defined in equations 5.13 and 5.14. The main variables of interest in both the models i.e. ΔFBBE, ΔPos_FBBE and ΔNeg_FBBE are consistent to the baseline and main FBBE models with comparable statistical significance, magnitude, and direction. Similarly, the response coefficient of unanticipated changes in ROA is positive and statistically significant in both the models which is closely related to that provided by FBBE baseline ($b=1.75$, $p<0.10$) and main models ($b=1.84$, $p<0.10$). The results of Hausman test for model equations 14(a) and 14(b) however fail to reject the null hypothesis of cross-sectional error variance favouring random effect over fixed effect estimation. Overall, these findings affirms that the ΔFBBE *baseline* and *main* models in equation 5.10 and 5.11 are robust to alternative firm value measurement approaches.

Table 5.22 Robustness check with abnormal stock returns.

	Model Equation 10(a) (Random-Effect)	Model Equation 10(b) (Random-Effect)
ΔFBBE	.182***	
	(.069)	
ΔPos FBBE		.067
		(.062)
ΔNeg FBBE		.666***
		(.199)
UΔROA	1.659*	1.627*
	(.971)	(.971)
Sales growth	-.075	-.016
	(.255)	(.252)
Leverage	-.028	-.029
	(.023)	(.024)
Intercept	-.022	.05
	(.047)	(.05)
N	490	490
F-Test (Model)		
Theta		
R-squared		
Adj. R-squared		
LM Test	292.83***	303.36***
F-Test (Fixed Effects)	6.96***	7.18***
Hausman Test	3.20	5.94

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

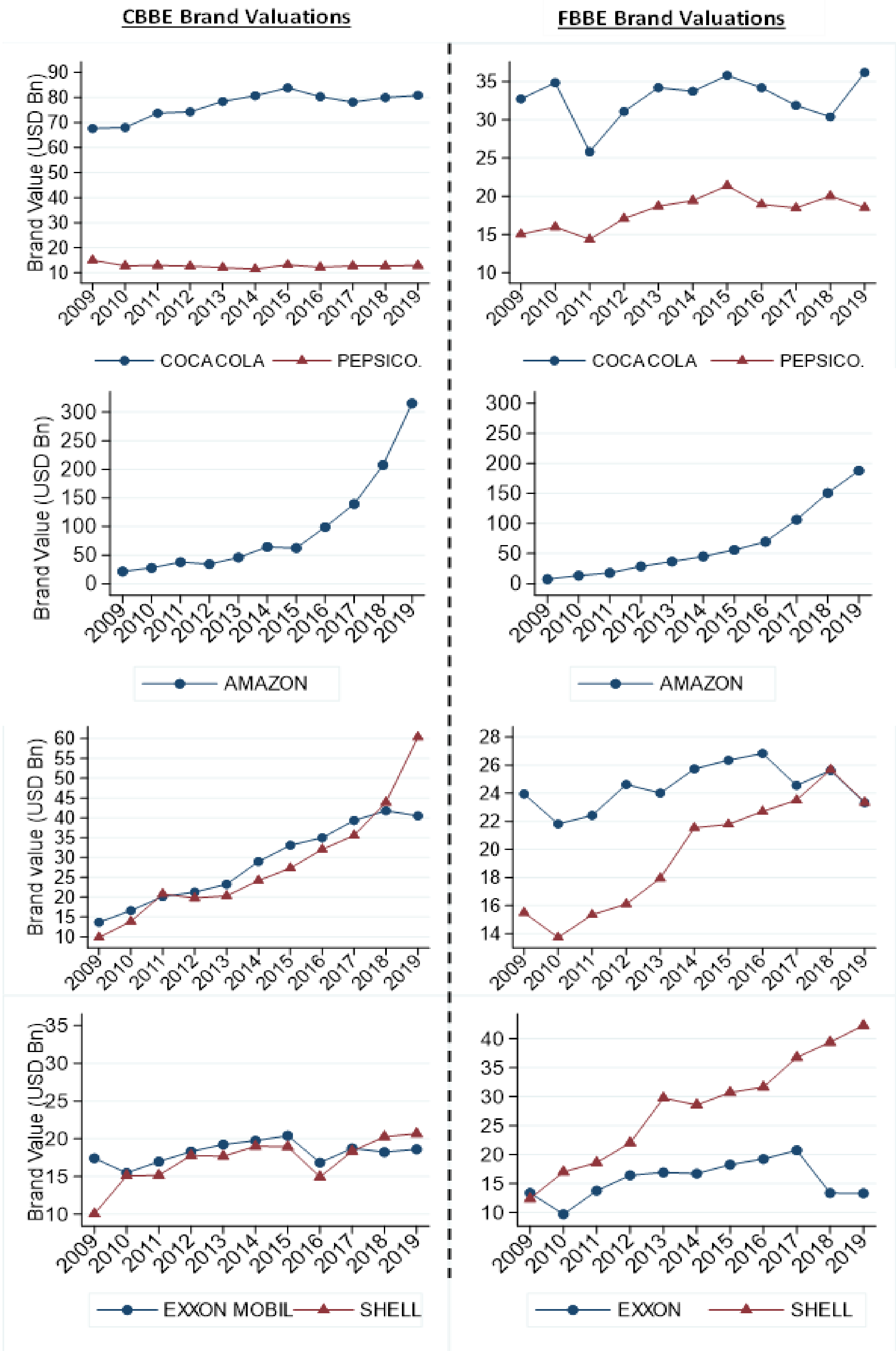
5.7 CBBE-FBBE Comparative Analysis

Previous two sections have provided novel insights about the directional effects of changes in consumer and firm based brand valuations on firm's future discounted cashflows. Both CBBE and FBBE models indicate that there is an asymmetry in the magnitude of the impact of rising and declining brand strength on firm value where the latter outpace the former with a significant margin. However, CBBE and FBBE represents two distinct measures of brand equity where consumer brand perception is subjective in nature while brand's financial earnings is purely objective (Veloutsou et al, 2020)**.** This discrepancy in their dimensional measures calls for a comparative examination of; i) their dynamics over time and ii) their individual impact on firm performance, which is the main aim of this section of the analysis. To begin with, the theoretical arguments proposed in hypothesis H3 are investigated i.e. whether the consumer and firm based brand equity measures are closely related to each other? If the answer to this question is yes, then conducting a comparative analysis of their individual impact on firm value will provide no additional empirical information. To achieve this, both visual and statistical approaches are employed to examine the interrelationship between CBBE and FBBE focussing on the common 44 brands in both the samples. After confirming the propositions of H3, the analysis further advances to examine the stock return response of changes in consumer and financial brand valuations of the 44 firms. Conducting such a comprehensive examination provides novel insights about the true association between CBBE and FBBE and their individual value relevance, which is still under-researched (Tasci, 2020).

5.7.1 Interrelationship between CBBE and FBBE

Figure 5.4 illustrates the temporal dynamics of CBBE and FBBE brand values for the selected brands in the first and second column respectively. Since it is infeasible to include all the 44 brands, some prominent brands from different industrial sectors are included for this visual comparison. Brands competing within an industry are deliberately overlayed in some graphs to demonstrate their comparative brand performance from both the CBBE and FBBE perspectives.

Figure 5.4 Evolution of CBBE versus FBBE valuations for selected brands



Source: Author's elaboration

In consumer staples category, there is a clear dominance of Coca-Cola over Pepsi in both the CBBE and FBBE measures. However the consumer based brand valuation levels of Coca-Cola are almost twice (ranging from 70 to 80 Bn USD) as compared to its FBBE valuations (25 to 35 Bn USD) in the entire 11 year period. This suggests that consumer's association and loyalty towards Coca-Cola has a much higher contribution towards its brand growth as compared to the incremental value gained from patents and trademarks. In contrary, the FBBE valuations of Pepsi are comparatively higher than its consumer based brand values. This discrepancy can be attributed to the diversified product profile of Pepsi which extends beyond the beverages into the snack business with prominent sub-brands such as Lays, Walkers, and Quaker oats. Infact the monetary value of Pepsi's intangible assets which constitutes the income from its copyrights, patents and trademarks reached 30.6 Bn USD in 2018 which is almost twice as compared to Coca Cola in the same year (17.2 Bn USD, Source: DataStream). In the online retail sector, amazon has shown a consistent growth in both consumer and financial brand value measures until 2015 reaching close to 60 Bn USD mark. However the two valuations depart significantly from each other after 2015 with CBBE quadrupling in next 4 years making Amazon the first ever brand to top the BrandZ "most valuable brands" list surpassing a 300 Bn dollar mark (Handley, 2019). A share of this behemoth rise can be attributed to the introduction of smart echo device "Alexa" by Amazon in November 2014. Consumers started associating with this product because of its "human-like" intricacies and ability to network with other devices and applications to perform day-to-day activities (Clark, 2017). This is reflected through the domination of Amazon's echo device in the US smart speaker market with a market share of more than 60% by the beginning of 2019 (Kinsella, 2019). In fact a recent article reports that the sales of Alexa have doubled just within a year from 2019 to 2020 due to its applicability to more than 100,000 different types of smart home products (Rubin, 2020). All these figures clearly indicate the contribution of Amazon's smart echo device in increasing its installed consumer-base, resulting in a whopping rise in its consumer based brand equity. In the automobile sector, German car maker Mercedes (Daimler) has shown a steep growth in its CBBE as compared to its competitor BMW from the period of 2010 till 2018. However, both brands have dropped in 2019 at almost similar brand value levels of 23 billion dollars. Their FBBE valuations however increase almost with an equal slope from 2009 till 2018 followed by a sharp spike in Mercedes brand value in 2019 which is conflicting to the CBBE dynamics. From the monetary value perspective, both the automobile brands reach 40 Bn dollar FBBE levels by 2018 whereas their CBBE valuations never exceed 27 billion USD.

In the energy sector, Royal Dutch Shell have experienced a steady-state growth in its brand equity over the 11 year period in comparison to its UK and US based rivals British Petroleum and Exxon Mobil, respectively. Since Brand Finance evaluates brands predominantly on an accounting scale, the superiority of Shell can be justified by its higher revenue stream and large operations base. According to a recently published report, sales of Shell were 22% higher than BP for the 10 year period from 2010 till 2019 and the gap has almost doubled in the recent four years (Vara, 2019). These relatively higher revenues and larger operations scale could possibly be an inflation factor in the Shell's brand values over its competitors during these years.

The above visual analysis indicates that CBBE and FBBE value estimates provided by BrandZ and Brand Finance, respectively, for same brands not only belong to a different monetary range, but also follow a relatively dissimilar performance dynamic (in changes over time). This further affirms that the two consultancies adopt relatively different valuation strategies where BrandZ focus centrally on consumer insights while Brand Finance relies on expert reviews and direct income from brand name. However, this should not imply that these brand valuations, in their absolute state, are entirely unrelated to each other as both these measures emerge from the same brand equity concept. Since both consultancies include some form of financial multiple in their valuation techniques (BrandZ term it as "financial value" and Brand Finance as "brand revenues"), certain degree of association between them is expected. However, generalizations cannot be made about the CBBE-FBBE linkage solely based on few selected brands. To test this relationship further, pairwise correlation test between the consumer and financial brand valuations for all the common 44 brands is conducted. The test compares the statistical relationship between the static (in levels) and dynamic (in changes) performance of BrandZ and Brand Finance brand values over time. Table 5.23 reports the correlation matrix for CBBE and FBBE annual brand valuations (from 2009 till 2019) and annual percentage changes (from 2010 till 2019).

Table 5.23 Correlation coefficients of CBBE and FBBE brand value dynamics

Variables	CBBE	FBBE	ΔCBBE	ΔFBBE
CBBE	1.00			
FBBE	**0.871***	1.00		
ΔCBBE	0.218*	0.180*	1.00	
ΔFBBE	0.13	0.164*	**0.263***	1.00

**** p<0.01, ** p<0.05, * p<0.1*

The coefficients of interest i.e. relationship between contemporaneous brand values (CBBE-FBBE) and yearly changes (ΔCBBE-ΔFBBE) are highlighted in the bold[28]. As

[28] Other correlation coefficients are pseudo in nature as they tend to compare "in levels" to "in changes" which come from two different datasets.

expected, even with a wide gap between the consumer and financial brand monetary values, they tend to exhibit close correspondence with each other (87% correlated, $p<0.10$). These findings are broadly in-line with the limited body of research exploring the contemporaneous interrelationship between different CBBE and FBBE components (Datta et al., 2017; Huang & Sarigöllü, 2014; Lehmann et al., 2008; Stahl et al., 2012). However, yearly percentage changes in CBBE and FBBE have a correlation coefficient of 0.26 ($p<0.10$) which is 70% less than its static relationship coefficient. First differencing the annual BrandZ and Brand Finance valuations tend to omit most of the commonalities between these two measures to a large extent. This significantly lower correlation coefficient between changes in CBBE and FBBE therefore suggests that although consumer and firm oriented brand equity measures emerge from a same theoretical concept, their evolution over time is not closely associated. These results therefore support the propositions of hypothesis H3 and are provide novel knowledge about the CBBE-FBBE interlinkage. After gaining supportive evidence for H3, an effective comparative analysis can now be conducted between the firm value impact of changes in consumer and firm based brand perspectives.

5.7.2 Relationship of CBBE versus FBBE with firm performance

Previous section unfolds that there is a significant deviation in how the consumer and firm based brand equity measures of a particular firm-brand change over time. The next step is to evaluate if the directional impact of their rise and decline on firm performance follows the same suite. To address this question, the *baseline* and *main* SRRM models proposed in sections 5.5 and 5.6 of this chapter (i.e. eq. 5.2 & 5.3 for CBBE and eq. 5.10 & 5.11 for FBBE samples) are re-examined including only 44 common brands from 2010 till 2019. Since ROA series does not follow a random walk (have unit root), unanticipated changes in ROA are re-estimated through AR1 fixed-effect panel data regression[29]. Compiling all the data yields a balanced panel dataset with 440 firm-year observations in each model.

Table 5.24 presents the empirical results for ΔCBBE *baseline* and *main* models in first two columns and ΔFBBE *baseline* and *main* models in the subsequent columns, respectively. From the overall effects perspective, both the coefficients of CBBE and FBBE are positive and statistically significant which is expected based on the previous results. However, a significant difference in their individual coefficients (ΔCBBE=0.33 vs ΔFBBE=0.19) suggests that the impact of annual changes in CBBE on firm performance is much higher as compared to FBBE changes. In other words, investors perceive information contained in variations in consumer brand perceptions more valuable than changes in brand's financial earnings when re-evaluating their expectations about firm's future cashflows. There is limited evidence in the existing marketing-finance literature of such a direct comparison between the value relevance of CBBE and FBBE[30]. These findings therefore provide valuable insights about the difference in the impact of these brand equity constructs on firm performance, where consumer loyalty and association outweigh brand evaluations by panel of experts. The obtain results therefore supports hypothesis H4 expecting the directional relationship

[29] Panel unit root test and "best-fit" panel regression test were conducted to justify the model selection and regression residuals are obtained as unanticipated ROA components.

[30] To date, only Bagna et al. (2017) and Johannsson et al. (2012) conducted a comparative analysis of the value relevance of CBBE and FBBE measures, however their results are broadly conflicting.

between positive and negative changes in CBBE and firm performance stronger as compared to FBBE changes.

Table 5.24 Comparative analytical results for CBBE and FBBE *baseline* and *main* models

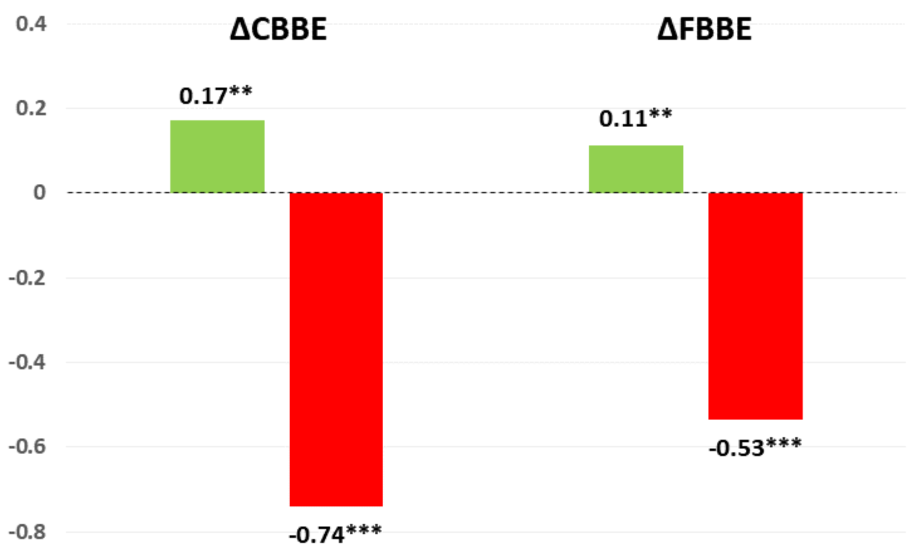
	∆CBBE Model		∆FBBE Model	
Panel: A	*Baseline*	*Main*	*Baseline*	*Main*
∆ Overall	.327***		.193***	
	(.059)		(.052)	
∆ POS		.173**		.113**
		(.084)		(.049)
∆ NEG		.74***		.534***
		(.134)		(.183)
Mktrf	.235**	.197**	.573***	.56***
	(.095)	(.092)	(.113)	(.113)
SMB	-.091	-.059	-.079	-.036
	(.203)	(.203)	(.27)	(.272)
HML	.526***	.556***	.088	.096
	(.146)	(.145)	(.181)	(.177)
MOM	.01	.032	.015	.012
	(.161)	(.157)	(.077)	(.077)
Loglag_MV	-.343***	-.367***	-.783**	-.785**
	(.102)	(.11)	(.374)	(.372)
Loglag_B2M	.077	.078	-.222	-.21
	(.06)	(.06)	(.194)	(.189)
∆ROA	1.071*	1.24*	1.80*	1.868*
	(.617)	(.655)	(.968)	(.98)
Sales Growth	.157	.166	-.293	-.253
	(.265)	(.269)	(.308)	(.305)
Leverage	-.004	-.004	-.03	-.031
	(.006)	(.006)	(.027)	(.027)
Intercept	3.874***	4.183***	8.654**	8.707**
	(1.122)	(1.211)	(4.106)	(4.097)
N	440	440	440	440
F-Test (Model)	5.71***	5.91***	6.65***	6.60***
R-squared	0.44	0.45	0.48	0.48
Adj. R-squared	0.36	0.38	0.41	0.41
Panel: B				
LM Test	0.00	0.00	0.00	0.00
F-Test (Fixed effects)	1.44**	1.64***	1.98***	2.02***
Hausman Test	55.11***	53.23***	60.27***	64.37***

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

The coefficient of unanticipated changes in ROA are much higher than their respective brand equity coefficients in both the ∆CBBE (b=1.07, p<0.10) and ∆FBBE (b=1.87, p<0.10) *baseline* models. This is again consistent with the proponents of stock return response modelling that marketing strategies cannot replace accounting performance in explaining stock returns (Mizik, 2014).

Figure 5.5 provides the graphical presentation of the results obtained from CBBE and FBBE main models for clearer comparison. The stock return response of positive CBBE and FBBE changes are shown with green columns and the red columns denote the deteriorating effects of declining CBBE and FBBE. As evident in the figure, the magnitude of impact of unanticipated changes in CBBE is significantly larger than FBBE variations in both the upward and downward directions. This further affirms the superiority of the value relevance of CBBE over FBBE in explaining firms future discounted cashflows.

Figure 5.5 CBBE and FBBE *Main* Model Results Comparison



**** p<0.01, ** p<0.05, * p<0.1*

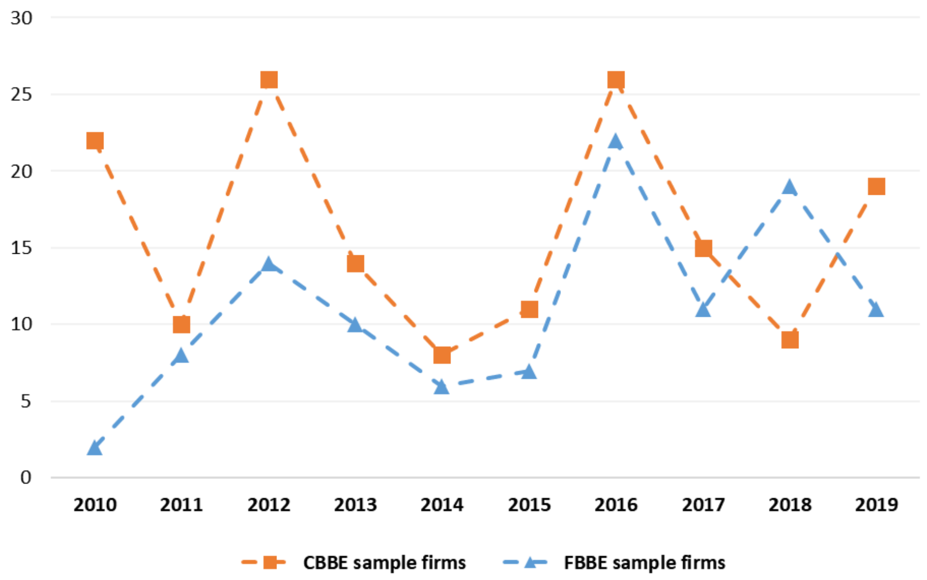
Source: Author's elaboration

Furthermore, the results seem more severe on the negative side of the brand equity-firm performance relationship for both CBBE and FBBE models. The impact of negative changes in FBBE is almost five times higher as compared to positive changes (b= -0.53, p<0.001). Similarly, the firm value deterioration due to unexpected downward shifts in consumer brand association is substantially higher than the positive shifts (ΔNeg CBBE = -0.74 vs (ΔPos CBBE = 0.17). Collectively, these findings indicate that irrespective of the brand measurement perspective, financial community gives more weight to declining brand equity when altering their investment decisions. From the dispersion perspective, the estimated coefficients of ΔCBBE *main* SRRM model exhibits higher upside and downside volatility as compared to the respective ΔFBBE model, affirming that consumer's cognitive brand attachment is a key firm value contributor (or even value destroyer).

The significance and direction of the elasticities of unanticipated ROA and other control variables in both CBBE and FBBE main models are as expected and comparable to that of their respective baseline models. The "best-fit" panel regression test results (reported in table 5.24, panel B) favour fixed effect estimator for all the four models suggesting the presence of unobserved heterogeneity across panels. Furthermore, in order to account for auto-correlation and heteroscedasticity, clustered-robust standard errors are obtained and reported.

Since now it is confirmed that negative changes in consumer and firm based brand equity have a much higher impact on stock returns, the analysis further evaluates the number of firms experiencing these declines on yearly basis. Comparative evaluation of the yearly frequency of firms with negative changes in CBBE and FBBE can help answer two vital questions. Firstly, are the number of firms experiencing a decline in either their consumer or firm oriented brand valuation equally distributed each year? Secondly, does decline in one brand equity measure in a particular year (CBBE or FBBE), has any influence on the other measure? Answers to these questions can provide information about the time-series behaviour of CBBE and FBBE declines and existence of any pattern for the 44 brands under investigation**.** Figure 5.6 attempts to address the first question and compares the number of firms with declining consumer and firm based brand equity valuations each year. It is clearly evident that in almost all the years (except 2018), more brands have experienced a decline in their consumer equity as compared to the financial based measure. In the entire 10 year study period, the average number of firms with declining CBBE each year are 16 whereas for FBBE, this number shrinks down to 11 brands per year. Notably, for some years (2012 and 2016) there are more than half of the total 44 firms that have experienced a fall in their consumer centric brand values. These figures signify that shifting consumer brand perception is not easy to comprehend as there are several internal (product quality and brand experience) and external market factors (competitors) which govern these changes.

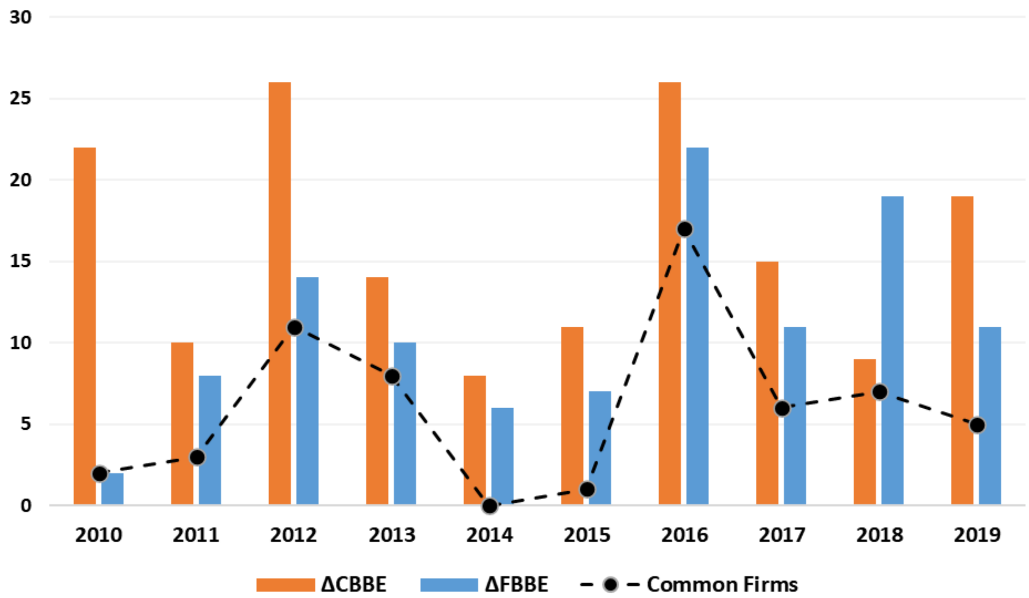
Figure 5.6 Frequency of negative changes in CBBE versus FBBE



Source: Author's elaboration

Figure 5.7 aims to answer the second question i.e. is it that the firms witnessing an unanticipated decline in one of their brand equity perspective in a particular year experience a similar effect on their other brand measurement dimension? In other words, does a negative change in CBBE (or FBBE) a signal of a similar directional shift in FBBE (or CBBE)? The two clustered columns for each year present the total number of firms with declining valuations in their CBBE (orange) and FBBE (blue) measures. The line graph, on the other hand, depicts the annual frequency of firms that have experienced a decline in both their CBBE and FBBE estimations. As evident in the figure, there is not a single year with equal number of brand-firms witnessing a negative shift in either their CBBE or FBBE. Furthermore, very few brands each year have undergone a downward shift in both their consumer and firm based brand dimensions over the 10 year study period. For example, in 2014 and 2015 there is mere any firm which is common in both the samples. In 2019, despite 18 and 11 firms experiencing a decline in their financial and consumer based brand valuations, only 5 are common amongst them. The data therefore provide strong evidence that an unfavourable change in one brand equity perspective does not drive a similar shift in the other measure. These mutually exclusive dynamics of declining CBBE and FBBE further affirm the earlier established weak association between these two key brand equity measures.

Figure 5.7 Assessment of common firms experiencing yearly decline in CBBE and FBBE



Source: Author’s elaboration

5.8 Summary

This chapter provided empirical evidence for all the underlined research objectives in the first section of the proposed conceptual framework. This was achieved by segregating the overall research questions into three themes. The first theme tested whether existing knowledge of strong brand equity-firm performance linkage holds its validity for the acquired sample brands. The empirical results of the ΔCBBE and ΔFBBE *baseline* SRRM models supported this assumption signifying that brand equity, irrespective of its measurement perspective is a promising source of long-term growth. The second theme extends the existing knowledge by unfolding the asymmetry in the stock return response of rising versus declining brand equity. Both the ΔCBBE and ΔFBBE *main* models signal that negative changes in brand equity have a much higher deteriorating impact on firm performance as compared to its contributions during positive changes. This is an important finding as it reveals that even strong brands with persistent growth over years are vulnerable if the consequences of such sudden shifts are ignored or misjudged. Finally the last theme provides novel insights about the level of association between consumer and firm based brand equity measures. The obtained results provide many valuable insights about their true inter-linkage. Firstly, CBBE and FBBE are strongly related to each other in their “steady-state” form which is logical as both these measures stem to the same brand equity concept. However, further analysis reveal that their dynamics of change follow a relatively distinctive path signalling a weak association between them as they evolve over time. Even from the value relevance perspective, these brand equity dimensions exhibit dissimilar effects where both the overall and directional effects of CBBE are much stronger as compared to FBBE. Collectively, these findings affirm that no single brand equity perspective can singularly define the holistic brand performance and therefore it is crucial to adopt multiple-dimensional approach to gauge its true value. In sum, all the proposed theoretical assumptions made under section-I of the conceptual model are strongly supported with the obtained empirical evidence.

Chapter 6: ANALYSIS PHASE – II

6.1 Introduction

The analysis phase-II is bonded to the second section of the proposed conceptual model and examines the moderating role of organizational efficiency in brand equity to firm performance translation process. From theoretical perspective, the empirical analysis conducted within this chapter examines the propositions of resource based theory (RBT) that firms should combine their strategical resources with their capabilities to gain sustainable competitive advantage (SCA) (Kozlenlova, 2014). In the context of this study, it opines that if the sample brand firms are efficient in managing their overall organizational competence, they should be able to enhance (mitigate) the positive (negative) financial effects of rising (declining) brand equity. Two such efficiency factors are identified: a) core business efficiency (CBEF) i.e. how well management converts its tangible resources like labour, infrastructure and capital stock into profitability and b) marketing capability (MCAP) i.e. the ability of management to exploit its available marketing resources to generate higher sales revenue. Both CBEF and MCAP are operationalized using multi-input output DEA Malmquist total factor productivity change (TFPCh) with constant returns to scale (CRS). Malmquist DEA amalgamates changes in firm's technical expertise (efficiency change) along with changing technology over time (technological change) to define total efficiency change. The linear programming software utilized for modelling CBEF and MCAP is DEAP (Coelli, 1996).

The chapter is structured as follows. The initial section provides a discussion of steps taken to prepare and compile all the collected data pertaining to operationalization of

CBEF and MCAP efficiency metrics. The section also overviews the challenges which were initially encountered while preparing the inputs and output data for DEA Malmquist benchmarking analysis. The next section then discusses the applied remedial approach to overcome these issues including both its conceptual and procedural aspects. The subsequent sections then empirically examine the moderating role of CBEF and MCAP, focussing at one efficiency variable at a time. Firstly, the interaction effects of CBEF are analysed through two separate SRRM models, one for directional changes in CBBE and the other for FBBE. In a similar manner, translating effects of marketing capability (MCAP) are investigated by first focusing on positive and negative variations in CBBE, followed by FBBE changes. Both CBEF and MCAP interaction models set out an overview of the estimated DEA Malmquist TFPCh efficiency dynamics over time before exploring their moderating effects. A short summary concludes the chapter.

6.2 Data preparation for DEA analysis

Firstly, all the accounting data required for operationalizing CBEF and MCAP through Malmquist DEA TFPCh analysis is annualized. Table 6.1 summarizes all the adopted inputs and outputs for modelling CBEF and MCAP. Following the procedure adopted in analysis phase-I, all the inputs and output variables are firstly aligned specifically with the BrandZ and Brand Finance brand value announcement waves for CBBE and FBBE models, respectively.

