

Strategic Value Implications of Transformative Marketing

by Manjunath Ramanand Padigar

Thesis submitted in fulfilment of the requirements for
the degree of

Doctor of Philosophy

under the supervision of Prof. Ashish Sinha, and
Dr. Valeria Noguti

Thesis format: *Thesis by compilation*

University of Technology Sydney
Faculty of Marketing

January 2021

Certificate of Original Authorship

I, Manjunath Padigar, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

Signature: Production Note:
 Signature removed prior to publication.

Date: 15th January, 2021

Acknowledgement

This work would not have been possible without the support and guidance of Prof. Ashish Sinha and Dr. Valeria Noguti, my principal and alternate supervisors, respectively. I am very fortunate to have had the opportunity to work under and learn directly from Prof. Ashish Sinha, who has supported me beyond the scope of work presented in this thesis. I find it impossible to give him enough credit here for all that he has done for me.

There are many others who have generously supported me with their time, guidance, and help, and I am extremely thankful to every one of them. First, I am indebted to the UTS Marketing Department's research committee for accepting me into the PhD program and giving me an opportunity to begin my scholarly pursuit. Special thanks to Dr. Hillbun Ho for providing mentorship and advice on various topics including my research. I am also thankful to the mentorship and help from the faculty members at the Indian School of Business including Prof. Rajendra Srivastava, Asst. Prof. Kiran Peddada, and Asst. Prof. Arunachalam. S.

Another group of people that I have been fortunate to interact with is that of my PhD colleagues including Dr. Ljubomir Pupovac, Dimitri Simonin, Dr. Alex Belli, Atya Zeb, Ella Bruce, Aristus Ochionuoha, and Aimee Smith. Without their support and friendship, my PhD journey would have been exanimated and infinitesimally more challenging. I am also thankful to every professional staff member at UTS Marketing Department and Business Research Office, particularly to Courtney O'Regan, Ashleigh Hall, Michael Lee, Mariana de Lucca Zaggia, and Aki Plume for providing timely support to all my queries.

It is needless to mention the role of family and friends in challenging times, which in case of a PhD student extends over several years! However, this acknowledgement would be incomplete without mentioning them. Chandana, my wife, has been a pillar of support and a constant source of inspiration and love. Her role in helping me carve a career of my choice, which is still work-in-progress, is undeniably critical. I would also like to thank my parents, Ramanand and Vijayalaxmi Padigar, for being the ultimate role models, and my lovely and supportive siblings Meera and Veena. To my friends - Pradhyumna, Dhananjay, Abhishek, Vaishnavi, and Shreya, I would like to say thank you for always being there for me.

Finally, I am also grateful to the financial support provided by the UTS Doctoral Scholarship and the support of Australian Government Research Training Program Scholarship, without which it would have been difficult to remain focused on my research.

Contents

Thesis Abstract.....	7
Thesis Introduction	9
References.....	16
Essay-1: The Effect of Marketing Department Power on Investor Response to Emerging Technology Adoption: Evidence from Artificial Intelligence-enabled New Product Announcements.....	
Abstract	17
Abstract	18
Introduction.....	19
Theoretical Framework.....	25
Hypotheses Development	27
Research Methodology	32
Research Context, Data, and Sample	32
Event Study	37
Measures	39
Model Specification.....	42
Specification Tests	43
Results.....	45
Descriptive Findings	45
Main Effects.....	45
Hypotheses Testing.....	47
Robustness Checks.....	49

General Discussion	50
Theoretical Contributions	51
Practical Implications.....	53
Limitations and Future Research	55
References.....	57
Lists of Figures and Tables	61
Appendix.....	67
Robustness Check Results	69
Essay-2: When does Emerging Customer Orientation Affect Shareholder Value? Interactive Effects of Emerging Customer Orientation and Marketing Capabilities.....	79
Abstract	80
Introduction.....	81
Conceptual Framework.....	85
Hypotheses.....	87
Methodology	91
Research Context, Design, and Data.....	91
Variable Measurement	93
Model Specification	96
Results.....	98
Descriptive Statistics and Main Effects	98
Hypotheses Tests	99

General Discussion	102
Theoretical Contribution.....	103
Implications.....	105
Limitations and future research	106
References.....	107
Lists of Tables and Figures	109
Appendix.....	120
Thesis Conclusion.....	125
References.....	129

Thesis Abstract

Transformative marketing is defined as the confluence of a firm's marketing strategies, assets, and resources in response to marketplace changes and future trends to leapfrog customers with superior value offerings over competition in exchange for profits for the firm and benefits to all stakeholders. The present thesis, a systematic exposition in a compilation of two essays, is focused on outcomes for shareholders, one of the key stakeholders of the firm, based on marketing's strategic choices made in response to emerging technologies and emerging customer segments. Specifically, the first essay, titled "*Investor Response to Emerging Technology-based New Product Innovations: Evidence from Stock Market Returns to Artificial Intelligence-enabled New Product Announcements*", is focused on understanding the impact of emerging technology adoption (henceforth ETA) on shareholder value. We develop a comprehensive framework to assess investor response based on screening, organization, and innovation theories, and we adopt an event study methodology to examine how investors respond to ETAs. We argue and demonstrate that investors respond favorably to ETA announcements from firms with high (vs low) marketing department power. Furthermore, we demonstrate the moderating role of the fit between resources and competences managed by marketing department power and those demanded by the innovation characteristics such as innovation stage (i.e., initiation, development, and commercialization), route to innovation (i.e., make, ally, and buy), and adoption level (i.e., product-platform level and component level). Next, in the second essay, titled "*Effects of Emerging Customer Orientation on Shareholder Value: The Moderating Role of Marketing Capabilities*", we investigate effects of firm's emerging customer orientation – i.e., the extent to which a firm is focused on the needs of emerging customer segments, on shareholder value. We develop a framework based on dynamic capabilities to argue and demonstrate that firm's emerging customer orientation can positively influence shareholder value but only

when complemented with the necessary marketing capabilities to build and leverage market-based assets. Overall, we believe that these two essays will contribute significantly to research on transformative marketing by establishing when and how it affects shareholder value. Further, the implications drawn from this thesis can help practitioners with actionable insights on how to respond to emerging technologies and emerging customer segments – two key forces that demand a transformational response.

Thesis Introduction

Transformative marketing is defined as the confluence of a firm's marketing strategies, assets, and resources in response to marketplace changes and future trends to leapfrog customers with superior value offerings over competition in exchange for profits for the firm and benefits to all stakeholders (Kumar 2018). According to Kumar (2018), the marketplace changes and future trends referred to in the definition above act as forces that challenge the organization's status quo and create a sense of urgency for the firm to respond. Further, when firms respond to these forces, they do so by ideating and deploying their assets and resources with the intent to deliver superior value offerings. Since such a response to the forces forms the core of transformative marketing (Kumar 2018), it can be said that innovation and resource attraction and allocation capabilities are the basic tenets of transformation.

As illustrated in Figure. 1 below, the framework provided by Kumar (2018) and enlists technology, customer preferences, environmental resources, economic forces, competition, and government regulations as the forces that demand transformational response from firms. The present thesis, a systematic exposition in a compilation of two essays, is focused on outcomes for shareholders, one of the key stakeholders of the firm, based on marketing's strategic choices made in response to emerging technologies and emerging customer segments. Among the environmental forces that demand transformational firm response, our decision to investigate emerging technologies and emerging customer segments is based on the following two reasons.

First, emerging technologies are science-based innovations with the potential to create a new industry or transform an existing one (Srinivasan, 2008). Thus, while they offer rich source of technological and market opportunities for some firms, they may also present significant challenges and heightened risks of obsolescence to others. However, as the most

prominent impact of emerging technologies is in the future, their impact in the emergence phase is somewhat uncertain and ambiguous (Rotolo, Hicks, and Martin, 2015). This implies that firms must strategically assess the threats and opportunities presented by emerging technologies. Typically, firms respond through innovations incorporating these emerging technologies. Prior innovation research in the marketing literature, for most part, does not explicitly consider the distinctive features of emerging technologies (Srinivasan, 2008). In our study, to address this limitation in the literature, we build on the distinctive features of emerging technologies, such as fast-evolving nature of the technological developments and high uncertainty. Moreover, because such innovations affect firms' future prospects, it is critical to understand which firms are "expected" to succeed with such innovations. The first essay in the present thesis aims to uncover insights about this by investigating investors' evaluation of such innovations.

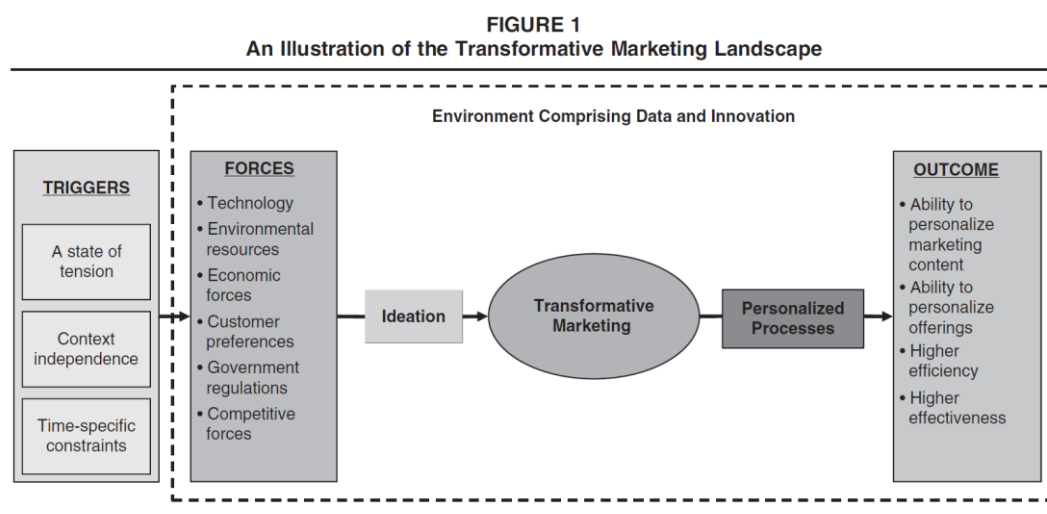


Image Source: Kumar (2018)

Second, as with emerging technologies, responding to the needs emerging customer segments have also been deemed as critical strategic actions in shaping future markets (e.g., Chandy and Tellis, 1998; Christensen and Raynor, 2003; Govindarajan, Kopalle, and Danneels, 2011). Consistent with prior literature, we define emerging customer segments as relatively small but fast-growing customer segments with fast-evolving needs and uses that

exhibit a certain degree of detachment from the predominant uses of existing offerings demanded by the mainstream customers due to their origins in either the low-end of the mainstream market or a completely detached new market. Although there is some evidence linking a firm's intent to address the needs of emerging customer segments and the disruptiveness of its innovation outcome (e.g., Chandy and Tellis, 1998; Govindarajan et al., 2011), no prior study has investigated how such a strategic intent affects shareholder value. Therefore, understanding the nuances of this under researched relationship is critical. The second essay in the present thesis aims to establish the nature of the relationship between firm's intent to address the needs of emerging customer segments and uncover nuances of this relationship.

Based on the discussions above about the importance of emerging technologies and emerging customer segments in shaping future markets and the strategic nature of the firm responses to these transformative forces, we investigate how firm responses to these forces affects shareholder value. Specifically, the first essay, titled "*Investor Response to Emerging Technology-based New Product Innovations: Evidence from Stock Market Returns to Artificial Intelligence-enabled New Product Announcements*", is focused on understanding the impact of emerging technology adoption (henceforth ETA) on shareholder value. Following Srinivasan (2008), we define emerging technology adoption as new products and services innovations where the core emerging technology's application domain is different from its original domain. For example, the original domain of Artificial Intelligence (AI) is software programming. Therefore, application of AI in a different domain such as in the automobiles domain to develop autonomous cars qualifies as an instance of technology adoption. Much of prior research on new product innovation has focused on adoption of radical technologies native to the firm or its industry (e.g., Sood and Tellis 2009; Sorescu and Spanjal 2008). However, ETAs are on the rise and extant theory lacks an understanding of

ETA's strategic value implications. Moreover, we conceptually differentiate ETAs from radical and technological breakthrough innovations (RBIs) along the dimensions of (1) the intended use of the emerging technology and (2) the scope of market contexts selection for the innovation. These conceptual differences between ETAs and RBIs further emphasize the need to study implications of ETAs on firm value.

To address the gap, we develop a comprehensive framework to assess investor response based on screening, organization, and innovation theories, and we adopt an event study methodology to examine how investors respond to ETAs. Based on screening theory, which posits that when responding to signals from firms, investors screen for additional information to assess (1) signaler veracity – i.e., the extent to which a firm possesses the unobservable quality that it intends to signal, and (2) signal fit - i.e., the extent to which the signal characteristics are correlated with the unobservable quality (Connelly et al 2011). We propose marketing department power (MDP) as an indicator of signaler veracity – i.e., its ability to deploy marketing resources, competences, and assets to commercialize the ETA successfully. Therefore, we predict that investors will respond favourably to ETA announcements from firms with high (vs low) MDP.

Further, our framework also proposes three innovation characteristics – (1) innovation stage (i.e., initiation, development, and commercialization), (2) route to innovation (i.e., make, ally, and buy), and (3) adoption level (i.e., product-platform level and component level), as moderators of the relationship between MDP and investor response because they may influence investors' perceptions of signal fit. In our case, investors may perceive higher fit when the resources and competences demanded by these innovation characteristics are highly correlated with the resources and competences managed by the marketing department.

Specifically, in assessing the moderating role of innovation stage, we argue that for a firm with high (vs low) MDP, investors will perceive higher fit with the ETA announcement

(i.e., the signal) when it announces an ETAs in the latter stage (i.e., development and commercialization), compared to initiation stage. This is because as the ETA progresses closer to commercialization, the resources and competences of MDP to be deployed for successful commercialization of the innovation become even more critical. Similarly, we argue that, compared to internal development (i.e., make), sourcing and leveraging external innovation assets via acquisitions and alliances may decrease the time required to reach advanced stages of innovation. As the marketing department's influence and impact is higher during latter stages of innovation (Rubera, Chandrasekaran, and Ordanini, 2016), compared to make, investor's perception of fit between firm's marketing department power and the ETA announcement should be higher for ally and buy announcements. Finally, compared to component level adoption, product-platform level adoption of the emerging technology requires (1) leveraging marketing assets, (2) attracting higher attention from top management team (TMT), and (3) communicating unique and differentiated benefits of the new product-platform as they may be significantly different from those offered by the firm's existing offerings. As these competencies can be provided by a strong marketing department, we argue that investors will perceive higher fit when a firm with high (vs low) MDP announces a product-platform (vs component) level of adoption.

To test our hypotheses, we conduct an event study using a sample of 341 ETA announcements by 77 S&P 500 firms between 2009-2018. The findings lend support to our predictions and are robust to various sensitivity analyses, which are reported in the Appendix of the first essay. We conclude the essay with a discussion on the theoretical contributions and managerial implications.

Next, in the second essay, titled "*Effects of Emerging Customer Orientation on Shareholder Value: The Moderating Role of Marketing Capabilities*", we investigate effects of firm's emerging customer orientation – i.e., the extent to which a firm is focused on the

needs of emerging customer segments (Govindarajan et al., 2011), on shareholder value. To investigate the relationship between emerging customer orientation and shareholder value, we develop a framework based on dynamic capabilities and the theory of market-based assets (MBAs) to argue that firm's emerging customer orientation can positively influence shareholder value but only when complemented with the necessary marketing capabilities to build and leverage MBAs.