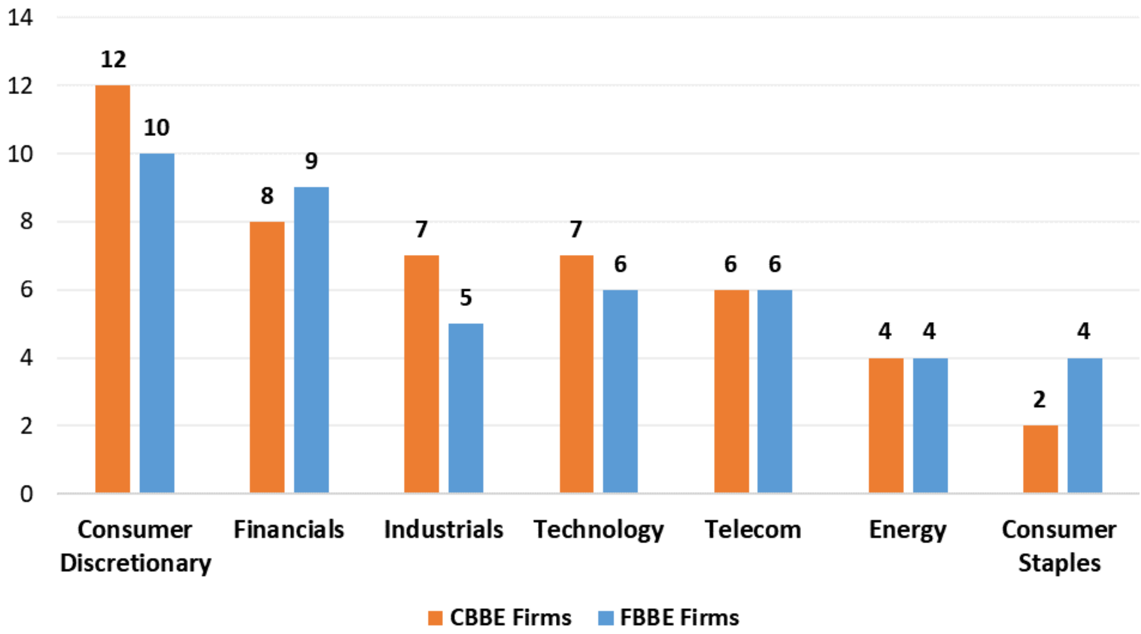
Table 6.1 DEA Inputs and Outputs for CBEF and MCAP

	Core Business Efficiency (CBEF)	Marketing capability (MCAP)
Inputs	Total Assets	Intangible Assets
	Total Employees	Sales, General & Administrative Expenses
	Total Shareholder's Equity	Accounts Receivables
Output	Operating income before depreciation	Total Sales

However, certain issues were faced during the compilation of the retrieved data for 54 CBBE and 49 FBBE firms, which restricts the application of standard DEA models for efficiency estimation. Firstly, basic DEA models are incapable of handling negative inputs and outputs and require all the data to be strictly positive (Sarkis, 2007:6). The most common remedy to deal with negative data is to invoke the "translation variance" property of DEA proposed by Ali and Seiford (1990). Under this process, a sufficiently large positive constant is added to all the values of the input or output which contain negative numbers. However DEA models with constant returns to scale (CRS) are translation invariant and such transformations cannot be applied to them (Zhu, 2000). Literature in operational research has proposed several other methods that can handle negative data such as slack based measure (Morita et al., 2005), modified slack based measure (Sharp et al., 2007), range directional measure (Portella, 2010) and semi-oriented radial measure (Emrouznejad et al, 2010). However due to their conceptual complexity and unavailability of open source software, application of these methods is beyond the scope of this study. Therefore, preserving the originality of the sample data and following Zhu (2000), all the firm brands with negative values in any of their inputs or outputs were dropped in the DEA Malmquist estimation process. This "negative data issue" however was only faced while modelling CBEF. This is because CBEF DEA model have shareholder's equity as one of its inputs and operating income as output, both of which can have negative values. After excluding the firms with negative data, the final sample size for CBEF estimation reduced to 48 decision making units (DMUs) for CBBE and 44 DMUs for the FBBE sample. From the MCAP perspective, all its employed inputs and outputs are inherently positive. However, the key problem in operationalizing MCAP was the unavailability of the required input data for all the firm brands. For example, firms in financial sector e.g. banks and insurance companies have a different balance sheet structure which does not include account receivables and SG&A. Apart from financial sector, some firms in other industrial segments also had missing values for these data measures. Lack of available accounting data has trimmed the total number of CBBE sample to 36 and FBBE sample to 32 firm-brands for the MCAP operationalization.

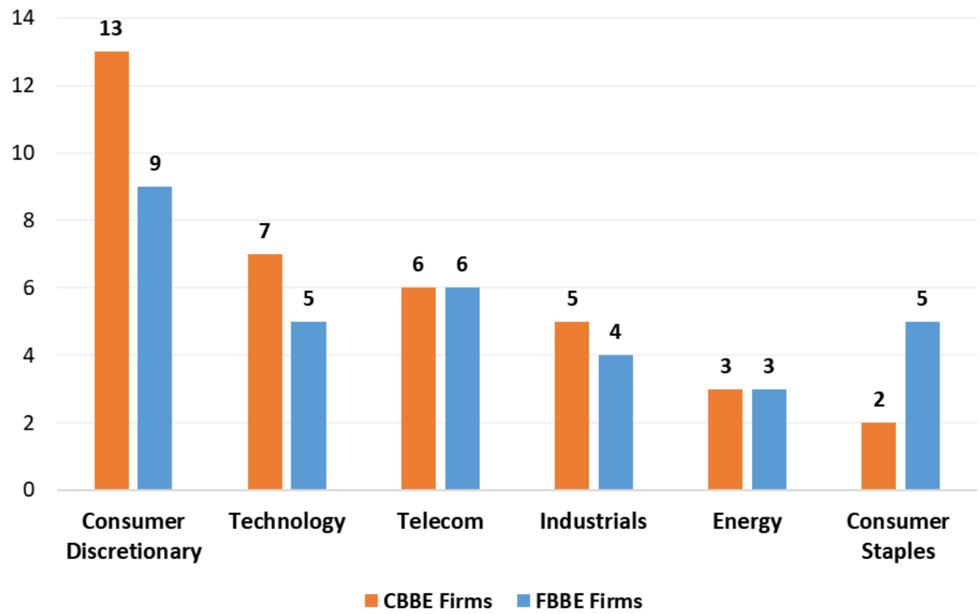
Another challenge encountered during DEA Malmquist application is its assumption of homogeneity i.e. it is only capable of comparing *"apples to apples"* (Rahman et al., 2018). Since DEA is a benchmarking tool which conducts a relative efficiency evaluation, it is desirable that all the DMUs under investigation operate under similar operational and productive technologies (Coelli, 1996). In other words all the DMUs enveloped under a single efficiency frontier should be exposed to same industrial sector. The clustered column chart in figure 6.1 summarizes the industry-wide distribution of the 46 CBBE and 44 FBBE sample firms for CBEF estimation. As evident in the figure, the CBBE and FBBE sample firms belong to 7 different industrial sectors with a wide difference in their frequency in each industry. A similar pattern can be seen for the MCAP estimation samples of CBBE and FBBE shown in figure 6.2**.**

Figure 6.1 CBBE and FBBE sample segmentation by industry for CBEF analysis



Source: Author's elaboration

Figure 6.2 CBBE and FBBE sample segmentation by industry for MCAP analysis



Source: Author's elaboration

Although with missing financial sector in the MCAP sample because of data unavailability, the frequency of firms in all other sectors are in close correspondence to that of CBEF sample. Both the samples have highest number of firms in consumer discretionary and very few brands in energy and consumer staples category. A standard DEA model would recommend sorting firms based on the industries and run separate DEA programs for each sector. For example, in case of CBEF modelling, 7 separate Malmquist DEA algorithms are to be executed for each industrial sector. However, this approach has some caveats. Firstly as explained through an illustrative example in the methodology chapter (see section 4.4), the total number of linear programmes executed in a single DEA model is a function of total number of included DMUs. Therefore, models with more DMUs will run higher number of linear programming combinations to allocate weights to each input or output (depending on if the model is input or output oriented). Furthermore, since relative efficiency analysis is being carried out between many observations, there is a higher chance of only few DMUs being efficient. These efficiency distortions caused due to "group size" effects have been recently validated by Demerjian (2018). Their study which specifically focus on DEA analysis in accounting and finance, report that with the reduction of number of DMUs, the distribution of efficiency scores is significantly compressed, "eliminating the informative cross-sectional variation" (Demerjian, 2018:2). As figures 6.1 and 6.2 presents, there are some sectors with very few firms e.g. only two consumer staple brands in CBBE sample for MCAP and CBEF (Pepsi and Coca Cola) and three each in the energy sector for MCAP estimation. It is highly likely that their efficiency scores will be much exaggerated as compared to the other industrial sectors with higher number of DMUs (e.g. consumer discretionary and financials). The recommended solution to account for these distorting inferences is to employ “year-based sorting” rather than “industry-based sorting”, especially when data is available in the longitudinal form (Demerjian, 2018:4). Under year-based sorting process, all the DMUs under examination are pooled together over year t and t+1 and DEA efficiency change in these two years is computed. The process is then repeated for all the subsequent years (in pairs) to calculate their respective annual efficiency changes. Adopting this approach ensures that all the estimated DEA models have same number of DMUs, thus eliminating the “group size distortion” and providing robust efficiency estimates.

Following above discussions and recommendations, Malmquist total factor productivity change for CBEF and MCAP operationalization is estimated through “year-based sorting” process. This has resulted in the execution of 10 separate DEA linear programmes representing 10 “consecutive year-groups” for estimating each efficiency variable for CBBE and FBBE samples (2009 till 2019). The subsequent sections first discuss the adopted analysis strategy followed by visually presenting the results of the estimated CBEF and MCAP measures along with their moderating effects on positive and negative changes in CBBE and FBBE.

6.3 Analysis Strategy

Following the approach adopted in the first phase of the analysis and for ease of reference, firstly all the research hypotheses examined within this chapter are listed in table 6.2. Jointly, these hypotheses validates whether sudden upward or downward shifts in CBBE and FBBE are sensitive to changes in firm’s organizational efficiency levels. Implementing DEA Malmquist benchmarking approach, two management functions are identified i.e. CBEF and MCAP which reflects firm’s *profitability* and *marketability* prospects, respectively. The empirical outcome of each hypothesis is presented using a two-step approach. Firstly, the Malmquist TFPCh results for the operationalized efficiency measure is visualized by plotting their dynamics of change over the 10 year study period (2010-2019). The plots include both the "technical change" (time based) and "efficiency change" (internal-efficiency based) components along with the TFPCh measures to clearly understand how variations in these two sub-components have affected the overall CBEF and MCAP dynamics. The second step is then to statistically investigate their interaction effects through SRRM modelling procedure. To maintain consistency throughout both the analysis chapters, the respective SRRM models examine the underlined research questions as per their sequence in the table 6.2. Firstly, the interaction effects of CBEF during positive and negative changes in CBBE are investigated (i.e. H5(a)), followed by directional shifts in FBBE, thereby testing H5(b). Afterwards, two separate SRRM regression models are proposed to investigate the pivoting role of MCAP in moderating the firm value impact of directional changes in CBBE and FBBE, capturing H6(a) and H6(b), respectively. Along with statistical analysis, the interaction effects of CBEF and MCAP are also visualized through predictive margin plots. All the four SRRM models are tested against heteroscedasticity and autocorrelation, multicollinearity, univariate and multivariate outliers and alternative measure of firm performance.

Table 6.2 Summary of all the hypotheses examined under analysis phase-II

Hyp. No.	**Theoretical Arguments** *(Model Section-II)*
H5(a)	The impact of rising and declining CBBE on firm performance is positively moderated the levels of firm's core business efficiency.
H5(b)	The impact of rising and declining FBBE on firm performance is positively moderated by the levels of firm's core business efficiency.
H6(a)	The relationship between rising (declining) CBBE and firm performance is stronger (weaker) for firms with enhanced marketing capabilities.
H6(b)	The relationship between rising (declining) CBBE and firm performance is stronger (weaker) for firms with enhanced marketing capabilities.

6.4 Moderating role of Core Business Efficiency (CBEF)

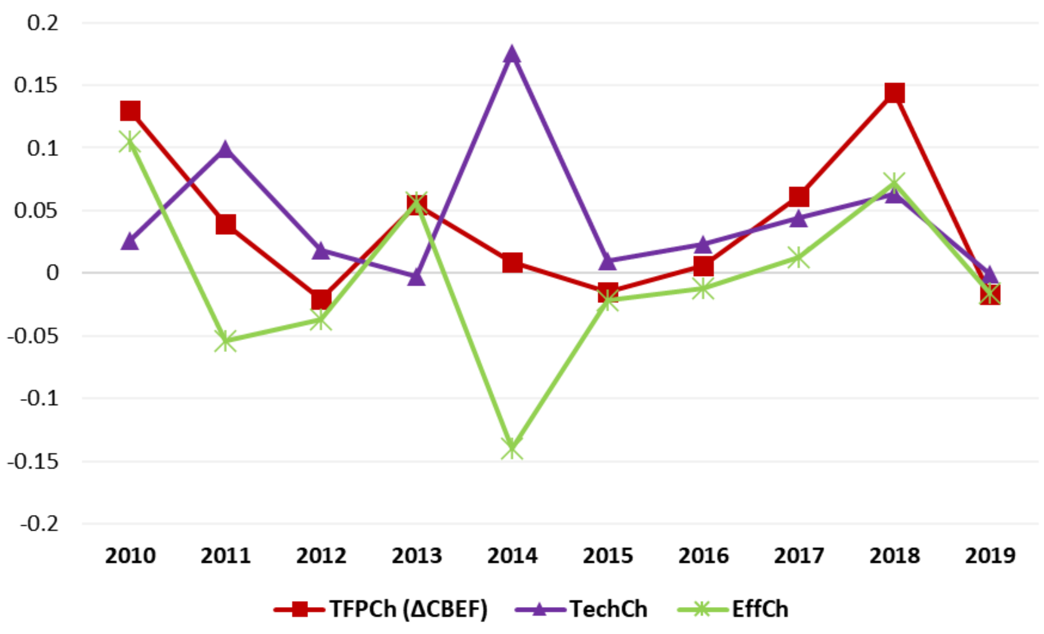
6.4.1 DEA results for CBEF and its interaction effects in ∆*CBBE SRRM Model*

Before analysing the translating role of firm's core business efficiency in the CBBE-firm value relationship, firstly the dynamics of the estimated total factor productivity and its sub-components is evaluated (Yang et al., 2015). The Malmquist total factor productivity index for the 46 CBBE sample firms along with their technical and efficiency change components are summarized in figure 6.3[31]. The data indicates that, overall, ∆CBEF have experienced a positive change for all the firms except in years 2012, 2015 and 2019 with a slight negative dip (<2%). The highest positive CBEF change is 14% recorded in 2018. In contrary, both efficiency and technological changes have been much more volatile in the 10 year period. There is a dramatic increase in the technology in 2014 whereas the overall efficiency of the firms fell to its lowest value of

[31] The three indexes are computed by taking yearly averages of TFPch, Effch and TechCh of all the sample firms.

-14% in the same period. Referring to figure 4.4 in the methodology chapter, this suggests that this decline in the firm efficiencies is principally caused due to a strong upward shift in the efficiency frontier itself. These violent opposite movements of TechCH and EffCh however has counteracted with each other, making the overall CBEF stable[32]. Similar counteractive effect, but on a smaller scale, can be seen in 2011. The TechCh index has never been negative in all these years signifying constant growth in technology and innovation over time. In summary, the performance of Malmquist productivity index suggests that along with firm's internal efficiencies, technological changes over time have played a decisive role in the resulting core business efficiency dynamics.

Figure 6.3 Malmquist productivity index and its components for CBBE firms



Source: Author's elaboration

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[32] Recall that TFPCh is a product of efficiency and technical change.

After evaluating average CBEF performance of CBBE sample firms, focus can now be shifted on examining its moderating role in ΔCBBE-firm performance relationship. Equation 6.1 below represents the stock return response model used for this analysis:

$$R_{iT} - R_f = \alpha + \beta_1 \Delta Pos\_CBBE_{iT} + \beta_2 \Delta Neg\_CBBE_{iT} + \beta_3 \Delta CBEF_{iT} + \beta_4 \Delta Pos\_CBBE_{iT} \text{ X } \Delta CBEF_{iT} + \beta_5 \Delta Neg\_CBBE_{iT} \text{ X } \Delta CBEF_{iT} + \beta_R Risk_T + \beta_6 U\Delta ROA_{iT} + \beta_7 U\Delta Sales_{iT} + \beta_8 LEV_{iT} + \varepsilon_{iT} \quad (6.1)$$

Where:

$R_{iT} – R_f$ =	Annual raw returns of firm "i" in year T adjusted for yearly risk-free rate;
ΔPos_CBBE_{iT} =	Continuous variable capturing positive changes in BrandZ brand values of firm "i" in year T;
ΔNeg_CBBE_{iT} =	Continuous variable capturing negative changes in BrandZ brand values of firm "i" in year T;
$\Delta CBEF_{iT}$ =	Change in core business efficiency of firm "i" in year T.
$RISK_T$ =	Vector of all the yearly risk factors defined in CBBE baseline and main models earlier;
$U\Delta ROA_{iT}$ =	Unanticipated component of earnings for firm "i" in year T;
$U\Delta Sales_{iT}$ =	Sales growth of firm "i" in year T;
LEV_{iT} =	Leverage of firm "i" in year T;
ε_{iT} =	idiosyncratic error term;
T =	Year encompassing BrandZ brand value announcement wave (June of previous year T-1 till May in current year T).

The coefficients of interest are β_4 and β_5 which captures the interactive role of firm's core business efficiency during a positive and negative CBBE change, respectively. Table 6.3 provides the descriptive statistics for the response and all the employed explanatory variables. The average yearly raw returns for the 48 sample firms from 2010 to 2019 is 12% with a standard deviation of 21%. This suggests that the annual stock returns are widely dispersed across the mean with upper and lower limits ranging from +89% to -60%. The total frequency of positive CBBE changes is 313 which is double as compared to negative yearly changes of 147. The maximum recorded positive change is 97% which is also more than twice as compared to the maximum decline of -45%. Overall, all the sample firms have experienced a positive change in their core business efficiencies in the 10 year study period. However these changes are more volatile (S.D = 21%) as compared to directional changes in CBBE (ΔPos $CBBE_{S.D}$ = 0.16; ΔNeg $CBBE_{S.D}$ = 0.07). The minimum and maximum values of -55% and 104% also coincides well with the CBEF volatility pattern observed in figure 6.3, where the upside change is almost double as compared to the downside shift. All the other control variables including Fama-French (1993) and Carhart (1997) economy-wide risk loadings, Daniel and Titman (1997) firm specific risk characteristics and accounting-performance measures of UΔROA, UΔSales and leverage exhibit almost similar type of distribution as observed in the phase-1 ΔCBBE SRRM models. Amongst them, leverage has the highest volatility above the mean with the maximum value of 39.69.

Table 6.3 Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max
Stock Return	460	0.12	0.21	-0.60	0.89
ΔPos CBBE	313	0.17	0.16	0.01	0.97
ΔNeg CBBE	147	-0.03	0.07	-0.01	-0.45
ΔCBEF	460	0.03	0.21	-0.55	1.04
MktRf	460	0.11	0.14	-0.12	0.30
SMB	460	0.00	0.05	-0.11	0.10
HML	460	-0.02	0.07	-0.10	0.10
MOM	460	0.06	0.05	-0.04	0.15
Loglag MV	460	11.00	0.31	10.15	11.96
Loglag B2M	460	-0.41	0.38	-2.26	0.26
UΔROA	460	-0.00	0.02	-0.13	0.11
Sales Growth	460	0.02	0.05	-0.32	0.22
Leverage	460	1.37	2.46	0.00	39.69

Table 6.4 reports the pairwise correlation results between all the variables included in the ΔCBBE-ΔCBEF moderation model. All the explanatory variables of interest i.e. ΔPos_FBBE, ΔNeg_FBBE and ΔCBEF have a significant positive relationship with stock returns (coeff. = 0.24, $p<0.10$). This suggests that similar to positive and negative changes in CBBE, variations in firm's core business efficiency tend to move in the same direction as stock returns. The relationship of other control variables with the response variable is also in the expected direction. Also, relatively high correlation within FF-C risk factors is also consistent with the previous estimated models. The matter of concern is the correlation coefficient between ΔCBEF and UΔROA which is over 50% (0.56, $p<0.10$). This might come as a surprise at the first glance, however, high level of association between them seems to be logical. From financial perspective, ROA is a profitability ratio which measures the portion of income generated, given the available physical assets (Masood & Ashraf, 2012). Therefore, ROA is basically a unidimensional efficiency metric with total assets as input and operating income as output. In contrast, the proposed CBEF metric is an enhanced version of ROA with a multi-input approach which includes human resources and capital stock as additional resources in explaining firm's profitability. The commonalities between the structural characterises of ROA and CBEF can thus be the main drivers behind a high degree of connection between them. The correlation coefficients of all the other independent variables are within the acceptable range.

Table 6.4 Pairwise corelation Matrix for CBBE CBEF model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) R_T - R_f	1.00												
(2) ΔPos CBBE	0.38*	1.00											
(3) ΔNeg CBBE	0.26*	0.36*	1.00										
(4) ΔCBEF	0.24*	0.11	0.03	1.00									
(5) MktRf	0.39*	0.20*	0.19*	0.14	1.00								
(6) SMB	0.23*	0.11	-0.03	0.17*	0.38*	1.00							
(7) HML	0.30*	0.07	0.02	0.14	0.61*	0.36*	1.00						
(8) MOM	0.00	0.12	0.08	-0.08	0.04	0.02	-0.36*	1.00					
(9) Loglag MV	-0.18*	0.00	0.06	-0.06	-0.16*	-0.20*	-0.16*	0.02	1.00				
(10) Loglag B2M	-0.10	-0.16*	-0.16*	0.04	0.09	0.08	0.09	0.00	-0.14	1.00			
(11) UΔROA	0.20*	0.14	-0.01	0.56*	0.17*	0.17*	0.09	0.08	-0.05	-0.01	1.00		
(12) Sales Growth	0.36*	0.30*	0.13	0.21*	0.23*	0.15	0.06	0.03	-0.08	-0.17*	0.26*	1.00	
(13) Leverage	-0.12	-0.08	-0.04	0.21*	-0.06	-0.02	-0.04	-0.05	-0.02	-0.20*	-0.05	-0.08	1.00

**** p<0.01, ** p<0.05, * p<0.1*

The first column of table 6.5 reports the results of the ΔCBBE-ΔCBEF moderation SRRM model outlined in equation 6.1**.** Both the positive and negative changes in consumer based brand valuations have significant effects and in expected magnitude and directions. Consistent, to ΔCBBE *main* model, the deteriorating impact of declining CBBE is almost three times higher than the rising CBBE. Surprisingly, the elasticity of the moderating effect of CBEF on rising CBBE-firm performance relationship is negative but is not significant ($p > .10$). In contrary, the interaction effect of core business efficiency between negative CBBE changes and stock returns is significant with the predicted sign (-0.96, $p < .10$). These results signify that changes in firm's core business efficiency levels have an inverse moderating effect on the declining CBBE-firm value relationship. In other words, a positive change in CBEF tend to mitigate the impulsive effect of sudden decline in CBBE on firm's expected future performance. Since the moderating role of ΔCBEF on the positive side is insignificant, theoretical arguments made in hypothesis H5(a) are partially supported.

The significance and direction of economy-wide risk loadings and firm specific risk factors are consistent with the findings of the *main* ΔCBBE SRRM model. Neither ΔROA nor ΔCBEF have any significant direct effects which may be due to the pre-determined high co-association between them. To further examine if this pairwise collinearity issue has affected the estimated coefficients, model equation 6.1 is re-estimated after excluding UΔROA. The second column of table 6.5 reports the results for the corrected model. The coefficient of interaction between ΔCBEF and negative CBBE changes has slightly increased from -0.96 to -1.13 but is still significant ($p < .10$). The main difference between the two models is that the significance of the direct effect of ΔCBEF on stock returns is now significant in the absence of UROA ($p < .05$).

Table 6.5 Empirical results for ΔCBBE CBEF Model

Panel: A	Rt - Rf *(Fixed-Effect)*	Rt – Rf *(without UΔROA)* *(Fixed-Effect)*
ΔPos CBBE	.206**	.214**
	(.089)	(.09)
ΔNeg CBBE	.568***	.543***
	(.141)	(.143)
ΔCBEF	.118	.161**
	(.08)	(.069)
ΔPos CBBE X ΔCBEF	-.496	-.483
	(.487)	(.481)
ΔNeg CBBE X ΔCBEF	-.957*	-1.131*
	(.569)	(.60)
UΔROA	.69	
	(.622)	
MktRf	.269***	.275***
	(.088)	(.088)
SMB	.022	.027
	(.165)	(.167)
HML	.256*	.257*
	(.15)	(.148)
MOM	.019	.047
	(.154)	(.154)
Loglag_MV	-.203**	-.215**
	(.099)	(.099)
Loglag_B2M	.166	.132
	(.117)	(.106)
Sales Growth	.245	.279
	(.201)	(.199)
Leverage	.001	-.001
	(.004)	(.003)
Intercept	2.374**	2.497**
	(1.07)	(1.074)
N	460	460
F-Test (Model)	5.74***	5.79***
R-squared	0.46	0.46
Adj. R-squared	0.38	0.38
Panel: B		
LM Test	0.00	0.00
F-Test (Fixed Effects)	1.47**	1.43**
Hausman Test	59.38***	55.75***

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

This statistical significance of ΔCBEF indicates that change in firm's core business efficiency drives stock returns only when there is no change in the annual CBBE brand valuation. The significance, polarity, and magnitude of all other independent variables in U∆ROA-free model closely match with the original model. Both the models are estimated through fixed effect regression to account for the presence of unobserved heterogeneity across sample firms. The choice of the estimator is driven by the outcomes of the "best model fit" tests, the results for which are reported in table 6.5, panel B.The dynamics of the moderating role of CBEF will be investigated further but before doing it, post estimations diagnostics tests are conducted. This is to ensure that the estimated model abide by the OLS assumptions and is robust to influential variables and alternative measure of firm performance.

6.4.1.1 Post-estimation Diagnostics Tests

In order to maintain consistency throughout the analysis, all the post estimation tests carried out in the first phase of analysis are imposed on the organizational efficiency moderation models proposed in analysis phase 2. Firstly, both Wooldridge (2012) and modified Wald tests (Greene, 2000) indicate the presence of serial correlation (F statistic: 4.11, $p<0.05$) and heteroscedasticity (Chi sq.: 495.90, $p<0.001$). Thus, clustered-robust standard errors are obtained and reported in table 6.5**.** Multicollinearity amongst the explanatory variables is detected through the variance inflation factor approach. Table 6.6 reports the VIF scores for each dependent variables with all the values in the acceptable range, suggesting absence of any multicollinearity issues.

Table 6.6 VIF scores

Variable	VIF Score
ΔPos CBBE	1.29
ΔNeg CBBE	1.23
ΔCBEF	1.71
MktRf	2.10
SMB	1.28
HML	2.28
MOM	1.38
LogLag_MV	1.08
LogLag_B2M	1.20
UΔROA	1.63
Sales Growth	1.27
Leverage	1.20
Mean VIF	**1.47**

The next step is to examine if the obtained estimates and their statistical inferences are influenced due to the presence of any outlying observations. Since the model is estimated through a fixed effect, "within" Z-scores are calculated for the detection of univariate outliers and reported in table 6.7. The highest negative dispersion is observed in ΔNeg CBBE whereas leverage has the extreme positive Z-score. Since all the scores are below the threshold value of 3, the obtained data is not contaminated with any univariate outliers.

Table 6.7 Univariate outlier detection

	Min Z-Score	Max Z-Score
ΔPos CBBE	-1.71	2.82
ΔNeg CBBE	-2.85	1.30
ΔCBEF	-2.71	2.65
MktRf	-1.60	1.34
SMB	-2.01	1.76
HML	-1.20	1.63
MOM	-1.72	1.55
LogLag_MV	-2.34	2.06
LogLag_B2M	-2.52	2.38
Leverage	-2.08	2.84
UΔROA	-2.76	2.21
Sales Growth	-2.75	2.73

In order to deal with panel data contamination issues caused due to the presence of multivariate outliers, fixed-effect robust estimation procedure proposed by Veradi and Wanger (2011) is adopted. After median-centring all the variables in the ΔCBBE-ΔCBEF moderation model defined in equation 6.1, standardized residuals are obtained from the robust S-estimator regression. Flagging the observations with absolute standardized error values above two, 39 multivariate outliers are detected representing 8.5% of the total sample. These contaminated observations are then allocated zero analytical weights and the model is re-estimated with fixed effect regression. Table 6.8 provides the results of the robust regression without the outlying multivariate observations. The magnitude, direction, and significance of the variables of interest i.e. ΔCBEF interaction effects is consistent with the full sample estimation results. The coefficient of "ΔNeg CBBE X ΔCBEF" however is slightly higher with lower significance level (-1.16, $p<.05$) which can be attributed to the presence of "high leverage points" in the original sample.

The regression estimates and significance of all other explanatory variables are also comparable to estimated model with outliers. Furthermore, a rise in adjusted R-squared from 0.38 to 0.44 imply that the explanatory power of the estimated model has increased in the absence of multivariate outliers. In sum, the findings from the fixed effect robust estimation indicates that the interaction effect size of core business efficiency on negative CBBE changes is not contaminated by the presence of multivariate outliers.

Table 6.8 ΔCBBE-ΔCBEF Model Robust-Estimation Results

	Rt - Rf *(Robust Estimation)*
ΔPos CBBE	.159**
	(.078)
ΔNeg CBBE	.514***
	(.132)
ΔCBEF	.081
	(.06)
ΔPos CBBE X ΔCBEF	-.491
	(.383)
ΔNeg CBBE X ΔCBEF	-1.164**
	(.562)
MktRf	.262***
	(.064)
SMB	.126
	(.134)
HML	.155
	(.157)
MOM	0
	(.138)
Loglag_MV	-.044
	(.079)
Loglag_B2M	.14
	(.103)
UΔROA	.021
	(.494)
Sales Growth	.393**
	(.162)
Leverage	-.001
	(.003)
Intercept	.618
	(.851)
N	421
F-Test (Model)	6.47***
R-squared	0.51
Adj. R-squared	0.44

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

The final step is to affirm if the estimated model is robust to alternate firm performance measures. Similar to analysis phase-I, abnormal stock return SRRM model has been adopted and is expressed as:

$$\begin{aligned} \mathrm{Abnr\_Ret}_{\mathbf{iT}} = \alpha \; &+ \beta_1 \Delta \mathrm{Pos\_CBBE}_{\mathbf{iT}} + \beta_2 \Delta \mathrm{Neg\_CBBE}_{\mathbf{iT}} + \beta_3 \Delta \mathrm{CBEF}_{\mathbf{iT}} \\ &+ \beta_4 \Delta \mathrm{Pos\_CBBE}_{\mathbf{iT}} \mathrm{\ X\ } \Delta \mathrm{CBEF}_{\mathbf{iT}} \\ &+ \beta_5 \Delta \mathrm{Neg\_CBBE}_{\mathbf{iT}} \mathrm{\ X\ } \Delta \mathrm{CBEF}_{\mathbf{iT}} + \beta_6 \mathrm{U} \Delta \mathrm{ROA}_{\mathbf{iT}} \\ &+ \beta_7 \mathrm{U} \Delta \mathrm{Sales}_{\mathbf{iT}} + \beta_8 \mathrm{LEV}_{\mathbf{iT}} + \varepsilon_{\mathbf{iT}} \end{aligned} \tag{6.2}$$

Where, $\mathrm{Abnr\_Ret}_{iT}$ is obtained as the residuals after regressing Fama-French (1996)-Carhart (1997) loading factors and Daniel and Titman (1997) firm based risk characteristics on the annual raw returns of firm i in year T. The time “T” represents the yearly time window corresponding to BrandZ brand valuation release waves. All the other variables are the same as defined in model equation 6.1**.** The empirical results of the abnormal stock return model are reported in table 6.9**.** Consistent with the main and robust-estimation models, the abnormal return model also implies that higher levels of CBEF mitigates the negative impact of declining consumer based brand equity on firm performance (β= -1.03, p<0.10). The moderating role of core business efficiency in case of a positive CBBE change is opposite as hypothesized, but not significant which accords with the previous findings. These results along with other diagnostic tests affirm that the findings of the estimated ΔCBEF-ΔCBBE moderation model for 46 sample brands are reliable and unbiased.

Table 6.9 ΔCBBE-ΔCBEF Abnormal Returns model results

	Abr_Rt *(Fixed-Effect)*
ΔPos CBBE	.187**
	(.091)
ΔNeg CBBE	.507***
	(.131)
ΔCBEF	.128*
	(.072)
ΔPos CBBE X ΔCBEF	-.514
	(.476)
ΔNeg CBBE X ΔCBEF	-1.028*
	(.565)
UΔROA	1.113*
	(.617)
Sales Growth	.14
	(.185)
Leverage	.001
	(.002)
Intercept	-.01
	(.013)
N	460
F-Test (Model)	6.36***
R-squared	.45
Adj. R-squared	.38

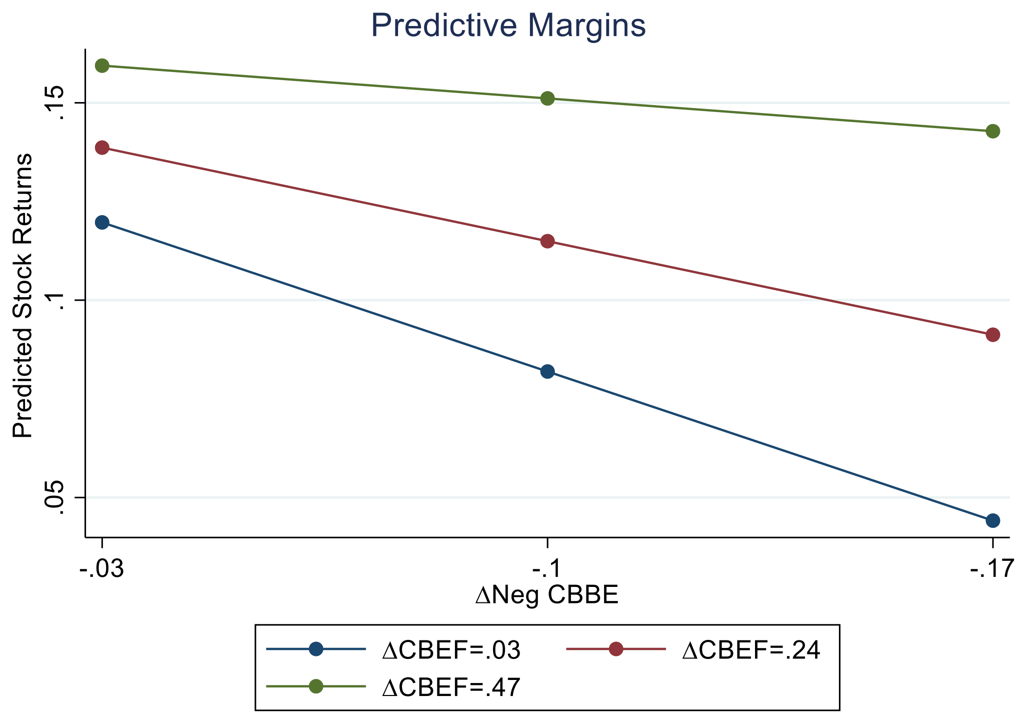
Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

After validating the estimations of the CBEF moderation model from multiple dimensions, focus can now be shifted on visualizing the interaction effects of CBEF on negative CBBE changes. This is illustrated in figure 6.4. Following the *spotlight analysis* approach proposed by Aiken and Stephen (1991), the moderating effects of ΔCBEF on the relationship between declining CBBE and stock returns are shown at the mean and two increments of standard deviation (1 SD and 2 SD)[33]. The figure demonstrates how positive changes in firm's core business efficiency weakens the negative effects of declining FBBE on stock returns. For example, the slope of negative relationship between declining CBBE and stock returns is much steeper during an

[33] Although Aiken and Stephen (1991) took one SD above and below the mean, this approach is not feasible in the case of ΔNeg CBBE since it is a directional variable with only negative values.

average 3% change in CBEF as compared to its change by 2 standard deviations above the mean (47%). In business terms, this suggest that the higher the change in the firm's core business efficiency levels, the higher is the confidence of investors and shareholders towards the firm's future prospects, even during a sudden fall in its brand's strength.

Figure 6.4 ΔCBEF-ΔCBBE Interaction Effects Margin Plot

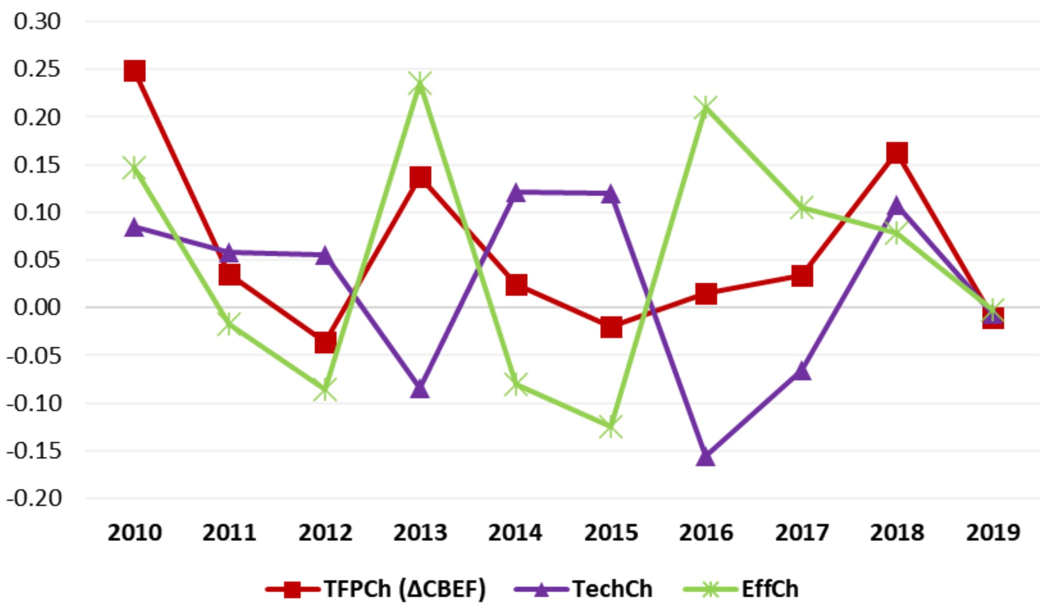


Source: Author's elaboration

6.4.2 DEA Results for CBEF and its interaction effects in Δ*FBBE SRRM Model*

This section focusses on examining the role of CBEF in moderating the relationship between rising and declining financial based brand equity. Due to the exclusion of the firms with negative inputs or outputs, the final sample includes 44 brands for the period of 2010 till 2019, thus comprising of 440 firm-year observations. Figure 6.3 presents the dynamics of Malmquist total factor productivity change over the 10 year period along with its components of efficiency change and technical change. On average, firms have experienced a positive change in their core business efficiencies in the entire 10 year period. Comparatively, the upside volatility of FBBE sample based CBEF change is higher as compared to the CBBE sample especially in 2010 and 2018 where they have crossed the 15% mark. However, there has been a steep decline in technology for FBBE firms when CBBE based technology has shown no such pattern. In contrary, the average efficiency performance of FBBE sample firms has performed well with comparatively higher instances of yearly growth than declines. Another notable dynamics in fig. 6.5 is whenever there is a strong variation within yearly changes in efficiency and technological components (e.g. in 2013 and 1016), the TFPch always gets drawn towards the component experiencing higher dispersion. This is because of the computational structure of total factor productivity change which is the product of efficiency and technological change.

Figure 6.5 CBEF Malmquist productivity index and its components for FBBE firms



Source: Author's elaboration

The stock return response model to examine the translating effects of changes in firm's core business efficiency on FBBE-firm value relationship focusing exclusively on positive and negative brand equity changes is defined as:

$$\begin{aligned} R_{iT} - R_f = \alpha &+ \beta_1 \Delta Pos\_FBBE_{iT} + \beta_2 \Delta Neg\_FBBE_{iT} + \beta_3 \Delta CBEF_{iT} \\ &+ \beta_4 \Delta Pos\_FBBE_{iT} \text{ X } \Delta CBEF_{iT} \\ &+ \beta_5 \Delta Neg\_FBBE_{iT} \text{ X } \Delta CBEF_{iT} + \beta_R Risk_T + \beta_6 U\Delta ROA_{iT} \\ &+ \beta_7 U\Delta Sales_{iT} + \beta_8 LEV_{iT} + \varepsilon_{iT} \end{aligned} \quad (6.3)$$

Where,

$R_{iT} - R_f$ = Annual raw returns of firm "i" in year T adjusted for yearly risk-free rate;

ΔPos_FBBE_{iT} = Continuous variable capturing positive changes in Brand Finance brand values of firm "i" in year T;

ΔNeg_CBBE_{iT} = Continuous variable capturing negative changes in Brand Finance brand values of firm "i" in year T;

$\Delta CBEF_{iT}$ = Change in core business efficiency of firm "i" in year T.

$RISK_T$ = Vector of all the yearly risk factors defined in FBBE baseline and main models earlier;

$U\Delta ROA_{iT}$ = Unanticipated component of earnings for firm "i" in year T;

$U\Delta Sales_{iT}$ = Sales growth of firm "i" in year T;

LEV_{iT} = Leverage of firm "i" in year T;

ε_{iT} = idiosyncratic error term;

T = Year encompassing Brand Finance brand value announcement wave.

Table 6.10 presents the descriptive summary statistics for all the explanatory and response variables included in the model. Annual raw returns have a mean of 12% and standard deviation of 26%, suggesting a wide dispersion in their cross-sectional values across the sample firms. Consistent with the prior FBBE models, the frequency of positive changes is three times higher as compared to negative changes. Even the volatility of positive FBBE changes is thrice as compared to negative changes (0.18 vs 0.06), with a maximum yearly rise recorded as 139% compared to a decline of -39%. The average change in the sample firms core business efficiency levels is 0.06 and the standard deviation is 0.37 suggesting a large variation. This is also evident in the divergence between the positive and negative CBEF changes which range from -0.68 to 4.22. This higher volatility co-aligns with the visual dynamics of the Malmquist total factor productivity observed in figure 6.5, where the index has experienced violent changes in some years. All the other control variables show almost similar characteristics as witnessed in the previously estimated FBBE models.

Table 6.10 Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max
Stock Return	440	0.12	0.26	-0.48	1.68
ΔPos FBBE	328	0.14	0.18	0.00	1.39
ΔNeg FBBE	112	-0.03	0.06	-0.00	-0.39
ΔCBEF	440	0.06	0.37	-0.68	4.22
MktRf	440	0.13	0.15	-0.09	0.39
SMB	440	0.01	0.05	-0.08	0.09
HML	440	-0.01	0.07	-0.08	0.13
MOM	440	0.02	0.16	-0.41	0.19
Loglag MV	440	11.05	0.30	10.14	11.93
Loglag B2M	440	-0.32	0.37	-2.25	0.72
UΔROA	440	-0.00	0.02	-0.13	0.11
Sales Growth	440	0.02	0.05	-0.23	0.22
Leverage	440	1.57	2.48	0.00	39.69

Table 6.11 outlines the pairwise correlation coefficients of all the explanatory variables with the response variable and between each other. Along with already established link of rising and declining FBBE, core business efficiency changes also exhibit a significant positive relationship with stock returns. This can be because a competitive management can convey their actions and strategies clearly to the financial community, thus retaining the existing shareholders and attracting new investment opportunities. However, the aim of the study is to examine whether rising (declining) CBEF levels enhance (mitigate) the financial impact of positive (negative) FBBE changes. The association of ΔCBEF with unanticipated changes in ROA is positive and significant (0.39, $p<.10$) which is logical as they both share comparable input-output characteristics. However, the magnitude of its coefficient is far less as compared to that observed in the ΔCBBE-CBEF model (0.56, $p<0.10$). It can be either due to different yearly window for FBBE-CBEF estimation or the presence of dissimilar firms in the two samples. In either case, the coefficient lies in the acceptable range and thus does not pose any collinearity issues. All the other pairwise correlation coefficients are having expected magnitude and direction, with strong association between FF-C factors as expected.

Table 6.11 Pairwise corelation Matrix for ΔFBBE CBEF model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) R_T - R_f	1.00												
(2) ΔPos FBBE	0.35*	1.00											
(3) ΔNeg FBBE	0.22*	0.33*	1.00										
(4) ΔCBEF	0.22*	0.05	-0.04	1.00									
(5) MktRf	0.54*	0.21*	0.07	0.19*	1.00								
(6) SMB	0.39*	0.22*	0.00	0.11	0.69*	1.00							
(7) HML	0.30*	0.14	0.06	0.09	0.54*	0.52*	1.00						
(8) MOM	-0.30*	-0.18*	-0.06	-0.12	-0.40*	-0.38*	-0.27*	1.00					
(9) Loglag MV	-0.25*	-0.12	-0.05	-0.07	-0.22*	-0.21*	-0.11	0.21*	1.00				
(10) Loglag B2M	0.05	0.04	-0.03	0.12	0.10	0.09	0.05	-0.10	-0.30*	1.00			
(11) UΔROA	0.21*	0.12	-0.01	0.39*	0.21*	0.15	0.05	-0.08	-0.05	-0.01	1.00		
(12) Sales Growth	0.31*	0.27*	0.04	0.15	0.26*	0.33*	0.00	-0.07	-0.07	-0.14	0.33*	1.00	
(13) Leverage	-0.05	-0.02	0.00	0.13	-0.05	0.00	-0.01	0.02	-0.10	-0.25*	-0.06	-0.07	1.00

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

The empirical results for the CBEF-FBBE interaction model outlined in equation 6.3 are reported in table 6.12, panel A. The elasticity of the impact of upward shifts in FBBE on stock returns is positive but insignificant. The estimated coefficient of declining FBBE is however significant with a much larger value as compared to positive change. From the interaction perspectives, the first coefficient of interest i.e. β_4 is positive and statistically significant (0.64, $p<0.001$). These novel findings indicate that yearly changes in core business efficiency reinforces the positive FBBE-firm performance relationship. However, no such moderating effect can be seen during negative changes in financial based brand equity. The elasticity of interaction between negative FBBE changes and ΔCBEF is in the expected direction but insignificant from statistical perspective (β_5=-0.68, $p>0.10$). From the developed hypothesis perspective, it suggests that changes in firm's core business efficiency enhance the positive impact of rising FBBE on firm future performance. Therefore H5(b) is partially supported, only in the positive direction. Furthermore, these findings are exactly opposite to that of the CBBE-CBEF moderation model where H5(a) is significant in the negative direction. In comparable terms, it can be stated that core business efficiency synergizes the positive effects of FBBE and mitigates the deteriorating effects of declining consumer centric brand equity. One explanation of this relatively "opposite side" effects can be due to the nature of BrandZ and Brand Finance estimation methodology. Brand Finance brand valuations predominantly focus on earnings and expert views in estimating brand's monetary strength (thus used as a proxy of FBBE in this study). A positive change in firm's core business efficiency reflect improved earnings given the same level of available physical and human resources, which would in-turn elevate its estimated brand values. These higher brand valuations further enhance the stock market expectations of the firm's future performance, thus impacting stock returns.

The direction and magnitude of other significant control variables are in the expected directions. The earnings response coefficient is positive and significant with its magnitude much higher as compared to the marketing variables under investigation (β = 1.11, $p<0.10$). This further suggest that the information content of accounting performance is one of the decisive factors in firm's future growth prospects. Negative coefficient of LogLag_MV (β = -0.45, $p<0.10$) suggests that firm size is negatively related to stock returns, which is well documented in existing finance (Astakhov et al., 2019). Similarly, as per capital asset pricing model proposed by Sharpe (1994), broader market index returns (MktRf) are reliable predictor of its constituent firm's expected future returns (β = 0.65, $p<0.10$). Both the LSDV based F-test and Hausman test favours fixed effect estimator over random effect and pooled OLS. The results for all the three tests are reported in panel B of table 6.12.

Table 6.12 Empirical results for ΔFBBE CBEF Model

Panel: A	Rt - Rf *(Fixed-Effect)*
ΔPos FBBE	.025
	(.061)
ΔNeg FBBE	.686***
	(.174)
ΔCBEF	-.061
	(.098)
ΔPos FBBE X ΔCBEF	.638***
	(.223)
ΔNeg FBBE X ΔCBEF	-.683
	(.555)
MktRf	.649***
	(.072)
SMB	-.268
	(.238)
HML	.17
	(.16)
MOM	.019
	(.07)
Loglag_MV	-.445**
	(.166)
Loglag_B2M	.114
	(.131)
UΔROA	1.112*
	(.601)
Sales Growth	.133
	(.295)
Leverage	.004
	(.004)
Intercept	5.001***
	(1.808)
N	440
F-Test (Model)	8.04***
R-squared	.55
Adj. R-squared	.48
Panel: B	
LM Test	0.00
F-Test (Fixed Effects)	2.34***
Hausman Test	114.45***

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

6.4.2.1 Post-estimation Diagnostics Tests

The results of Wooldridge (2012) test for autocorrelation (F statistic: 27.39, $p<0.001$) and modified Wald test for heteroscedasticity (Chi sq.: 1156.15, $p<0.001$) indicates the violation of the OLS assumption of error independence and homoscedasticity. The obtained standard errors are therefore clustered across 44 panels to obtain the robust statistical estimates (and reported in table 6.12). Table 6.13 reports the individual VIF scores for all the explanatory variables included in the model. The highest VIF scores are exhibited by FF-C risk factors which is expected based on their high pairwise collinearity. All the estimated VIFs are however below 3 with an average of 1.48. Thus, no issues of multicollinearity can be established.

Table 6.13 VIF Scores

	VIF Score
ΔPos FBBE	1.27
ΔNeg FBBE	1.15
ΔCBEF	1.30
MktRf	2.32
SMB	2.32
HML	1.59
MOM	1.27
LogLag_MV	1.24
LogLag_B2M	1.33
UΔROA	1.32
Sales Growth	1.44
Leverage	1.20
Mean VIF	**1.48**

The next step is the detection of any influential observations in the prepared dataset. Table 6.4 reports the within Z-scores for all the independent variables. There is no observation with its estimate score beyond the value of +/- 3 indicating the absence of any univariate outliers.

Table 6.14 Univariate outlier detection

	Min Z-Score	Max Z-Score
ΔPos FBBE	-1.80	2.84
ΔNeg FBBE	-2.85	0.82
ΔCBEF	-2.72	2.74
MktRf	-1.42	1.69
SMB	-1.54	1.43
HML	-0.99	1.94
MOM	-2.50	0.98
LogLag_MV	-2.78	2.02
LogLag_B2M	-2.51	2.72
Leverage	-2.08	2.50
UΔROA	-2.69	2.22
Sales Growth	-2.37	2.47

Similar to CBBE-CBEF model, the presence of multivariate outliers and its effects on the statistical inferences is examined through employing the robust S-estimator on the median centred panel data. The regression output flagged 49 multivariate influential observations having their standardized residuals above and beyond the threshold value of 2 (Veradi & Wanger, 2011). After de-contaminating the original panel sample by allocating zero weights to the outliers, the model equation 6.3 is re-estimated with fixed-effect estimator. The results of this roust estimation is provided in the table 6.15. Broadly, the findings are consistent with the full sample results, especially the coefficients of interest i.e. significantly positive β_4 (0.41, $p<0.10$) and negative yet insignificant β_5 (-.68, $p>0.10$). The magnitude and direction of other significant explanatory variables is also in-line with the findings of the model with outliers. It can therefore be concluded that even though the original sample with 440 firm-year observations is contaminated with multivariate outliers, their impact on the estimated elasticities is not significant.

Table 6.15 ΔCBBE-ΔCBEF Model Robust-Estimation Results

	Rt - Rf *(Robust Estimation)*
ΔPos FBBE	.051
	(.051)
ΔNeg FBBE	.503***
	(.178)
ΔCBEF	.054
	(.071)
ΔPos FBBE X ΔCBEF	.406*
	(.227)
ΔNeg FBBE X ΔCBEF	-.288
	(.677)
MktRf	.595***
	(.067)
SMB	-.372**
	(.18)
HML	.24**
	(.101)
MOM	-.012
	(.052)
Loglag_MV	-.351***
	(.088)
Loglag_B2M	.008
	(.076)
UΔROA	1.366**
	(.522)
Sales Growth	.097
	(.202)
Leverage	.001
	(.003)
Intercept	3.913***
	(.963)
N	391
F-Test (Model)	10.50***
R-squared	0.69
Adj. R-squared	0.59

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

Finally, the moderating role of core business efficiency on directional changes in financial brand equity is estimated through an alternative measure of firm performance i.e. abnormal stock returns:

$$\begin{aligned}\mathrm{Abnr\_Ret_{iT}} = \alpha\ &+ \beta_1 \Delta\mathrm{Pos\_FBBE_{iT}} + \beta_2 \Delta\mathrm{Neg\_FBBE_{iT}} + \beta_3 \Delta\mathrm{CBEF_{iT}} \\ &+ \beta_4 \Delta\mathrm{Pos\_FBBE_{iT}}\ \mathrm{X}\ \Delta\mathrm{CBEF_{iT}} \\ &+ \beta_5 \Delta\mathrm{Neg\_FBBE_{iT}}\ \mathrm{X}\ \Delta\mathrm{CBEF_{iT}} + \beta_6 \mathrm{U}\Delta\mathrm{ROA_{iT}} \\ &+ \beta_7 \mathrm{U}\Delta\mathrm{Sales_{iT}} + \beta_8 \mathrm{LEV_{iT}} + \varepsilon_{\mathrm{iT}}\end{aligned} \tag{6.4}$$

The abnormal stock returns represent the residuals obtained from the Fama-French (1994) and Carhart (1997) fixed-effect regression including Daniel and Titman (1996) firm risk factors of size and book-to-market. Table 6.16 provides the empirical results of the estimated model. The obtained elasticities, their direction and significance are coherent to that of the model equation 6.3 for all the explanatory variables of interest. These outcomes further affirms that the novel findings that changes in firm's core efficiency augments the positive ∆FBBE-firm performance relationship is robust to alternative firm value measures, influential observations, and other statistical anomalies.

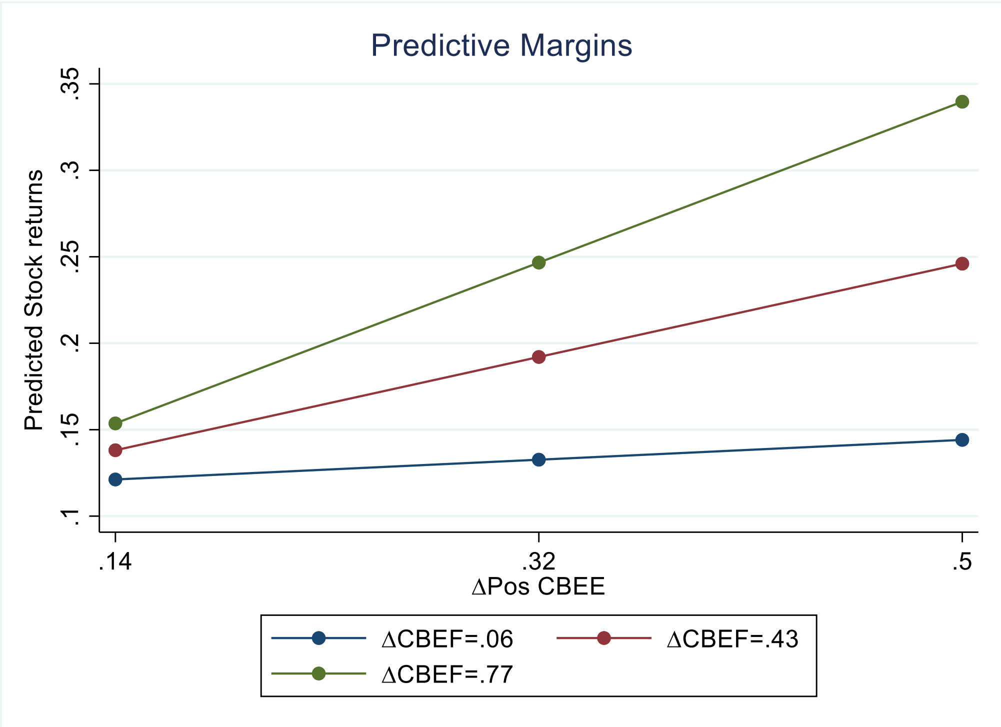
Table 6.16 ∆CBBE-∆CBEF Model Robust-Estimation Results

	Abr_Rt *(Fixed-Effect)*
∆Pos FBBE	.004
	(.053)
∆Neg FBBE	.686***
	(.171)
∆CBEF	-.063
	(.093)
∆Pos FBBE X ∆CBEF	.588***
	(.219)
∆Neg FBBE X ∆CBEF	-.693
	(.501)
U∆ROA	1.085*
	(.588)
Sales Growth	.033
	(.257)
Leverage	.005***
	(.002)
Intercept	.004
	(.009)
N	440
F-Test (Model)	7.96***
R-squared	0.51
Adj. R-squared	0.45

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

The predictive margin plot shown in figure 6.6 further demonstrates how favourable changes in firm's core business efficiency compliments the ΔCBBE-firm performance interface. This can be realized by looking at the change in the relationship slope of ΔPos FBBE and stock returns when MCAP increases to 43% (1 SD) and 77% (2 SD) above its mean value of 6%. The slope experiences a consistent rise with every positive increment in CBEF indicating the benefits of building strong core business efficiency in order to further exploit the incremental value gained from strong consumer brand association.

Figure 6.6 ΔCBEF-ΔFBBE Interaction Effects Margin Plot



Source: Author's elaboration

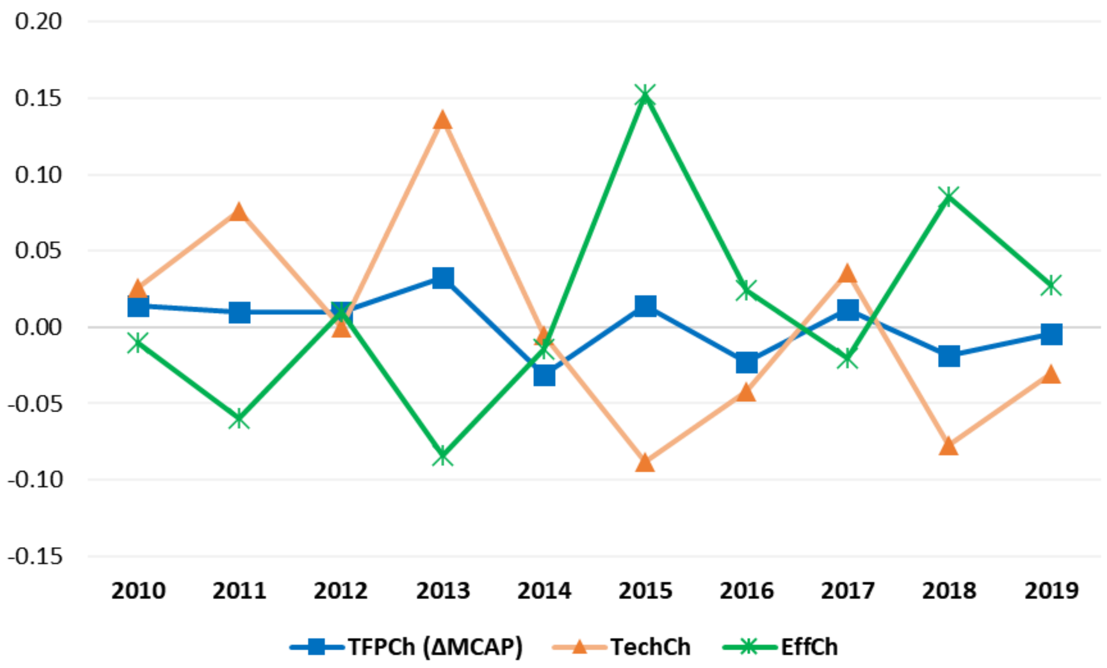
6.5 Moderating role of Marketing Capability (MCAP)

Previous sections examined as to how firm's core business efficiency moderates the link between brand equity and firm performance by presenting a polarized view of two key brand measurement metrics i.e. consumers and brand-level equity. This section determines the portion of stock price appreciation (depreciation) from positive (negative) changes in CBBE and FBBE attributable to the changes in firm's marketing capability. Marketing capability (MCAP) represents the effectiveness with which a firm can exploit its marketing resources to generate an outcome which is difficult for the competitors to translate (Sun et al. 2019). This organization level construct aligns well with the central tenet of resource based theory that firms should strategically employ their available sources to achieve sustained competitive advantage (Lin & Wu, 2014). Building superior levels of marketing capability takes years of knowledge and understanding about customer needs and other market based factors. Therefore it is expected that improvements in marketing capability over time could enable firms to mitigate the deteriorating effects of negative changes in CBBE and FBBE on firm performance. These theoretical arguments outlined in the hypotheses H6(a) and H6(b) are therefore the foundations of this part of the analysis.

6.5.1 DEA Results for MCAP and its interaction effects in ∆*CBBE SRRM Model*

The analysis begins by first visualising the temporal dynamics of the average Malmquist total factor productivity (which is a proxy of firm's marketing capability) over the 10 year study period. Figure 6.7 presents the average TFPCh (∆MCAP) for all the 36 sample firms each year along with the sub-components of efficiency and technological changes.

Figure 6.7 MCAP Malmquist productivity index and its components for CBBE firms



Source: Author's elaboration

Despite high volatility in efficiency and technological change, the overall TFPch has shown a stable performance in all these years. This stability can be broadly attributed to the counteractive effects of TechCh and EffCh which have also demonstrated some interesting patterns over time. For example, in the first half of the 10 year period, efficiency change has shown downside volatility which is exactly opposite to that experienced by technological change. Referring this phenomenon back to the figure 4.4 in the methodology chapter, it indicates that during these years the decline in average firm efficiencies is predominantly due to a positive shift in the efficiency frontier. The pattern has reversed in the subsequent half, where the technology has largely experienced a decline whereas average efficiency has displayed an opposite effect. These significant improvements in the firm efficiencies during these periods can therefore be partially attributed to the downswing in the efficiency frontier itself. Overall, the behaviour of the Malmquist productivity index over the 10 year period indicates two things. Firstly, on average, all the 36 CBBE sample firms have exhibited streamlined yearly performance in their marketing capabilities. Secondly, in some years, some firms have outperformed their peers either due to a significant change in either their internal efficiency or taking advantage of the available technology at that time. It will be interesting to explore if the resulting change in their overall marketing capability mitigates the negative effects of declining brand equity on firm's future performance. In order to answer this question, the interaction effects of MCAP are statistically examined by the following stock return response model:

$$\begin{aligned} R_{i\mathbf{T}} - R_f = \alpha \ &+ \beta_1 \Delta Pos\_CBBE_{i\mathbf{T}} + \beta_2 \Delta Neg\_CBBE_{i\mathbf{T}} + \beta_3 \Delta MCAP_{i\mathbf{T}} \\ &+ \beta_4 \Delta Pos\_CBBE_{i\mathbf{T}} \text{ X } \Delta MCAP_{i\mathbf{T}} \\ &+ \beta_5 \Delta Neg\_CBBE_{i\mathbf{T}} \text{ X } \Delta MCAP_{i\mathbf{T}} + \beta_R Risk_{\mathbf{T}} + \beta_6 U\Delta ROA_{i\mathbf{T}} \\ &+ \beta_7 U\Delta Sales_{i\mathbf{T}} + \beta_8 LEV_{i\mathbf{T}} + \varepsilon_{i\mathbf{T}} \end{aligned} \qquad (6.4)$$

Where:

$R_{iT} - R_f$ =	Annual raw returns of firm "i" in year T adjusted for yearly risk-free rate;
ΔPos_CBBE_{iT} =	Continuous variable capturing positive changes in BrandZ brand values of firm "i" in year T;
ΔNeg_CBBE_{iT} =	Continuous variable capturing negative changes in BrandZ brand values of firm "i" in year T;
$\Delta MCAP_{iT}$ =	Change in marketing capability of firm "i" in year T.
$RISK_T$ =	Vector of all the yearly risk factors defined in CBBE baseline and main models earlier;
$U\Delta ROA_{iT}$ =	Unanticipated component of earnings for firm "i" in year T;
$U\Delta Sales_{iT}$ =	Sales growth of firm "i" in year T;
LEV_{iT} =	Leverage of firm "i" in year T;
ε_{iT} =	idiosyncratic error term;

T = Year encompassing BrandZ brand value announcement wave (June of previous year T-1 till May in current year T).