MBAs are intangible assets that a firm's marketing investments create and are principally of two types: relational and intellectual (Srivastava, Shervani, and Fahey, 1998). According to Srivastava et al. (1998), building MBAs, such as (1) knowledge about customer needs in a new market and suitable ways to address the market needs, and (2) relationships and communication channels with the new customers and value chain partners are critical for a firm to succeed in any market. However, developing such MBAs in emerging customer segments maybe challenging because of the needs of these segments are often ill-identified and fast evolving (Govindarajan et al., 2011). Therefore, building new MBAs related to emerging customer segments efficiently and effectively is critical to succeed with emerging customer orientation. Similarly, such MBAs can be leveraged via market-facing and core business processes to deliver superior corporate performance and shareholder value through superior customer value and competitive advantages (Srivastava, Fahey, and Christensen 2001). Thus, to successfully reap the benefits of emerging customer orientation, firms require capability to not only build and maintain MBAs, but also to combine, deploy, and mobilize MBAs (i.e., leverage the MBAs) in novel, meaningful and efficient ways for new uses. Overall, our conceptual framework argues that firms with higher emerging customer orientation can create shareholder value but only when complemented with marketing capabilities to build and leverage MBAs.

We test our predictions using an unbalanced panel data set of 919 firm-year observations consisting of 127 U.S. retail firms with an average of seven years of observations per firm over a period of ten years from 2009-2018. Our findings lend support to the predictions that firms with higher (vs lower) emerging customer orientation increase firm value when complemented with MBA-building and MBA-leveraging capabilities. Further, we find partial support to our prediction that joint effects of emerging customer orientation and marketing capabilities will lower the firm's risk.

We contribute to marketing and innovation literature by (1) providing a framework to understand how firms with emerging customer orientation can succeed and (2) extending the knowledge on MBA-building and MBA-leveraging capabilities (Feng, Morgan, and Rego, 2015; Srivastava et al 1998). Moreover, several scholars in the past have implied that emerging customer orientation has a positive effect on firm value (e.g., Chandy and Tellis 1998; Govindarajan et al. 2011; Kumar 2018; Tellis, Prabhu, and Chandy 2009). However, to date, no prior study has empirically tested this relationship. Our study provides empirical evidence that emerging customer orientation does indeed affect shareholder value positively, but this positive relationship is contingent on the firm's marketing capabilities.

Overall, we believe that these two essays will contribute significantly to research on transformative marketing by establishing when and how it affects shareholder value. Further, the implications drawn from this thesis can help practitioners with actionable insights on how to respond to emerging technologies and emerging customer segments – two key forces that demand a transformational response.

References

- Chandy, R. K., & Tellis, G. J. (1998). Organizing for radical product innovation: The overlooked role of willingness to cannibalize. *Journal of marketing research*, 35(4), 474-487.
- Christensen Clayton, M. and Raynor Michael, E. (2003). *The Innovator's Solution, Creating and Sustaining Successful Growth*. Harvard Business School Press, Boston, MA.
- Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of management*, 37(1), 39-67.
- Feng, H., Morgan, N. A., & Rego, L. L. (2015). Marketing department power and firm performance. *Journal of Marketing*, 79(5), 1-20.
- Govindarajan, V., Kopalle, P. K., & Danneels, E. (2011). The effects of mainstream and emerging customer orientations on radical and disruptive innovations. *Journal of Product Innovation Management*, 28(s1), 121-132.
- Kumar, V. (2018). Transformative Marketing: The Next 20 Years. *Journal of Marketing*, 82(4), 1-12.
- Rotolo, D., Hicks, D., & Martin, B. R. (2015). What is an emerging technology?. *Research policy*, 44(10), 1827-1843.
- Rubera, G., Chandrasekaran, D., & Ordanini, A. (2016). Open innovation, product portfolio innovativeness and firm performance: the dual role of new product development capabilities. *Journal of the Academy of Marketing Science*, 44(2), 166-184.
- Sood, A., & Tellis, G. J. (2009). Do innovations really pay off? Total stock market returns to innovation. *Marketing Science*, 28(3), 442-456.
- Sorescu, A. B., & Spanjol, J. (2008). Innovation's effect on firm value and risk: Insights from consumer packaged goods. *Journal of Marketing*, 72(2), 114-132.
- Srinivasan, R. (2008). Sources, characteristics and effects of emerging technologies: Research opportunities in innovation. *Industrial Marketing Management*, 37(6), 633-640.
- Srivastava, R. K., Fahey, L., & Christensen, H. K. (2001). The resource-based view and marketing: The role of market-based assets in gaining competitive advantage. *Journal of management*, 27(6), 777-802.
- Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of marketing*, 62(1), 2-18.
- Tellis, G. J., Prabhu, J. C., & Chandy, R. K. (2009). Radical innovation across nations: The preeminence of corporate culture. *Journal of marketing*, 73(1), 3-23.

Essay-1: The Effect of Marketing Department Power on Investor Response to Emerging Technology Adoption: Evidence from Artificial Intelligence-enabled New Product Announcements

Abstract

A growing number of companies are engaging in the adoption of emerging technologies from a domain different from their own in new products and services (ETA). However, there is little guidance from research on strategic implications of such innovations. The study addresses this gap by highlighting the conceptual differences between ETAs and radical and breakthrough innovations and examining stock-market response to ETAs. The adoption of Artificial Intelligence in new products by non-software firms is used as a representational case of ETA in the study. Findings from a sample of 341 announcements by 77 S&P 500 firms between 2009-2018 reveal that investors respond positively to ETA announcements by firms with powerful marketing department and that the effect of marketing department power on investor response is moderated by the following innovation characteristics: innovation stage, route to innovation, and adoption level. Theoretical contributions and managerial implications of the findings are discussed.

Keywords: Emerging technology adoption, artificial intelligence, digital technologies, marketing department power, new product innovation

Introduction

The number of companies adopting¹ various emerging technologies from other domains in their new products and services is growing (Forbes 2019; Srinivasan 2008). For example, several leading automobile manufactures including General Motors (GM) and Ford are now adopting Artificial Intelligence (AI) in various use cases ranging from development of cars with AI-enabled components (e.g., braking system) to development of AI-driven autonomous cars. Increasing instances of adoption of AI across several industries may be the reason why business spend on AI-based solutions development is expected to cross \$97.7 billion by 2023 (IDC 2019). Given the increasing instances of emerging technology adoption in new products and services innovations (henceforth emerging technology adoption: ETA) involving significant investments, a better understanding of ETA and its effect on firm value is not only warranted, but crucial. However, extant literature does not provide guidance on strategic value implications of ETA.

The focus of our investigation is on how shareholders value ETA. Specifically, we examine stock market response to AI-enabled new product announcements. Understanding how ETAs are valued by shareholders is critical because such strategic initiatives can have unprecedented effects and unfamiliar outcomes, and marketers must get ahead of the knowledge curve (Grewal et al. 2019). For instance, consider the following case of differential investor response to two similar announcements by Ford and GM about development of purpose-built autonomous vehicles (e.g., delivery vehicles) in February and October 2018, respectively. While Ford's stock price dropped by 4.7% following the

¹ Following Srinivasan (2008), we define emerging technology adoption as new products and services innovations where the core emerging technology's application domain is different from its original domain. For example, the original domain of Artificial Intelligence (AI) is software programming. Therefore, application of AI in a different domain such as in the automobiles domain to develop autonomous cars qualifies as an instance of technology adoption.

announcement, GM's announcement was assessed positively by investors as its stock prices jumped by 4.6%. Both announcements came from leading automobile manufacturers and involved adoption of AI - an emerging technology from computer programming and software domain. Yet, in this instance, investors evidently expected GM (vs Ford) to extract economic rents from the ETA. The differential returns to these announcements imply that investors do not expect all firms to benefit from ETAs. If true, the observation raises our research question: what are the drivers of investor response to ETA?

To address our research question, we develop a framework using signaling (e.g., Spence 1973; Connelly et al. 2011), screening (Bergh et al 2014; Sanders and Boivie 2004), and organization theories (e.g., Salancik and Pfeffer 1974). We argue that although ETA presents firms with a rich source of technological and market opportunities, firms may find it challenging to envision viable marketing strategies and profitable business models for the products and markets created by the ETA (Srinivasan 2008). Therefore, the ETA announcement by itself may not be sufficient for investors to predict firm's future cash flows and in such situations, investors may "screen" for additional signaler characteristics (i.e., firm-level indicators) and the fit between the signaler and the signal (i.e., ETA) characteristics to update their expectations of firm's prospects from the ETA (Connelly et al. 2011).

An understanding of how ETAs differ from other innovations such as radical and breakthrough innovations (henceforth RBIs) - which also rely on emerging technologies (e.g., Chandy and Tellis 1998; Sood and Tellis 2005; Sorescu and Spanjol 2008), may help us identify the drivers influencing investor response. There are two important differences between ETAs and RBIs which may affect investor response. First, the use of emerging technology in RBIs is intended to replace the established core technology by providing higher performance per dollar (Chandy and Tellis 1998; Sood and Tellis 2005). For example, information technology (IT) firms such as Google and Microsoft may develop sophisticated

AI algorithms to improve their decision accuracy and processing efficiency to replace their existing intelligent technologies by providing better customer benefits in terms of performance per dollar. In contrast, the emerging technology use in ETAs is intended to improve customer benefits beyond the price-performance ratio. For example, the use of AI in autonomous cars is neither intended to replace the core engine technology nor to improve the vehicle's miles per gallon – a key performance dimension for automobile customers. Instead, it is intended to provide convenience by reducing the effort to use the car to commute from point A to point B.

Second, RBIs and ETAs differ in their scopes of market context. While RBI is a consequence of selection of a new technology for a fixed market context, ETA involves selection of one or more appropriate market contexts for the emerging technology (Adner and Levinthal 2002). For example, RBIs in the domain of AI advanced from the use of decision trees to neural networks. When neural network technology was first introduced, IT firms in the business of developing intelligent systems had to select from the two competing technologies – i.e., established decision trees vs emerging neural networks. In contrast, the development of AI-enabled technologies in the automobile industry is a case of ETA where the car manufacturers must select from a number of potential market contexts such as purpose-built vehicle and fleet management services (e.g., self-driving delivery vehicles), ridesharing services, catering to the market needs of improved passenger safety (e.g., alerting the driver to risks or simply overriding driver action to avoid lane departures and/or crashes) and convenience (e.g., integration of AI-enabled voice assistants). The need for selection of appropriate market contexts for ETAs makes it difficult for firms to envision the most suitable market contexts and the associated changes required to their business models to ensure the success of ETAs (Srinivasan 2008) presents a heightened risk of commercialization failure and thus impacting the firm value differently, compared to RBIs.

Overall, the differences in (1) the intended use of the technology (i.e., to provide customer benefits beyond price-performance ratio) and (2) the scope of market contexts suggest that, beyond a firm's technological investments, ETA's impact on firm value may heavily depend on resources and competences managed by the marketing department. These resources and competences include cultivation and leveraging of market-based intellectual and relational assets (Srivastava, Fahey, and Christensen 2001; Srivastava, Shervani, and Fahey 1998) to identify emergent customer needs and suitable business models, effective communication of unique and differentiated benefits of the new product, and a high degree of inter-departmental coordination between marketing and other strategic functions. Because powerful departments possess more valuable resources that can influence a firm's strategy (e.g., Salancik and Pfeffer 1974), and the marketing department is the custodian of the resources and competences necessary for the success of ETA, marketing department's power in top management team (TMT) can reduce uncertainties regarding the firm's future performance. Going back to the previous example of differential investor responses to Ford and GM's announcements, as reported in their 2017's annual proxy statements (DEF14A form), we observe that while GM's TMT comprised of 17% marketing executives, Ford, in contrast, did not report any marketing executives in its TMT. Therefore, we argue that investors use marketing department power as an important firm-level indicator in their forecasting of firm's future cash flows from the ETA.

Furthermore, the fit between resources and competencies managed by the marketing department and those demanded by the innovation characteristics (i.e., innovation stage, route to innovation, and adoption level) should affect investor response as it increases reliability of the ETA signal (Connelly et al. 2011). Specifically, investors are likely to perceive a greater fit between resources and competencies managed by the marketing department and those required for (1) latter stages of innovation (i.e., development and commercialization),

compared to initiation stage, (2) external sourcing of innovation through alliance (i.e., ally) and acquisition (i.e., buy), compared to in-house development (i.e., make), and (3) product-platform level adoption of the emerging technology, compared to component level adoption, and therefore investors respond positively to such ETAs.

We test our hypotheses using a sample of 341 ETA announcements made by 77 of the S&P 500 firms over ten years between 2009 and 2018. As there are several emerging technologies in different stages of technology lifecycle, we identified AI as a representative emerging technology to minimize confounds due to variance in perceptions of business potential of different emerging technologies. AI is expected to have a profound effect on marketing (Davenport et al. 2019) and is widely recognized by business leaders and experts as a source of competitive advantage and a transformational technology across industry sectors (e.g., The CMO Survey 2019; Gartner 2019). Further, using AI alone as a representative technology of emerging technologies is unlikely to reduce the generalizability of our findings as AI is a general-purpose technology that serves as a backbone for a significant number of emerging technologies. For example, after analyzing more than 150 emerging technologies, PriceWaterhouseCoopers categorized AI as an essential technology that not only fosters innovation and improve productivity, but also as an enabler of other predominant emerging technologies, such as robotics, Internet of Things, and data analytics solutions (PwC 2017). Therefore, AI serves an appropriate representative of emerging technologies in our context.

We find that, on average, stock market response to ETA announcements do not significantly differ from zero which confirms that investors are unable to forecast firm's expected future cash flow from the ETA purely based on the announcement. Further, our findings confirm our hypotheses that investors will use the firm's marketing department power as an indicator of its ability to benefit from the ETA and that the fit between marketing department power and ETA characteristics positively moderate investor response.

Our study makes the following three contributions to innovation and marketing literature. First, we extend new product innovation literature by developing a comprehensive framework to analyze investor response to ETA. To the best of our knowledge, no previous study has investigated the strategic value implications of ETA. Confirming our assumption that impact of ETA and the mechanisms through which it affects firm value may be different, in contrast to extant literature on RBI which finds a positive stock market response to RBI announcement (e.g., Chandy et al. 2006; Sood and Tellis 2009; Sorescu, Chandy, and Prabhu 2003), we find that investor response to ETA announcements is not significantly different from zero. This finding further provides us with the impetus to examine the drivers of investor response to ETAs. Second, we extend the scant literature on marketing department power (Feng, Morgan, and Rego 2015; Srinivasan and Ramani 2019) by uncovering an additional mechanism through which powerful marketing departments can boost firm value – by acting as a confidence-boosting firm-level characteristic for investors to assess the firm’s prospects through expensive and risky ETAs. The role of TMT, and particularly that of marketing department, in investor’s assessment of future firm performance from innovation initiatives is unexplored in the prior literature although recent studies suggest that marketing department plays an important role in innovation outcomes (e.g., Stock and Reiferscheid 2014; Kashmiri, Nicol, and Arora 2017; Arunachalam et al 2018). Our study addresses this critical gap in the literature and demonstrate that investors rely on firm’s marketing department power to update their beliefs about a firm’s prospects from its new product innovation. Finally, we extend the literature exploring the effects of innovation characteristics on firm value (e.g., Borah and Tellis 2014; Sood and Tellis 2009; Sawhney 1998). We demonstrate that the fit between innovation characteristics (i.e., innovation stage, route to innovation, and adoption level) and the firm indicator of interest (i.e., marketing department power) can positively affect investor response to the signal.