The coefficient of interest as per hypothesis H6(a) are β_4 and β_5, which captures the effectiveness of changes in firm's marketing capability in enhancing (weathering) the positive (negative) effects of rising (declining) CBBE on long-term firm performance. Before statistically evaluating the model in equation 6.4, descriptive summary of all the variables is reported in table 6.7 tabulating their frequency, average, volatility, highest and the lowest value. The instances of positive changes in CBBE are much higher as compared to negative changes. This is expected as these 36 sample firms are basically the sub-set of the "main-effects" CBBE sample which have shown similar dynamics. The average change in firm's marketing capability is close to zero (for up to 2 decimal places). This statistic closely aligns with the overall stable performance of ΔMCAP as seen in figure 6.7. Similarly, consistent with the visual dynamics, firms have experienced high dispersion in their marketing capability across the mean with highest and lowest percentage change being +110% and -67%, respectively.

Table 6.17 Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max
Stock Return	360	0.12	0.21	-0.60	0.80
ΔPos CBBE	247	0.16	0.14	0.001	0.74
ΔNeg CBBE	113	-0.10	0.08	-0.001	-0.38
ΔMCAP	360	0.00	0.14	-0.67	1.10
MktRf	360	0.11	0.14	-0.12	0.30
SMB	360	0.00	0.05	-0.11	0.10
HML	360	-0.02	0.07	-0.10	0.10
MOM	360	0.06	0.05	-0.04	0.15
Loglag MV	360	10.96	0.30	10.01	11.92
Loglag B2M	360	-0.49	0.41	-2.26	0.22
UΔROA	360	-0.00	0.04	-0.12	0.13
Sales Growth	360	0.02	0.05	-0.33	0.15
Leverage	360	1.10	3.27	-15.55	39.69

Table 6.18 presents the matrix exploring the pairwise correlation between explanatory and response variables. The direct relationship between changes in marketing capability and stock prices is positive but weak and statistically insignificant ($b = 0.06$, $p>.10$). This suggest although firms' level of marketing capability and its financial performance move in the same direction, but they are not closely associated with each other. The polarity and significance of correlation coefficients of other explanatory variables with stock returns is also consistent with prior evaluations. The pairwise correlation coefficients between all other independent variables are within the acceptable range (except the expected Fama-French risk factors of MktRf and HML $b=0.61$, $p<.10$). Since these factors are only time-varying, overall, it can be affirmed that the estimated model is free of any cross-sectional collinearity issues.

Table 6.18 Pairwise corelation Matrix for CBBE MCAP model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) R_T - R_f	1.00												
(2) ΔPos CBBE	0.38*	1.00											
(3) ΔNeg CBBE	0.23*	0.38*	1.00										
(4) ΔMCAP	0.06	0.03	0.00	1.00									
(5) MktRf	0.36*	0.11	0.11	0.04	1.00								
(6) SMB	0.26*	0.08	-0.04	0.00	0.38*	1.00							
(7) HML	0.26*	0.02	-0.06	0.04	0.61*	0.36*	1.00						
(8) MOM	-0.01	0.09	0.10	-0.02	0.04	0.02	-0.36*	1.00					
(9) Loglag MV	-0.22*	0.04	0.09	-0.09	-0.16	-0.20*	-0.15	0.01	1.00				
(10) Loglag B2M	-0.08	-0.18*	-0.15	0.06	0.08	0.06	0.08	-0.01	-0.15	1.00			
(11) UΔROA	0.22*	0.14	-0.02	0.30*	0.16	0.23*	0.12	0.01	-0.06	-0.06	1.00		
(12) Sales Growth	0.39*	0.29*	0.14	-0.05	0.26*	0.17	0.09	0.03	-0.08	-0.13	0.19*	1.00	
(13) Leverage	-0.09	-0.04	0.00	-0.05	-0.02	0.00	0.00	-0.07	0.00	-0.28*	-0.11	-0.01	1.00

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6.19, panel A, reports the empirical results for the MCAP moderation model outlined in equation 6.4. The stock market effects of positive and negative changes in CBBE in the absence any MCAP shifts are significant and in expected directions. Changes in marketing capability however has no direct effects on stock returns (β_3 = -.052, p>.10). The ΔMCAP interaction response on declining CBBE has a negative sign and is statistically significant (β_5= -1.68, p<0.10). These novel findings therefore support the theoretical underpinnings of H6(a) that higher levels of marketing capability mitigate the deteriorating effects of negative changes in CBBE on firm performance. In other words, firms efficient of exploiting their marketing resources to retain or enhance their consumer-base are favoured by the stock market community even during a sudden decline in their CBBE valuations. The moderating effects of MCAP, however, are negative yet insignificant during a positive changes in consumer based brand equity. The elasticities of other significant control variables are in-line with the findings of the ΔCBBE main model. For example, unanticipated changes in earnings have a value relevance (b = 0.98, p<.10). Similarly, coefficient of firm characteristics of size (MV) is negative suggesting that smaller firms tend to be risky but generate relatively higher returns.

The panel B of table 6.19 reports the results for the tests carried out to identify best panel data estimation model. The outcomes of all the three tests are in favour of fixed effect regression over random effect or pooled OLS suggesting that the 36 firms included in the sample exhibit unobserved heterogeneity.

Table 6.19 ΔMCAP-ΔCBBE Interaction effects model results

Panel: A	Rt - Rf *(Fixed-Effect)*
ΔPos CBBE	.362***
	(.094)
ΔNeg CBBE	.381*
	(.204)
ΔMCAP	-.052
	(.093)
ΔPos CBBE X ΔMCAP	-.486
	(.693)
ΔNeg CBBE X ΔMCAP	-1.684*
	(.981)
MktRf	.208**
	(.089)
SMB	.128
	(.191)
HML	.137
	(.188)
MOM	-.141
	(.17)
Loglag_MV	-.352***
	(.091)
Loglag_B2M	.079
	(.061)
UΔROA	.984*
	(.556)
Sales Growth	.503
	(.32)
Leverage	0.00
	(.002)
Intercept	3.973***
	(.986)
N	360
F-Test (Model)	5.67***
R-squared	0.47
Adj. R-squared	0.39
Panel: B	
LM Test	0.00
F-Test (Fixed Effects)	1.46**
Hausman Test	39.74***

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

6.5.1.1 Post estimation diagnostics tests

The test results to detect the presence of serial correlation and heteroskedasticity in the estimated model are presented in the table 6.20. The outcome of the Wooldridge test

(2012) fails to reject the null hypothesis that there error terms are serially correlated. In contrary, modified Wald test proposed by Greene (2000: 598) rejects the null hypothesis that the error term is homoscedastic. In order to account for heteroscedasticity, the obtained idiosyncratic disturbances are clustered at the panel levels (Gow et al., 2009).

Table 6.20 Test results of Autocorrelation and Heteroscedasticity

Wooldridge Test (F-Statistic)	Wald-Test (Chi-Sq.)	Autocorrelation	Heteroscedasticity
2.23	244.10***	No	Yes

**** p<.01, ** p<.05, * p<.1*

Variance inflation factors to test for multicollinearity are computed for all the explanatory variables and reported in table 6.21. With all the VIF scores under the threshold value of 5, no multicollinearity issues are detected in the estimated CBBE-MCAP moderation model (Heiberger & Holland, 2015).

Table 6.21 VIF Scores

	VIF Score
ΔPos CBBE	1.29
ΔNeg CBBE	1.22
ΔMCAP	1.10
MktRf	2.07
SMB	1.29
HML	2.28
MOM	1.35
LogLag_MV	1.15
LogLag_B2M	1.82
UΔROA	1.76
Sales Growth	1.21
Leverage	1.26
Mean VIF	**1.48**

The minimum and maximum Z-scores for all the main and control variables reported in table 6.22 are below the absolute value of 3, thus indicating the absence of any univariate influential observation in the acquired panel dataset (Kannan et al., 2015).

Table 6.22 Univariate outlier detection

	Min Z-Score	Max Z-Score
ΔPos CBBE	-1.71	2.85
ΔNeg CBBE	-2.85	1.30
ΔMCAP	-2.72	2.79
MktRf	-1.60	1.34
SMB	-2.01	1.76
HML	-1.20	1.63
MOM	-1.72	1.55
LogLag_MV	-2.34	2.06
LogLag_B2M	-2.52	2.35
Leverage	-2.39	2.84
UΔROA	-2.76	2.43
Sales Growth	-2.75	2.73

In order to investigate if the acquired sample is contaminated due to the presence of multivariate outliers, firstly the longitudinal data sample is median-centred across panel and then the transformed data is estimated through S-estimator regression (Verardi & McCathie, 2012). Afterwards, following Veradi and Wanger (2011), observations with their standardized residual values outside the range of + and – 2 are flagged as multivariate outliers. The S-estimator resulted a total of 37 influential multivariate observations which accounts for 10% data contamination. In order to obtain unbiased coefficient estimates, the original model was re-estimated through fixed effects with outliers allocated zero weights. Table 6.23 reports the results of robust fixed effects regression with remaining 323 observations. The obtained estimates are broadly consistent with the contaminated model but with higher statistical significance of the variable of interest i.e. ΔNeg CBBE X ΔMCAP ($\beta_5 = -1.93$, $p<.05$). The coefficient of ΔPos CBBE X ΔMCAP is however still insignificant ($\beta_4 = -0.63$, $p>.10$). The increase in adj. R-squared from 0.39 to 0.46 further supports the increase in the explanatory power of the re-tested model without multivariate outliers. These results indicate that the findings of the model with all the 360 firm-year observations are robust to presence of any influential observations.

Table 6.23 ΔCBBE-ΔMCAP Model Robust-Estimation Results

	Rt - Rf *(Robust Estimation)*
ΔPos CBBE	.35***
	(.085)
ΔNeg CBBE	.51***
	(.172)
ΔMCAP	-.086
	(.093)
ΔPos CBBE X ΔMCAP	-.633
	(.549)
ΔNeg CBBE X ΔMCAP	-1.931**
	(.854)
MktRf	.163**
	(.071)
SMB	-.117
	(.173)
HML	.106
	(.164)
MOM	-.128
	(.155)
Loglag_MV	-.268***
	(.065)
Loglag_B2M	.012
	(.039)
UΔROA	.301
	(.407)
Sales Growth	.852***
	(.236)
Leverage	-.002
	(.002)
Intercept	3.008***
	(.707)
N	323
F-Test (Model)	6.66***
R-squared	0.54
Adj. R-squared	0.46

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

6.5.1.2 Robustness Check

To further test if the proposed MCAP interaction SRRM model is robust to alternate measure of firm performance, abnormal stock return approach is adopted (Mizik, 2014). Under this investigation, the model is estimated in two steps. Firstly, abnormal stock returns are calculated using Fama French (1996) and Carhart (1997) model, augmented with Daniel and Titman (1997) firm based risk characteristics as follows:

$$R_{iT} - R_f = \alpha + \beta_i(R_{mt} - R_f) + \beta_S(SMB_T) + \beta_H(HML_T) + \beta_M(MOM_T) + \eta_t(Size_{iT-1}) + \vartheta_t(B2M_{iT-1}) + \epsilon_{iT} \tag{6.5}$$

Where, R_{iT}-R_f is the annual raw returns of firm "i" in year T adjusted for risk free rate R_f. R_{mT}-R_f, SMB, HML and MOM represents the yearly FF-C loading factors. The firm based risk factors of $Size_{iT-1}$ is the log of previous period market value and $B2M_{iT-1}$ is the lagged book-to-market value. The time T represents the 12 month period encompassing the BrandZ annual brand value announcement yearly window. The error term ε_{iT} is the estimated abnormal stock returns ($Abnr\_Ret_{iT}$) of firm "i" in year T which are the portion of the raw returns that are over or below the expected returns after accounting for other economy wide and firm based risk factors. The above model is estimated through a fixed-effect regression in order to allow the unobserved effects across panels to correlate with the explanatory variables[34]. The abnormal return based robustness test models can then be expressed as:

$$Abnr\_Ret_{\mathbf{iT}} = \alpha + \beta_1 \Delta Pos\_CBBE_{\mathbf{iT}} + \beta_2 \Delta Neg\_CBBE_{\mathbf{iT}} + \beta_3 \Delta MCAP_{\mathbf{iT}} + \beta_4 \Delta Pos\_CBBE_{\mathbf{iT}} \text{ X } \Delta MCAP_{\mathbf{iT}} + \beta_5 \Delta Neg\_CBBE_{\mathbf{iT}} \text{ X } \Delta MCAP_{\mathbf{iT}} + \beta_6 U\Delta ROA_{\mathbf{iT}} + \beta_7 U\Delta Sales_{\mathbf{iT}} + \beta_8 LEV_{\mathbf{iT}} + \varepsilon_{\mathbf{iT}} \tag{6.6}$$

All the included main and control variables are same as in the main interaction effect model defined in equation 6.4 earlier and therefore are self-explanatory. Table 6.24 reports the pairwise correlation coefficients for all the variables. All the coefficients

[34] The choice of model is governed by the results of LSDV based F-test, LM test and Hausman test.

between the explanatory variables are within the acceptable range. Moreover, high correlation issues due to Fama-French loading factors is also not a concern in the abnormal returns model.

Table 6.24 Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Abr_Rt	1.00						
(2) ΔPos CBBE	0.39*	1.00					
(3) ΔNeg CBBE	0.27*	0.38*	1.00				
(4) ΔMCAP	0.00	0.03	0.00	1.00			
(5) UΔROA	0.27*	0.20*	0.10	0.20*	1.00		
(6) Sales Growth	0.30*	0.29*	0.14	-0.05	0.20*	1.00	
(7) Leverage	-0.04	-0.04	0.00	-0.05	-0.14	-0.01	1.00

*** *p<0.01, ** p<0.05, * p<0.1*

Table 6.25 reports the estimations for the robustness test model outlined in equation 6.6. Aligning with the stock return model, the interaction effect of MCAP in ΔPos CBBE-firm performance linkage (β_4) is negative but statistically insignificant. Similarly, the coefficient β_5 which captures the moderating role of MCAP during declining CBBE is negative and statistically significant with its magnitude almost identical to the original model. These results further support the initial novel findings that firm's marketing capability decreases the effectiveness of negative changes in CBBE on firm performance. All other estimated coefficients are also broadly consistent with the raw returns model. The only difference is that the elasticity of sales growth is positive and statistically significant (b=0.38, p<0.10). It indicates that a surprise in the top line of the income statement tend to generate excess returns in long term. However, its contribution to the firm's future cashflows is still lower than the earnings performance (b=0.86, p<0.05), which financial community perceives as key accounting performance indicator. Overall, it can be concluded that the theoretical propositions made in hypothesis H6(a) are supported even when alternative measures of firm performance are adopted.

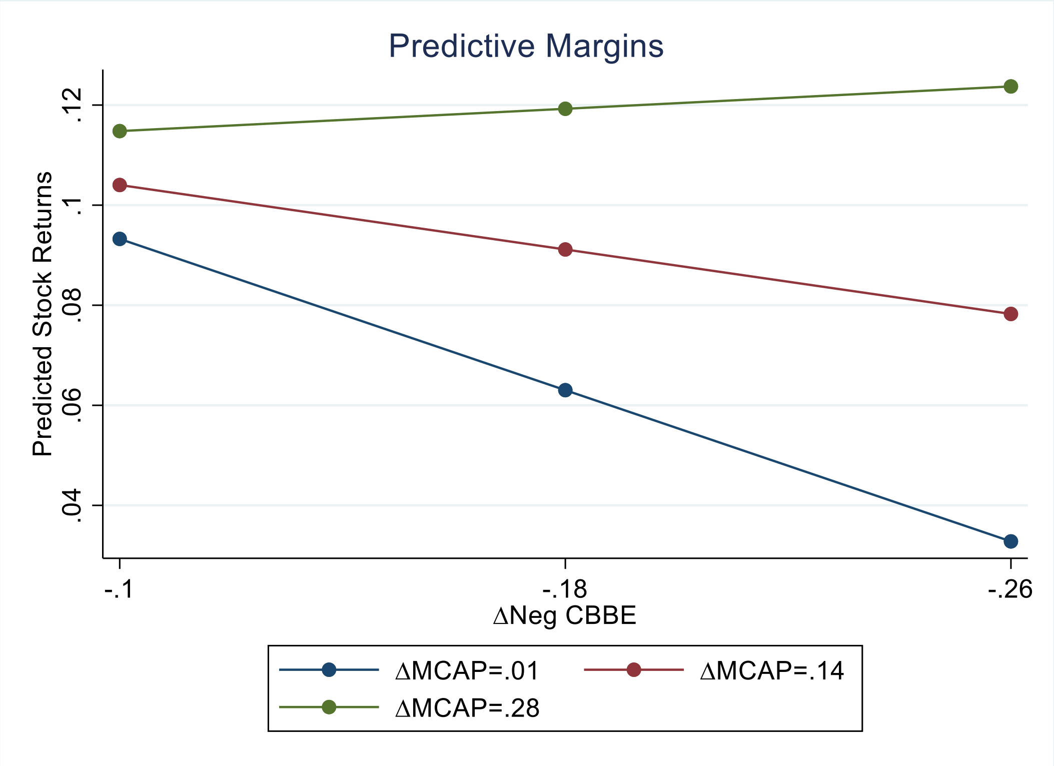
Table 6.25 ΔCBBE-ΔMCAP Abnormal Stock Return Model Results

	Abr_Rt *(Fixed-Effect)*
ΔPos CBBE	.343***
	(.085)
ΔNeg CBBE	.325*
	(.168)
ΔMCAP	-.037
	(.106)
ΔPos CBBE X ΔMCAP	-.431
	(.659)
ΔNeg CBBE X ΔMCAP	-1.61*
	(.876)
UΔROA	.861**
	(.411)
Sales Growth	.382*
	(.202)
Leverage	0.00
	(.003)
Intercept	-.034**
	(.016)
N	360
F-Test (Model)	6.02***
R-squared	.45
Adj. R-squared	.38

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

Figure 6.8 visualizes the dynamics by which changes in firm's marketing capabilities moderates the link between negative CBBE changes and stock returns through the *spotlight analysis*. It helps in clearly understanding how incremental positive shifts in CBEF diminishes the negative stock return response of declining FBBE. For example, the severity of ΔNeg FBBE-firm performance relationship is significantly reduced when there is a rise in firm's marketing capability by a factor of 1 standard deviation (i.e. 14%) above its mean. Infact, favourable changes in MCAP around 2 standard deviations above average results in a marginally positive slope for ΔNeg FBBE-stock return impact. Jointly, these predictive margins coney the mechanism by which superior marketing capabilities can provide competitive edge to a brand-firm even during unfavourable market conditions such as unexpected downward shift if brand-level incremental value (i.e. FBBE).

Figure 6.8 ΔMCAP-ΔCBBE Interaction Effects Margin Plot

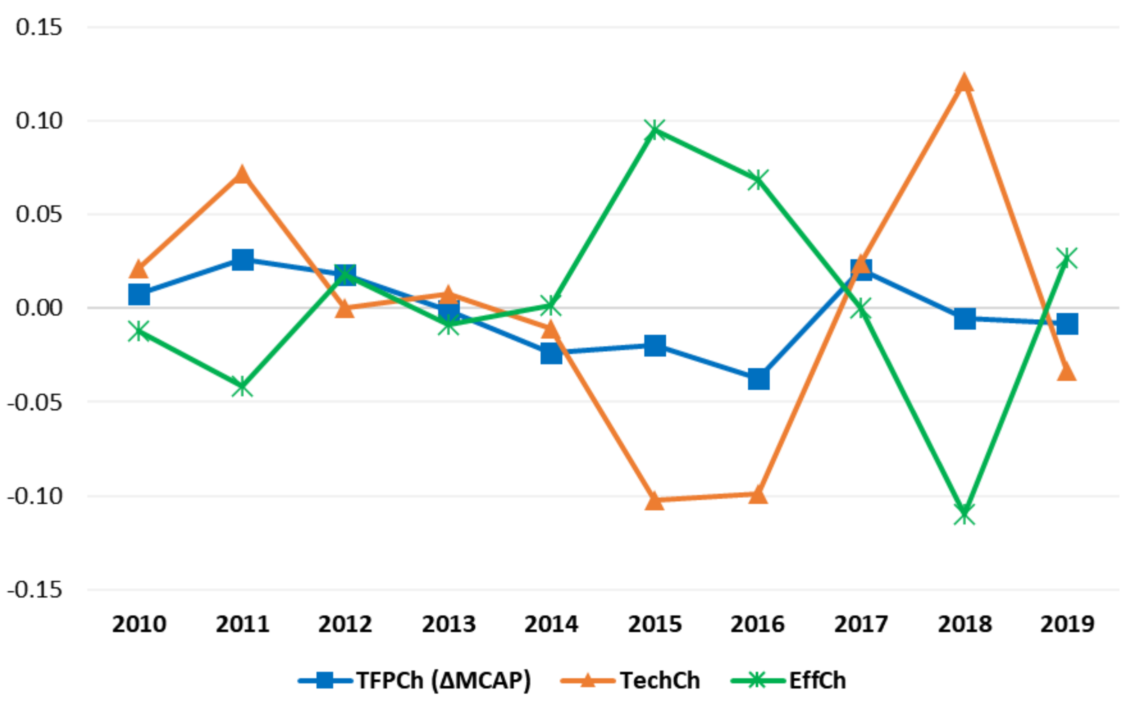


Source: Author's elaboration

6.5.2 DEA Results for MCAP and its interaction effects in Δ*FBBE SRRM Model*

Figure 6.9 outlines the overall behaviour of the estimated yearly changes in total factor productivity (TFPCh) for 32 FFBE sample firms, which is a proxy of ΔMCAP for this analysis. The performance of technological and efficiency change is also included to understand their contributions to the resulting average yearly marketing capability changes. The average yearly MCAP changes for the FBBE sample firms are stable and rangebound between +/- 5%. However, from 2011 till 2016, it has shown a continuous weakness in its yearly growth declining from its highest rise of 2.6% in 2011 to a maximum drop of -3.8% in 2016. In contrary, MCAP for CBBE model has shown a relatively better performance in the same years (refer to figure 6.7). This can be either due to the comparative sample size (with many uncommon firm brands) or ΔMCAP estimation in different yearly waves. However, from the efficiency and technological change perspective, they have been equally volatile. The key difference in their relative performance is the direction of their individual changes over time. For example, for the CBBE sample the downside volatility in efficiency changes in the first five years is almost similar to the upside volatility in the subsequent years. In contrary, FBBE firms exhibit relatively stable internal efficiency changes in the first five years followed by relatively higher volatility in the subsequent period. Similar pattern can be seen in FBBE based technology changes as compared to the CBBE technological changes. However, as realized earlier, both efficiency and technological changes have counteracted each other, resulting in overall stable ΔMCAP throughout the 10 year sample period.

Figure 6.9 MCAP Malmquist productivity index and its components for FBBE firms



Source: Author's elaboration

The SRRM model designed to evaluate the role of marketing capability in moderating the relationship between directional changes in FBBE and firm performance is expressed as:

$$\begin{aligned} R_{iT} - R_f = \alpha &+ \beta_1 \Delta Pos\_FBBE_{iT} + \beta_2 \Delta Neg\_FBBE_{iT} + \beta_3 \Delta MCAP_{iT} \\ &+ \beta_4 \Delta Pos\_FBBE_{iT} \text{ X } \Delta MCAP_{iT} \\ &+ \beta_5 \Delta Neg\_FBBE_{iT} \text{ X } \Delta MCAP_{iT} + \beta_R Risk_T + \beta_6 U\Delta ROA_{iT} \\ &+ \beta_7 U\Delta Sales_{iT} + \beta_8 LEV_{iT} + \varepsilon_{iT} \end{aligned} \quad (6.7)$$

Where:

$R_{iT} - R_f$ =	Annual raw returns of firm "i" in year T adjusted for risk-free rate;
ΔPos_FBBE_{iT} =	Continuous variable capturing positive changes in Brand Finance brand values of firm "i" in year T;

ΔNeg_FBBE_{iT} =	Continuous variable capturing negative changes in Brand Finance brand values of firm "i" in year T;
$\Delta MCAP_{iT}$ =	Change in marketing capability of firm "i" in year T.
$RISK_{T}$ =	Vector of all the yearly risk factors defined earlier;
$U\Delta ROA_{iT}$ =	Unanticipated component of earnings for firm "i" in year T;
$U\Delta Sales_{iT}$ =	Sales growth of firm "i" in year T;
LEV_{iT} =	Leverage of firm "i" in year T;
ε_{iT} =	idiosyncratic error term;
T =	Year encompassing Brand Finance brand value announcement wave (February of current year T till December in current year T).

Table 6.26 outlines the descriptive statistics of all the variables included in the ΔMCAP-ΔFBBE interaction model. The first noticeable statistic is the frequency of negative FBBE changes as compared to positive changes in the entire 10 year period. Due to the sample limited to 32 firms (i.e. 320 firm-year observations), there are only 74 cases of a declining firm oriented brand equity which is almost one-fourth of the total frequency. The average change in MCAP is almost negligible which is also confirmed through the visual inspection through figure 6.9**.** However, its maximum recorded negative change is higher as compared to the positive change (-0.68 vs 0.48). Interestingly, the dispersion and extremities for all other control variables are in tandem with the ΔMCAP-ΔCBBE sample firms. This is because the majority of firms are common in both the datasets. Additionally, even though their respective inputs and outputs are aligned with the BrandZ and Brand Finance waves, they differ only by 2 quarters (6 months). However, since there is a weak correlation within yearly changes in consumer and firm based brand equity, the comparative moderating effect of MCAP is expected to be dissimilar (as seen in the ΔCBEF models).

Table 6.26 Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max
Stock Return	320	0.13	0.25	-0.46	1.68
ΔPos FBBE	246	0.18	0.16	0.001	1.03
ΔNeg FBBE	74	-0.09	0.09	-0.001	-0.53
ΔMCAP	320	-0.00	0.11	-0.68	0.48
MktRf	320	0.13	0.15	-0.09	0.39
SMB	320	0.01	0.05	-0.08	0.09
HML	320	-0.01	0.07	-0.08	0.13
MOM	320	0.02	0.16	-0.41	0.19
Loglag MV	320	11.00	0.29	10.14	11.85
Loglag B2M	320	-0.42	0.41	-2.25	0.37
UΔROA	320	0.00	0.02	-0.13	0.11
Sales Growth	320	0.02	0.05	-0.23	0.15
Leverage	320	1.27	3.33	-15.55	39.69

The pairwise correlation matrix evaluating the association between the response and explanatory variables as well as within all the independent variables is presented in table 6.27. Similar to CBBE sample, changes in MCAP estimations for FBBE sample firms exhibit a positive yet insignificant relationship with stock returns. As expected, both the directional FBBE metrics along with the accounting variables of sales and ROA have a significant positive relationship with firm performance. Apart from cross-sectionally fixed Fama-French and Carhart loading factors, all the other explanatory variables have acceptable levels of association between them which is desirable for an unbiased regression analysis.

Table 6.27 Pairwise corelation Matrix for ∆FBBE MCAP model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) R_T - R_f	1.00												
(2) ∆Pos FBBE	0.27*	1.00											
(3) ∆Neg FBBE	0.20*	0.31*	1.00										
(4) ∆MCAP	0.08	0.00	-0.01	1.00									
(5) MktRf	0.46*	0.16	0.03	0.07	1.00								
(6) SMB	0.34*	0.15	0.00	0.08	0.69*	1.00							
(7) HML	0.19*	0.12	-0.03	0.07	0.54*	0.52*	1.00						
(8) MOM	-0.23*	-0.13	-0.08	-0.06	-0.40*	-0.38*	-0.27*	1.00					
(9) Loglag MV	-0.25*	-0.12	-0.02	-0.06	-0.21*	-0.20*	-0.09	0.18*	1.00				
(10) Loglag B2M	-0.02	0.06	-0.03	0.07	0.07	0.07	0.03	-0.09	-0.34*	1.00			
(11) U∆ROA	0.21*	0.02	-0.04	0.28*	0.22*	0.18	0.08	-0.09	-0.02	-0.08	1.00		
(12) Sales Growth	0.31*	0.19*	0.07	0.24*	0.27*	0.34*	0.00	-0.10	-0.08	-0.08	0.27*	1.00	
(13) Leverage	-0.06	-0.01	0.13	-0.01	-0.05	0.02	0.04	0.02	-0.08	-0.31*	-0.07	0.00	1.00

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results after analysing the moderating effects of marketing capability for FBBE sample firms through SRRM model equation are reported in panel A of table 6.28. The impact of positive changes in financial based brand equity on stock returns is positive but insignificant ($b=0.06$, $p>0.10$). Consistent with the findings from the main ΔFBBE model estimated earlier, deteriorating effects of declining FBBE is much higher than positive changes and the coefficient is statistically significant ($b= 0.71$, $p<0.05$). However, both the coefficients of interest i.e. β_4 and β_5 are statistically insignificant. From the polarity perspective, the moderating effects of marketing capability on positive FBBE changes is positive, which is expected. However, the negative ΔMCAP moderation is in the opposite direction to what is presumed through hypotheses H6(b) ($\beta_5 = 0.12$, $p>0.10$). The earnings response coefficient is positive and significant which is expected as firm's balance-sheet performance is one of the key drivers of firm's future profitability.

Table 6.28 ΔMCAP-ΔFBBE Interaction effects model results

Panel: A	Rt - Rf *(Fixed-Effect)*
ΔPos FBBE	.06
	(.061)
ΔNeg FBBE	.71***
	(.206)
ΔCBEF	.119
	(.12)
ΔPos FBBE X ΔMCAP	.211
	(.577)
ΔNeg FBBE X ΔMCAP	1.664
	(1.217)
MktRf	.629***
	(.104)
SMB	-.084
	(.317)
HML	-.174
	(.183)
MOM	.042
	(.084)
Loglag_MV	-.468***
	(.161)
Loglag_B2M	-.02
	(.061)
UΔROA	1.332**
	(.634)
Sales Growth	-.106
	(.344)
Leverage	-.003
	(.004)
Intercept	5.201***
	(1.758)
N	320
F-Test (Model)	5.24***
R-squared	.46
Adj. R-squared	.37
Panel: B	
LM Test	0.00
F-Test (Fixed Effects)	1.88***
Hausman Test	58.45***

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

In order to further examine whether the obtained estimates are not biased due to violation of the OLS assumptions or presence of influential variables, all the outlined post estimation diagnostics tests are conducted. Firstly, the results of both Wooldridge

(2012) and modified Wald test by Greene (2000: 598) indicate that the estimated model is serially-correlated and heteroskedastic. (Wooldridge (2012) test F statistic: 27.57, p<0.001; Wald Test Chi sq.: 847.98, p<0.001). To account for these anomalies, clustered-robust standard errors are obtained and reported in table 6.28. The estimated VIF scores reported in table 6.29 suggest that the model does not face any multi-collinearity issues.

Table 6.29 VIF Scores

Variables	**VIF Score**
ΔPos FBBE	1.19
ΔNeg FBBE	1.15
ΔMCAP	1.16
MktRf	2.31
SMB	2.28
HML	1.64
MOM	1.25
LogLag_MV	1.26
LogLag_B2M	1.35
UΔROA	1.20
Sales Growth	1.39
Leverage	1.21
Mean VIF	**1.45**

The attention is therefore turned towards the influence of any univariate or multivariate outliers on the estimated elasticities. All the computed Z-scores reported in table 6.30 are below the absolute threshold value of 3, suggesting absence of any outlying observations in each of the explanatory variables.