The remainder of the paper is organized as follows. Next, we develop the conceptual framework followed by discussion on research methodology including data sources, variable operationalization, and model specification. We then present our findings from the hypotheses testing and finally, conclude with a general discussion including contributions, implications, and limitations of our study.

Theoretical Framework

To understand how marketing department power may affect investor response to ETA announcements, we develop our conceptual framework using information asymmetry, signaling, and screening theories. Information asymmetry theory is based on imperfect information availability between two parties engaged in a transaction (Stiglitz 2002). According to Stiglitz (2000), information asymmetry arises when one party does not have complete information about (1) quality or (2) behavioral intentions of the other party. In financial markets, information asymmetry arises because managers hold private information which is unavailable to investors (Chen, Ganesan, and Liu 2009; Myers and Majluf 1984; Sorescu, Shankar, and Kushwaha 2007) and the lack of complete information leads to lower firm value as investors perceive higher risk and discount the asset price for the risk premium (Luo 2008).

To resolve issues arising from information asymmetry, according to signaling theory, *senders* – i.e., party with more information (e.g., managers) may send *signals* to the *receivers* – i.e., party with incomplete information (e.g., investors) to influence the receivers' behavior (Spence 1973, 1974). In our context, firms may choose to signal their quality and future performance (Connelly et al. 2011) through ETA announcements as adoption of emerging technologies in new products can serve as a rich source of technological and market opportunities for the firm. However, investors may not be able to estimate future cash flows

generated by the ETA because emerging technologies are highly complex, fast-evolving, and stricken with high levels of uncertainties making it challenging to envision viable marketing strategies and profitable business models for the products and markets that are created from the ETA (Morris, Schindehutte, and Allen, 2005; Srinivasan 2008). In such situations, screening theory serves as a suitable theoretical approach to understand investors' valuation based on observable firm factors, ETA characteristics, and their fit (Bergh et al 2014; Sanders and Boivie 2004).

Screening theory is analogous to signalling theory in that it posits that the receiver (i.e., investors) actively screens for additional information about the sender (i.e., firm) and the signal (i.e., ETA announcement) to reduce information asymmetry (Bergh et al 2014; Sanders and Boivie 2004; Weiss 1995). When responding to signals from firms, investors screen for additional information to assess (1) *signaler veracity* – i.e., the extent to which a firm possesses the unobservable quality that it intends to signal, and (2) *signal fit* - i.e., the extent to which the signal characteristics are correlated with the unobservable quality (Connelly et al 2011). A combination of signaler veracity and signal fit improve *signal reliability* – i.e., the extent to which investors can rely on the signal to project future performance of the firm, and therefore affects investor response (Connelly et al 2011).

Signaler veracity: In the context of investor response to ETA announcements, signaler veracity refers to a firm's abilities to extract economic rents from the new product. Economic rents from ETA can be extracted only if the new product offers meaningful value to its market (Stock and Reiferscheid 2014) and is supported by effective marketing strategy (e.g., Sorescu, Chandy, and Prabhu 2003). Prior research has demonstrated that companies must leverage their critical resources and assets (e.g., market-based assets such as intelligence about emergent customer needs and competitive environment changes) to reduce market risk and extract superior value from the innovation (Arunachalam et al. 2018; Srivastava et al.

1998). Therefore, based on organization theory, which posits that powerful departments possess more valuable resource that can influence a firm's strategy (e.g., Salancik and Pfeffer 1974), we argue that a powerful marketing department is used by the investors as a factor to update their beliefs about the firm's ability extract economic rent from the new product.

Signal fit: Signal fit is the extent to which the receivers perceive the signal characteristics to be correlated with the signaler veracity – i.e., signalers unobservable qualities. In our context, with marketing department power serving as an observable factor indicating signaler veracity, prior research (e.g., Prašnikar, and Škerlj 2006; Sawhney 1998; Story, Hart, and O'Malley 2009) suggests that there may be three such signal characteristics, namely *innovation stage*, *route to innovation*, and *adoption level*, that can affect perceptions of fit between the signal and the competencies and assets managed by the marketing department. Therefore, we propose that innovation stage, route to innovation, and adoption level are expected to moderate the effect of marketing department power on investor response to ETA announcement.

Hypotheses Development

Marketing Department Power and Investor Response to ETA Announcement

The power of a functional department reflects its ability to influence other resources and departments in the firm (Hickson et al., 1971). Furthermore, according to organization theory (e.g., Salancik and Pfeffer 1974), powerful departments possess more valuable resources that can influence a firm's strategy. Accordingly, we define marketing department power as the degree to which marketing resources such as customers, brands, and channels, by the virtue of the marketing department's influence on other resources and departments, play a key role in a firm's strategy and performance (Feng et al 2015; Srinivasan and Ramani 2019). Marketing department is the custodian of marketing resources such as market-based

assets that can enable firms to exploit market opportunities, penetrate markets faster, respond to competitors, and avoid penalties associated with brash market moves (Kerin, Varadarajan, and Peterson 1992; Srivastava et al. 1998). Therefore, marketing department power of a firm should positively influence investor's perception about the firm's ability to mobilize such assets more effectively and with relative ease to gain competitive advantage from the ETA.

Further, marketing department is responsible for providing a wide-range of product-relevant information (Ernst, Hoyer & Rübsaamen, 2010; Troy et al. 2008) which can improve product meaningfulness – i.e., product's superiority in terms of its quality and benefits (Stock and Zacharias 2011). Prior research has demonstrated that it is only the product meaningfulness which increases firm's competitive advantage (Atuahene-Gima and Ko 2001; Barney 1991; Montoya-Weiss and Calantone 1994) and ultimately leads to superior firm performance (Stock and Reiferscheid 2014). Therefore, marketing department power should indicate the extent to which the firm can translate product-relevant information into developing and commercializing a meaningful product desired by its target market.

Based on the preceding observations from previous research, when firms make ETA announcements to signal their potential future performance, investors will use marketing department power to assess signaler veracity – i.e., firm's ability to create and extract value from ETA. Extending this logic, the effect of marketing department power of a firm should have a positive effect on investor's response to its ETA announcement. Formally stated,

H1: Investors react positively to ETA announcements by firms with high (vs low) marketing department power.

Moderating effects of Innovation Characteristics

We predict that, in the context of investor response to ETA announcement, innovation stage, route to innovation, and adoption level will have moderating effects on the relationship between marketing department power and investor response due to perceptions of signal fit.

Moderating effect of Innovation Stage

Innovation Stage: An innovation initiative comprises of three stages, namely: initiation, development, and commercialization (Sood and Tellis 2009), reflecting the market readiness of the new product (Prašnikar, and Škerlj 2006) and require different set of resources and competences at different stages (Story et al. 2011). Although marketing department is likely to play a key role across all stages of the ETA, its influence and impact during latter stages of the innovation, compared to initiation stage, is likely to be more. Previous research has demonstrated that marketing decisions related to targeting and positioning, customer relationship management strategy, and marketing mix processes can help firms capture the value created through innovations (e.g., Arunachalam et al. 2018; Srivastava et al. 1999). Typically, such strategic decisions are made during latter stages of innovation (e.g., Rubera, Chandrasekaran, and Ordanini 2016) as (1) the focus during initiation stage is on opportunity articulation and assessment and (2) many identified opportunities during initiation stage may not be commercialized at all (Prašnikar, and Škerlj 2006). Since marketing department is responsible and accountable for decisions related to value-capturing activities made during latter stages of innovation, compared to ETA initiation announcements, investor's perception of signal fit should be higher when a firm with higher marketing department power announces ETA during latter stages of innovation. Therefore, we predict that, compared to ETA initiation announcements, investor response to development and commercialization announcements by firms with higher marketing department power will be positive. Formally stated,

H2: Innovation stage will positively moderate the relationship between marketing department power and investor response to ETA announcement such that, compared to announcements made during the initiation stage, investor response to **(a)** development and

(b) commercialization stage announcements by firms with high (vs low) marketing department power will be positive.

Moderating effect of Route to Innovation

Route to Innovation: Previous research has documented three widely used strategies to expand a firm's innovation portfolio: (1) make – i.e., internal development of the new product; (2) buy – i.e., acquire the innovation-related assets such as patents, technology, and product; and (3) ally – i.e., collaborating with one or more external entities such as other firms and universities to develop an innovation (e.g., Borah and Tellis 2014; Geyskens, Steenkamp, and Kumar 2006; Kalaignanam, Kushwaha, and Swartz 2017; Xue 2007).

The choice of route to innovation affects product development time such that, compared to developing the product internally, new product's time-to-market is faster through buy or ally as the firm can immediately source, access, and leverage the external innovation-related assets (e.g., Borah and Tellis 2014; Nambisan and Sawney 2007; Prašnikar, and Škerlj 2006; Rubera et al. 2016; Xue 2007). Moreover, according to Srinivasan (2008), adoption of emerging technology requires a shift in the loci of innovation to outside the firm because the knowledge domains in emerging technology are interconnected and arise from convergence of several distinct technologies located across several firms or even different industries. Hence, the combination of complexity, distributed knowledge domains, and fast-evolving landscape of an emerging technology may not only make the ETA journey difficult for a single company, but also longer and highly unpredictable. Hence, a firm with access to external innovation-related assets through alliances and acquisitions (vs make) will advance through the new product development faster with fewer roadblocks. Since marketing department's influence and impact is higher during latter stages of innovation (Rubera et al. 2016), investor's perception of fit between firm's marketing department power and the ETA announcement should be higher for ally and

buy announcements, compared to make. Therefore, we predict that, compared to make, investor response to ETA announcements by firms with high (vs low) marketing department power will be positive for ally and buy announcements (vs make). Formally stated,

H3: Route to innovation will positively moderate the relationship between marketing department power and investor response to ETA announcement such that, compared to make announcements, investor response to **(a)** ally and **(b)** buy announcements will be positive.

Moderating effect of Adoption Level

Adoption Level: ETA may involve adoption of the emerging technology at a product-platform level or at a component level. Product-platform is defined as a set of subsystems and interfaces that form a common structure from which a product family – i.e., stream of related products can be developed and produced efficiently (Sawhney 1998). As product-platform consists of components that can be shared across product-lines, a firm can choose to adopt a technology at the product-platform level or at the shared component level. However, product-platform adoption (vs component adoption) requires resources and competencies such as (1) leveraging marketing assets (e.g., insights on customer behavior) to identify a “beachhead” – a customer segment that can serve as a base for expansion into related segments and application markets (Sawhney 1998), (2) attracting higher attention from top management team (TMT) and improved coordination between the concerned departments (Robertson and Ulrich 1998), and (3) communicating the unique and differentiated benefits of their new product-platforms as they may be significantly different from those offered by the firm’s existing offerings.

Prior research establishes the role played by the marketing department power in managing such resources and competencies effectively. For example, Feng et al. (2015) demonstrate that firms with high (vs low) marketing department power leverage market-based intellectual assets more effectively and can direct TMT’s attention to such strategic

issues and command improved inter-departmental cooperation. Similarly, firms with higher (vs low) marketing department power are proven to be more effective in translating market knowledge into customer value by communicating the unique and differentiated benefits of their innovations (Vorhies, Morgan, and Autry 2009). Therefore, a product-platform (vs component) adoption is likely to be a better fit for firms with high (vs low) marketing department power and evoke a positive response from the investors. Formally stated,

H4: Adoption level will moderate the relationship between marketing department power and investor response such that, compared to component adoption, investor will respond positively (negatively) to product-platform adoption announcements by firms with high (low) marketing department power.

Insert Figure 1 About Here

Research Methodology

Research Context, Data, and Sample

Context: The event of interest for our study is a public announcement by a firm about adoption of emerging technology in a new product. There is plethora of emerging technologies in different technology lifecycles. For example, Gartner (2020), in its “Hype Cycle for Emerging Technologies” report, identifies more than 1,700 unique technologies in different stages of hype cycle – i.e., maturity and relevance to solving real business problems and exploiting new opportunities. To minimize any confounds due to variance in technology lifecycles and perceptions of business potential of different emerging technologies, it is best to focus on adoption of the same emerging technology by businesses. We use the following criteria to find a representative candidate of emerging technologies. The technology must (1)

have a profound effect on marketing, (2) be widely accepted by business leaders as a source of business advantage, and (3) be recognized as a transformational technology for all industry sectors by experts. Based on these criteria, we find that Artificial Intelligence (AI) can be used as a representative candidate of emerging technologies.

First, AI is expected to significantly affect the domain of marketing. For example, Davenport et al. (2019) note that artificial intelligence (AI) appears likely to influence marketing strategies, including business models, sales processes, and customer service options, as well as customer behaviors. Further, according to The CMO Survey (2019), marketing leaders are accelerating AI's use cases and will increasingly adopt the technology in the next three years following the survey. Therefore, it is evident that marketing will witness profound effects of AI in the future. Next, there is significant interest in AI adoption in the business community. According to PwC Global CEO Survey (2017), 72% of business leaders agreed that AI will be the business advantage of the future. A recent report by International Data Corporation (IDC) states that business spend on developing AI solutions will reach \$97.7 billion by 2023 (IDC 2019). Similarly, Bughin et al (2018) note that AI has the potential to deliver additional global economic activity of around \$13 trillion by 2030. These estimates clearly indicate business leaders' current and growing interest in AI. Finally, experts argue that AI is one of the transformative technologies of our time. For example, several reports suggest that every organization and industry must consider AI adoption as it will have profound global impact on businesses and customers in the next decade (Gartner 2019; McKinsey 2018; PwC 2017). Furthermore, using AI alone as a representative technology of emerging technologies is unlikely to reduce the generalizability of our findings as AI is a general-purpose technology that serves as a backbone for a significant number of emerging technologies. For example, after analyzing more than 150 emerging technologies, PriceWaterhouseCoopers categorized AI as an essential technology that not only fosters

innovation and improve productivity, but also as an enabler of other predominant emerging technologies, such as robotics, Internet of Things, and data analytics solutions (PwC 2017). Therefore, in the context of our study, we identify firm announcements about adoption of AI in a new product as the specific event of interest.

Data and Sample: We use the following two criteria to select sample firms. First, to ensure that we have a large sample of announcements, we must identify sample firms that are more likely to invest in emerging technologies. Marketing scholars and practitioners suggest that large firms are more likely to adopt emerging technologies. For example, Chandy and Tellis (2000) find that large firms (vs small) more likely to introduce radical innovations, which by definition, are based on substantially new cutting-edge technologies (e.g., Chandy and Tellis 1998). Similarly, a recent report by Spiceworks², a leading marketplace for information technology solutions, indicates that adoption rates of emerging technology in large enterprises are up to 10 times higher than in small businesses. Therefore, we decided to identify sample of large firms. Second, to ensure data availability to assess investor response, the sample firms must be listed in the U.S. stock market. Based on these criteria, we identify Standard and Poor 500 (S&P 500) firms for our study. The S&P 500 consists of 500 leading companies and is widely regarded as the best single gauge of large-cap U.S. equities covering 80% of total U.S. stock market capitalization³. Further, S&P 500 list of firms have been used previously by marketing scholars (e.g., Bendig et al. 2018; Bommaraju et al. 2019). As the list of constituent firms in the S&P 500 index change on yearly basis, following the approach in prior research using S&P 500, we use the constituent firms as of 2019.