Table 6.30 Univariate outlier detection

	Min Z-Score	Max Z-Score
ΔPos FBBE	-1.80	2.69
ΔNeg FBBE	-2.85	0.73
ΔMCAP	-2.76	2.35
MktRf	-1.42	1.69
SMB	-1.54	1.43
HML	-0.99	1.94
MOM	-2.50	0.98
LogLag_MV	-2.78	2.02
LogLag_B2M	-2.51	2.64
Leverage	-2.08	2.50
UΔROA	-2.47	2.24
Sales Growth	-2.21	2.50

The results of the multivariate outlier detection however unfold a very different picture. Firstly, 32 observations are identified as atypical after employing the S-estimator regression on the median centred panel data sample. Table 6.31 reports the results of the re-estimated robust fixed effect model with outliers allocated zero weights. Surprisingly, the coefficient of CBEF interaction effects on negative FBBE changes is still positive but is now statistically significant ($\beta_5 = 2.62$, $p<0.001$). These results are in contradiction to the theoretical arguments made in H6(b) suggesting that changes in firm's marketing capability amplifies the deteriorating effects of FBBE decline on stock returns.

Table 6.31 ΔFBBE-ΔMCAP Model Robust-Estimation Results

	Rt - Rf *(Robust Estimation)*
ΔPos FBBE	.053
	(.053)
ΔNeg FBBE	.418***
	(.131)
ΔCBEF	.104
	(.116)
ΔPos FBBE X ΔMCAP	-.216
	(.551)
ΔNeg FBBE X ΔMCAP	2.624***
	(.829)
MktRf	.498***
	(.089)
SMB	-.518**
	(.247)
HML	.095
	(.132)
MOM	-.037
	(.058)
Loglag_MV	-.355***
	(.104)
Loglag_B2M	-.069
	(.046)
UΔROA	1.176**
	(.569)
Sales Growth	.318
	(.255)
Leverage	-.004
	(.003)
Intercept	3.916***
	(1.129)
N	288
F-Test (Model)	6.19***
R-squared	0.54
Adj. R-squared	0.45

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

In order to further affirm if these conflicting revelations through the outlier free robust-regression model are unbiased to alternative measures of firm performance, abnormal return SRRM model is also estimated with and without outliers. The results for both the estimations are presented in table 6.32. The empirical results obtained for the full sample are in close correspondence with its raw returns model, where both the interaction coefficients are insignificant. However after assigning zero weights to the 28 multivariate outliers, the magnitude and significance of β_5 is consistent with the stock return model, affirming that growth in firm's firm marketing capability in-fact worsen the negative effects of declining FBBE on firm long-term performance. Increase in adjusted R-squared from 0.31 to 0.52 further signifies the robustness of the estimated results due to due to significant improvement in the model's explanatory power.

Table 6.32 ΔCBBE-ΔMCAP Abnormal Stock Return Models Results

	Abr_Rt *(Fixed-Effect)*	Abr_Rt *(Robust-Estimation)*
ΔPos FBBE	.052	.025
	(.061)	(.048)
ΔNeg FBBE	.693***	.519***
	(.198)	(.137)
ΔCBEF	.129	.199*
	(.113)	(.114)
ΔPos FBBE X ΔMCAP	.208	-.361
	(.598)	(.494)
ΔNeg FBBE X ΔMCAP	1.672	2.74***
	(1.162)	(.715)
UΔROA	1.237**	1.335**
	(.595)	(.565)
Sales Growth	-.181	-.178
	(.266)	(.196)
Leverage	-.003	-.003
	(.003)	(.003)
Intercept	.015	-.005
	(.012)	(.01)
N	320	292
F-Test (Model)	4.69***	9.03***
R-squared	0.39	0.58
Adj. R-squared	0.31	0.52

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

There is no clear explanation about these unexpected findings in the current marketing-finance literature. Infact no study until now have attempted to closely examine the moderating effect of marketing capability on FBBE-firm performance relationship, let alone the directional changes. However some possible explanations to these contradictory interacting effects of MCAP in FBBE-firm performance linkage are provided while discussing the results in-detail in the next chapter.

6.6 Summary

This chapter focussed on the second section of the proposed conceptual framework to examine the validity of the path relationships in support of the main argument that organizational efficiency is a possible moderator in brand equity-firm performance relationship. Organizational competence was represented through firm's core business efficiency (CBEF) which reflects its *profitability* prospects and marketing capability (MCAP) which corresponds to strategic marketing resource management. Both the efficiency measures were operationalized through multi input-output based Malmquist DEA total factor productivity change modelling. A major advantage of TFPCh based efficiencies over standard DEA models is that it incorporates both time and internal efficiency components while benchmarking firms against each other. The individual interaction effects of MCAP and CBEF were systematically examined for unanticipated positive and negative shifts in consumer and firm based brand equity and the results were compared against the proposed hypotheses. Firstly, the study identifies new mechanism by which CBEF contribute to firm performance: as a complementary asset by enhancing the positive effects of rising FBBE (H5(b)) and as a remedy in mitigating the unfavourable impact of declining CBBE (H5(a)). From RBT perspective these outcomes signal that CBEF is a valuable organizational efficiency component which synergises brand equity dynamics to provide sustainable long term performance. However the empirical evidence for the moderating role of marketing capability yields mixed outcomes. While MCAP weathers the deteriorating effects of declining CBBE thereby supporting H6(a), it aggravates the deteriorating effects of negative FBBE changes, contradicting the hypothesized directionality of H6(b). Potential reasons for the unforeseen effects of MCAP are reviewed further in the discussions chapter. In sum, the empirical outcomes broadly support the theoretical arguments made in this study that valuable, rare, and inimitable marketing resource like brand equity can lead to sustainable competitive advantage (even during unexpected upward and downward shifts) in the presence of superior organizational efficiency. All the obtained results are robust to the presence of heteroscedasticity, serial correlation, multicollinearity, influential observations, and alternative firm performance measure i.e. abnormal stock returns.

Chapter 7: DISCUSSIONS

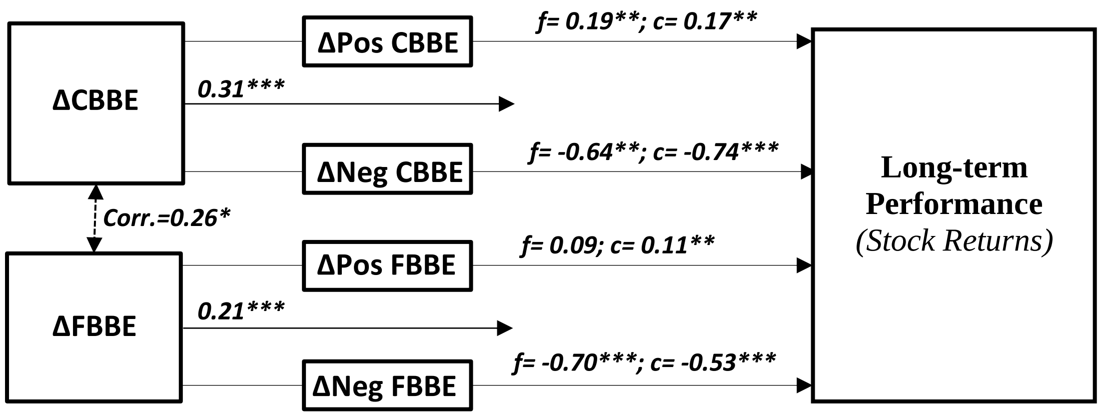
7.1 Introduction

This chapter provides in-depth insights emerging from the statistical analysis presented in previous two chapters encapsulating all the relationships defined in the proposed conceptual model. Maintaining consistency with the conducted empirical analysis, the discussions are also presented adopting a two-part segmentation approach. The first section elaborates on the empirical results obtained from linking brand equity directly to firm performance, from both the overall and directional perspective (i.e. analysis phase-I). The segment also discusses the empirical outcomes of CBBE-FBBE comparative analysis. The hypotheses encompassed within these sections, therefore, are H1(a & b), H2(a & b), H3 and H4. The chapter then proceeds to discuss the results obtained from examining the interaction effects of “organizational efficiency” in brand equity-firm performance linkage (i.e. analysis phase-II). Centred around the theoretical assumptions of Resource Based Theory (RBT) (Barney, 1991), this section reviews whether the obtained empirical evidence validates that superior levels of organizational efficiency (O) can transform a valuable (V), rare (R) and Inimitable (I) marketing resource like brand equity from a source of competitive advantage to be a provider of sustainable long-term growth. More specifically, the section discusses the moderating role of firm’s core business efficiency (CBEF), and marketing capability (MCAP) in brand equity to firm value translation process, focussing separately on directional changes in CBBE and FBBE. The research hypotheses reviewed in this section are H5(a), H5(b), H6(a) and H6(b). For the ease of reference, both sections begin with a visual representation of all the hypothesised path relationships with their obtained elasticities and statistical significance. Overall, this chapter captures all the important findings emanating from the comprehensive empirical analysis conducted in this thesis, which ultimately leads to the conclusion chapter.

7.2 Section-I: Relationship between brand equity and firm performance

This section discusses the empirical results of analysis phase-I encompassing brand equity-firm performance linkage and comparative assessment of consumer and firm based brand equity. Figure 7.1 outlines the first section of the original conceptual model visualizing all the hypothesised path relationships examined in the first phase of analysis (i.e. chapter 5)[35]. It also includes the empirical results of all the hypothesised relationships including the estimated coefficients and their significance levels.

Figure 7.1 Empirical results for analysis phase-I



Δ = Change, CBBE = Consumer based brand equity, FBBE = Financial based brand equity, ΔPos = Positive Changes, ΔNeg = Negative Changes

****p<0.01, **p<0.05, *p<0.10*

f = full sample; c = common firms in CBBE and FBBE samples

[35] Refer to the conceptual framework chapter for a detailed discussion about the two-section division of the proposed model.

Source: Author's elaboration

7.2.1 The impact of overall changes in CBBE and FBBE on firm performance

Prior disaggregating yearly changes in CBBE and FBBE into its positive and negative components, the conceptual model firstly defines path relationships connecting their overall changes (i.e. ΔCBBE and ΔFBBE) to firm performance. The obtained results are in-line with the proposed hypotheses H1(a) and H1(b) indicating that unanticipated changes in consumer and firm based brand equity measures, respectively, have a significant positive impact on stock returns (ΔCBBE=0.31, $p<0.01$; ΔFBBE=0.21, $p<0.01$). These findings suggest that information contained in CBBE and FBBE changes over time is associated with information that stock market participants use to update their expectations about firm's future discounted cashflows. The evidence further supports existing knowledge that brand equity, irrespective of its measurement perspective, is a valuable intangible marketing asset which provides competitive edge to the brand owning firm through its long-term firm performance implications (Dutordoir et al., 2015; Mizik, 2014; Mizik and Jacobson, 2009; Rahman et al. 2019; Yang et al., 2015; Yildiz & Camgoz, 2019) In particular, financial community weigh shifts in both consumer and firm based brand equity measures as vital signals in interpreting firm's future growth prospects. The results also indicate that unanticipated changes in firm's current period earnings (i.e. ΔROA) have a superior power in explaining firm performance as compared to changes in CBBE and FBBE ($\beta\Delta ROA_{CBBE} = 1.12$, $p<0.01$; $\beta\Delta ROA_{FBBE} = 1.75$, $p<0.10$). These findings support the arguments that although intangible marketing asset like brand equity is value relevant, it cannot substitute firm's profitability measures in explaining long-term firm performance (Mizik & Jacobson, 2004). Alternatively, changes in consumer or firm based brand strength provide financial markets with information that is incremental to that of the current-term balance sheet performance (Mizik & Jacobson, 2008). The findings also support the notion that strategic marketing assets like brand equity have lasting effects on firm value (Srivastava et al., 1998) and the holistic effects of its unanticipated changes are unlikely to be fully captured in short-term. Therefore, superior levels of brand equity tend to compliment firm performance over the positive effects of current-term profitability, thus providing a competitive edge to firms maintaining a strong brand name. The obtained empirical evidence also contends that research examining the value relevance of any non-financial assets (e.g. brand equity) must include firm's balance-sheet performance metrics to assess its true contributory role towards future firm performance. Developing empirical models without including these decisive accounting variables would otherwise provide unreliable interpretations about the actual brand equity-firm value relationship.

Supportive evidence for hypotheses H1(a) and H1(b) lays a concrete foundation for this research to further extend the knowledge about brand equity-firm performance translational process in several ways. Firstly, significant results for testing CBBE and FBBE *baseline* hypotheses affirm that the sample brands included in this study exhibit similar association with firm performance as claimed by previous studies[36]. This in-turn justifies the efforts made by this research to explore the directional effects of positive and negative changes in CBBE and FBBE on firm performance. Unsupported or contradictory outcomes would otherwise have made it inappropriate to investigate this

[36] See table 2.3 in the literature review chapter for the list of representative studies.

polarized relationship. Additionally, retesting the value relevance of CBBE and FBBE in the most recent decade (2010 to 2019) also validates that the "incremental value" gained from building strong brands is eternal. Besides reinforcing existing knowledge about brand equity-firm performance relationship, the supporting evidence also makes some potential contributions to the current branding literature. Recall that the obtained CBBE and FBBE sample for testing H1(a) and H1(b) consist of unequal number of sample firms (CBBE = 54, FBBE = 49) and have dissimilar sector segmentation. Also, the compiled yearly data for CBBE and FBBE models belong to different monthly windows based on BrandZ and Brand Finance brand value announcement waves[37]. Even with these discrepancies, the coefficients of estimated stock return response for both the models are positive and statistically significant. These comparable findings corroborate that the long-term value relevance of brand equity is consistent regardless of its measurement perspective, data acquisition time window or brand-firm type.

Furthermore, these findings when compared to closely related empirical work of Mizik (2014) leads to some other interesting insights[38]. Mizik (2014) studied the impact of changes in consumer brand perceptions data acquired from Y&R BAV database (representing CBBE) from the period of 2000 till 2010 which immediately precedes the current study's time span of 2010 to 2019. Additionally, majority of firm-brands

[37] Since BrandZ publish their yearly brand values in May each year, the 12 monthly window range from June (previous year) to May (current year). In contrary, Brand Finance brand value announcement month is January, therefore the data is compiled from February (previous year) to January (current year).

[38] The study by Mizik (2014) is closely associated to current study's CBBE *baseline* model in many ways. Firstly, the author also examines changes in CBBE on firm performance rather than their contemporaneous values. Additionally, the time span (10 years), data structure (panel data) and adopted methodology (SRRM) also coincide with the current research. Even majority of brands are common in both the studies.

included in this study are also potentially the sub-set of the sample acquired by Mizik (2014)[39]. Their findings also broadly coincide with the empirical outcomes of this study indicating a significant positive relationship between CBBE brand measure and long-term firm performance. These relatable outcomes indicate that CBBE estimations provided Y&R BAV and BrandZ are both value relevant, i.e. investors and shareholders view information contained in their brand valuations as a key factor in projecting firm's future term prospects. Additionally, as table 2.1 in the literature review chapter demonstrates, although Y&R BAV and BrandZ brand equity measures centres around consumer mind-set, their operationalization methodologies are entirely different. Y&R BAV model measures consumer brand perceptions based on five "brand pillars" identified as brand differentiation, relevance, esteem, knowledge, and energy (Mizik, 2014). On the other hand, BrandZ operationalize CBBE through a "brand dynamics pyramid" approach where they gauge consumers perceptual brand attributes at each level of the pyramid (Vasileva, 2016). Apart from the adopted methodology, the units of evaluated CBBE measures of Y&R consultants and BrandZ are also distinct, where the former provide CBBE estimates as a score while the latter values it in monetary terms (US dollars). Despite these methodological differences, the obtained evidence for H1(a) aligns well to that of Mizik (2014). These comparative outcomes signal that the obtained results could not have occurred by chance, rather firm value contributions of

[39] Although their sample size is much larger than the current study (with around 2000 firm-year observations), but many reported brands are similar to the current study e.g. Coca-Cola, Pepsi Co., IBM, HP, and Mc Donald's. Even though the full list of all the acquired firm-brands is not provided by Mizik (2014), but considering relatively smaller sample size, it is likely that majority firms included in this study correspond to their sample.

strong consumer brand association are consistent regardless of the adopted CBBE measurement approach.

The current study departs from that of Mizik (2014) in the aspect that it also includes an alternative measure of brand equity i.e. firm based brand equity. Supporting evidence pertaining to H1(b) unfolds that like CBBE, FBBE also enhances shareholder’s wealth by positively impacting stock returns. Although existing research has explored FBBE-firm performance linkage, but majority of studies have included this brand equity measure in its absolute form (e.g. Chang & Young, 2016; Kirk et al., 2013; Rahman et al., 2019; Wang & Sengupta, 2016) which is known to provide unreliable and spurious theoretical and statistical inferences (Mizik & Jacobson, 2009a; Srinivasan & Hanssens, 2009). To the best of researcher’s knowledge, only two studies till date have explored the stock return response of changes in firm based brand equity. The first is an event study by Dutordoir et al. (2015) where they investigate the immediate stock market response of changes in FBBE, following the annual *Interbrand’s* brand value announcements. Although their findings indicate that unanticipated changes in FBBE drive generate abnormal returns but evaluating this relationship in a such a short time window has limited value. This is because brand equity is a slow developing process and its true financial contributions take years to materialize (Datta et al. 2017; Kirk et al., 2013; Mizik, 2014). The second study is of Yang et al. (2015) where they link changes in FBBE to stock returns but found insignificant empirical outcomes. The authors argue these unexpected results may be due to the lack of considering different dimensions of brand equity, thereby advising future research to adopt comprehensive approaches in order to explore true implications of branding (Yang et al., 2015:557). This research addresses the potential anomalies of both Dutordoir et al. (2015) and

Yang et al. (2015). Firstly, adopting stock return response modelling, long-term firm performance implications of FBBE are investigated, rather its immediate effects. Secondly, this relationship is examined simultaneously for consumer and firm based brand equity measurement perspectives. Adopting such a comprehensive approach enables this study to provide much richer insights about the holistic long-term value relevance of brand equity, which is still not fully known.

From statistical perspective, the empirical outcomes of H1(a) and H1(b) indicate that the strong brand equity-firm performance relationship holds its validity even after accounting for unobserved heterogeneity across sample firms through fixed-effects panel data estimation techniques (Yeung & Ramasamy, 2008). In other words, the obtained empirical evidence affirm that brand equity is a reliable predictor of firm's future growth, and these contributory effects are not dependent on firm specific factors such as country of origin, industry-sector, etc. In sum, the overall findings for the *baseline* models hypothesized through H1(a) and H1(b) provide sufficient evidence to suggest that financial community view brands with growing consumer and firm based equity as a guarantor of enhanced future returns as compared to weak brands. Furthermore, this relationship is independent of the brand equity measurement dimensions, the adopted estimation approach, analysis time period or any other firm-specific characteristics that are constant over time.

7.2.2 The impact of directional changes in CBBE and FBBE on firm performance

Following the supporting evidence from the *baseline* models, focus can now be shifted on discussing the outcomes of the main research objective i.e. results of the *main* SRRM models exploring the directional firm performance impact of consumer and firm based brand equity. As evident in figure 7.1, the defined path relationships disintegrate the overall changes in CBBE and FBBE into its positive and negative components (i.e. ∆Pos CBBE & ∆Neg CBBE; ∆Pos FBBE & ∆Neg FBBE) connecting them individually to long-term firm performance i.e. stock returns.

First, results examining H2(a) lend strong support that the magnitude of impact of declining consumer based brand equity on firm performance is significantly higher as compared to its rise (∆Neg CBBE = -0.64 versus ∆Pos CBBE = 0.19). This is a crucial finding because majority of existing research has explored the overall relationship between changes in CBBE and firm performance (Aaker & Jacobson, 2001; Bhardwaj et al., 2011; Mizik, 2014; Nam & Kannan, 2014), largely ignoring its directional effects. These findings therefore provide novel insights suggesting that the information contained in unanticipated negative changes in CBBE have greater value relevance as compared to positive changes. From financial markets perspective, this signifies that investors and shareholders are more sceptical towards a sudden decline in consumer brand perceptions as compared to a positive consumer response. This asymmetry prevails even after controlling for current period accounting performance measures, firm specific risk characteristics of size and book-to-market value and other macroeconomic factors captured through Fama-French (1993) and Carhart (1997) risk loadings. Additionally, as discussed previously in analysis phase-I (See fig. 5.2), over the 10 year study period, the instances of yearly declines in CBBE valuations are 177 which is significantly less than the frequency of positive changes (N=363). However, even with 1:2 ratio of negative to positive change; its deterioration firm value effects are three times larger. This is a vital information as it signals that persistent decline in CBBE, even for short periods, can erase all the growth that a firm has gained from its rising CBBE over several years. These findings therefore highlight the importance of investigating the polarized view of changes in consumer's cognitive brand attachment (and not simply relying on overall changes) when evaluating its true value relevance. Ignoring the firm value eroding effects of declining CBBE can have serious and potentially irreversible consequences on firm's long term growth prospects.

From a broader perspective, the asymmetrical effects that this study reveals, are closely related to those obtained by Luo et al. (2013) where they report a stronger negative impact of downside dispersion in brand equity as compared to the upside dispersion. These comparable findings assert the propositions of "negativity bias theory" that investment community give more weight to negative information than positive information when reviewing their future investment decisions (Baumeister et al., 2001). Second, financial community react more aggressively to the falling stock prices caused due to sudden decline in parent firm's CBBE because "losses loom larger than gains" (Kahneman and Tversky, 1979). As discussed earlier, a major limitation of the novel work of Luo et al. (2013) is that their empirical results come from high frequency consumer response data i.e. daily observations[40]. Since, such data is not publicly circulated, there is a high probability that the information contained in daily consumer reviews is not efficiently absorbed in the firm's current market value. Even if such information is available, it is highly unlikely that investors (especially big institutional) will react to daily (or even weekly) consumer reviews due to low signal to noise ratio (Tirunillai & Tellis, 2013). Therefore, analysing value relevance of favourable and unfavourable consumer brand response within short-time unit of analysis provide

[40] In fact, majority of the studies listed in table 2.4 of the literature review chapter have used very narrow time intervals for collecting the consumer response data e.g. days, weeks, and months.

limited and anecdotal information. Brand equity is built over years not days, weeks, or even months, thereby its true value dynamics can only be assessed over longer time horizons (Datta et al. 2017:15). Addressing these anomalies, this study analyses the directional CBBE-firm performance relationship with annually spaced data collection wave. Adopting such approach also reduces the noise significantly, enabling stock markets to analyse the information residing in these unanticipated changes more comprehensively. Furthermore, yearly consumer based brand valuations by BrandZ are released through public announcements (such as press release) making it easily accessible to the stock market community. Therefore, the evidence obtained from the current study provide more credible interpretations about the stock return response of positive and negative CBBE changes, which until now were not clearly known.

Apart from Luo et al. (2013), supporting evidence for H2(a) also relate well to the empirical findings of other studies belonging to this research genre (see table 2.4 in the literature review chapter for list of representative studies). For example, Tellis and Johnson (2007) report that negative consumer reviews about a product's quality deteriorates parent brand's market value by 5% within five days of the information release. This is marginally higher as compared to the abnormal returns generated in an event positive reviews (i.e. 4.4%). Similarly, Tirunillai and Tellis (2013) find that the coefficient of impact of negative consumer product ratings (-8.4) on stock returns is significant and greater in magnitude that the positive ratings estimate of 6.27. However, these studies have some caveats which this research addresses. Firstly, Tellis and Johnson (2007) analyse the immediate stock market reaction to positive and negative changes in consumer product quality perceptions. It is highly unlikely that stock market participants can evaluate long-term financial implications of such favourable and unfavourable reviews within such short time window (5 days). The current study, on the other hand, adopts a longitudinal approach thus providing a future view of relationship between directional changes in consumer perceptions and firm performance. Interestingly, the data suggests that in long run, there is a much wider gap between the magnitude of declining consumer brand association on stock returns as compared to rising CBBE (ΔNeg CBBE = -0.64 versus ΔPos CBBE = 0.19). These findings reveal that the future term impact of declining consumer brand association on stock returns is even severer as compared to its immediate effects.

Similar to CBBE, the directional relationship of FBBE with firm performance was also expected to be stronger on the negative side. The obtained results support these theoretical assumptions (made through hypothesis H2(b)) conveying that positive and negative changes in firm based brand values have an asymmetric impact on firm performance. In particular, a sudden decline in firm based brand equity negatively effects future profitability with much greater magnitude as compared to its complementary effects during rising FBBE (ΔNeg FBBE = -0.70 versus ΔPos CBBE = 0.09). Although initially the proposed SRRM model yields statistically insignificant coefficient of positive FBBE change, retesting it after treating influential observations fully supports H2(b). The outlier free SRRM model reveals an unevenness in the stock return response of directional FBBE changes, where the magnitude of negative ΔFBBE component is four times higher as compared to the positive change component (ΔNeg FBBE = -0.48 versus ΔPos CBBE = 0.11). These results signify that along with diminishing consumer brand association, stock markets also pay close attention to information release about decline in brand's projected earnings through royalties and trademarks. Most importantly, they respond much aggressively to downward changes in

FBBE as compared to upward changes, thus having stronger negative impact on firm future performance.

Although these findings cannot be directly compared with any existing studies due to lack of relevant literature, certain explanations can be given for this asymmetrical FBBE-firm value relationship. Firstly, positive information about firm based brand equity attributes such as enhanced brand based earnings or positive analyst forecast is actively circulated by mainstream and social media, but negative views are generally not propagated so candidly. Because of information overload and multiple sources, investors and shareholders generally believe positive information to be biased and less reliable (Tirunillai & Tellis, 2013:213). That is why investors perceive any unfavourable information to be more diagnostic as they are keener in knowing the "worst about a brand rather than the best" (Tirunillai & Tellis, 2013:213). Additionally, as discussed in section 5.6.1 of chapter 5, the instances of negative yearly changes in FBBE (n=122) are fairly less as compared to positive shifts (n= 368) making this information even more vital. Therefore, rarity of these events and the propositions of "negativity bias" theory (Luo & Homburg, 2007; Rozin & Royzman, 2001; Tellis & Johnson, 2007) can possibly explain why sudden decline in FBBE attracts more aggressive stock market attention than rising FBBE. Additionally, since FBBE specifically captures income generated directly through strong brand name (in the form of royalties from patents and trademarks), investors may perceive any unanticipated decline in its magnitude as a direct hit to firm's future profitability prospects, thus impacting stock returns. These arguments along with the propositions of "loss aversion theory" (Tversky & Kahneman, 1981), that investors weigh losses more than gains (Luo, 2007:76; Maxham & Netemeyer, 2003:58)**,** can be other reasons why firm value impact of downward shifts in FBBE is significantly higher as compared to upward shifts.

No study until now have explored the directional effects of positive and negative changes in FBBE on firm performance (to the best of researcher's knowledge). This is important because like CBBE, FBBE is another vital dimension of brand equity (Nguyen et al., 2015; Tasci, 2020) and as this study demonstrates, investors and shareholders treat it as a valuable asset in projecting firms' future profitability. This research therefore is the first to fill in this void and provide novel insights about polarized FBBE-firm value relationship. As with CBBE changes, the study finds similar asymmetry in directional firm performance impact of FBBE. However, a direct comparison between the value relevance of these two brand equity measures cannot be made at this point. This is because the SRRM models testing H2(a) and H2(b) contain discrete set of CBBE and FBBE sample firms, respectively (CBBE=54; FBBE=49). To understand their interlinkage and unique effects on firm value, a systematic comparative analysis was separately conducted including only the common 44 brands in both the samples. The empirical evidence obtained from this final theme of the conceptual model section-I is discussed in detail in the following section of this thesis.

7.2.3 Comparative assessment of CBBE and FBBE

Along with investigating the impact of unanticipated shifts in consumer and firm based brand equity on firm performance, the analysis phase-I also investigates the connection between these two brand equity measures. As mentioned earlier, the dataset for this comparative assessment comprises of 44 brands common in both the CBBE and FBBE samples for the ten year study period (2010-2019). While the current literature is still inconclusive about the degree to which these two key brand equity measures align with each other (Tasci, 2020), this research provides new and valuable explanations about their inter-relationship by adopting a bi-dimensional approach. Firstly, the conceptual framework links the acquired CBBE and FBBE brand equity estimations directly to each other through the path relationship hypothesised via H3. The second path (H4) then compares their unique directional effects on firm performance expecting this relationship to be stronger for CBBE as compared to FBBE. Sub-sections below discuss the research outcomes of these two theoretical assumptions, focusing on one at a time.

7.2.3.1 Comparison of inter-relationship between CBBE and FBBE

Drawing on the yearly dollar brand valuations published by BrandZ and Brand Finance for 44 common brands across ten years, the study examined the empirical association between CBBE and FBBE. The proposed hypothesis H3 assumes a weak relationship between changes in consumer and firm based brand equity measures over time. But before testing H3, the analysis first begins with investigating the contemporaneous linkage between CBBE and FBBE. This is because existing literature have extrapolated the association between these two brand equity measures solely from the contemporaneous perspective (refer to table 2.5 in the literature review chapter). Therefore, beginning with the same analogy enables this study to re-examine existing knowledge before extending it further and exploring commonalities or dissimilarities in their “in change” behaviour. This would also aid this research to offer credible and valuable insights to the current branding literature, which is still lacking consensus about the true association between consumer and firm based brand equity measurement perspectives (Tasci, 2020).

The contemporaneous relationship examination begins by plotting the time series data of CBBE and FBBE brand valuations for some prominent brands to visually inspect their intertemporal associations (refer to figure 5.4 in chapter 5). The graphs indicate that although their respective consumer and firm based brand values belong to different monetary range, they seem to follow a similar overall pattern, signalling a potential interlink. To further affirm this inter-relationship statistically, a pairwise correlation test was conducted between all the 44 brands common in the CBBE and FBBE sample. The acquired results supported the visual ques revealing that the "in level" association between consumer and firm based brand valuations is positive and fairly strong (correlation coeff. = 0.87,$p < 0.01$). These results are not surprising as both CBBE and FBBE stem from a common theoretical foundation (Christodoulides & Veloutsou, 2011), therefore are expected to be intertwined in their steady state. Brands with superior CBBE levels are more likely to command deep consumer loyalty resulting in augmented sales due to high purchase intention (Hoeffler & Keller, 2003; Johansson et al., 2012). These benefits enable firm-brands to enjoy stable revenue levels and low cost of capital (Rego et al., 2009). This would in-turn enhance brand's market share enabling firms to charge higher royalty rates from its licensees due to strong market presence (Jayachandran et al., 2013). As a result, such firms are expected to be favoured by branding experts due to a likely growth in their future brand income through patents and trademarks, thus improving their FBBE. Additionally, the obtained findings of strong contemporaneous association between consumer and firm based brand equity are also in close correspondence with the existing marketing literature (Datta et. al 2017; Kamakura & Russel 1993; Lehmann et al. 2008; Stahl et al. 2012).

After inspecting the steady-state relationship, the analysis turns to its main objective i.e. testing H3 which assumes a weak link between CBBE and FBBE as they evolve over time. To empirically examine this association, pairwise correlation analysis was conducted between the yearly percentage changes in CBBE and FBBE for the 44 common brand-firms. The obtained correlation coefficient of 0.26 is statistically significant and much smaller in magnitude as compared to their "in-level" coefficient (0.87), thereby supporting the theoretical arguments made in H3. Infact, the degree of linkage between changes in CBBE and FBBE over time is less than one-third of their contemporaneous relationship indicating a substantial disparity between them. These findings provide novel insights denoting that although there is a strong contemporaneous association between these two brand equity measures, but how they evolve over time does not follow a same suite. In other words, the overall consumer cognitive brand attachment may align well with firm based brand attributes but there is a considerable difference in their dynamics of change. This discrepancy can be primarily due to the fact that consumer affection towards a brand is a psychological phenomenon which takes years to manifest (Datta et al., 2017), therefore it is unlikely that these perceptions will change substantially within a short period of time (e.g. in one year). On the other hand, FBBE tracks the financial performance of the brand e.g. royalties from brand licensing, projected earnings, etc. Changes in such firm based brand attributes are susceptible to external market forces such as market size, intellectual property rights and varying profit margins (Jayachandran et al., 2013). Since these factors are continuously evolving in real business world, changes in firm based brand equity are expected to be more abrupt as compared to change in customer's cognitive connection with a brand. These arguments are further supported by the acquired sample characteristics where the volatility of change in FBBE valuations for the 44 firms (S.D=0.21) is relatively higher as compared to their corresponding CBBE change (S.D=0.18). The upper and lower bounds for yearly shifts in FBBE (ΔPos FBBE=139%, ΔNeg FBBE= -53%) are also more dispersed compared to its CBBE counterpart (ΔPos CBBE=97%, ΔNeg CBBE= -45%). This data signifies that changes in these two brand equity dimensions over time tend to deviate from each other from both the volatility and dispersion perspectives thereby resulting in a weak inter-relationship.