² Available at <https://www.spiceworks.com/marketing/state-of-it-2019/future-tech/>

³ <https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview>

Next, since we are interested to capture effect of adoption of AI on firm value, we remove firms belonging to “*Computer Programming, Data Processing, and other Computer Related Services*” classification (SIC Code 7371 to 7379). Approximately 20% of S&P 500 firms belong to this sector. Additionally, we exclude any firm whose operations are entirely based online because such firms rely extensively on software programming for their business operations and therefore using AI in their products will not qualify as an instance of emerging technology adoption. Among the S&P 500 firms, only Amazon and Netflix met this exclusion criteria.

As these firms are pioneering radical and breakthrough innovations using AI technology, they could serve as a control group for comparing the effects of RBIs and ETAs. However, this is not a viable study design as each of these firms are likely to have several thousands of AI related announcements. Further, the scope of our study is to understand investor response to ETA and not to study the differential effect of ETAs and RBIs on investor response. We have discussed theoretical motivations behind why ETAs must be studied separately. Moreover, to understand the differential investor responses, we can draw comparisons between the main effect of investor response to ETAs in the present study with investor responses to RBIs as documented in the prior studies. For example, prior studies have documented a positive investor response to RBIs. Based on the findings from the present study, we can conclude whether investors also perceive ETAs as positive or if they respond in different manner. Therefore, we exclude the firms from SIC code 7131-39 along with Amazon and Netflix from our sample.

Further, there may be concerns regarding software programming being a practice rather than an industry domain. While software program is indeed a practice, it is also a domain/industry sector on its own with separate Standard Industry Codes (SIC) ranging from 7371-7379, which comprise of companies, such as Microsoft and Google. In our sample, we

only consider firms that do not belong to these SIC codes. Thus, our definition of development domain and application domain is consistent with prior literature, which uses SIC codes as primary identifier of different industry sectors.

Furthermore, following extant literature (e.g., Colla, Ippolito, and Li 2013; Saboo, Kumar, and Anand 2017) we exclude utilities (SIC Codes from 4900 to 4949) and financial firms (SIC Codes from 6000 to 6999) because the financial policies of these firms are subject to statutory capital requirements or regulatory supervision in a number of states. Overall, our sampling frame was narrowed down to 324 firms over a decade between 2009 to 2018.

To limit the identification of announcements to new products adopting AI, we identified a set of keywords based on literature on business applications of AI. Specifically, Garbuio and Lin (2019) note the following three fundamental ways in which businesses can or will use AI⁴: (1) *assisted* AI - automation of routine tasks (e.g., robotic process automation), (2) *augmented* AI – learning from data and augmenting human decision-making with prediction (e.g., personalization and fraud detection), and (3) *autonomous* AI – learns from data and acts on its own without the need for human intervention (e.g., driverless cars and chatbots). Hence, we include (1) “*robotics*”, “*robotic process automation*”, “*RPA*” as keywords to search for assisted AI, (2) “*machine learning*”, “*deep learning*”, and “*neural network*” for augmented AI, and (3) “*autonomous*”, “*chatbot*”, “*virtual agent*”, “*digital assistant*”, “*natural language processing*”, “*NLP*” and “*computer vision*” for autonomous AI. In addition to these keywords specific to their respective business application, we also include generic keywords such as “*artificial intelligence*” and “*AI*” to cover as many potential use-cases as possible. Therefore, our complete list of search keywords is as follows:

⁴ Insights from other experts, although follow different typology (e.g., Davenport and Ronanki 2018), also suggest similar business applications.

“artificial intelligence”, “AI” “robotics”, “robotic process automation”, “RPA”, “machine learning”, “deep learning”, “neural network”, “autonomous”, “chatbot”, “virtual agent”, “digital assistant”, “natural language processing”, “NLP” and “computer vision”.

Next, to compile announcements by the sample firms about adoption of AI in their new products, we searched Factiva⁵ for announcements using firm’s name and *“new products and services”* filter. Finally, following criteria are applied for inclusion of the announcement in the final sample: (1) the announcement must be about a new product or service introduced or to be introduced by the company and (2) the new product or service must have at least one component based on AI. Overall, our final sample consists of 341 announcements by 77 of the 324 eligible S&P 500 firms between 2009 to 2018.

Event Study

We employed event study methodology (e.g., Sorescu, Warren, and Ertekin 2017) to test our hypotheses. The underlying assumption behind event study methodology is the efficient market hypothesis – i.e., stock price of a firm adjusts to reflect new information based on expectations of the firm’s future performance. Therefore, the effect of the new information – i.e., event such as ETA announcement, on future performance expectations will be captured as “abnormal returns” which represents the stock returns in excess of the expected stock returns estimated based on market returns. Event study has been widely employed by marketing researchers (e.g., Boyd and Spekman 2008; Kalaighnam and Bahadir 2013; Swaminathan and Moorman 2009) because it allows researchers to (1) accurately isolate and assess the immediate response to the newly available information with

⁵ Factiva database covers several major news and business publications in the USA including The Wall Street Journal. Although the procedure required filtering through considerably large number of announcements, we are confident that it is a robust approach that allowed us to capture as many unique announcements as possible. It is still possible that our approach may result in some announcements not being identified. However, we believe that such events are less likely to reach the wide investment community and their impact is likely to have low or no impact on investor response.

minimal confounds, (2) measure expected future cash flows as the stock market response is a forward-looking measure and full benefits of innovation may not be realized for several years (Raassens et al. 2012), and (3) design controlled quasi-experiments, in which the post-event behavior of the stock price is tested relative to the expected pre-event behavior, making the causal inference is direct (Srinivasan and Hansens 2009).

The market model estimation method, where market returns are used to estimate the normal stock performance, has been widely used in the literature (e.g., Bhagwat et al. 2020; Lee, Chen, and Hartmann 2016; Sorescu et al. 2017). Hence, following extant literature, we use the market model and specify the stock return for firm i on day t , R_{it} , as a linear function of the returns on a market portfolio, R_{mt} :

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad (1)$$

We use 240 days starting 250 days before and ending 10 days before the event to estimate the expected returns. Therefore, expected returns, $E[R_{it}]$, is computed as:

$$E[R_{it}] = \hat{\alpha}_i + \hat{\beta}_i R_{mt} \quad (2)$$

Also, we use GARCH estimation because it produces more efficient estimates than traditional event study methodologies (Corhay and Rad 1996; Talay et al. 2019). Next, we calculated the abnormal returns as the difference between the actual and expected returns.

$$AR_{it} = R_{it} - E[R_{it}] \quad (3)$$

Finally, following prior research, we compute cumulative abnormal returns (CAR) for several windows around the event day to address the possibility of information leakage and spill-over in the stock market (e.g., Bhagwat et al. 2020; Geyskens, Gielens, and Dekimpe 2002). CAR within a time window between t_1 and t_2 is computed as the sum of abnormal returns on the stock from t_1 to t_2 . Therefore,

$$CAR_i[t_1, t_2] = \sum_{t_1}^{t_2} AR_{it} \quad (4)$$

Measures

In the current section, we discuss operationalization and data sources of every variable. We also summarize the discussion in Table 1 below.

Dependent Variable (CAR $[t_1, t_2]$): Sorescu et al. (2017) recommend inclusion of at least one day prior and one day after the announcement date in computing CAR to account for potential information leakage and dispersion across investors. Following the recommendation and extant literature (e.g., Bhagwat et al. 2020; Swaminathan and Moorman 2009), we report results based on the CAR computed using $[-2, +2]$ time window – i.e., two days prior and two days after the event date as it can more accurately capture the range in stock prices attributable to change in investor's expectations due to the announcement (Sorescu et al. 2017). As part of robustness check, we also report our analyses on CARs computed using $[-1, +1]$, and $[-1, +2]$ time windows which have been used in extant literature to account for information leakage and spill over.

Independent Variable (*Marketing Department Power*): We follow extant literature (Feng, Morgan, and Rego 2015; Srinivasan and Ramani 2019) and operationalize a firm's marketing department power as the principal component analysis score of the following five items: (1) ratio of number of marketing executives to the total number of executives in the TMT, (2) compensation of marketing TMT executives relative to all TMT executive compensation, (3) highest level among the marketing TMT executives in the TMT hierarchical level, (4) the cumulative levels of all marketing executives in the TMT, and (5) the number of unique job responsibilities in the job titles of marketing TMT executives. All items are scaled relative to each year's industry average using the primary Standard Industry Classification (SIC) listed by the firm. Finally, to compute relative marketing department power (RELMDP), we use the standardization approach recommended in the literature (e.g., Campello 2006; Kurt and Holland 2013) by dividing the difference between firm's marketing

department power and marketing department power of all other firms in the same two-digit industry by the standard deviation of the industry. This allows us to account for relative difference in the measures rather than absolute difference (Campello 2006). In robustness checks, we report analysis based on absolute marketing department power as well.

Moderators: Our conceptual framework proposes (1) innovation stage, (2) route to innovation, and (3) adoption level as the three innovation-specific moderators of the relationship between marketing department power and firm-value. All three moderator variables are codified manually based on the information provided in the announcement. Thus, we relied on two independent coders to code all of the announcement-specific variables. The inter-coder agreement for these variables was greater than 86%. We resolved the few differences by discussion. Next, we discuss the operationalization of these variables.

Innovation Stage: Following extant literature (e.g., Sood and Tellis 2009), innovation stage (STAGE) is operationalized as follows: (1) Initiation stage includes announcements about funding (including grants, advanced orders, and funded contracts), events about alliance formation including joint ventures and acquisitions, and expansions for new innovation projects adopting ETA. (2) Development stage includes events about prototypes (working prototypes, demonstration in exhibitions, and new materials, equipment, and processes) patents, and preannouncements (i.e., more than one week ahead of future events). (3) Commercialization stage activities include events about new product launch (including launches, initial shipments, and new applications), and awards (external recognition of quality).

Route to Innovation: We follow Borah and Tellis (2014) to operationalize innovation route (ROUTE). Specifically, make, buy, or ally events are defined as follows. (1) A firm adopts a *make* strategy if the announcement indicates that it will develop the new product internally. (2) A firm is considered as following a *buy* strategy to ETA if the announcement is

about acquiring another firm, entirely or in part, explicitly for the ETA initiative. (3) A firm chooses *ally* route to innovation if the new product announcement mentions the firm collaborating with one or more external entities, specifically for ETA. The nature of the collaboration could include joint ventures or co-development with other companies, licensing of technology, hiring expert(s) or vendors on contract basis, collaborations with universities or other research institutes, and participation in networks.

Adoption Level: We operationalized adoption level (PLATFORM) as a dummy variable coded as 1 to indicate if the emerging technology is being adopted at a product-platform level and 0 for component level adoption. For example, an automobile manufacturer may leverage AI to develop an autonomous car (i.e., product-platform adoption) which may consist of several shared components controlled by the central AI controller or to improve the performance of a shared component such as AI-enabled braking system (i.e., component adoption).

Control Variables: We use several control variables including an announcement-specific variable that capture the market-focus of ETA, and other firm- level and industry-level variables as control variables. We describe the operationalization of these variables below.

U.S. Vs international market focus (MARKET): dummy variable coded as 1 to indicate if the new product was announced for the U.S. market and 0 otherwise. Note that the coding for this variable followed the same manual coding process as described in discussion on operationalization of moderator variables (i.e., innovation stage, route to innovation, and adoption level). There were no disagreements between the coders on this variable.

Firm-level control variables: We use financial leverage (LEV), strategic emphasis (STEMPH), firm size (SIZE), sales-growth of the firm (SGR), and slack resources (SLACK) as firm-specific control variables. Financial leverage is operationalized as ratio of firm's

long-term debt to total assets. Strategic emphasis refers to the emphasis of a firm on value creation, relative to value appropriation (e.g., Sharma, Saboo, and Kumar 2018; Kim, Xiong, and Kim 2018; Mizik and Jacobson 2003) – i.e., the difference between firm’s value creation and value appropriation. We measure firm’s emphasis on value creation as the ratio of R&D expenses to total assets and emphasis on value appropriation as the ratio of the difference between SG&A and R&D expenses to total assets. Firm’s total assets is used as a representation of firm size. Sales growth is computed as year-on-year growth in company’s revenues. Finally, following previous literature (e.g., Lee and Grewal 2004; Fang, Palmatier, and Steenkamp 2008), SLACK is operationalized as the principal component analysis of retained earnings to asset and working capital to asset ratios. To be consistent with the operationalization of relative measure of firm’s marketing department power (RELMDP), we follow a similar standardization procedure for all the firm-level control variables described above.

Industry-level control variables: To control for industry level factors, we use industry’s competitive intensity – measured as the Herfindahl-Hirschman Index (HHI), and industry’s sales growth (INDSGR) – measured as year-on-year growth in industry sales. Further, we also include a dummy variable to indicate firm’s membership to a manufacturing industry (MANF) – i.e., two digits SIC code between 20 to 39.

 Insert Table 1 About Here

Model Specification

To respond to ETA, investors can only use publicly available firm-level observable factors to update their beliefs about firm’s future performance. At the time of announcement, only the preceding time period’s firm-level measures are likely to be made publicly available.

Therefore, to test our hypotheses, we specify the model using CAR [-2,+2] as the dependent variable and one-year lagged measures of relative marketing department power and other firm-level control variables as investors are likely to use only the publicly available firm-level information – i.e., prior time period measures, to respond to the ETA. Further, we specify the model as below with robust standard errors to account for heteroskedasticity.

$$\begin{aligned}
CAR_{ij} = & \alpha_0 + \beta_1 RELMDP_i + \beta_2 STAGE_j + \beta_3 ROUTE_j + \beta_4 PLATFORM_j \\
& + \beta_5 RELMDP_i * STAGE_j + \beta_5 RELMDP_i * ROUTE_j \\
& + \beta_5 RELMDP_i * PLATFORM_j + \beta'_6 CONTROLS_i + \varepsilon_{ij}
\end{aligned} \tag{5}$$

where, for the firm i and announcement j , CAR_{ij} is cumulative abnormal returns over the five-day window – i.e., [-2, +2]; $RELMDP_i$ is the marketing department power of the firm, $STAGE_j$ is the innovation stage, $ROUTE_j$ is the route to innovation, and $PLATFORM_j$ is the adoption level. $CONTROLS_i$ represents a vector of control variables specific to the ETA market-focus (MARKET), firm-level control variables (LEV, STEMPH, SIZE, SGR, and SLACK), and industry-level control variables (HHI, INDSGR, MANF), respectively.

Specification Tests

Multi-Collinearity: We present summary statistics and bivariate correlation matrix of the variables in Table 2. Low correlations among variables and variance inflation factors less than the critical value of 10 suggest that issues related to multi-collinearity are unlikely to influence the results.