Another reason for a divergence between changes in consumer and firm based brand attributes can be understood from the "Martha Stewart ImClone stock selling scandal of 2002" discussed in detail by Mizik (2014:692). The case highlights the negative consequences on Martha Stewart brand after the firm was exposed for selling ImClone stocks based on an insider tip (Hoffman, 2007). The evaluation of the after-effects of this scandal unfolds that although there was a steep decline in consumer perceptions towards the Martha Stewart brand (measured through Y&R BAV brand asset index), the firm sales and earnings remained broadly unchanged in the same period. Even with a further decline in CBBE in the subsequent years (2003 till 2005), there was no significant change in firm's accounting performance. These interesting findings suggest that there is a substantial lag in response of firm's *objective* performance measures even in extreme scenarios of sudden consumer exodus from a brand. Since the acquired FBBE metric in this research captures brand level financial performance, the footprints of this case study are indicative of similar disparity in its deviations over time in contrast to CBBE changes. Additionally, Nguyen et al. (2015) points out that the key role of firm based brand equity is to quantify accrual value emanated from brand name and its proprietary assets. This involves estimating brand's current financial performance and projecting future brand-based earnings based on the available market information. Due to these characteristics FBBE is a *forward looking* brand equity measurement perspective. On the other hand, CBBE signals the past performance of the brand through consumer cognitive assessment and therefore is a *backward looking* measure (Nguyen et al., 2015:556). These mutually exclusive characteristics of CBBE and FBBE also partially explains a significant difference in their evolution over time. Overall, the empirical outcomes of testing H3 provide novel insights about CBBE-FBBE interrelationship suggesting that although these two brand equity dimensions are co-aligned in their absolute form, their dynamics of change over time vary by a significant margin.

7.2.3.2 Comparing directional relationship of CBBE and FBBE with firm performance

Along with exploring the inter-linkage between consumer and firm based brand equity measures, the second objective within this research context was to compare their unique directional effects on firm performance. The investigation was carried out by disaggregating the positive and negative components of yearly CBBE and FBBE valuations and regressing them on firm performance through their respective SRRM models (including only the 44 common sample firms). The defined path relationship, hypothesised through H4, expects that the value enhancing (deteriorating) impact of rising (declining) CBBE will be stronger as compared to FBBE changes. However, before comparing their directional financial consequences, the analysis first contrasts the impact of overall changes in CBBE and FBBE on firm performance. This approach aids in evaluating the obtained evidence against existing research which is limited to comparing only the overall value relevance of these brand equity dimensions (e.g. Bagna et al., 2017 and Johansson et al, 2012). The empirical results report a significantly higher impact of unanticipated changes in CBBE on firm performance ($b=0.33$, $p<0.001$) as compared to FBBE changes ($b=0.19$, $p<0.001$). This indicates that in general, stock market participants perceive shifts in consumer brand allegiance to be more diagnostic than changes in projected brand-based profitability measures. These findings provide both supporting and contradicting evidence to that of Johansson et al. (2012). Firstly, their results indicate that investors and shareholders interpret brands with strong consumer bonding as a "safe harbour" during periods of financial turmoil (Johansson et al., 2012:240). Obtaining similar findings, the current study extends the knowledge further by revealing that such strong CBBE-firm performance association not only prevails during extreme macro-economic conditions but also in long-term when markets are generally in equilibrium.

Their results for the acquired FBBE measure, however, depart from the empirical outcomes of this research. Johansson et al. (2012) found that financial community did not considered brands with superior FBBE levels (estimated by *Interbrand*) as potential assets which can sustain extreme market conditions such as 2008 financial crisis. At first instance, it may seem like FBBE is not value relevant (when compared to CBBE) but this is probably not true. For example, Bagna et al. (2017) compare the annual brand valuations provided by *Interbrand* to that of consumer centric *BrandZ* estimates and report both having a significant positive impact on firm value. There are several other studies that have linked *Interbrand's* brand equity valuations to stock market performance indicators and found strong relationship between them (Dutordoir et al. 2015; Kirk et al., 2013; Rahman et al. 2019; Wang & Sengupta, 2016; Yeung &

Ramasamy, 2008). Contradictory results of Johansson et al. (2012) may be due to the fact that the authors analyse CBBE-FBBE relationship within a relatively shorter timeframe (4 months) and in a period of world-wide financial distress. Besides this, a common limitation of the empirical research by Johannsson et al. (2012) and Bagna et al. (2017) is their inclusion of the acquired brand equity metrics in absolute values which has limited significance due to their incompliance with the efficient market theory (EMT) (Mizik & Jacobson, 2008; Srinivasan & Hanssens, 2009). The current study, on the other hand, explores these linkages by comparing the stock return response of changes in consumer and firm based brand equity measures, therefore providing robust statistical inferences. Along with extending the novel work of Bagna et al. (2017) and Johansson et al (2012), the obtained results also lead to another interesting interpretation. Since it has already been established in the previous section that changes in CBBE over time are not closely related to FBBE, these results therefore suggest that both these brand equity measures contain information, which is not only relevant but, at the same time, non-overlapping to each other. In other words, not only their dynamics of change are mutually exclusive, but they also possess a unique relationship with long-term firm performance. These novel outcomes therefore provide further evidence that no single dimension of brand equity can capture its holistic value relevance (Oliveira et al., 2015).

The next step is to compare the directional firm value impact of positive and negative changes in CBBE and FBBE and evaluate whether the acquired data supports the assumptions made in hypothesis H4. Overall, the results reveal a significant asymmetry within the financial impact of positive and negative changes in the CBBE and FBBE valuations for the common 44 brands. Firstly, aligning with the empirical outcomes of the full CBBE and FBBE samples, it is found that the deteriorating effects of declining brand equity on firm performance are much severe than the positive change impact. More specifically, the obtained elasticities reveal that these effects are significantly higher for CBBE as compared to FBBE in both the directions (ΔPos CBBE=0.17 vs ΔPos FBBE=0.11 and ΔNeg CBBE=-0.74 vs ΔNeg FBBE=-0.53). The empirical evidence therefore fully supports H4 indicating that although the deteriorating effects of decline in both the brand equity measures are significantly severer than their positive contributions, this polarized relationship is much stronger for CBBE than FBBE. In generic terms, it implies that even from a directional perspective, unanticipated changes in CBBE possesses more diagnostic information than firm based brand value measure. Where upward shifts in CBBE exhibit relatively higher stock market appreciation, investors react more aggressively on information of declining CBBE as compared to similar changes in FBBE. No study until now have provided such comprehensive insights about the polarized firm value dynamics of CBBE versus FBBE by comparing their positive and negative components separately (to the best of author's knowledge).

Although the research is first of its kind, certain explanations can be drawn from existing literature for stronger stock market response towards fluctuating consumer brand perceptions over equity gained directly at brand level. Marketing academics argue that consumer based brand equity is paramount as compared to other brand equity measurement dimensions as any "brand vision" is ultimately an outcome of the value delivered to the consumers (Ailawadi et al., 2003; Oliveira et al., 2015:2560; Tong & Hawley, 2009). Leone et al. (2006:126) also contend that "the power of a brand lies in the minds of consumers" and any change in consumer's cognitive behaviour towards a brand will in-turn alter firm's market performance such as profitability (Huang &

Sarigollu, 2014). These arguments provide strong insights that information contained in changing consumer brand attachment is highly diagnostic in projecting firm's future growth prospects. Therefore investors and shareholders are expected to pay closer attention and respond much aggressively towards sudden rise or decline in consumer centric brand equity as compared to other brand performance measures such as FBBE. These arguments also align with the findings of Johannsson et al. (2012) that investors prefer strong consumer brands over firms with superior FBBE levels during unprecedented market conditions.

Furthermore, brand equity represents all the current and past investments in brand value creation and therefore is a long-term concept. While consumer's brand perspective reflects the direct outcomes of these brand building activities, FBBE measures provide an *objective* assessment of the after-effects of consumer cognitive brand attachment (Stahl et al., 2012). Due to this *objectivity*, any changes in FBBE measures such as revenue premium or brand based earnings will be flagged immediately either directly or through firm's periodic balance-sheet performance (such as earnings release). Due to ease of understanding and rapid availability, changes in FBBE will be immediately absorbed in the firm's market value. This can be why Stahl et al. (2012:3) posit that FBBE measures have limited diagnostic value. In contrary, CBBE is a direct measure of brand equity and is known to have long-term effects (Huang & Sarigollu, 2014). Additionally, changes in consumer mindset are *subjective* and therefore any substantial shifts in it are challenging to comprehend (Nguyen et al., 2015). Since capital markets are forward looking (Mizik, 2014), any unanticipated swings in CBBE create uncertainty amongst investors about firm's future financial performance. Due to these reasons, release of any credible information about such changes in consumer brand association (e.g. through third party valuation reports) would attract a much aggressive invertor response as compared to alterations in FBBE measures. Additionally, the *backward* and *forward* looking characteristics of CBBE and FBBE, respectively, can also be an additional driving force for a discrepancy between their directional firm value effects (Nguyen et al., 2015:556).

The novel evidence obtained after testing H3 and H4 leads to further interesting insights when viewed from the brand value change dynamics of the acquired CBBE and FBBE sample firms. Recall from figure 5.6 in chapter 5 that in the entire 10 year study period (2019 till 2019), on average, more firms have experienced a decline in their annual consumer based brand valuations as compared to firm based brand equity measure ($N_{\Delta Neg\ CBBE} = 16$; $N_{\Delta Neg\ FBBE} = 11$). Infact, the data indicates that for some years (e.g. 2012 and 2016) more than half of the sample brands experience a sudden decline in their consumer oriented equity. No such pattern is observed for their corresponding FBBE valuations. Additionally, figure 5.7, which assesses the number of firms experiencing a simultaneous decline in both their CBBE and FBBE valuations within a single year reveals that such cases are also relatively rare. Jointly, these findings indicate that even during negative market conditions, decline in one brand equity perspective does not have a significant direct impact on the other measurement dimension. More specifically, the obtained facts suggest that even though consumers are the epicentre of any brand (Oliveira et al., 2015), it does not imply that an unanticipated decline in their brand sentiments is as an indication that a similar effect is to be felt in other sources of equity which a brand enjoys. Therefore, although negative shifts in both consumer and firm based brand equity have much severer firm performance consequences than positive changes, these effects are mutually exclusive to each other.

This dynamics further support the obtained evidence of weak correlation between changes in CBBE and FBBE as hypothesized through H3.

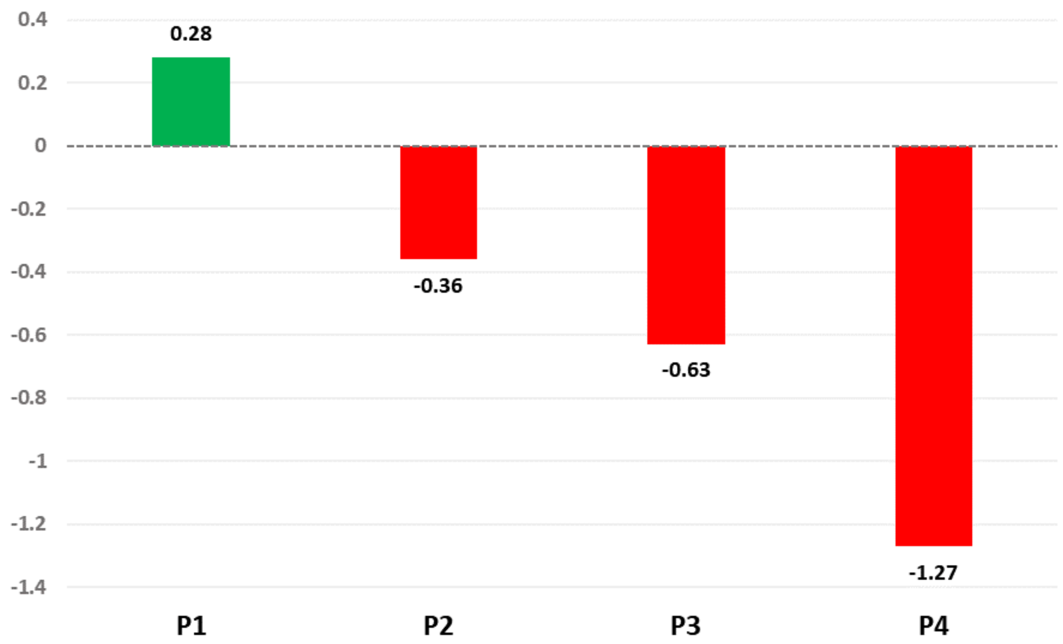
To further understand how this discrete value relevance of unanticipated changes in CBBE and FBBE can have severe consequences on firm's future growth, a visual illustration of "possible scenarios" is presented in figure 7.2. Firstly, table 7.1 outlines all the four possibilities that can occur in a given year following the BrandZ and Brand Finance brand valuation release for CBBE and FBBE, respectively. The table reports the coefficients of impact of positive and negative changes in CBBE and FBBE on firm performance as obtained from their respective SRRM models (refer to table 5.24 in chapter 5). It also outlines the total financial impact for each scenario by adding the individual coefficients of the respective CBBE and FBBE directional changes. For example, possibility P1 represents favourable shifts in both CBBE and FBBE in a given year. Therefore, the total firm value impact in such a case will be 0.28, which is the sum of coefficients of positive CBBE change (b=0.17) and positive FBBE change (b=0.11). In similar manner, the total financial effects of other three possible combinations are calculated. Cases P1 and P4 illustrate the joint stock return response when both CBBE and FBBE move in the same direction within a single year. As evident in figure 7.2, a distinguishable feature between these two possibilities is the severity of the firm value deterioration due to a simultaneous decline in both the measures which is significantly higher as compared to their cumulative positive contributions. This further highlights why focusing on negative brand valence is crucial for long term brand success.

Table 7.1 CBBE-FBBE yearly change possibility scenarios

Possibility	Brand Equity Change Combination	Total Financial Impact
P1	ΔPos CBBE - ΔPos FBBE	0.28
P2	ΔPos CBBE - ΔNeg FBBE	-0.36
P3	ΔPos FBBE - ΔNeg FBBE	-0.63
P4	ΔNeg CBBE - ΔNeg CBBE	-1.27

ΔPos: Positive Change, ΔNeg: Negative Change, CBBE: Consumer based brand equity, FBBE: Firm based brand equity

Figure 7.2 Total financial impact of the possibility scenarios



Source: Author's elaboration

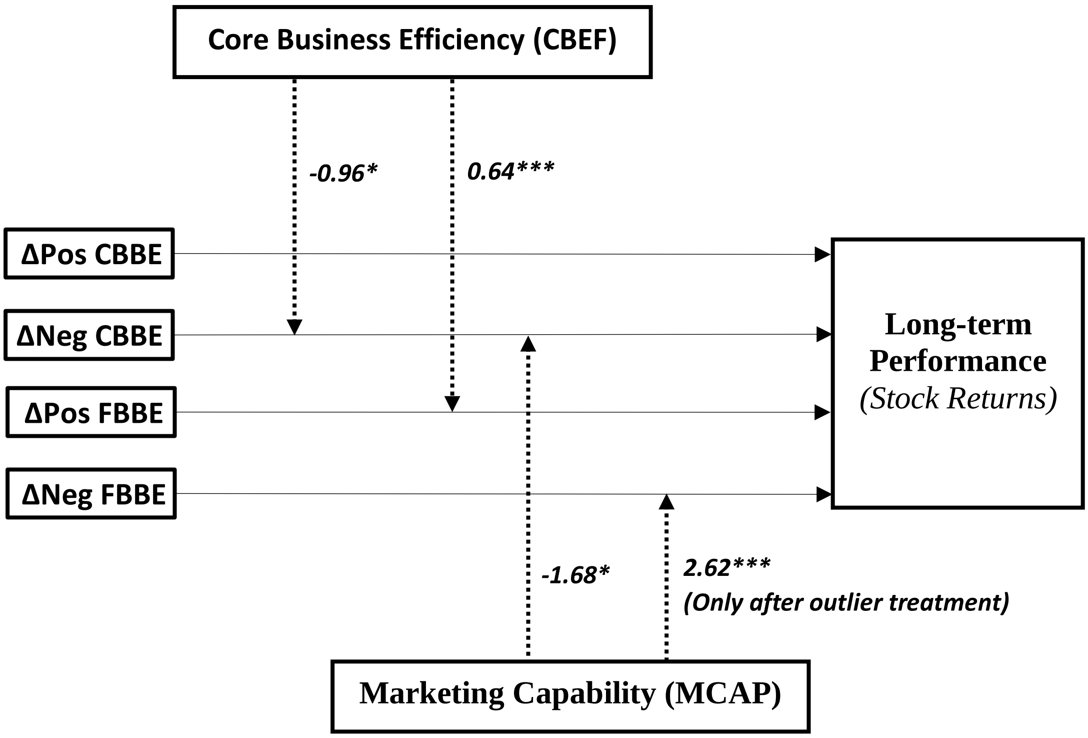
Even further notable revelations emerge from "possibility scenarios" P2 and P3, where change in one brand equity perspective is in the opposite direction to its counterpart. For instance, despite P2 witnessing growing consumer loyalty, an unfavourable shift in brand's firm based equity has eradicated all its positive value contributions resulting in an overall negative response coefficient (b= -0.36). This reflects that even if a brand exhibits strong consumer association, it cannot create shareholder wealth if the value attained from its proprietary assets such as patents and trademarks continue to plummet. Same is the case with P3 where FBBE rises while CBBE declines, still the net financial impact remains negative (b= -0.63). A notable difference in P3 is the magnitude of the total impact which is significantly higher as compared to P2. This informs that even during mutually opposite changes in CBBE and FBBE, the impact of unfavourable shifts in consumer brand sentiments is the strongest. This is because the ultimate strength of the brand is reflective through its positive consumer disposition (Christodoulides & de Chernatony, 2010; Veloutsou et al., 2013; Veloutsou et al., 2020) and therefore any undesirable shifts in their emotional attachment towards a brand can significantly jeopardize firm's future growth prospects. Infact, nowadays there are generally more customers with negative brand sentiments than positive brand feelings (Alvarez & Fournier, 2016). Consequently, special attention needs to be paid to pursue dissatisfied customers and possible brand haters rather than simply relying on bonded consumers and brand lovers.

Collaboratively, the above illustration and the empirical evidence obtained from empirically investigating the theoretical assumptions of H3 and H4 lead to several interesting insights. Firstly, changes in CBBE and FBBE are not only mutually exclusive, but they also possess unique firm performance implications. More interestingly, the data demonstrates that an unanticipated decline in one brand equity measurement metric does not directly impact the other measure. This is a vital revelation because existing branding literature is still struggling to understand the true linkage between these two fundamental brand equity measurement perspectives (Nguyen et al., 2015; Tasci, 2020). The study provides novel insights that although a decline in CBBE is not a determinant of a similar change in FBBE (or vice versa) but an unfavourable change in any of these dimensions can erode the entire positive effects of the other measure. Moreover, such negative firm value erosion is severer during declining CBBE as compared to FBBE. All these evidence emphasize on the importance of embracing multi brand equity perspectives to fully understand the holistic value relevance of brand equity (Lehmann et al., 2008). This is because brand equity is a multifaceted construct and none of its dimension can single handily capture its depth and breadth (Molinillo et al., 2019). The findings also highlight the need to direct more focus on understanding the potential consequences of deteriorating brand equity. The research in this area is still scarce and have focussed solely on financial consequences of negative consumer sentiments (Luo, 2007, 2009; Luo et al., 2013), ignoring other sources of brand equity such as FBBE. Since both CBBE and FBBE are the key constituents of brand equity (Christodoulides et al., 2015; Torres et al, 2015) and assess different levels of brand value chain (Ailawadi et al., 2003; Huang & Sarigollu, 2014), analysing their joint consequences on firm performance is vital to gauge the holistic brand relevance. Without adopting such a comprehensive approach, marketers can over or underrate the true long-term potential of branding (either in value creation or destruction).

7.3 Section-II: Moderating Role of Organizational Efficiency

The second part of empirical analysis investigates the role of organizational efficiency in moderating the brand equity-firm performance relationship. The discussions revolve around the translating roles of two organizational efficiency functions identified as core business efficiency (CBEF) and marketing capability (MCAP). As explained in chapter 3, both the acquired efficiency variables follow a multi input-output integration approach for their operationalization. From the methodological perspective, MCAP and CBEF are modelled through Malmquist total factor productivity (TFP) which is an advanced version of linear programming based DEA analysis (Charnes et al., 1978; Fare et al., 1994; Malmquist, 1953). The TFP based efficiency measures accounts for both firm's internal input to output transformation capabilities and external technological changes over time and therefore is an ideal benchmarking approach for panel-data type studies (Demerjian, 2018). Figure 7.3 explicitly extracts the segment of the main conceptual model which pertains to the path relationships defined for this section. For simplification purposes, only those interaction paths are displayed which are statistically significant. The obtained response coefficient along with its significance levels are also included with each path for clearer interpretations. This section firstly overviews the empirical results obtained after investigating the interaction of effects of CBEF, separately for consumer and firm based brand equity models. The proposed CBBE and FBBE interaction models expect the impact of unanticipated rise and decline in brand equity to be positively moderated by firm's CBEF and are hypothesised through H5(a) and H5(b), respectively. In a similar manner, the succeeding sections then evaluate whether firms with growing marketing capability mitigates (enhances) the negative (positive) firm performance effects of declining (rising) CBBE (H6(a)) and FBBE (H6(b)). Overall, the aim is to verify if the theoretical underpinnings of RBT holds its relevance in the brand equity-firm performance nexus. The significant contributions of MCAP and CBEF would therefore establish that the "organization" component of RBT's VRIO framework is crucial in exploiting strategic marketing resources like brand equity to gain SCA.

Figure 7.3 Empirical results for analysis phase-II



Δ = Change, CBBE = Consumer based brand equity, FBBE = Financial based brand equity, ΔPos = Positive Changes, ΔNeg = Negative Changes

****p<0.01, *p<0.10*

Source: Author's elaboration

7.3.1 Interaction Effects of Core Business Efficiency (CBEF)

Examining H5(a), the results suggest that positive changes in firm's core business efficiency levels weakens the relationship between declining CBBE and firm performance (ΔNeg CBBE X ΔCBEF= -0.96, $p<0.10$). No such opposing effects are however realized during a positive CBBE change. The significant findings indicate that management which is capable of running its fundamental business operations to its maximum potential tend to weather the adverse firm value impact of declining consumer based brand equity. On the other hand, the empirical results for H5(b) reveal that favourable shifts in CBEF complements the positive stock return response of rising firm based brand equity (ΔPos FBBE X ΔCBEF= 0.64, $p<0.001$). In other words, positive changes in FBBE have stronger impact on firm performance for firms which are capable of strategically managing their fundamental business operations. No such effects are however realized during declining FBBE. Together, supporting evidence for H5(a) and H5(b) implies that while CBEF mitigates the adverse effects of declining consumer brand association, it reinforces firm performance during positive changes in brand-related income.

These "opposite side" complementary effects of CBEF for consumer versus firm based brand measures can be due to their mutually exclusive characteristics. For example, as discussed earlier, CBBE captures consumer's intuitive brand judgements which are challenging to fully comprehend. Due to this subjectivity, the reliable data pertaining to consumer brand association is not readily available. Furthermore, consumer cognitive behaviour may change abruptly due to many market factors which are not under management's direct control. Besides this, previously conducted analysis (i.e. ΔCBBE *Main* model) also indicates that the firm value impact of declining CBBE is the strongest. Therefore, due to unavailability of credible information, higher firm performance impact and uncertainty due to *subjectivity bias*, it is likely that financial community seek other management factors when revising their investment decisions during a sudden decline in consumer brand perceptions. Since CBEF represents how well a management scrutinize its available tangible resources such as infrastructure, workforce, and capital stock to maximize productivity, it is a key indicator of profitability (Nath et al., 2010). Therefore, during unprecedented changes in CBBE, investors are more confident towards the future performance of brands that are managed by organizations with superior CBEF. In other words, they treat firms with growing core business efficiency capable of handling such unfavourable shifts in consumer behaviour more effectively as compared to inefficient firms.

Firm based brand equity, on the other hand, is an *objective* based measurement perspective as it reflects future cashflows attributable to a brand based on its current and historic performance (Bagna et al., 2017; Chang & Young, 2016). These characteristics makes it relatively easier to extrapolate any changes in its magnitude as compared to consumer's cognitive brand attachment. Since FBBE valuations are derived from accounting methods, it is likely that a portion of this information is already absorbed by stock markets during firm's periodic performance reports (i.e. quarterly or annual earnings release). Furthermore, recall that the modelled core business efficiency measure also evaluates firm's capabilities to maximize profitability (through OIBD)[41]. Therefore there seems to be a potential information overlap between changes in FBBE and changes in CBEF. Additionally, it is already established earlier (both from section-I analysis results and "loss aversion" and "negativity bias" theories) that investors react more aggressively to any negative information as compared to positive information. Based on these findings and ease of interpreting FBBE, it can be assumed that financial community put more weight to the negative information contained in unanticipated decline in firm based brand equity over the positive information such as growing firm's core business efficiency. This can be potentially why the coefficient of CBEF interaction effect during negative FBBE changes (ΔCBEF X ΔNeg FBBE) is statistically insignificant.

[41] Refer to figure 3.2 in the conceptual framework chapter.

However, the significant contributing role of CBEF during positive FBBE changes can be explained based on its fundamental characteristics. Business efficiency represents firm's ability to maximize its productivity with minimal allocation of underlying resources such as infrastructure, manpower, and capital stock (Nath et al., 2010). This enables organizations with superior CBEF levels to minimize their production costs while offering high quality products. High product quality in-turn induce higher demand as the consumers apparently make repeated purchase of such brand products over other competitors (Gourio & Rudanko, 2011). Due to this "quality-demand" linkage, such brand firms enjoy enhanced profitability levels because of higher than expected future discounted cashflows (Aaker & Jacobson, 1994; Tellis & Johnson, 2007). Since Brand Finance considers both current and future brand performance when evaluating firm based brand equity, superior CBEF levels are likely to complement these valuations, therefore elevating positive FBBE change to firm performance translation dynamics. From stock market perspective, these arguments signify that investors perceive information contained in improved core business efficiency incremental in explaining future discounted cashflows due to soaring FBBE.

7.3.2 Interaction effects of Marketing Capability (MCAP)

In order to empirically investigate whether the firm performance impact of positive and negative shifts in CBBE and FBBE are sensitive to firm's marketing capability, H6(a) and H6(b) were proposed. The empirical results for H6(a) move in tandem with the CBEF interaction effects revealing that changes in firm's marketing capability moderates the negative impact of declining CBBE on stock returns (ΔNeg CBBE X ΔMCAP = -1.68, $p<0.10$). MCAP however does not play any decisive role in translating the positive firm value effects of rising CBBE. Therefore, theoretical arguments made in H6(a) are partially supported revealing that superior levels of MCAP buffer the financial consequences of unanticipated decline in consumer's cognitive brand attachment. From SRRM perspective (Mizik & Jacobson, 2008), the supporting evidence suggest that information contained in changes in firm's MCAP is in fact value relevant i.e. investors and shareholders seek these changes as a crucial factor when evaluating firm's future growth, especially during the periods of weakening consumer brand sentiments. Although no study till date has directly explored the complementary role marketing capabilities in brand equity-firm performance relationship, the evidence in support of H6(a) align well with the existing work in this relatively small body of research stream. For example, Modi and Mishra (2016) observed that high marketing capability significantly reduces stock price volatility during negative changes in CSR perceptions. The authors argue that such counteractive dynamics is due to the ability of firms with strong MCAP to effectively respond to any adverse effects of firm's CSR efforts, thus lowering idiosyncratic risk. Similarly, Nguyen and Oyotode (2015) found that MCAP moderates CSR-brand performance linkage by mitigating the deteriorating impact of negative changes in CSR perceptions on brand equity. The current study advances the knowledge further signifying that firms with proactive market orientation also mitigate the negative effects of declining consumer centric brand equity on long-term firm performance. From RBT perspective, these empirical outcomes indicate that firms possessing strategic marketing resource management capabilities can preserve the value relevance of their V, R, I market resource like CBBE even during unfavourable market conditions, thus enjoying a sustainable competitive advantage (SCA) over their competitors.

There are several factors that can explain why translating effects of negative CBBE changes on firm performance are sensitive to firm's market oriented efficiency. Firstly, Bahadir et al. (2008) suggest that investors and shareholders consider levels of firm's marketing capability as a crucial organizational function when appraising its stock market valuation. This is because firms with complementary marketing capabilities are able to generate relatively higher cashflows from their brand assets as compared to firms with weaker MCAP (Wiles et al., 2012:9). Research also shows that firms operating at optimal levels of marketing capability tend to better predict any changes in consumer behaviour and reactions towards any negative information (Xiong & Bharadwaj, 2013). Therefore, strong MCAP firms are likely to better convey stakeholders about their commitment towards understanding consumer needs and taking remedial actions to address any unfavourable shifts in CBBE. Additionally, MCAP by definition revolves around the consumers where focus is strategic allocation of available marketing resources to enhance consumer experience resulting in higher sales revenue (Dutta et al., 1999). Organizations with richer MCAP are also capable of better handling consumer grievances during the challenging times when their brand is exposed to public criticism (Xiong & Bharadwaj, 2013:712). Thus, positive changes in firm's marketing capabilities enhance firm's market share through strong customer intelligence leading to potential growth in consumer brand loyalty. This can be why RBT proponents argue that MCAP is in itself a valuable, rare, and inimitable marketing asset that provides competitive edge to a firm over its competitors (Morgan et al., 2009; Nguyen & Oyotode, 2015). Due to these reasons, firms with superior or growing marketing capability strengthen investors' confidence towards their brand's future potential, thereby "softening the landing" during sudden downward shifts in brand's CBBE levels.

The second path relationship theorized through H6(b) investigates whether MCAP exhibits similar moderating effect during unanticipated shifts in firm based brand equity measurement perspective. With the smallest sample size in the entire analysis comprising of 32 sample brands (i.e. 320 firm year observations), the initial empirical outcomes of MCAP interaction effects for both positive and negative FBBE changes were statistically insignificant. However, a further investigation revealed the presence of potential outliers and their treatment through robust fixed-effect estimation returns significant coefficient for ΔMCAP X ΔNeg FBBE but with the opposite polarity ($b=2.62.$, $p<0.001$). The obtained results therefore contradict the theoretical assumptions made in H6(b) signifying that marketing capability negatively moderates the declining FBBE-firm performance relationship. In other words, diminishing stock returns due to negative shifts in firm based brand equity are further escalated in the presence of favourable changes in MCAP. The statistical results for positive FBBE side still remain insignificant, even after outlier treatment, demonstrating no MCAP moderation in ΔPos FBBE-firm performance linkage.