Addressing self-selection bias: As the decision by firms to announce the ETA is endogenous, there may be potential self-selection bias in our data. To overcome self-selection bias, we use the two-stage Heckman (1979) procedure. To satisfy the exclusion criteria, as prescribed by extant literature (e.g., Sorescu et al. 2017), we include measures of firm's (1) resources such as number of employees and profits, and (2) absolute value of strategic

emphasis as instruments in the selection model to estimate the inverse Mills ratio (λ) in addition to all the firm and industry level variables used in the specified model in equation (1). Firm resources – financial and human, are known to influence firm's innovativeness (e.g., Chandy and Tellis 2000). Similarly, firm's strategic emphasis – i.e., extent to which the firm is focused on value creation, is also known to affect firm innovativeness (Mizik and Jacobson 2003). Therefore, they are likely to be good instruments to use in the selection model. In the second stage, we include the inverse Mills ratio estimated from the selection model in our analysis to account for potential selection bias. However, the inverse Mills ratio is not significant ($p > .1$). We report the results of Heckman correction in Table A1 (Appendix).

Further, there may also be concerns about selection bias regarding firms with higher marketing department power having a higher propensity to adopt emerging technologies. However, as evident from the results of the Heckman two-stage test in Table A1, marketing department power does not significantly influence the likelihood of adopting emerging technology in selection model. Based on these findings, we conclude that issues related to self-selection bias are unlikely to affect our results.

Addressing endogeneity: In addition to self-selection bias, there may also be concerns regarding endogeneity as reasons behind marketing department power are unobserved. To address such issues, we perform a two-stage instrument variable correction using industry average of marketing department power, prior year's lagged measure of marketing department power, and prior year's lagged returns on assets (ROA) as instruments. Prior research has demonstrated that industry average and lagged values of the endogenous variables can serve as valid instruments (e.g., Ebbes, Papies, and van Heerde 2016; Srinivasan and Ramani 2019; Feng et al. 2015). Further, accountability is an antecedent of marketing department influence (e.g., Moorman and Rust 1999; Verhoef and Leeflang 2009).

Accountability refers to the impact of marketing strategies and actions to financial performance measures. Therefore, we include ROA of the past period as a measure of accountability of the marketing department. The test for endogeneity after the second stage failed to reject the null hypothesis that the variable is exogenous ($p > .1$). Hence, we conclude that endogeneity is unlikely to affect our results and following extant literature (e.g., Dinner, van Heerde, and Neslin 2014; Woolridge 2002) we report our results without the endogeneity correction. The results of the two-stage instrumental variable regression are provided in Table A2 (Appendix).

Results

Descriptive Findings

Announcement Trend. Our data indicate that the number of ETA announcements have been on the rise in recent years. In fact, as shown in Figure 2, more than 75% of all ETA announcements in our sample occur between 2016-2018. The finding also demonstrates the importance and relevance of our study AI. As evident, there is growing interest in the business community regarding AI-based new products, and therefore an understanding of how investors perceive such firm initiatives is crucial.

Insert Figure 3 About Here

Main Effects

ETA Announcement: We find that, on average, the CAR [-2, +2] of -0.01% to the ETA announcements is not significantly different from zero at 10% significance level. Further, find a large variability in investor response to ETA announcements. For example, while the CAR [-2, +2] for 173 of the 341 ETA announcements are positive, the remaining

168 announcements have negative returns. Additionally, the CAR [-2, +2] has a large standard deviation of 3.1%. These findings indicate that investors do not expect all announcing firms to have positive future performance from the ETA and instead, they are likely to update their beliefs about firm's future performance based on signaler (i.e., firm) and signal (i.e., ETA announcement) characteristics. Next, we discuss how the hypothesized relationships affect investor's response.

Insert Table 2 About Here

Innovation Stage: Given the complexities and uncertainties involved in ETA, one can expect firms to make more announcements during latter stages of ETA as announcement during initiation stage may lead to negative returns due to high investments, long gestation periods, and high risk of failure (Kelm et al. 1995). However, firms do not exhibit any pattern of preference to make ETA announcement based on innovation stage with each stage roughly making up for about one-third of the announcements.

Route to Innovation: As the loci of innovation in emerging technologies is external (Srinivasan 2008), one would expect to see firms adopting a predominantly external route to innovation. However, to our surprise, we find most of the ETA are make announcements (approx. 48%). Among the external routes to innovation, ally (approx. 40%) seems to be preferred more than buy (approx. 12%).

Adoption Level: Interestingly, approx. 67% of the ETA announcements in our sample are product-platform level adoption indicating the firms adopting an emerging technology are also adopting platform-thinking (Sawhney 1998) in their new products. These findings suggest that firms consider AI to be a significant source of competitive advantage in the future and are therefore investing significant resources in developing cutting-edge product-

platforms of the future despite the combined uncertainties and complexities associated with both emerging technology and product-platform development.

Hypotheses Testing

We estimate the model specified in equation (1) using main-effects only model (M1) to test H1, and the full model with interactions (M2) to test H2-H4. We report the estimation results in Table 3.

Insert Table 3 About Here

Effect of Marketing Department Power (H1): In support of H1, we find a significant effect of marketing department power on investor response ($\beta = .0016$, $t = 2.61$). Hence, investors are likely to update their expectations of firm's future performance from the ETA positively if the firm has higher (vs low) marketing department power. This indicates that marketing department power of a firm serves as an indicator of signaler veracity to the investors – i.e., a firm-level characteristic that indicates the ability of the firm to earn economic rents from strategic initiatives such as ETA.

Moderating Effects of ETA Characteristics: Next, we discuss the findings about the moderating effects of ETA characteristics on the relationship between marketing department power and investor response (H2-H4).

Innovation Stage (H2): As predicted, we find that compared to initiation stage, the conditional effect of marketing department power on investor response is (1) positive and marginally significant ($\beta = .0022$, $t = 1.88$) in development stage, lending partial support to H2a, and (2) positive and significant ($\beta = .0028$, $t = 2.08$) in commercialization stage, lending support to H2b. Hence, investors seem to value marketing department power more during the

latter stages of ETA lending support to our explanation that compared to initiation stage, the fit between resources and competences manage by the marketing department and those required during latter stages of ETA is higher. An illustration of these findings is provided in Figure 3a.

Insert Figure 3a About Here

Route to Innovation (H3): We predict that, compared to make, investor response to buy (H3a) and ally (H3b) announcements by firms with high (vs low) marketing department power will be positive. Findings from our analyses support both these predictions. Compared to make, the effect of marketing department power was positive and significant for both ally ($\beta = .0033$, $t = 3.17$) and buy ($\beta = .0057$, $t = 3.59$) announcements. Figure 2b shows the interactive effects of marketing department power and route to innovation on investor response visually. These findings indicate that compared to make, investors perceive a greater fit between resources and competences managed by marketing department power and those required for external routes to innovation.

Insert Figure 3b About Here

Adoption Level(H4): The interaction between marketing department and adoption level is also significant such that, compared to component level adoption, the effect of marketing department power is positive and significant for product-platform level adoption of AI ($\beta = .0030$, $t = 2.55$). The finding lends support to perception of greater fit between resources and competences managed by marketing department power and those required by

product-platform level of adoption (vs component level). The interactive effects of marketing department power and adoption level is illustrated in Figure 2c.

Insert Figure 3c About Here

Robustness Checks

The strength and significance of our results might be affected by the operationalization of the variables in our model and by some of the observations from our dataset. Thus, to estimate the robustness of our results to these concerns, we conduct the following additional analyses. Overall, our results are robust to issues concerning variable operationalization, outliers, removal of isolated industry level events in the sample, removal of observations from industries with higher familiarity with AI, and inclusion of time fixed effects. We describe these findings briefly below and more elaborately in the Appendix along with the results.

First, we re-estimate the model using an alternative operationalization of the dependent variable. Specifically, we use CAR [-1, +2] (see Table A3) and CAR [-1, +1] (see Table A4), and find support for H1 in both instances. When testing H2-H4, we find support for (1) H2 and H3 when we use CAR [-1, +2], and (2) H3 when using CAR [-1, +1].

Second, we use Winsorized variables (at 5% level) to ensure that the findings are not biased due to outliers and report the results in Table A5. We find support for all our hypotheses which indicates that our results are not biased due to outliers in our sample.

Third, in Table A6, we report estimation based on the use absolute values of the focal independent variable (i.e., marketing department power) and other control variables. We find support for all our hypotheses except H2a and thus our results are robust to operationalization of the focal independent variable and the control variables.

Fourth, we remove 7 observations from our sample which were the only announcements in their respective industries (see Table A7 for results). Except for H2a, we find support for all our hypotheses. Hence, we rule out that our results may be biased due to isolated industry level events. Further, readers may argue that for companies such as Apple & Intel from the “Electronics and Electrical Equipment Manufacturing” (2-digit SIC = 36) industry segment, AI may be a familiar technology and therefore may not qualify as instances of adoption. To address such concerns, we re-estimate the model without 111 observations from this industry (see Table A8 for results) and reassuringly our results largely remain the same with support for all our hypotheses. Therefore, we find that our results are robust to removing observations from industries that may be more familiar with the emerging technology being adopted.

Finally, we include year dummies to control for time fixed effects (see Table A9 for results) and find that the results remain largely unchanged indicating that our results are robust after controlling for year effects.

General Discussion

Emerging technologies, particularly AI-based technologies, are pervasively affecting the competitive dynamics, business models and customer behavior across a wide range of industries including those not traditionally considered to be technology-intensive (Davenport et al. 2020; Srinivasan 2008). However, past research has not examined how new product innovations based on adoption of a pervasive emerging technology such as AI can affect firm value.

The current research attempts to bridge this gap by providing insights into how investors incorporate new information about a firm’s decision to adopt an emerging technology in its new products to update their expectations about firm’s future performance.

Our findings indicate that investors response is not driven entirely by the newly available information through firm's ETA announcements, but rather by their beliefs about firm's abilities to reap economic benefits from the ETA and the corresponding congruent characteristics of the ETA. Specifically, we find that investors are likely to respond positively to ETA announcements by firms with high (vs low) marketing department power because they expect such firms to develop more meaningful products for the market and successfully commercialize them. Further, we find that the effect of marketing department power on investor response is positively amplified by signal characteristics such as innovation stage, route to innovation, and adoption level as they can improve the signal fit. Next, we discuss the theoretical and practical implications of our findings.

Theoretical Contributions

Adoption of emerging technologies offers a rich source of market opportunities for some firms and challenges for others, and in some cases destroys the existence of incumbent firms (Srinivasan 2008). However, there is lack of guidance from research about who benefits the most through ETA and when. Our research attempts to provide some insights about this under-researched area and makes the following contributions.

First, we extend the new product innovation literature by developing a comprehensive framework to analyze investor response to ETA announcements. Prior literature offers valuable insights on RBI (e.g., Chandy et al. 2006; Sood and Tellis 2009; Sorescu and Spanjol 2008; Srinivasan et al. 2009). To the best of our knowledge, no prior study to date has investigated strategic value implications ETAs. In addition to increasing instances of ETAs in the industry (Forbes 2019; Srinivasan 2008), because RBI and ETA differ in the scope of their market contexts (Adner and Levinthal 2002) and therefore compared to RBI, ETAs may involve applications outside the scope of a firm's activities (Srinivasan 2008), we argue that systematic investigation of ETAs and their effect on firm value will provide valuable critical

insights for researchers and practitioners. The differential effects of radical innovations and ETAs on firm value further accentuate the importance of the investigating how ETAs affect firm value. While most of the previous studies on radical innovations has established a positive effect on firm value (e.g., Sood and Tellis 2009; Sorescu and Spanjol 2008), we do not find significant returns to ETAs. Such differences in findings imply that the technology origins of the adopted technology in the new product innovation affects firm value through different mechanisms. Furthermore, several marketing scholars have noted that investigation of how innovation affects firm value in stock market remains largely ignored in the literature (e.g., Hanssens, Rust, and Srivastava 2009, Rubera and Kirca 2012), and only a few studies to date have paid attention to the gap (e.g., Borah and Tellis 2014; Sood and Tellis 2009; Sorescu, Shankar, and Kushwaha 2007; Sorescu and Spanjol 2008; Srinivasan et al. 2009). Our study builds on this body of work and provides key insights on investor response process and demonstrates that when responding to ETAs, investors use additional firm level indicators and their fit with the innovation characteristics to update their beliefs about firm's prospects from the ETA.

Second, we extend scant research stream on how marketing department affects firm outcomes (Feng et al. 2015; Srinivasan and Ramani 2019) Specifically, research on marketing department power and shareholder value is scarce. While marketing department power can potentially impact firm value through several mechanisms, prior research has, so far, investigated three such mechanisms, viz, through (1) improved resource attraction and inter-departmental coordination (Feng et al. 2015), (2) reduced myopic spending (Srinivasan and Ramani 2019), and (3) reduced likelihood of product-harm crisis due to innovation strategies of narcissistic CEOs. Extending this stream of literature, we uncover yet another important mechanism through which powerful marketing departments can boost firm value. We demonstrate that investors recognize the value of marketing department power and

incorporate it as a key factor to update their beliefs about a firm's ability to benefit from a strategic but risky investment like ETA. This is an important finding because provides evidence that presence of a powerful marketing department can provide reassurance to the market about the firm's ability to extract economic rents from costly and risky investments such as ETAs.

Finally, we extend the literature exploring effect of innovation characteristics on firm value (e.g., Borah and Tellis 2014; Sood and Tellis 2009; Sawhney 1998). Prior literature in this domain has three main limitations: (1) to the best of our knowledge, previous studies have not investigated effect of adoption level on firm value, (2) prior research has only examined the main effects of innovation stage and route to innovation on firm value, and (3) with the exception of Sood and Tellis (2009) who included both innovation stage and route to innovation in their framework, previous studies have examined the effects of innovation characteristics in silo. We overcome these limitations through our comprehensive framework and demonstrate the moderating effects of innovation characteristics on firm value. Specifically, our findings reveal that innovation characteristics such as innovation stage, route to innovation, and adoption level can affect investor's perception of fit between the signal (i.e., innovation announcement) and the signaler characteristic (e.g., marketing department power). These findings indicate the importance of investigating the joint effects of innovation characteristics and firm factors on firm value, especially when studying investor response.

Practical Implications

Firms are spending billions of dollars on adoption of emerging technologies, and particularly AI. The current research can aid managers with a better understanding of the stock-market response to ETA announcements in the following ways.

First, since ETA is a costly endeavor, managers may believe that an ETA announcement can serve as a strong signal of the firm's future performance. However, our

findings indicate that although ETA is a costly signal, announcing ETAs may not fully overcome information asymmetry from investors perspective. In turn, their response is guided by their beliefs about the firm's ability to benefit from the ETA. In support of this view, we find that only 51% of the announcements in our sample generated positive response from investors while the rest generated negative returns. Managers should, therefore, note that an ETA announcement, by itself, may not be an effective signal. In fact, in many cases, it may negatively impact firm value.

Second, our research provides valuable guidance to practitioners in understanding when investors perceive ETAs as reliable signals of firm's prospects. We find that ETA announcement can serve as a reliable signal of future performance for firms with high (vs low) marketing department power. Following recommendations from extant literature (e.g., Lenz, Wetzel, and Hammerschmidt 2017; Spiller et al. 2013; Wilson, Giebelhausen, and Brady 2017), we conduct a "floodlight analysis" or the Johnson-Neyman procedure to test the effect of ETA on investor response across the observed range of marketing department power. The ETA beta estimates are plotted in Figure 4 along with its 95% confidence interval band. Moreover, the difference between predicted returns to ETA announcement by firms with high vs low marketing department power (i.e., one standard deviation above and below the mean) is approximately 0.8%. For an average firm with a value of approx. \$110.3 billion in our sample, this translates into approx. \$870 million in market capitalization. Therefore, firms with lower marketing department power should either avoid announcing their ETA plans or consider ramping up their marketing department power relative to their industry peers at least a year before the announcement.