There are no clear explanations about these contradictory findings in the current marketing-finance literature. Infact no study until now (to the best of researcher's knowledge) have attempted to closely examine the moderating effect of marketing capability on FBBE-firm performance relationship, let alone the directional changes. One plausible justification of this can be given from the "input-side implications" of superior marketing efficiency. Recall that MCAP has been operationalized through a multi input-output approach with "marketing expenditures" being one of the key inputs, which represents firm's yearly advertisement and R&D expenses[42]. The choice of this input is driven by current literature which argue that in order to build strong MCAP, firms need to continuously invest both in their marketing activities (advertisements) and innovation through rigorous research and development (R&D) (Xiong & Bharadwaj, 2013). However, acquiring such strategic marketing inputs require substantial investments over prolonged periods with no clear affirmation whether they will actually materialize in future or not (Edeling & Fischer, 2016). Arguably, these marketing spendings can have a negative impact on firm value as investors may perceive them as additional costs, especially, if it fails to boost revenue (Lu &Beamish, 2004). To further support of this argument, a recent meta-analysis conducted by Edeling & Fischer (2016) reports that approximately one fourth of the elasticity estimates of "advertisement spending-firm value" models are negative. These findings suggest that if investments in acquiring these strategic marketing resources fail to attract new customers and transform them to be loyal and satisfied, then it can be a costly venture especially from firm's future growth prospects (Himme & Fischer, 2014; Lehmann, 2004; Rust et al., 2004). This can be a key reason why marketing managers generally find it challenging to justify their marketing budgets (Joshi & Hanssens, 2010). Since the acquired FBBE measure in this study is exclusively derived from brand royalties from patents and trademarks, an increase in marketing expenditures can therefore be viewed as a liability on these earnings. Kirk et al. (2013:2) also posit that although the financial benefits of marketing investments in strengthening brand equity may not substantiate for many years, but the accounting impact of these expenditures are felt immediately. Due to

[42] Refer to figure 3.3 in the conceptual framework chapter.

these “cost related issues” and uncertainty of potential future payoffs from current marketing investments, stock markets may perceive growth in firm’s marketing capability as a burden on brand’s projected cashflows. This can be why the negative firm performance impact of deteriorating firm based brand equity is inversely related to changes in marketing capability.

Chapter 8: CONCLUSION

8.1 Overview

This final chapter of the thesis provides the concluding remarks pertaining to the main research question i.e. how positive and negative changes in consumer and firm based brand equity impact firm performance and the intermediary role of superior organizational capabilities in this brand equity-firm performance relationship. Firstly, the overall objective is segregated into different themes so as to systematically review all the path relationships defined in the proposed conceptual model. Each theme provides critical insights about the level to which the obtained empirical evidence supports or contradict existing knowledge about brand equity-firm performance interface. Focus is also directed to provide a broad overview of the acquired firm performance metric, adopted investigative methodologies and procedures to model the acquired marketing and organizational efficiency variables under investigation. The subsequent sections then highlight the key contributions which this study claims to have made both in marketing-finance literature as well as research linking resource based perspective to marketing. Along with theoretical contributions, the study also has several managerial and investor related implications which are discussed separately in the subsequent sections. The chapter finally informs potential limitations of this study which open several new directions for future research.

8.2 Research Objectives

The central aim of this research was to investigate the impact of rising and declining brand equity on long-term firm performance and the how organizational efficiency moderates this relationship. The study also compares two key dimensions of brand equity i.e. consumer and firm based brand equity. The comparative assessment includes i) examining the level of their co-association and ii) their unique link with firm value. The underlying research objectives were accomplished by developing a comprehensive conceptual framework which systematically connects all the marketing and organizational measures under investigation directly or indirectly to firm performance. In order to reflect long-term firm performance, the study relies on stock market based mechanism rather that current period balance sheet measures such as profits, sales revenue, or market share (e.g. Ailawadi et al., 2003, Keller & Lehmann, 2006). Marketing academics advocate that brands have lasting effects and therefore contemporaneous accounting performance outcomes cannot capture its total financial impact (Goldfarb et al., 2009; Mizik, 2014:691; Srinivasan et al., 2005). Stock markets, on the other hand, are forward looking, and the current market value of a firm represents investor and shareholder's expectations about firm's future growth prospects (Mizik & Jacobson, 2008). Therefore, any unanticipated changes in firm's key strategic assets like brand equity are likely to alter its stock market valuation, thus impacting future returns. From the methodological perspective, all the proposed research questions are empirically tested by implementing stock return response modelling technique (SRRM) (Mizik & Jacobson, 2004). SRRM emerges from traditional accounting and finance research stream and has gained wide popularity amongst marketing academics examining the value relevance of various marketing assets and strategies[43]. A major advantage of SRRM over other econometric models is its inclusion of current-term firm

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[43] Refer to section 4.3.3 of the methodology chapter for a detailed discussion about SRRM or else see Srinivasan & Hanssens (2018:14).

performance and other economy-wide and firm specific risk factors which are main drivers of firm's future discounted cashflows (Carhart, 1997; Daniel & Titman, 1997; Fama & French, 1996). Modelling the marketing variable of interest after considering these accounting and financial factors therefore significantly reduce the omitted variable bias, thus providing much richer insights (Mizik & Jacobson, 2008).

The main research objective is assessed along three themes. First, the directional impact of rise and decline in consumer and firm based brand equity on firm performance is investigated. This is then followed by comparing as to what extent these two brand equity measurement perspectives are related to each other and their unique relationship with firm performance. Finally, the applicability of RBT in marketing is examined by exploring whether organizational efficiency can transform strategic intangible resource like brand equity into a provider of sustainable long-term growth. The statistical models investigating these three themes vary in sample size ranging from 35 to 54 firm-brands per year across 2010 till 2019. The following sections outline these themes separately focusing on the developed research questions, how they were empirically addressed and the key findings.

8.2.1 The impact of rise and decline in brand equity on firm performance

The first section of the proposed conceptual model investigates whether there exists an asymmetry in the firm performance impact of unanticipated rise and decline in brand equity. The model also tests the validity of existing marketing-finance knowledge that, overall, brand equity has a significant positive impact on firm future performance (Dutordoir we al., 2015; Hsu et al., 2013; Mizik, 2014; Yeung & Ramasamy, 2008; Yildiz & Camgoz, 2019). Employing two separate panel data econometric (*baseline*) models for CBBE and FBBE samples with 540 and 490 firm-year observations, respectively, the results affirmed that changes in these brand equity measures significantly improve firm performance. These findings reinforce that brand equity, irrespective of its measurement perspective, is a key provider of incremental value to the firm. The model then turns its attention to investigate its main objective of exploring their directional firm performance impact. To achieve this, overall changes in CBBE and FBBE were segregated into their positive and negative components before including them in the *main* SRRM models. The empirical results provide strong support for all the individual path relationships connecting ΔPos CBBE, ΔNeg CBBE, ΔPos FBBE and ΔNeg FBBE to firm performance with expected polarities[44]. More importantly, the findings aligned well with the hypothesized theoretical assumptions revealing that the firm value erosion due to downside shift in both CBBE and FBBE is significantly larger than the stock price appreciation because of upside shifts. The study therefore emphasizes on the importance of adopting a polarized view in order to critically examine the true value relance of brand equity.

8.2.2 Comparative assessment of consumer and firm based brand equity

Apart from unfolding the directional financial implications of CBBE and FBBE, the first section of the conceptual model also conducts a comparative assessment between these two brand equity measures. This is accomplished by discarding all the uncommon brand-firms in the both the original CBBE and FBBE samples, leaving only the 44 common brands. Initially, the defined path relationships cross-compare their association

[44] Although initially the path relationship "ΔPos FBBE→Stock returns" was statistically insignificant, but omission of outliers affirmed that this link is in fact statistically significant in the expected direction.

with each other focusing simultaneously on their contemporaneous and dynamic relationship. The pairwise correlation tests inform that there is a close association between CBBE and FBBE in their absolute form, but they depart from each other as they evolve over time. In other words, changes in consumer and firm based brand equity over time are weakly related thereby fully supporting the theoretical arguments proposed in this study. Apart from the mutual relationship, their individual value relevance is also compared by linking changes in CBBE and FBBE valuations for the common 44 brands separately with stock returns. Since consumer brand cognitive response is difficult to fully understand in relation to objective FBBE measures (Nguyen et al., 2015), it was assumed that the firm value impact of unanticipated changes in CBBE will be higher as compared to FBBE. The obtained empirical evidence binds well with these expectations indicating a stronger relationship of growth and decline in CBBE with firm performance as compared to similar directional changes in FBBE. Jointly, the obtained evidence for cross-comparison and individual stock return response of CBBE and FBBE provide valuable clarifications to current branding research, which is still inconclusive about their true inter-relationship (Nguyen et al, 2015; Oliveira et al, 2015; Tasci, 2020).

8.2.3 Moderating role of organizational efficiency in brand equity-firm performance relationship

Apart from unfolding the asymmetrical firm performance impact of positive and negative changes in brand equity, this research also identifies key organizational factors which can moderate these directional effects to the firm’s benefit. Anchored to the theoretical assumptions of Resource Based Theory (RBT), this section focusses on the “organization” factor of RBT’s VRIO framework and identify firm’s core business efficiency (CBEF) and marketing capability (MCAP) as two possible moderators. Both these organizational efficiency measures are conceptualized through a multi input-output modelling perspective rather than simple ratio analysis because of its ability to incorporate several operational characteristics simultaneously into a single efficiency metric (Donthu et al., 2005; Roh & Choi, 2010). Both CBEF and MCAP are modelled using a non-parametric linear programming benchmarking tool, borrowed from operations research, namely data envelopment analysis (DEA) (Charnes et al., 1978; Khezrimotlagh et al., 2019). Instead of simple DEA benchmarking, the study takes advantage of its panel data structure and model CBEF and MCAP using its advanced version namely, Malmquist (1953) “total factor productivity change (TFPCh)” analysis. Malmquist TFPCh based efficiencies are superior to that of basic DEA models in that it accounts for both changes in firm’s internal efficiencies and technological changes over time (Tavana et al., 2020). This added time dynamism within the measured CBEF and MCAP support the fact that organizations modify their resource allocation strategies from time to time in order to keep up with the constantly changing market conditions such as technology, demand, and competitor’s actions (Rahman, 2020:352). Therefore, embracing Malmquist TFPCh over traditional DEA efficiencies provide much richer insights about the moderating roles of CBEF and MCAP in long-term due to the incorporation of time-series characteristics. However, not all the firm-brands (for CBBE and FBBE samples) acquired in this research could be included in the CBEF and MCAP interaction models. This is primarily due to the inability of DEA to account for negative values of inputs or outputs in its benchmarking process (Sarkis, 2007). The second reason is the unavailability of marketing input data (e.g. SG&A) for the brands operating in the financial sector. Due to these limitations, different MCAP and CBEF based SRRM models have different number of total sample firms. For example, the CBBE and FBBE models investigating the moderating role of core business efficiency consist of 460 and 440 firm-year observations, respectively. Aggregately, their empirical results indicate that CBEF synergizes the positive stock return response of rising FBBE and mitigates the negative effects of declining CBBE. On the other hand, the SRRM models exploring the sensitivity of brand equity- firm performance linkage to changes in marketing capability are limited to 360 and 320 firm-year observations for CBBE and FBBE datasets, respectively. The acquired results for CBBE model reveal that superior marketing capabilities diminish the firm value erosion caused due to unfavourable shifts in consumer sentiments towards a brand. On the other hand, the empirical outcomes for MCAP-FBBE model yields contradictory results suggesting that favourable changes in firm's marketing capabilities indeed aggravates the negative effects of declining FBBE on firm's long-term growth. These "against the hypothesized direction" interaction effects of MCAP in ΔNeg FBBE→ firm performance can be possibly due to its "cost side" implications, which is discussed in-detail in section 7.3.2 of the previous chapter.

8.3 Theoretical Contributions

The novel findings of this research offer several implications for existing theory in marketing-finance interface linking brand equity to long-term firm performance. Where existing research focus on overall brand equity-firm value translation mechanism, this study exposes the polarized stock return response of positive and negative changes in brand equity. This is crucial because until now, marketing academics have perceived brand equity solely as an “incremental value provider” (Christodoulides & de Chernatony, 2010; Keller, 1993; Keller, 2016) because of its significant positive association with future firm performance (Bagna et al., 2017; Himme & fischer, 2014; Mizik, 2014; Srinivasan et al., 2010). Although it is true that brand equity does provide competitive edge to a firm, these arguments however, take into account, only the positive side of brand equity-firm performance dynamics. Taking a directional approach, the current research reveals that long-term value eroding effects of declining brand equity are much severer than its positive contributions. The study therefore provides new and valuable insights indicating that brand equity can be a potential “value destroyer” instead of “value creator” if its declining effects are ignored or misunderstood. Rise and decline in brand’s strength is a common phenomenon in real world (Veloutsou & Guzman, 2017) and such variations can occur due to several internal (management based) and external (market based) forces. Therefore, it becomes vital to understand the downside financial implications of declining brand strength in addition to its overall value relevance. Only handful of studies so far have explored the negative brand effects, but their focus is limited to consumers and products, rather than brand as a whole (Luo et al., 2013; Sun, 2012; Tellis & Johnson, 2007; Tirunillai & Tellis; 2013). This research therefore adds a new dimension in understanding brand equity-firm value interface by unfolding the possible competing effects of strategic marketing asset like brand equity, which until now has largely been ignored.

Another notable contribution of this study is its focus on understanding the comparative dynamics of two key brand equity measurement perspectives i.e. consumer and firm based. Marketing academics are still struggling to understand the degree to which these two brand equity measures relate to each other (Cristodoulides & De Chernatony, 2010;

Veloutsou et al., 2013; Taci, 2020). Where some studies have found a close association between different components of CBBE and FBBE (Datta et al., 2017; Kamakura & Russel, 1993; Lehmann et al., 2008; Stahl et al., 2012), others advocate that they are in fact mutually exclusive (Nguyen et al., 2015; Tasci, 2020). This study is the first to perform a systematic comparative analysis to better understand the true link between these two brand equity dimensions. The analysis first evaluates their steady-state relationship, which is the approach predominantly followed by all the existing studies pertaining to this research stream (refer to table 2.5 in the literature review chapter). However, exploring steady-state estimations of brand equity is known to have limited theoretical and practical implications (Srinivasan & Hanssens, 2009). This study addresses this anomaly and follows the recommendations by Tasci (2010) to extend the knowledge further by comparing their evolution over time, which has much more diagnostic importance (Mizik, 2014). In addition to this, their individual contribution to future firm performance is also inspected. The knowledge gained after such a comprehensive analysis adds to the ongoing debate about CBBE-FBBE interrelationship by unfolding three key insights. Firstly, in its absolute state, consumer and firm based brand equity are closely associated. This strong contemporaneous interrelationship supports the arguments that strong cognitive attachment of consumers with a brand has quantifiable ramifications on firm's profitability (such as brand based earnings) (Stahl et al., 2012). However, a further examination informs that although these brand equity metrics co-align with each other "in-levels," their dynamics of change over time does not follow a similar pattern. These findings provide new insights suggesting that CBBE and FBBE captures two mutually exclusive components of brand equity and therefore they must be investigated individually in order to understand the holistic success of a brand.

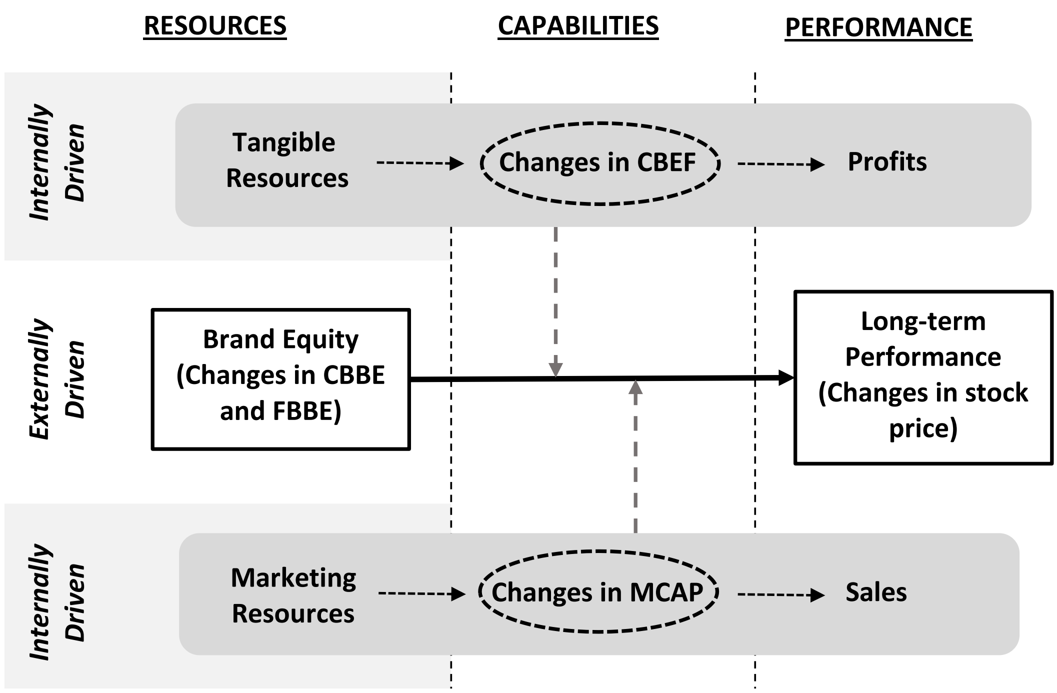
Thirdly, this thesis also makes a distinct contribution to the existing knowledge by contrasting CBBE and FBBE in the context of their unique relationship with firm performance. The obtained evidence suggests that overall, changes in firm's consumer based brand values have a much higher influence on firm future performance as compared to their firm based brand equity estimations. From financial markets perspective, these findings suggest that CBBE possesses more diagnostic information than FBBE in explaining firm's future discounted cashflows. These facts become even more interesting after disaggregating the overall CBBE and FBBE changes into their positive and negative components and re-comparing their firm value impact. The novel findings indicate that on the positive side, brands with growing consumer allegiance tend to generate higher returns as compared to growth in their firm based brand strength. However, during unanticipated negative changes, the firm value eroding effects due to declining consumer brand association are significantly higher as compared to FBBE change. These outcomes offer additional import because firms generally ignore or underappreciate their bottom customers (Homburg et al., 2009; Luo et al., 2013). Firms should therefore not simply rely on benefits gained from strong brand equity through consumer brand association and loyalty as portrayed in the existing marketing literature (Aaker, 1991; Agarwal & Rao, 1996; Keller & Lehmann, 2006). Rather, companies even with high equity brands should be aware of the potential risk associated with negative CBBE changes because, as this study shows, such unfavourable shifts can significantly dilute firm value. These novel findings thus emphasize on understanding the negative side of brand equity-firm performance nexus and paying close attention to brand haters along with brand lovers when reviewing brand performance.

Overall the CBBE-FBBE comparative analysis conducted in this study not only provide explanations about their relationship with each other (both from steady-state and "in change" perspective) but also unfolds how they individually impact firm future performance (both from overall and directional change perspective). To the best of researcher's knowledge, no study until now has adopted such a comprehensive approach in understanding the association between these two key brand equity metrics. Apart from its novel contributions, this research also highlights the importance of including multiple brand equity perspectives to capture the full richness of brand equity (Lehmann et al., 2008). Additionally, it also encourages the use of multi-dimensional analytical approach in order to fully understand the true linkage between different brand equity perspectives. Another advantage of this study is its longitudinal data structure which tracks CBBE and FBBE estimations for same brands continuously over multiple years. Adopting such approach, not only accounts for heterogeneity across different brands (through fixed-effects panel estimations) but also addresses the fact that the true brand equity dynamics can only be realized in longer time horizons (Datta et al, 2017). Therefore, the obtained findings are not only rich theoretically but also possess superior methodological inferences.

Along with contributing to the burgeoning literature linking brand equity to firm performance from multiple dimensions, this study also offers new knowledge to the research linking Resource Based Theory (RBT) to market-based resources. These implications can be broadly segregated into "reformation of theory" and "application of theory" perspectives. From the first standpoint, this research improves the conceptual underpinnings of resource based theory of sustainable competitive advantage (SCA) by addressing some of its key limitations. As explained earlier in section 2.5.1 of the literature review chapter, one of the main caveats of RBT is its lone focus on firm's internal resources in determining its success or failure in the marketplace (Dicksen,1996). Although internal resource development is critical for business success, critics of RBT argue that firm's external resources are equal contributors of competitive advantage (Andrevski & Ferrier, 2019; Lavie, 2006). For example, even though the incremental value gained from consumer's brand allegiance (CBBE) or royalties from strong brand name (FBBE) is not under management's direct control, its contributary firm value effects are realized both in short-term (Fischer & Himme, 2017; Stahl et al., 2012; Steenkamp, 2014; Wang et al., 2015) and long-term (Bhardwaj et al., 2011; Mizik, 2014; Oliveira et al., 2018; Rahman et al., 2019). This is why brand equity is recognized as one the key "externally driven" marketing resource that provides competitive edge to its owner over the competitors (Dutta et al., 1999; Kozlenkova et al., 2014). CBEF and MCAP, on the other hand, reflect management's ability to transform their core-business and marketing resources to maximize profits and sales, respectively. Both these organizational efficiency measures are therefore "internally driven". By linking these *inside-out* capabilities to the *outside-in* resources, this study contradicts the proprietary assumptions of RBT that the value of the firm is reflective solely of its internal resource contributions. Rather, the obtained empirical evidence advances the theory by establishing that firms must integrate their internal and external resources and exploit them cohesively to attain sustainable competitive advantage (Lavie, 2006). These novel contributions are also visualized through figure 8.1 which provides a simplistic view of the proposed conceptual focusing explicitly on the delved

RBT refinements. The figure demonstrates how "internally driven" resource-performance transformation capabilities of CBEF and MCAP interact with "externally driven" brand equity dimensions of CBBE and FBBE in enhancing long-term firm performance.

Figure 8.1 Simplified conceptual model showcasing RBT refinements



CBBE: Consumer based brand equity; FBBE: Firm based brand equity; CBEF: Core business efficiency; MCAP: Marketing capability

Source: Author's Elaboration

Resource based perspective has also prompted criticism due to its reliance on static resource-performance association rather than dealing with dynamic issues (Day, 2011). Even RBT proponents (e.g. Barney, 2002) agree that the theory may not fully explain firm's SCA in unpredictable market environments where new technologies evolve and the value of resources change drastically over time (Kraaijenbrink et al., 2010:353). To improve the ability of resource based view in explaining SCA, it is crucial to understand how firm's resources and capabilities evolve in a dynamic setting (Day, 2011; Kozlenkova et al., 2014:13). Following these arguments, this research advances a "time-series" variant of RBT by unfolding how changes in firm's internally and externally driven resources lead to sustainable long term firm performance. This is clearly illustrated in figure 8.1 where all the adopted resources, capabilities and performance variables are included "in changes" rather in their contemporaneous form. Also, it is important to note that yearly changes in both CBBE and FBBE follow a random walk and therefore cannot be projected from its previous period valuations[45]. Furthermore, recall that both CBEF and MCAP are operationalized using Malmquist DEA benchmarking analysis which incorporates both i) shifts in firm's internal efficiency and ii) technological change over time (Demerjian, 2018). Due to these time-series characteristics, these estimated efficiencies also reflect the carry-over effects of the previous period resource utilization in the subsequent year, which steady-state efficiency measures could not capture (Luo & Donthu, 2006). Collectively, by analysing the resource-performance relationship longitudinally (over 10 year period) and in an unpredictable dynamic environment, this study advances RBT by refining it from "inherently static" to a more viable theory.

Another limitation of RBT this study addresses is the "construct validity" issue which emanates from its fundamental logic that despite operating within the same industry, different firms possess different sets of resources and capabilities (Peteraf & Barney, 2003) . Due to this uniqueness of "resource bundles", RBT critics argue that any

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[45] Refer to panel unit root test results in section 5.2.3 of chapter 5.

empirical findings about such assets or capabilities cannot be generalized across all types of firms or industries (Almarri & Gardiner, 2014). This is because RBT cannot explain how individual factors such as knowledge, experience or employee morale interact with the deployed resources in gaining superior market performance (Levitas & Chi,2002). The only way to address this "construct validity" problem is that the "researcher must literally enumerate and anticipate all of the background factors that could interact with these treatments (Levitas & Ndofor, 2006:138). However, in practice, it is extremely difficult to identify all these aspects because "systems under which the individuals operate are open ones" (Almarri & Gardiner, 2014:443; Cronbach, 1975). Providing a possible solution, Levitas & Ndofor (2006) argue that although construct validity cannot be achieved in RBT, such anomalies can be handled statistically through "fixed-firm effects" modelling techniques. Fixed-effects models can effectively isolate the unobserved heterogeneities across sample firms (Wooldridge, 2010), thus providing reliable interpretations about how resources or capabilities under investigation generate competitive advantage. Since all the SRRM models proposed in this study are tested through fixed-effects panel data estimations, RBT's issues of construct validity and generalizability are addressed appropriately.

Besides advancing resource based theory by addressing some of its key critiques, the empirical outcomes also contribute towards its application in the marketing research. Most importantly, it demonstrates how strategic intangible assets like brands can generate SCA even when both its consumer and firm based measurement dimensions are prone to rise or decline over time. Aligning with the underpinnings of RBT, the findings indicate that organizations that are efficient in exploiting their available resources can enhance (mitigate) the positive (negative) effects of upward (downward) shifts in brand equity on firm performance. More specifically, the study is first of its kind to unfold the interactive role of two key organizational functions i.e. core business efficiency (CBEF) and marketing capability (MCAP) in the brand equity-firm performance interface. This is imperative because CBEF and MCAP capture two fundamentally exclusive dimensions of organizational structure. Where core business efficiency represents firm's strategic fundamental resource exploitation capabilities, MCAP is the firm's ability to retain or enhance its consumer-base with efficient allocation of available marketing resources. Also, "in practice, organizational capabilities never exist alone" (Feng et al., 2017:13). Therefore, by incorporating the *profitability* and *marketability* measures of CBEF and MCAP, respectively, within a single research framework, this study provides more "realistic" interpretations of how organizational efficiency drive firm performance through its interactions with brand equity.

Secondly, focus is directed in understanding the pivoting roles of CBEF and MCAP during unanticipated positive and negative changes in brand equity and not simply on the overall changes. This ensures that along with the reported directional effects of upward and downward shifts in brand equity on firm performance, potential remedies are also provided within the similar context. Thirdly, the pivoting roles of CBEF and MCAP are examined independently for changes in consumer and firm based brand equity measures. Such detailed investigation provides novel insights about whether the moderating effects of these organizational efficiency measures vary based on the unanticipated directional change in a specific brand equity measurement perspective. No study to date has linked RBT to brand equity-firm performance nexus by i) including multiple organizational functions; ii) studying their moderating effects during rising and declining brand equity and iii) focusing simultaneously on consumer and firm based brand equity. This research can therefore be perceived as a benchmark or a guidance tool to fully understand the ways by which brand equity can be transformed into an asset that provides sustainable competitive advantage to the brand owning firm.

Another area where this study contributes to the RBT marketing literature is towards the completeness of its VRIO framework. Majority of prevailing research has provided supporting evidence of brand equity being valuable (Apelbaum et al., 2003; Keller, 2016; Vomberg et al., 2015), rare (Aaker & Joachimsthaler, 2000; King & Burgess, 2008; Makadok, 1999), and inimitable (Crook et al., 2008; Hooley et al, 2005; Ouyang, 2009), widely neglecting the "organization" aspect (Kozlenkova et al., 2014). This is crucial because, as this study finds, the deteriorating firm value effects of declining brand equity are significantly stronger than its positive change contributions. Therefore, if organization is not structured to effectively respond to such unanticipated shifts, then even a V, R, I source like brand equity can only impart limited financial value. By empirically demonstrating significant contributions of CBEF and MCAP in directional brand equity-firm performance relationship, this research establishes its proposed stance that without "organizational competence", brand equity can only be perceived as a source of competitive advantage but not a guarantor of SCA (refer to figure 2.3 in chapter 2 for a visual representation of this narrative). Adopting this contingency approach also refines the tautological issue of resource based theory as explained in section 2.5.1 of the literature review chapter. By unfolding the long-term value contributions of brand equity through the intermediatory role of organizational efficiency, this study supports the notion that "VRI resources are necessary but not sufficient conditions for achieving SCA" (Kozlenkova et al., 2014:5).

Until now, only two studies e.g. Zhu (2000) and Nath et al. (2010) have been found to have focussed towards understanding the decisive role of business efficiency in enhancing future firm performance (refer to table 2.6 in chapter 2). While the first research links efficiency directly to firm performance, revealing a strong linkage between them, the latter found that superior business efficiency also enhances the effects of marketing efforts on firm performance. Besides these studies, there is no further evidence in current literature about the financial implications of this key organizational construct, especially during unexpected variations in brand's equity over time. This study therefore stands as a contributor to this small body of research and draws attention to the role of firm's core business efficiency in elevating firm performance both through CBBE and FBBE. The findings reveal that CBEF not only mitigates firm value erosion as a result of negative changes in consumer brand sentiments but also reinforce the positive effects of growing brand projected earnings (FBBE). Collectively, these outcomes provide novel evidence that CBEF is a key organizational asset which can transform a strategic marketing resource like brand equity to a provider of sustainable competitive advantage. To the best of researcher's knowledge, no study until now has linked firm's core business operations efficiency directly to the brand equity-firm value linkage, let alone adopting a multiple brand dimensions approach.

Additionally, this study provides novel insights into the interactive manner in which firm's marketing capabilities affect firm long-term performance during unanticipated changes in brand equity. There is an extant body of research stressing on the direct and indirect significance of MCAP on long-term firm performance (see table 2.6 in the literature review chapter). To the best of researcher's knowledge, only two studies (i.e.

Bahadir et al., 2008; Nguyen & Oyotode, 2015) have explored the relationship between MCAP and brand equity. However, both the studies have established a direct positive impact of firm's marketing capabilities on brand equity. The literature still lacks the knowledge about whether market-oriented organizations complement the financial implications of brand equity, especially during unanticipated rise or decline it its magnitude. This research fills this lacuna by providing first evidence that marketing capabilities amplify the positive firm value contributions of rising consumer based brand equity. This is a significant finding in that it unfolds that MCAP is a strategic organizational resource which synergizes brand's competitive edge gained through strong consumer bonding. These outcomes therefore extend the novel work of Bahadir et al (2008) and Nguyen and Oyotode (2015) emphasizing that apart from directly enhancing brand strength, MCAP also positively moderates the CBBE-firm performance interface.

Apart from its complementary effects, this research also uncovers that favourable changes in MCAP amplifies the negative firm value impact of declining FBBE. Although these findings are contradictory to the theoretical arguments made in this study, it still offers new knowledge to the existing RBT literature. Opposing the existing view that marketing capability always does good for the firm (Nguyen & Oyotode, 2015), this research demonstrates that MCAP may have competing effects as well, especially if perceived from its cost related implications. Building superior marketing capabilities require substantive and continuous investments (Xoing & Bhardwaj, 2013), consequences of which may or may not fully materialize. Therefore, if management is incapable of justifying these expenditures effectively to its stakeholders, then growing MCAP can be perceived as an induced financial burden on firm's profitability e.g.

income generated through strong brand name. The obtained conflicting results also tend to reform the conceptualization of resource based theory which has been criticized for laying its entire focus on the acquisition and development of strategic resources while overlooking the costs associated with acquiring such assets (Lavie, 2006:651). The research outcomes thus formalize the concept of "resource-based costs" and its competing effects on the value ascribed to complex organizational proficiencies such as marketing capability. Without accounting for the rent paid to build and maintain such market intelligence, treating it as a promising source of SCA seems dubious. Interestingly, existing research has solely debated about the "output side" of marketing capability in gauging its complementary effects on firm's future profitability. This study opens a new research dimension challenging marketing academics to "revisit the potential goodness" of MCAP considering its possible adverse effects, especially from its substantially expensive "input side". Collectively, these novel findings add to the growing marketing-finance literature indicating that financial markets recognize and value firm's marketing capabilities when evaluating long-term consequences of unanticipated changes in brand equity.

8.4 Managerial Implications

Along with complementing current marketing-finance and RBT literature, the research outcomes also offer useful insights for practitioners. First, managers should include brand equity estimations provided by globally recognised commercial consultants such as Millward Brown BrandZ and Brand Finance in their marketing research framework. This is crucial because of two reasons. Firstly, as this study explains, both these brand consultants focus on two distinctive perspectives of brand equity. Therefore, by monitoring the performance of different brand equity dimensions simultaneously, managers can gain full understanding about their brand's overall performance. Secondly, brand equity estimations published by these commercial bodies are value relevant such that any unanticipated changes in them have a significant impact on stock returns, above and beyond to that of short-term accounting measures. More importantly, the realized asymmetry in these effects during positive versus negative changes suggest that brand managers should monitor such deviations to make accurate judgements about their brand's firm value implications. Since this study discovers that the determinantal firm performance impact of declining CBBE and FBBE are particularly stronger, a closer attention needs to be paid to such abrupt downward swings. Failing to do so can jeopardize firm's long-term growth significantly, especially if the brand gets prone to such subsequent declines over prolonged periods.

Secondly, the comparative examination of CBBE and FBBE also provides important insights for marketing managers. The empirical results indicate that: i) changes in consumer and firm based brand equity over time are largely independent to each other, and ii) the magnitude of directional changes in consumer brand perceptions is significantly higher compared to similar changes in its firm-based measure. These novel findings signal that management should not just focus on loyal customers but must also identify potential brand haters so as to engage with them and understand their negative brand experiences. This would in-turn aid in reversing this "vicious cycle" of negative impact of declining CBBE on firm performance. This also calls for a need to look beyond the overall brand performance and understand how each dimension of their brand's overall equity is creating or destroying firm value. When making future brand building strategies, brand managers need to broaden their vision and focus cohesively on different scales through which their brand's total strength (or even weakness) is measured (i.e. consider brand-based performance along with consumer-brand response). Marketing academics argue that consumer and firm based brand equity captures distinct stages of brand value chain (Ailawadi et al., 2003; Keller & Lehmann, 2006). Therefore, by adopting a multi-dimensional approach, managers can better understand their brand's true dynamics and the areas where their overall brand structure needs special or immediate attention. For example, management may initiate aggressive advertisement campaigns following a sudden decline in brand's strength unknowingly that this has probably occurred due to deteriorating brand's projected earnings (i.e. FBBE) and not because of declining CBBE.

Thirdly, brand owners need to identify their organizational efficiency levels so as to enhance (mitigate) the positive (negative) effects of growing (declining) brand's strength on firm performance, thus gaining sustainable competitive advantage in the marketplace. The obtained evidence emphasizes that in order to achieve brand sustainability, management need to build and maintain their core business efficiency (CBEF) and marketing capability (MCAP). The propose conceptual model unfold several ways through which managers can deploy these organizational capabilities to "best fit" the favourable and unfavourable shifts in their brand's overall strength. For example, superior core business efficiency is the key to synergise firm performance during positive changes in firm based brand equity. Similarly, during an unanticipated decline in consumer's perceptual brand attributes, strong CBEF levels are a prerequisite to mitigate its adverse effects. Therefore, organizations that are efficient in maximizing their profitability with optimal resource allocation not only generate higher market returns from their proprietary assets (such as patents and trademarks) but also minimize firm value dilution during declining CBBE. Higher MCAP levels, on the other hand, enable firms to enhance investor and consumer confidence towards their growing consumer brand association thus complementing its firm value translation dynamics. By providing specific paths through which CBEF and MCAP moderates the impact of directional changes in CBBE and FBBE on firm performance, the study aids organizations to better understand their set of capabilities and its effectiveness under different market conditions. This can enable managers to deploy "best capability combination" strategies so as to exploit their brands' maximum potential and gain SCA.

Even the contradictory results of negative MCAP-FBBE interaction provides managers with critical information about potential trade-offs of building strong marketing capabilities. More specifically, the novel findings caution marketing professionals to also consider the detrimental effects of such investments on firm future performance, especially when investors perceive it as liability on brand income. It is therefore recommended that managers should not simply seek their marketing capabilities as a strategic asset but also understand the possible ramifications of substantial costs induced to achieve such market intelligence levels. A potential remedy to overcome this negative bias can be effective communication of long-term benefits of such marketing expenditures. For example, if brand managers can clearly convey how their marketing efforts amplify stock returns during positive CBBE changes (which this study finds), they can build stakeholder confidence towards their brand's overall equity. This can potentially lessen the severity of firm value erosion during instances of declining FBBE, thus improving long term growth prospects.

Lastly, this research also explains the mechanism and analytical tool by which brand owners can systematically measure their core business efficiency and marketing capability. Brand managers constantly struggle to improve their marketing accountability and to identify scientific measures that can objectivise their competitive levels (Luo & Homburg, 2007). This research addresses this challenge and demonstrates how DEAP software developed by Coelli (1996) can be systematically employed to operationalize dynamic efficiency measures of CBEF and MCAP (through DEA Malmquist total factor productivity change). DEAP is an open source linear programming benchmarking package and is widely popular amongst the research community for its ease of use and ability to compute both *static* and *dynamic* multi input-output based efficiencies (Iliyasu et al., 2015). Since organizations managing global brands are tech savvy, adopting this simple yet impactful benchmarking tool can enable them to periodically track their internal performance measures of CBEF and MCAP. Another advantage of DEA based analysis is its unique methodology which involves allocating efficiencies based on a cross-comparison with the competitor's best practices (Luo & Homburg, 2007). Therefore, DEAP offers managers with a rigorous scientific technique which does not just track their capabilities "in isolation", rather provide a comprehensive overview as to where they stand related to their competitors. Overall, application of DEAP along with an in-depth understanding of the conducive roles of their organizational efficiencies in brand performance dynamics can prove to be a valuable strategy for sustained future growth.

8.5 Investor Related Implications

"Shareholder value is the ultimate measure of a firm's business success" (Xiong & Bharadwaj, 2013:721). Driven by this view, the research outcomes also impart some implications for investment community in better understanding brands and the mechanisms by which they can enhance shareholder's wealth. First and foremost, using panel data and stock return response modelling, the study demonstrates that brand equity, irrespective of its dimensions, has long-term financial implications which is incremental to that of current-term balance sheet performance. Additionally, different brand equity measures (e.g. CBBE and FBBE) have different magnitude of impact on firm's future discounted cashflows. Future brand investment decisions should therefore be made adopting a long-term view and focusing on both the consumer and firm-level brand performance. This would provide investors and shareholders with a more holistic picture of the firm value effects of unanticipated changes in brand equity, enabling them to appreciate the brand equity-stock price dynamics in a much profound manner.

Although it is clear that stock markets react more aggressively to declining brand strength than growing brand equity possibly due to negativity bias and loss aversion, this study provides additional factors which they need to account when deciding to buy or sell a brand-stock based on these unanticipated changes. Documenting significant complementary effects of MCAP and CBEF on firm future returns, this research recommends that financial community should consider these organizational efficiency measures when re-evaluating their investment during sudden shifts in brand's equity. Investing in brands that are managed by core business efficient firms could result in a significant appreciation in shareholder's wealth in long term. Similarly, when unanticipated changes in brand equity are complemented with firm's marketing capabilities, shareholders are benefited with substantial improvement in stock returns. This is because brand managers with superior marketing capabilities can systematically inform their consumers and shareholders as to how their brand value is being created and managed, thus enhancing their confidence. This study therefore encourages investment community not to simply rely on rise and decline in brand equity when reviewing their investment decisions, rather conduct a more in-depth analysis of the organization's competence for better returns.

One may however argue that individual investors (e.g. retail or novice investors) may not be able to gain access to such information due to lack of scientific knowledge and relevant data to model these dynamic efficiency measures. Even in the absence of such technical expertise, investors can still get a fair view about the growth or decline in firm's MCAP and CBEF from its historical performance measures such as sales and profits. For example, for two firms operating in the same industrial sector and having access to comparable marketing resources, the firm with relatively higher sales (as reported during earning release) is likely to possess superior marketing capability than its competitor. Similarly, two competing brands with comparable firm size (e.g. tangible assets, no. of employees, etc) can be broadly distinguished as efficient or inefficient based on their simple profitability ratios such as ROA and ROCE. Although these accounting metrics may not provide the most accurate predictions about changes in firm's MCAP and CBEF, but it can still aid them in making informed investment decisions following unanticipated changes in CBBE and FBBE.

Lastly, it is recommended that investment institutions and financial analysts should add management's core business efficiency and marketing capability in in their toolkit when predicting the future performances of brands. More specifically, they should incorporate DEA benchmarking methodology in their "stock evaluation tool-box" to accurately predict firm's CBEF and MCAP changes over time. This would significantly improve their skills in predicting future stock prices based on yearly changes in consumer and firm based brand valuations released by BrandZ and Brand Finance, respectively.

Without incorporating these management functions in their research, they can potentially over or underestimate the true stock return impact of sudden shifts in these brand equity dimensions. The observed findings of complementary role of CBEF and MCAP are therefore relevant to both private and privileged (e.g. institutional) investors.

8.6 Limitations and directions of future research

No empirical research is without limitations and this study is not an exception. First, although the study unfolds novel insights that deteriorating consumer and firm based brand equity have a much stronger impact on firm performance than rising brand values, it did not provide factors that drives these changes. Unanticipated growth and decline in brand's strength can be due to several internal (e.g. poor strategies, brand inconsistency) or external factors (e.g. change in consumer preferences, royalty rates and competitor actions). Investigation of such behavioural (consumer focussed) and non-behavioural (other market forces) causes that drive these shifts in CBBE and FBBE is, therefore, warranted. This may lead to a better understanding about holistic brand management. Furthermore, since this study establishes that upside and downside movements in brand equity significantly impact stock returns, future research can explore if volatility in these changes have further explanatory power. In other words, if a brand experiences violent swings in its consumer or firm based brand valuations (above and below the mean) year on year, investors may perceive it as inconsistent and unreliable, thus further harming firm's growth. Gaining an understanding of the stock market effects of such upside and downside dispersion in brand equity would therefore be valuable. Bedsides this, academics can also extend this study by evaluating the impact of positive and negative changes in brand equity on firm's idiosyncratic risk (See Rego et al., 2009 and Yildiz & Camgoz, 2019 for brand equity-firm risk related studies).

This research also provides a comprehensive view of the relationship between consumer and firm based brand equity measures adopting multiple analytical perspectives. However, due to data constraints, an industry level comparison could not be conducted for these two key brand equity measures. This is important because it will be more crucial for firms operating in B2C environment to build and maintain strong consumer based brand equity as compared to B2B brand-firms. On similar grounds, brands managed by B2B firms are expected to be affected more by unanticipated changes in their firm based brand equity. It will therefore be interesting to see whether the brand equity-firm performance dynamics for CBBE and FBBE measures differs based on firm's business operating model. Additionally, as this study finds, neither consumer nor firm based brand equity dimension fully explain firm performance as they both have their unique relationship with it. This fully aligns with the existing arguments that brand equity is a complex and multi-faceted concept and none of its measure can singularly estimate its overall strength (Buil et al, 2013; Raggio & Leone, 2007). To address this, future research can attempt to develop bi-dimensional brand equity models by amalgamating consumer and firm based brand equity measures. Although this research stream already exists (e.g. Ferjani et al., 2009; Oliveira et al., 2015) but it is still in its infancy stage. This is a promising area as it can aid academics and practitioners in i) evaluating brand's strength at different levels of aggregation, ii) formulate customized strategies to address both brand's financial health and consumer response and iii) better resource allocation for effective brand management. Lastly, it is also recommended to conduct such comparative analyses between other popular brand equity measurement perspectives such as sales-based (Datta et al, 2017), employee-based (King & Grace, 2010), and stakeholders-based (Nyadzayo et al., 2011) for having even richer perception of this intangible marketing asset.

Another limitation of this study is its inability to conduct a country-specific analysis due to data constraints. As evident in table 4.4 of chapter 4, although the acquired CBBE and FBBE samples focus on developed countries, still majority of representative brands are domiciled in the US. Due to US dominance, it was not feasible to disaggregate the acquired datasets based on countries and run separate SRRM models for each, as this would have significantly reduced the sample size especially for the non-US sample brands. Furthermore, since all the proposed SRRM models are estimated through fixed-effects regression (guided by the best-fit model tests), characterizing each country, for example, with a dummy variable was also not possible[46]**.** It is therefore advisable that future scholarship should re-investigate the obtained findings from a country-based perspective. This is important because there is a plethora of existing literature affirming that the level of equity which global brands enjoy, varies significantly based on their country-of-origin (COO) (Mostafa, 2015; Murtiasih et al., 2014; Pappu et al., 2006; Sanyal & Dutta, 2011; Yasin et al., 2007). Additionally, marketing research also suggests that COO based branding strategies can offset the negative effects of country-specific financial shocks (Gerrath & Leenders, 2013). Following these outcomes, it will be interesting to understand whether firm performance impact of unanticipated market conditions such as rising or declining brand CBBE and FBBE differs across countries. Such an analysis will not only aid managers in assessing their brand's true performance

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[46] Since fixed effects estimation involves time demeaning of the panel data, any variable which is fixed over time will be differenced away**.**

in a global environment but also extend the emerging concepts of international brand equity (Christodoulides et al., 2015; Veloutsou et al., 2013) and country brand equity (Mariutti & Giraldi, 2020).

A methodological weakness of this research is its incapability of dealing with negative inputs and outputs while operationalizing core business efficiency through DEA Malmquist benchmarking technique. Standard DEA models cannot manage negative data (Sarkis, 2007). Furthermore, due to subject complexity and software unavailability, it was infeasible to apply other advanced methods which can accommodate such inputs and outputs e.g. slack based measure (Morita et al., 2005), range directional measure (Portella, 2010) and semi-oriented radial measure (Emrouznejad et al, 2010). Since DEA works on the principle of benchmarking all the DMUs against each other through weight allocation technique (Roh & Choi, 2010), including negative inputs and outputs could have possibly reflected additional information in the calculated efficiencies. For example, firms having negative values of shareholder’s equity (as input) and operating income (as output) would have significantly impacted the computed CBEF estimates. Forthcoming RBT based studies in marketing should therefore retest the contributory role of CBEF in brand equity-firm performance nexus by applying one of the recommended methods and compare the results.

Finally, this study finds contradictory results while examining the sensitivity of the impact of negative CBBE changes on firm performance to firm’s marketing capability. While existing research provide exhaustive evidence that strong marketing capabilities contribute to firm’s profitability from multiple dimensions (Mishra & Modi, 2016; Rahman, 2020; Angulo-Ruiz et al., 2018; Sun et al., 2019; Wiles et al., 2012), these conflicting findings may be either due to its “cost side effects” as explained earlier or lack of adequate data (only 32 firms). It is therefore recommended that future studies should re-examine these MCAP interactive effects and provide additional evidence either in support or opposition to the novel findings of this research. This can unfold new mechanisms by which the possible competing effects of building strong marketing capabilities can be explored.

Besides the recommendations discussed above, the comprehensive brand equity-firm performance view provided by this research also offers the best approaches to embrace when exploring this marketing-finance interface. Firstly, the long-term value relevance of brand equity should be explored in changes and not contemporaneously, since stock markets only react to new information (Mizik & Jacobson, 2003; Srinivasan & Hanssens. 2009). Secondly, more emphasis needs to be directed in understanding the disaggregated firm value effects of positive and negative changes in brand equity as they contain incremental information to that of overall changes. Thirdly, future studies should dig more deeper into the negative side of the brand equity-firm performance linkage instead of simply advocating it as an "incremental value provider". Focusing solely on the positive brand equity contributions can cast an illusion amongst brand managers, which may fall victim of past glories as a sign of future success. Due to significantly higher severity of firm value dilution from declining brand equity (as this research demonstrates), misinterpretation of such declines can significantly damage firm's future performance, sometimes beyond recovery. Fourthly, simply knowing the asymmetrical effects of rising and declining brand equity would be theoretically and practically incomplete. A more valuable approach would be to include different organizational or strategic factors through which information residing in these directional changes can be exploited to firm's benefit. As highlighted in the beginning of this thesis and demonstrated empirically, future research should not just explore *"**how** brand equity creates value?"* rather, should understand *"**when** does brand equity create or destroy value?"* and *"**what** can be done to capitalize on this information?".*

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APPENDICES

8.7 Appendix A: Cross-sectional dependence issue with long-term event studies

To understand the correlation issues caused by event studies capturing longer period stock performance when the events are clustered over time, let us consider the example in fig. 1. The timelines on the top outlines the months and days. Suppose there were four marketing announcements made by to two brands A & B. Brand A made first announcement on the 1st of January and the 2nd announcement on 1st March denoted by A1 and A2, respectively. The similar marketing event occurred for brand B on 1st Feb and 1st April in the same year resulting in a total of four firm events. Now the aim is to employ event study to examine if these individual events were able to generate long-term abnormal returns. Let the time period be 12 months succeeding the event date. Firstly, we need to calculate abnormal stock returns for each firm event during the estimation period. The measurement window for each event is shown in fig. 1 through four coloured lines, each colour representing an individual event. It is evident from the figure that the lines pertaining to two different events for firm A overlap each other for 10 months starting from March of 1st year till January next year. Same is the case with brand B for its respective months. Due to sharing same stock return measurement period, brand events A1-A2 and B1-B2 exhibit significant correlation between them. Additionally, event B1 could potentially show cross-sectional correlation with A1 and A2 (and vice-versa) due to similar industry-wide events that might be occurring during this period (Mitchell & Stafford, 2004). These strong correlations within firm events cause the standard errors of regression to shrink, therefore yielding unreliable statistical inferences (high t-statistics). The cross-sectional dependence anomaly tends to inflate with increasing estimation window due to the inclusion of more clustered events over longer periods. However, in shorter time periods, there is minimal chance of event overlapping and thus event study methodology holds its relevance/The event study methodology however holds its relevance in shorter timeframes due to minimal chance of event overlapping.

This anomaly can be addressed using a calendar time-portfolio approach for the same events. The bottom part of fig.1 demonstrates this phenomena. The approach involves maintaining an equal-weighted portfolio which means investing same amount of money for each event. Additionally the portfolio is rebalanced monthly to account for any similar future events occurring during the period of the study. Following this, on the first day of the first event (A1 on 1st Jan in our case), a hypothetical portfolio was created by investing 1 pound in stock A. Now this stock needs to be held in the portfolio for the pre-determined estimation time period which i.e. 12 months in our case (till Jan 1st the following year). Since another event B2 occurs next month, the portfolio was rebalanced by investing another pound in stock B, the holding period of which ends on 31st Jan next year. Same investment strategy was followed to account for events A2 and B2 in the following two months. This leaves the total portfolio worth 4 pounds by the end of April with 2 pounds investment in each firm A and B. The portfolio composition by end of each month is shown in the figure. These positions are then maintained until measurement period for at least one of the events is over.

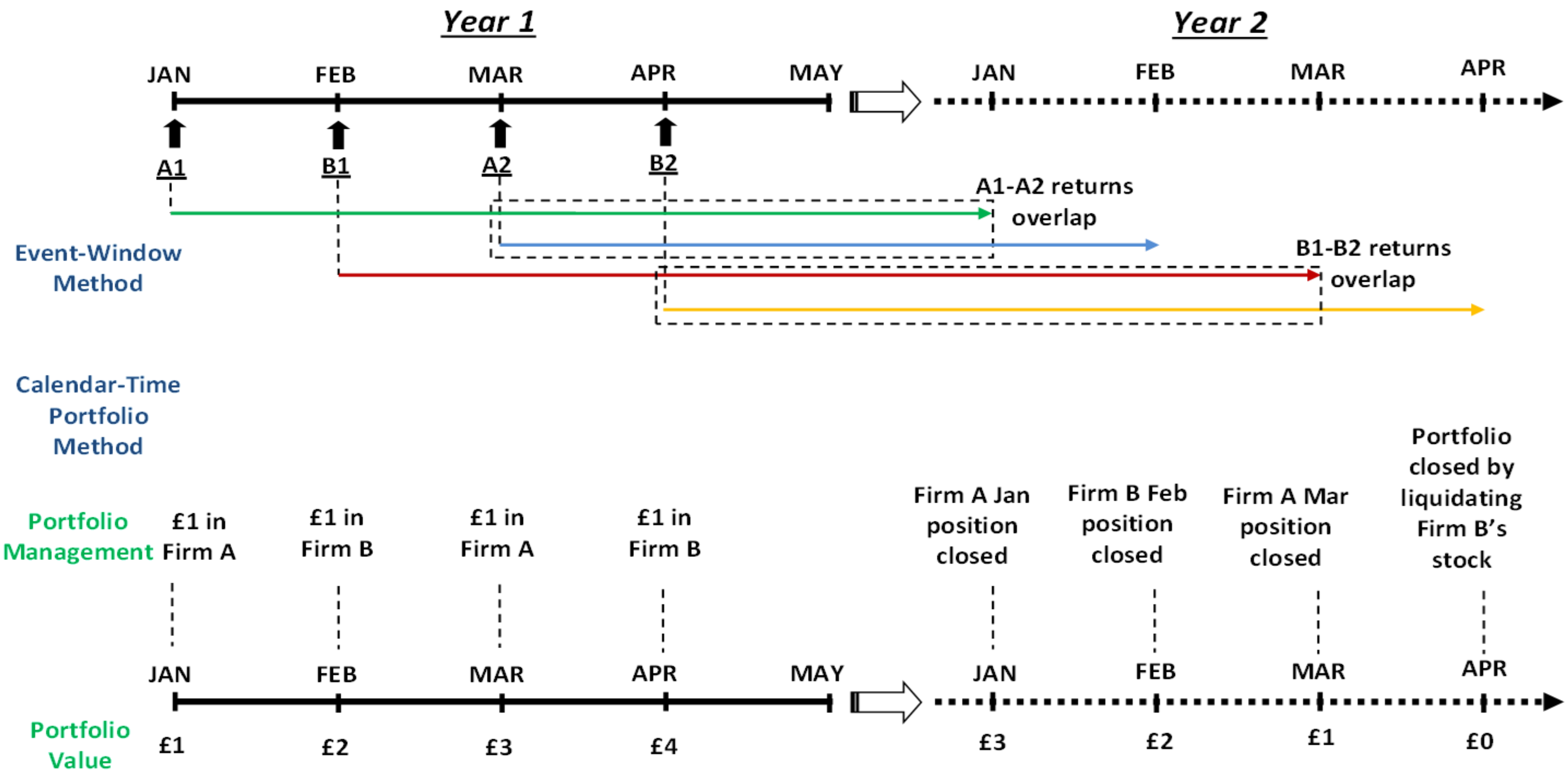

Fig. 1 Event Study vs Calendar Portfolio Method

On Jan 1st next year, event A1 completes 12 month period and therefore one pound position in firm A is liquidated. Similarly, in the following months of Feb and March, 1 pound worth holdings of stock B and A are sold, respectively. This leaves the portfolio with only 1 pound position in stock B by March end. Finally the month of April brings the end of measurement period of event B2, therefore the position is liquidated, and the portfolio is closed. Now the monthly stock returns of the portfolio are calculated for the entire 15 month period and regressed on various risk factors through the model in equation 4.1. Following CPA, a single measure of abnormal return is obtained as compared to event studies where excess returns are calculated for each firm event. Since monthly stock returns are serially uncorrelated, the calculated portfolio returns through CPA methodology are immune to autocorrelation issues (Kothari & Warner, 2006).

8.8 Appendix B: Illustrative example of DEA input and output oriented linear programming execution

Let us consider 2 DMUs A and B with 2 inputs and 2 outputs as defined in the table below:

DMU	Input 1	Input 2	Output 1	Output 2
A	3	2	7	8
B	5	1	9	6

The DEA software will run the conditions and restrictions outlined in the linear program for each DMU based on selected orientation. For input-oriented model, following executions will occur (highlighted in blue):

For DMU A

$$\theta_k = \min\left(\sum_{i=1}^{m} v_i\, x_{ik}\right)$$

$$\Theta_A = \min\,(3v_1 + 2v_2)$$

Subject to:

$$\sum_{i=1}^{m} v_i\, x_{ij} - \sum_{r=1}^{s} u_r\, y_{rj} \geq 0 \quad (j = 1,2,\ldots.,n)$$

$$3v_1 + 2v_2 - 7u_1 - 8u_2 \geq 0$$

$$5v_1 + 1v_2 - 9u_1 - 6u_2 \geq 0$$

$$\sum_{r=1}^{s} u_r\, y_{rk} = 1$$

$$7u_1 + 8u_2 = 1$$

For DMU B

$$\theta_k = \min\left(\sum_{i=1}^{m} v_i\, x_{ik}\right)$$

$$\Theta_B = \min\,(5v_1 + 1v_2)$$

Subject to:

$$\sum_{i=1}^{m} v_i\, x_{ij} - \sum_{r=1}^{s} u_r\, y_{rj} \geq 0 \quad (j = 1,2,\ldots.,n)$$

$$3v_1 + 2v_2 - 7u_1 - 8u_2 \geq 0$$

$$5v_1 + 1v_2 - 9u_1 - 6u_2 \geq 0$$

$$\sum_{r=1}^{s} u_r\, y_{rk} = 1$$

$$9u_1 + 6u_2 = 1$$

Where v_i and u_r are the implied weights to the corresponding inputs and outputs respectively and zero or positive numbers.

$$u_r \geq 0;\ (r = 1,\ldots,s) \qquad v_i \geq 0; (i = 1,\ldots,m)$$

Similarly, for an output oriented model, following mathematical programming logics will be implemented:

For DMU A

$$\theta_o = \max\left(\sum_{r=1}^{s} u_r \, y_{ro}\right)$$

$$\Theta_A = \max\ (7u_1 + 8u_2)$$

Subject to:

$$\sum_{r=1}^{s} u_r \, y_{rj} - \sum_{i=1}^{m} v_i \, x_{ij} \leq 0 \quad (j = 1,2,\ldots,n)$$

$$7u_1 + 8u_2 - 3v_1 - 2v_2 \leq 0$$

$$9u_1 + 6u_2 - 5v_1 - 1v_2 \leq 0$$

$$\sum_{i=1}^{m} v_i \, x_{io} = 1$$

$$3v_1 + 2v_2 = 1$$

For DMU B

$$\theta_o = \max\left(\sum_{r=1}^{s} u_r \, y_{ro}\right)$$

$$\Theta_A = \max (9u_1 + 6u_2)$$

Subject to:

$$\sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i\, x_{ij} \leq 0 \quad (j = 1,2,\ldots,n)$$

$$7u_1 + 8u_2 - 3v_1 - 2v_2 \leq 0$$

$$9u_1 + 6u_2 - 5v_1 - 1v_2 \leq 0$$

$$\sum_{i=1}^{m} v_i\, x_{io} = 1$$

$$5v_1 + 1v_2 = 1$$

8.9 Appendix C: List of industries represented in the acquired CBBE & FBBE samples and their ICB Codes

Industry	ICB Code
Consumer Discretionary	40
Consumer Staples	45
Energy	60
Financials	30
Industrials	50
Technology	10
Telecommunications	15

8.10 Appendix D: Understanding the polarities and effects of examining positive and negative brand equity changes separately.

This illustrative example focuses on understanding the polarities and effects of the regression coefficients of positive and negative changes in CBBE (and FBBE) after separating them in two separate directional variables. Let's consider the hypothetical data presented in the table below.

Y	**X**	**Pos X**	**Neg X**
2	1	1	0
4	2	2	0
6	3	3	0
8	4	4	0
10	5	5	0
12	6	6	0
14	7	7	0
16	8	8	0
18	9	9	0
20	10	10	0
-4	-1	0	-1
-8	-2	0	-2
-12	-3	0	-3
-16	-4	0	-4
-20	-5	0	-5

The data is deliberately arranged in such a way that with a 1 unit increase in the value of X, Y increases two times and when X decreases by a unit, Y falls by four times the value of X. The regression equation between Y and X can be expressed as:

$$Y = \alpha + \beta X$$

Table below summarises the regression results:

Regression Statistics				
R Square	0.977			
Adj. Square	0.975			
Observations	15			
F- Statistic	553.60 (p<0.000)			
	Coeff.	*Std. Error*	*t Stat*	*P-value*
Intercept	-3.520	0.592	-5.950	0.000
X	2.570	0.109	23.529	0.000

The coefficient Of X is 2.57 and is significant indicating the positive relationship of X with Y. In the overall model, with every unit increase in X, Y increase by a factor of 2.6 and the explanatory power of the model is 97.5%.

The next step is to separate the overall variable X into two directional variables Pos X (capturing only the positive changes) and Neg X (capturing only the negative changes). In order to maintain consistency with the originally obtained CBBE and FBBE samples, the instances of positive changes are higher than (exactly double) the negative changes (although changing these frequencies does not affect the results). The regression model capturing the directional effects therefore can be expressed as:

$$Y = \alpha + \beta_1 \text{ Pos X} + \beta_2 \text{ Neg X} \qquad \textit{Eq. (A)}$$

The regression results are as follows:

Regression Statistics				
R Square	1.00			
Adj. Square	1.00			
Observations	15			
F- Statistic	6.7E+32 (p<0.000)			
	Coeff.	*Std. Error*	*t Stat*	*P-value*
Intercept	0.00	0.000	1.801	0.000
Pos X	2.00	0.000	2E+16	0.000
Neg X	4.00	0.000	2E+16	0.000

The coefficient of Pos X and Neg X are obvious but special attention should be paid on the sign of Neg X which is in fact positive. This is because the variable Neg X contains only the negative values of the main variable X. Therefore the regression model defined in equation (A) can be mathematically expressed as:

$$Y = a + b_1 \text{ (Pos X)} + b_2 \text{ (-Neg X)}$$

The above expression clearly indicates that if the constant b_2 is positive, it is actually increasing the negative effects of Neg X on Y. Also, it is interesting to see that the Adj. R-squared has jumped from 97.5% to 100%. This further indicates that the directional model is much superior to the overall model in explaining the variance in Y due to changes in X.

8.11 Appendix E: CBBE baseline and main model results after dropping HML risk loading factor

	$R_t - R_f$ *(Baseline Model)*	$R_t - R_f$ *(Main Model)*
ΔCBBE	.309***	
	(.05)	
ΔPos CBBE		.20***
		(.066)
ΔNeg CBBE		.616***
		(.133)
Mktrf	.372***	.352***
	(.066)	(.066)
SMB	.005	.029
	(.166)	(.166)
HML	-.244*	-.238
	(.146)	(.145)
Loglag_MV	-.288***	-.304***
	(.067)	(.067)
Loglag_B2M	.097*	.10*
	(.058)	(.058)
UΔROA	1.145***	1.251***
	(.385)	(.385)
Sales Growth	.256	.274
	(.183)	(.182)
Leverage	-.004	-.004
	(.003)	(.003)
Intercept	3.272***	3.474***
	(.721)	(.722)
N	540	540
F-Test (Model)	5.87***	5.94***
R-squared	.43	.44
Adj. R-squared	.36	.37

Robust-Clustered Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
N = No. of observations

8.12 Appendix F: FBBE baseline and main model results after dropping SMB, HML and MOM risk loading factors

	R_t - R_f (*Baseline Model*)	R_t - R_f (*Main Model*)
ΔFBBE	.21***	
	(.051)	
ΔPos FBBE		.086
		(.052)
ΔNeg FBBE		.707***
		(.187)
Mktrf	.572***	.572***
	(.097)	(.093)
Loglag_MV	-.771**	-.781**
	(.344)	(.343)
Loglag_B2M	-.21	-.194
	(.191)	(.186)
UΔROA	1.777*	1.869**
	(.907)	(.915)
Sales Growth	-.153	-.095
	(.287)	(.287)
Leverage	-.03	-.03
	(.027)	(.027)
Intercept	8.526**	8.665**
	(3.776)	(3.765)
N	490	490
F-Test (Model)	7.17***	7.26***
R-squared	.48	.48
Adj. R-squared	.41	.42

Clustered-Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*