Insert Figure 4 About Here

Third, how should innovation characteristics such as innovation stage, route to innovation, and adoption level be incorporated in formulating ETA announcement strategy? According to our results, compared to announcing the ETA during the initiation stage, every unit increase in firm's marketing department power can enhance returns to the ETA announcement by approximately 0.22% during development stage and 0.33% during commercialization stage. For the average firm in our sample, this translates \$243 million and \$364 million in market capitalization, respectively. Hence, even firms with high marketing department are likely to benefit more by announcing their ETA plans during latter stages of innovation (vs initiation stage). Similarly, we find that, compared to make announcements, firms with high marketing department power are likely to benefit more by announcing ETA through buy and ally. Specifically, based on our model estimations, compared to make, every unit increase in marketing department power is likely to yield higher returns by 0.58% for buy and 0.34% for ally announcements. This translates to approx. \$640 million and \$375 million in market capitalization, respectively. Finally, we recommend that high (vs low) marketing department firms undertaking product-platform level (vs component level) ETAs are likely to be rewarded more by investors. Our estimated returns for every unit increase in marketing department power when firms announce a product-platform (vs component) level ETA is 0.3% or approx. \$331 million in market capitalization.

Limitations and Future Research

Our study is not without limitations. Perhaps, the biggest limitation is that we investigate adoption of only one of the several emerging technologies. Although AI is arguably the most influential of the emerging technologies and helps in parsimonious exposition, studying adoption of different emerging technologies might shed further light on the nuances and improve our understanding about the role of technology characteristics, maturity, and the nature of capabilities and advantages it brings to the adopting firm in

improving shareholder value. Future research can explore this avenue further. Next, our sample consists of large, publicly listed firms belonging to S&P 500 list. Future research should examine whether our framework can be extended to smaller firms (e.g., start-ups). For example, it is possible that marketing experience of founding members of a start-up with a product based on an emerging technology is evaluated positively by investors as such an experience can help the firm grow faster and acquire customers more quickly and efficiently. Finally, although we identify and control for the most significant announcement related text variables identified in the prior literature (i.e., innovation stage, route to innovation, adoption level) and other important variables, such as announcement market, sentiment, and whether the announcement mentions monetizing innovation, there is a possibility of some potential omitted variable bias related to the differences in announcement texts. Future research can employ methodologies, such as automated text analysis and natural language processing, to uncover any such potential effects of the differences in announcement texts.

References

- Adner, R., & Levinthal, D. A. (2002). The emergence of emerging technologies. *California management review*, 45(1), 50-66.
- Arunachalam, S., Ramaswami, S. N., Herrmann, P., & Walker, D. (2018). Innovation pathway to profitability: The role of entrepreneurial orientation and marketing capabilities. *Journal of the Academy of Marketing Science*, 46(4), 744-766.
- Atuahene-Gima, K., & Ko, A. (2001). An empirical investigation of the effect of market orientation and entrepreneurship orientation alignment on product innovation. *Organization science*, 12(1), 54-74.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management*, 17(1), 99-120.
- Bendig, D., Willmann, D., Strese, S., & Brettel, M. (2018). Share repurchases and myopia: Implications on the stock and customer markets. *Journal of Marketing*, 82(2), 19-41.
- Bergh, D. D., Connelly, B. L., Ketchen Jr, D. J., & Shannon, L. M. (2014). Signalling theory and equilibrium in strategic management research: An assessment and a research agenda. *Journal of Management Studies*, 51(8), 1334-1360.
- Bhagwat, Y., Warren, N. L., Beck, J. T., & Watson IV, G. F. (2020). Corporate Sociopolitical Activism and Firm Value. *Journal of Marketing*, 84(5), 1-21.
- Bommaraju, R., Ahearne, M., Krause, R., & Tirunillai, S. (2019). Does a customer on the board of directors affect business-to-business firm performance?. *Journal of Marketing*, 83(1), 8-23.
- Borah, A., & Tellis, G. J. (2014). Make, buy, or ally? Choice of and payoff from announcements of alternate strategies for innovations. *Marketing Science*, 33(1), 114-133.
- Boyd, D. E., & Spekman, R. E. (2008). The market value impact of indirect ties within technology alliances. *Journal of the Academy of Marketing Science*, 36(4), 488.
- Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Modeling the global economic impact of AI. McKinsey Global Institute, Tech. Rep.
- Campello, M. (2006). Debt financing: Does it boost or hurt firm performance in product markets?. *Journal of Financial Economics*, 82(1), 135-172.
- Chandy, R. K., & Tellis, G. J. (1998). Organizing for radical product innovation: The overlooked role of willingness to cannibalize. *Journal of marketing research*, 35(4), 474-487.
- Chandy, R. K., & Tellis, G. J. (2000). The incumbent's curse? Incumbency, size, and radical product innovation. *Journal of marketing*, 64(3), 1-17.
- Chandy, R., Hopstaken, B., Narasimhan, O., & Prabhu, J. (2006). From invention to innovation: Conversion ability in product development. *Journal of Marketing Research*, 43(3), 494-508.
- Chen, Y., Ganesan, S., & Liu, Y. (2009). Does a firm's product-recall strategy affect its financial value? An examination of strategic alternatives during product-harm crises. *Journal of Marketing*, 73(6), 214-226.
- Colla, P., Ippolito, F., & Li, K. (2013). Debt specialization. *The Journal of Finance*, 68(5), 2117-2141.
- Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of management*, 37(1), 39-67.
- Corhay, A., & Rad, A. T. (1996). Conditional heteroskedasticity adjusted market model and an event study. *The Quarterly Review of Economics and Finance*, 36(4), 529-538.
- Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, 1(2), 73-80.
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard business review*, 96(1), 108-116.
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24-42.
- Dinner, I. M., Heerde Van, H. J., & Neslin, S. A. (2014). Driving online and offline sales: The cross-channel effects of traditional, online display, and paid search advertising. *Journal of marketing research*, 51(5), 527-545.
- Ebbes, P., Papies, D., & van Heerde, H. J. (2016). Dealing with endogeneity: A nontechnical guide for marketing researchers. *Handbook of market research*.
- Ernst, H., Hoyer, W., & Rübsaamen, C. (2010). Sales, Marketing, and Research-and-Development Cooperation across New Product Development Stages: Implications for Success. *Journal of Marketing*, 74(5), 80-92.
- Fang, E., Palmatier, R. W., & Steenkamp, J. B. E. (2008). Effect of service transition strategies on firm value. *Journal of marketing*, 72(5), 1-14.
- Feng, H., Morgan, N. A., & Rego, L. L. (2015). Marketing department power and firm performance. *Journal of Marketing*, 79(5), 1-20.
- Forbes. (2019). How Can Non-Tech Companies Compete In The Digital Age?. Retrieved 9 September 2020, from <https://www.forbes.com/sites/quora/2019/03/06/how-can-non-tech-companies-compete-in-the-digital-age/#300dd4552b59>

Garbuio, M., & Lin, N. (2019). Artificial intelligence as a growth engine for health care startups: emerging business models. *California Management Review*, 61(2), 59-83.

Gartner. (2019). Hype Cycle for Emerging Technologies, 2019. Retrieved from <https://www.gartner.com/document/3956015>

Gartner. (2020). Hype Cycle for Emerging Technologies, 2020. Retrieved from <https://www.gartner.com/document/3987951?toggle=1>

Geyskens, I., Gielens, K., & Dekimpe, M. G. (2002). The market valuation of internet channel additions. *Journal of marketing*, 66(2), 102-119.

Geyskens, I., Steenkamp, J. B. E., & Kumar, N. (2006). Make, buy, or ally: A transaction cost theory meta-analysis. *Academy of management journal*, 49(3), 519-543.

Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: a multidisciplinary perspective.

Hanssens, D. M., Rust, R. T., & Srivastava, R. K. (2009). Marketing strategy and Wall Street: nailing down marketing's impact. *Journal of Marketing*, 73(6), 115-118.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153-161.

IDC. (2019). Worldwide Spending on Artificial Intelligence Systems Will Be Nearly \$98 Billion in 2023, According to New IDC Spending Guide. Retrieved 9 September 2020, from <https://www.idc.com/getdoc.jsp?containerId=prUS45481219#:~:text=According%20to%20the%20recently%20updated,will%20be%20spent%20in%202019.>

Kalaigianam, K., & Bahadir, S. C. (2013). Corporate brand name changes and business restructuring: is the relationship complementary or substitutive?. *Journal of the Academy of Marketing Science*, 41(4), 456-472.

Kalaigianam, K., Kushwaha, T., & Swartz, T. A. (2017). The differential impact of new product development "make/buy" choices on immediate and future product quality: insights from the automobile industry. *Journal of Marketing*, 81(6), 1-23.

Kashmiri, S., Nicol, C. D., & Arora, S. (2017). Me, myself, and I: influence of CEO narcissism on firms' innovation strategy and the likelihood of product-harm crises. *Journal of the Academy of Marketing Science*, 45(5), 633-656.

Kelm, K. M., Narayanan, V. K., & Pinches, G. E. (1995). Shareholder value creation during R&D innovation and commercialization stages. *Academy of Management Journal*, 38(3), 770-786.

Kerin, R. A., Varadarajan, P. R., & Peterson, R. A. (1992). First-mover advantage: A synthesis, conceptual framework, and research propositions. *Journal of marketing*, 56(4), 33-52.

Kim, M., Xiong, G., & Kim, K. H. (2018). Where does pride lead? Corporate managerial hubris and strategic emphasis. *Journal of the Academy of Marketing Science*, 46(3), 537-556.

Kurt, D., & Hulland, J. (2013). Aggressive marketing strategy following equity offerings and firm value: the role of relative strategic flexibility. *Journal of Marketing*, 77(5), 57-74.

Lee, R. P., & Grewal, R. (2004). Strategic responses to new technologies and their impact on firm performance. *Journal of Marketing*, 68(4), 157-171.

Lee, R. P., Chen, Q., & Hartmann, N. N. (2016). Enhancing stock market return with new product preannouncements: the role of information quality and innovativeness. *Journal of Product Innovation Management*, 33(4), 455-471.

Lenz, I., Wetzel, H. A., & Hammerschmidt, M. (2017). Can doing good lead to doing poorly? Firm value implications of CSR in the face of CSI. *Journal of the Academy of Marketing Science*, 45(5), 677-697.

Luo, X. (2008). When marketing strategy first meets wall street: Marketing spendings and firms' initial public offerings. *Journal of Marketing*, 72(5), 98-109.

Mizik, N., & Jacobson, R. (2003). Trading off between value creation and value appropriation: The financial implications of shifts in strategic emphasis. *Journal of marketing*, 67(1), 63-76.

Montoya-Weiss, M. M., & Calantone, R. (1994). Determinants of new product performance: a review and meta-analysis. *Journal of Product Innovation Management: An International Publication of the Product Development & Management Association*, 11(5), 397-417.

Moorman, C., & Rust, R. T. (1999). The role of marketing. *Journal of marketing*, 63(4_suppl1), 180-197.

Morris, M., Schindehutte, M., & Allen, J. (2005). The entrepreneur's business model: toward a unified perspective. *Journal of business research*, 58(6), 726-735.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have (No. w1396). National Bureau of Economic Research.

Nambisan, S., & Sawhney, M. (2007). Meet the innovation capitalist. *Harvard Business Review*, 85(3), 24-25.

Prašnikar, J., & Škerlj, T. (2006). New product development process and time-to-market in the generic pharmaceutical industry. *Industrial Marketing Management*, 35(6), 690-702.

PwC. (2017). The Essential Eight technologies Board byte: artificial intelligence. Retrieved from <https://www.pwc.com.au/pdf/essential-8-emerging-technologies-artificial-intelligence.pdf>

Raassens, N., Wuyts, S., & Geyskens, I. (2012). The market valuation of outsourcing new product development. *Journal of Marketing Research*, 49(5), 682-695.

Robertson, D., & Ulrich, K. (1998). Planning for product platforms. *Sloan management review*, 39(4), 19.

Rubera, G., & Kirca, A. H. (2012). Firm innovativeness and its performance outcomes: A meta-analytic review and theoretical integration. *Journal of Marketing*, 76(3), 130-147.

Rubera, G., Chandrasekaran, D., & Ordanini, A. (2016). Open innovation, product portfolio innovativeness and firm performance: the dual role of new product development capabilities. *Journal of the Academy of Marketing Science*, 44(2), 166-184.

Saboo, A. R., Kumar, V., & Anand, A. (2017). Assessing the impact of customer concentration on initial public offering and balance sheet-Based outcomes. *Journal of Marketing*, 81(6), 42-61.

Salancik, G. R., & Pfeffer, J. (1974). The bases and use of power in organizational decision making: The case of a university. *Administrative Science Quarterly*, 453-473.

Sanders, W. G., & Boivie, S. (2004). Sorting things out: Valuation of new firms in uncertain markets. *Strategic Management Journal*, 25(2), 167-186.

Sawhney, M. S. (1998). Leveraged high-variety strategies: From portfolio thinking to platform thinking. *Journal of the academy of marketing Science*, 26(1), 54-61.

Sharma, A., Saboo, A. R., & Kumar, V. (2018). Investigating the influence of characteristics of the new product introduction process on firm value: The case of the pharmaceutical industry. *Journal of Marketing*, 82(5), 66-85.

Sood, A., & Tellis, G. J. (2005). Technological evolution and radical innovation. *Journal of Marketing*, 69(3), 152-168.

Sood, A., & Tellis, G. J. (2009). Do innovations really pay off? Total stock market returns to innovation. *Marketing Science*, 28(3), 442-456.

Sorescu, A. B., & Spanjol, J. (2008). Innovation's effect on firm value and risk: Insights from customer packaged goods. *Journal of Marketing*, 72(2), 114-132.

Sorescu, A. B., Chandy, R. K., & Prabhu, J. C. (2003). Sources and financial consequences of radical innovation: Insights from pharmaceuticals. *Journal of marketing*, 67(4), 82-102.

Sorescu, A., Shankar, V., & Kushwaha, T. (2007). New product preannouncements and shareholder value: Don't make promises you can't keep. *Journal of Marketing Research*, 44(3), 468-489.

Sorescu, A., Warren, N. L., & Ertekin, L. (2017). Event study methodology in the marketing literature: An overview. *Journal of the Academy of Marketing Science*, 45(2), 186-207.

Spence, A. M. (1973). Labour market signalling. *Quarterly Journal of Economics*, 87(3), 355-74.

Spence, M. (1974). Competitive and optimal responses to signals: An analysis of efficiency and distribution. *Journal of Economic theory*, 7(3), 296-332.

Spiller, S. A., Fitzsimons, G. J., Lynch Jr, J. G., & McClelland, G. H. (2013). Spotlights, floodlights, and the magic number zero: Simple effects tests in moderated regression. *Journal of marketing research*, 50(2), 277-288.

Srinivasan, R. (2008). Sources, characteristics and effects of emerging technologies: Research opportunities in innovation. *Industrial Marketing Management*, 37(6), 633-640.

Srinivasan, R., & Ramani, N. (2019). With power comes responsibility: How powerful marketing departments can help prevent myopic management. *Journal of Marketing*, 83(3), 108-125.

Srinivasan, S., & Hanssens, D. M. (2009). Marketing and firm value: Metrics, methods, findings, and future directions. *Journal of Marketing research*, 46(3), 293-312.

Srinivasan, S., Pauwels, K., Silva-Risso, J., & Hanssens, D. M. (2009). Product innovations, advertising, and stock returns. *Journal of Marketing*, 73(1), 24-43.

Srivastava, R. K., Fahey, L., & Christensen, H. K. (2001). The resource-based view and marketing: The role of market-based assets in gaining competitive advantage. *Journal of management*, 27(6), 777-802.

Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of marketing*, 62(1), 2-18.

Stiglitz, J. E. (2000). The contributions of the economics of information to twentieth century economics. *The quarterly journal of economics*, 115(4), 1441-1478.

Stiglitz, J. E. (2002). Information and the Change in the Paradigm in Economics. *American economic review*, 92(3), 460-501.

Stock, R. M., & Reiferscheid, I. (2014). Who should be in power to encourage product program innovativeness, R&D or marketing?. *Journal of the Academy of Marketing Science*, 42(3), 264-276.

Story, V., Hart, S., & O'Malley, L. (2009). Relational resources and competences for radical product innovation. *Journal of Marketing Management*, 25(5-6), 461-481.

Story, V., Hart, S., & O'Malley, L. (2009). Relational resources and competences for radical product innovation. *Journal of Marketing Management*, 25(5-6), 461-481.

- Swaminathan, V., & Moorman, C. (2009). Marketing alliances, firm networks, and firm value creation. *Journal of Marketing*, 73(5), 52-69.
- Talay, M. B., Akdeniz, M. B., Obal, M., & Townsend, J. D. (2019). Stock Market Reactions to New Product Launches in International Markets: The Moderating Role of Culture. *Journal of International Marketing*, 27(4), 81-98.
- The CMO Survey. (2019). Top Marketing Trends of the Decade (p. 12). Retrieved from https://cmosurvey.org/wp-content/uploads/sites/15/2019/08/2019CMOSurvey_ebook.pdf
- Troy, L. C., Hirunyawipada, T., & Paswan, A. K. (2008). Cross-functional integration and new product success: an empirical investigation of the findings. *Journal of Marketing*, 72(6), 132-146.
- Verhoef, P. C., & Leeflang, P. S. (2009). Understanding the marketing department's influence within the firm. *Journal of marketing*, 73(2), 14-37.
- Vorhies, D. W., Morgan, R. E., & Autry, C. W. (2009). Product-market strategy and the marketing capabilities of the firm: impact on market effectiveness and cash flow performance. *Strategic Management Journal*, 30(12), 1310-1334.
- Weiss, A. (1995). Human capital vs. signalling explanations of wages. *Journal of Economic perspectives*, 9(4), 133-154.
- Whitler, K. A., Lee, B., Krause, R., & Morgan, N. A. (2020). Upper echelons research in marketing. *Journal of the Academy of Marketing Science*, 1-22.
- Wilson, A. E., Giebelhausen, M. D., & Brady, M. K. (2017). Negative word of mouth can be a positive for customers connected to the brand. *Journal of the Academy of Marketing Science*, 45(4), 534-547.
- Wooldridge, Jeffrey M. (2002), *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.
- Xue, Y. (2007). Make or buy new technology: The role of CEO compensation contract in a firm's route to innovation. *Review of Accounting Studies*, 12(4), 659-690.

Lists of Figures and Tables

Figure 1.
Conceptual Framework

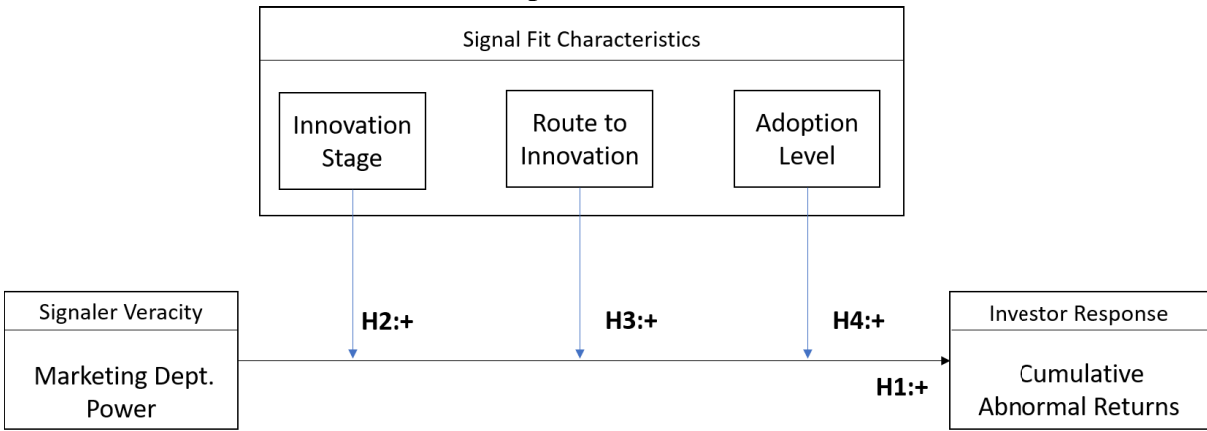


Figure 2
AI-enabled new product innovation announcement trend over time

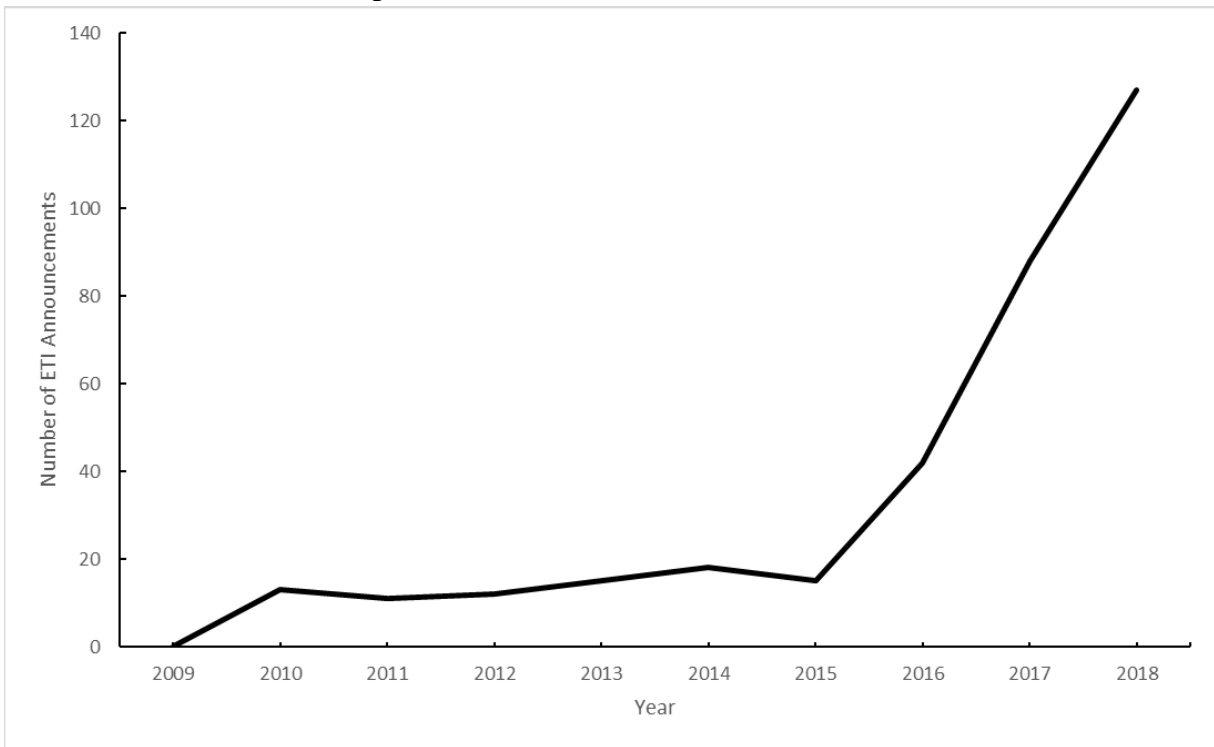


Figure 3a:
Investor response as a function of marketing department power (MDP) and innovation stage

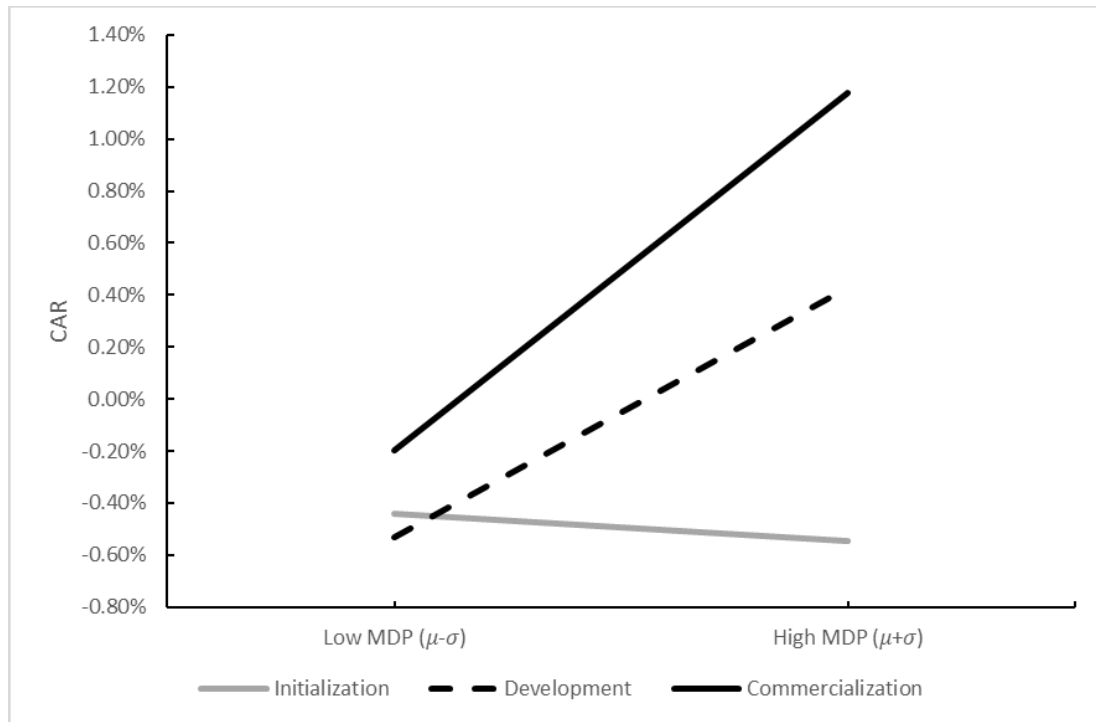


Figure 3b:
Investor response as a function of marketing department power (MDP) and route to innovation

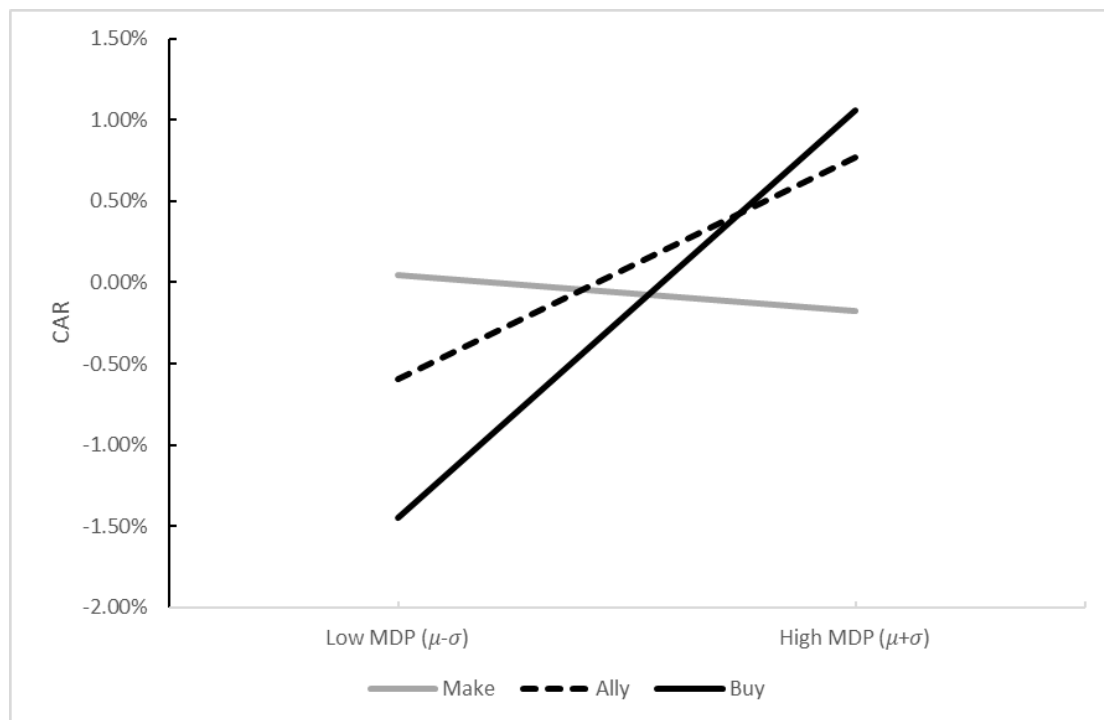


Figure 3c:
Investor response as a function of marketing department power (MDP) and adoption level

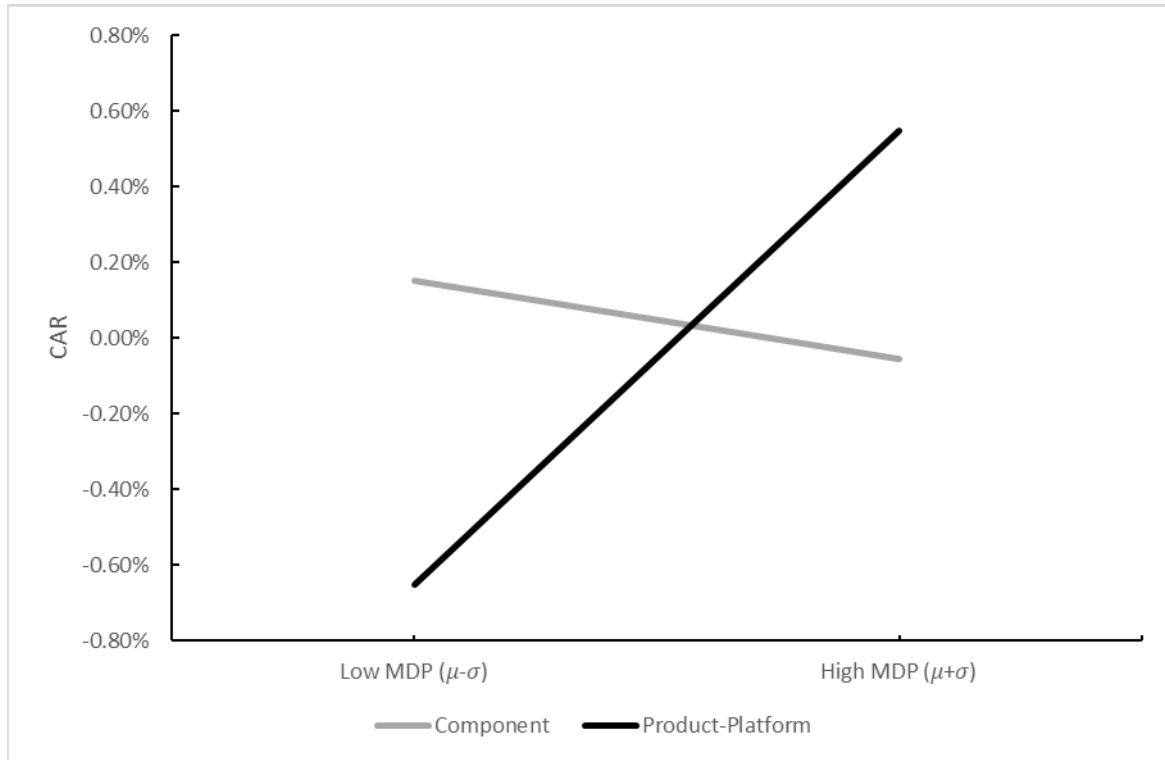


Figure 4:
Floodlight analysis

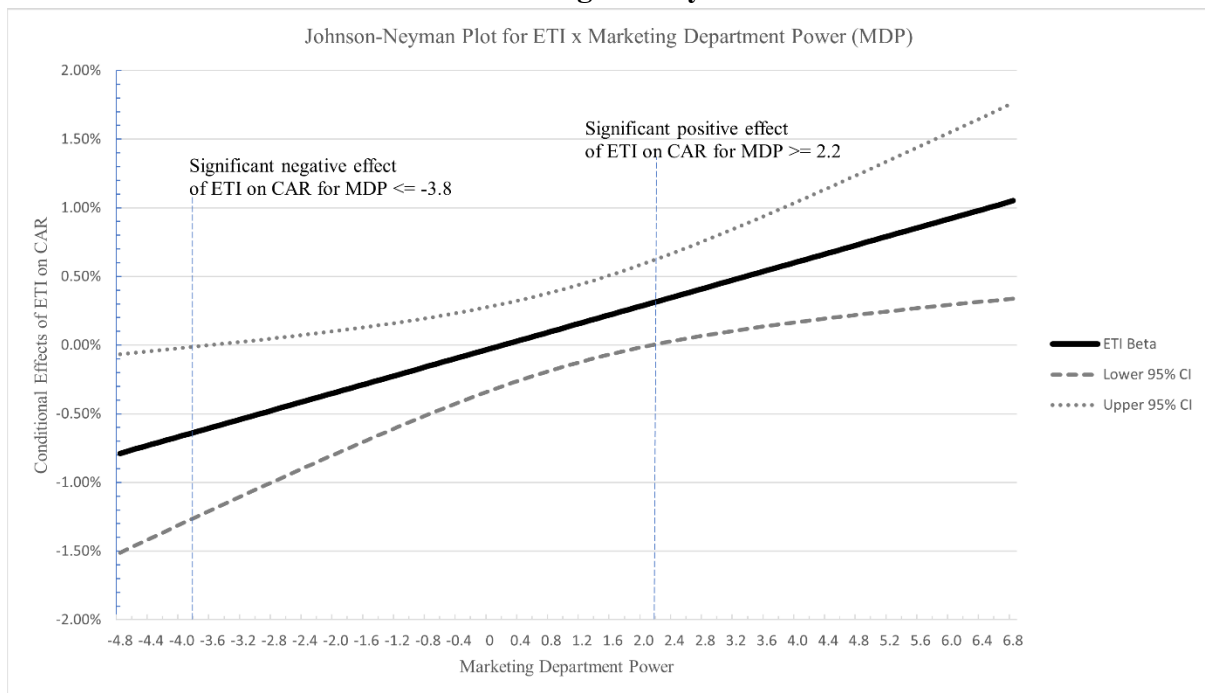


Table 1
Variable Descriptions

Variable	Description	Source
Dependent variable		
CAR: $[t_1, t_2]$	Cumulative abnormal return, with event window of t_1 as the beginning of the observed period and t_2 as the end of the observed period.	CRSP
Independent variables		
RELMDP	Marketing department power relative to industry mean.	Compustat Execucomp
STAGE	Innovation stage (1 = initiation; 2 = development; 3 = commercialization)	Study database
ROUTE	Route to innovation (1 = make; 2 = buy; 3 = ally)	Study database
PLATFORM	Adoption level (0 = component; 1 = product-platform)	Study database
Control variables		
MARKET	ETA market-focus (1 = U.S. market; 0 = otherwise)	Study database
LEV	Firm's financial leverage (long-term debt to asset) relative to industry	Compustat
STEMPH	Firm's strategic emphasis (ratio of difference between R&D and SG&A expenses to assets) relative to industry mean	Compustat
SIZE	Firm size (total assets) relative to industry mean	Compustat
SGR	Firm's year-on-year sales growth relative to industry mean	Compustat
SLACK	Firm's slack resources relative to industry mean	Compustat
HHI	Competitive intensity of respective industries	Compustat
INDSGR	Year-on-year sales growth of respective industries	Compustat
MANF	Firm's membership to manufacturing industries – i.e., 2-digit SIC between 20-39 (1 = manufacturer; 0 = otherwise)	Compustat

Table 2
Summary Statistics and Correlation Matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	CAR[-2,+2]	1													
2	RELMDP	0.11*	1												
3	STAGE	0.15*	-0.07	1											
4	ROUTE	0.02	-0.03	0.33*	1										
5	PLATFORM	-0.02	0.04	-0.03	0.03	1									
6	MARKET	0.04	0.00	0.08	0.02	0.08	1								
7	MANF	-0.02	0.04	-0.10	0.06	0.14*	0.11*	1							
8	LEV	0.04	-0.10	0.10*	0.09	0.09	-0.18*	0.13*	1						
9	STEMPH	-0.05	-0.08	0.00	0.02	0.12*	0.15*	0.32*	0.10	1					
10	SIZE	-0.04	0.09	-0.15*	0.05	-0.13*	-0.12*	-0.04	0.02	0.03	1				
11	SGR	-0.20*	-0.03	-0.03	-0.02	0.06	-0.07	0.01	-0.02	0.02	-0.05	1			
12	SLACK	-0.02	-0.09	-0.02	-0.02	0.13*	0.01	0.11*	0.16*	-0.03	-0.27*	0.24*	1		
13	HHI	-0.04	0.01	-0.02	-0.03	-0.13*	-0.08	-0.52*	0.01	-0.36*	-0.03	-0.05	0.00	1	
14	INDSGR	0.04	-0.06	-0.07	0.07	-0.08	0.05	-0.06	0.07	0.02	0.02	-0.40*	-0.17*	0.16*	1
	Mean	0.00	0.04	1.99	1.07	0.67	0.92	0.78	-0.25	0.09	0.65	0.05	-0.22	0.24	0.04
	SD	0.03	2.33	0.82	0.94	0.47	0.27	0.42	1.30	0.48	1.72	1.02	1.48	0.15	0.08

N = 341; * p < .05

Table 3
Regression Estimates of Equation (1)

M1: Main effects only model; **M2:** Full model with interaction effects

<i>N</i> = 341		Dependent Variable: CAR [-2, +2]			
		(M1)		(M2)	
		β	SE	β	SE
Intercept		8.43E-04	8.96E-03	2.92E-03	7.67E-03
RELMDP (Relative Marketing Department Power)		1.59E-03*	6.08E-04	-4.06E-03**	1.18E-03
STAGE (Innovation Stage)					
	Development (Vs Initiation)	5.43E-03	4.61E-03	3.75E-03	4.60E-03
	Commercialization (Vs Initiation)	1.06E-02*	4.67E-03	8.65E-03**	4.13E-03
ROUTE (Route to Innovation)					
	Ally (Vs Make)	1.84E-03	3.94E-03	1.03E-03	3.47E-03
	Buy (Vs Make)	1.10E-03	5.02E-03	-1.76E-03	5.14E-03
PLATFORM (Vs Component)		-1.72E-03	3.72E-03	-7.09E-04	3.29E-03
RELMDP * STAGE					
	Development (Vs Initiation)			2.18E-03[†]	1.16E-03
	Commercialization (Vs Initiation)			2.83E-03*	1.36E-03
RELMDP * ROUTE					
	Ally (Vs Make)			3.27E-03**	1.03E-03
	Buy (Vs Make)			5.74E-03**	1.60E-03
RELMDP * PLATFORM (Vs Component)				2.91E-03*	1.18E-03
MARKET (Announcement Market)		3.02E-03	5.15E-03	2.50E-03	5.27E-03
LEV (Relative Financial Leverage)		1.12E-03	1.39E-03	7.87E-04	1.41E-03
STEMPH (Relative Strategic Emphasis)		-3.55E-03	3.66E-03	-3.39E-03	3.73E-03
SIZE (Relative Firm Size)		-5.63E-04	9.90E-04	-6.59E-04	9.15E-04
SGR (Relative Sales Growth)		-6.09E-03**	2.05E-03	-6.67E-03*	1.92E-03
SLACK (Relative Resource Slack)		5.77E-04	1.83E-03	6.85E-04	1.87E-03
HHI (Industry Competitive Index)		-1.98E-02[†]	9.93E-03	-1.57E-02	1.04E-02
INDSGR (Industry Sales Growth)		-1.98E-03	2.04E-02	-3.79E-03	1.87E-02
MANF (Manufacturing Industry Dummy)		-3.46E-03	4.83E-03	-3.19E-03	4.72E-03
F (15, 76)			1.71	2.57	
R ²			.08	.11	

[†] $p < .1$; * $p < .05$; ** $p < .01$

Supported Hypotheses: H1, H2a (Marginal), H2b, H3a, H3b, H4

Appendix

Table A1
Two-step Regression Estimates of with Heckman Selection Model.

<i>Bootstrap replications = 500; Selection Model N = 2210; Specified Model N = 341</i>				
	Selection Model (DV = Dummy to indicate ETA)		Specified Model (DV = CAR [-2, +2])	
	β	SE	β	SE
Intercept	-1.56E+00	1.39E-01	2.92E-03	1.19E-02
RELMDP	-2.44E-02	1.96E-02	1.55E-03*	7.51E-04
STAGE				
Development (Vs Initiation)			5.76E-03	4.52E-03
Commercialization (Vs Initiation)			1.11E-02*	4.66E-03
ROUTE				
Ally (Vs Make)			2.05E-03	3.92E-03
Buy (Vs Make)			1.19E-03	5.89E-03
PLATFORM (Vs Component)			-1.48E-03	3.29E-03
MARKET			3.18E-03	6.20E-03
LEV	-5.59E-02[†]	3.28E-02	1.28E-03	1.57E-03
STEMPH	-4.03E-01**	8.23E-02	-3.50E-03	3.99E-03
SIZE	-9.84E-02*	5.00E-02	-8.35E-04	1.50E-03
SGR	-3.26E-02	3.05E-02	-5.99E-03**	1.92E-03
SLACK	1.29E-02	2.80E-02	5.00E-04	1.53E-03
HHI	6.50E-01**	2.12E-01	-2.13E-02[†]	1.22E-02
INDSGR	-2.13E-01	2.70E-01	-1.64E-03	2.03E-02
MANF	4.85E-01**	1.06E-01	-4.33E-03	5.65E-03
Employees	4.58E-03**	5.95E-04		
Profits	2.42E-05**	4.41E-06		
Strategic Emphasis (Absolute value)	5.34E+00**	6.62E-01		
λ (Mills Lambda)			-1.45E-03	3.85E-03

[†] $p < .1$; * $p < .05$; ** $p < .01$; $\rho = -0.049$; $\sigma = 0.030$

Table A2
Results of 2-Stage Instrumental Variable Regression

<i>N</i> = 341 (First Stage)				
	First Stage (DV = RELMDP)		Second Stage (DV = CAR [-2, +2])	
	β	SE		
Intercept	-1.63E+00*	6.59E-01	-2.44E-03	9.75E-03
RELMDP			1.06E-03	1.31E-03
STAGE				
Development (Vs Initiation)	6.01E-03	4.71E-03	5.57E-03	4.70E-03
Commercialization (Vs Initiation)	1.21E-02*	4.75E-03	1.14E-02*	4.78E-03
ROUTE				
Ally (Vs Make)	2.41E-03	3.93E-03	2.27E-03	3.82E-03
Buy (Vs Make)	1.39E-03	5.03E-03	1.33E-03	6.34E-03
PLATFORM (Vs Component)	-1.46E-03	3.74E-03	-1.54E-03	3.63E-03
MARKET	5.73E-01	4.29E-01	3.50E-03	6.44E-03
LEV	-1.30E-01	9.22E-02	1.20E-03	1.36E-03
STEMPH	-2.97E-01	2.57E-01	-3.73E-03	3.89E-03
SIZE	5.08E-02	6.78E-02	-4.58E-04	1.03E-03
SGR	1.32E-01	1.21E-01	-6.10E-03**	1.80E-03
SLACK	-1.59E-01†	8.34E-02	5.78E-04	1.22E-03
HHI	1.13E+00	8.94E-01	-1.34E-02	1.31E-02
INDSGR	-1.94E+00	1.53E+00	-3.11E-03	2.26E-02
MANF	5.51E-01	3.45E-01	-2.26E-03	4.88E-03
INDMDP	3.38E-01**	2.38E-01		
RELMDP _{t-1}	5.70E-01	5.03E-02		
ROA _{t-1}	1.62E+00	2.32E+00		
F		9.12		
Wald χ^2			26.94	
R ²		.32	.08	
<i>Tests of endogeneity</i>				
Ho: variables are exogenous				
Durbin (score) $\chi^2(1)$		.33 (p = 0.57)		
Wu-Hausman F(1,326)		.31 (p = 0.58)		
<i>Tests of overidentifying restrictions:</i>				
Sargan (score) $\chi^2(2)$		2.58 (p = 0.28)		
Basmann $\chi^2(2)$		2.46 (p = 0.29)		
† <i>p</i> < .1; * <i>p</i> < .05; ** <i>p</i> < .01				

Robustness Check Results

Alternate measures of CAR: We report results of our analyses on alternative measures of investor response using CAR [-1, +2] in Table A3 and CAR [-1, +1] in Table A4 below. The results remain qualitatively similar with the following differences.

In the model estimated using CAR [-1, +2], similar to the main model estimated with CAR [-2, +2], we find support for H1 with a significant main effect of marketing department power on investor response ($\beta = .0012$, $t = 2.19$). Furthermore, lending additional support to H2, the interactive effect of marketing department power and innovation stage is significant and positive. Specifically, compared to initiation, investors perceive higher fit between marketing department power and latter stages of innovation – i.e., development ($\beta = .0025$, $t = 2.10$) and commercialization ($\beta = .0025$, $t = 1.96$). Similarly, we find support for H3 lending support to our prediction that, compared to make, investors respond positively when high (vs low) marketing department power firms choose to source external innovation assets through buy ($\beta = .0050$, $t = 3.40$) and ally ($\beta = .0022$, $t = 1.89$). However, we do not find support for H4 as the interaction between marketing department power and adoption level is not significant ($\beta = .0013$, $t = 1.28$). On the other hand, in the main effect model estimated using CAR [-1,+1], we find partial support for H1 as the main effect of marketing department power on investor response is marginally significant ($\beta = .00088$, $t = 1.85$). However, in the interaction model, we only find supporting evidence for H3 – i.e., interaction between marketing department power and route to innovation. Specifically, compared to make, the effect of marketing department power on investor response is significant and positive for buy ($\beta = .0029$, $t = 3.14$) and ally ($\beta = .0021$, $t = 1.99$). These findings indicate that when responding to ETA, investors update their expectations about firm's future performance over a relatively bigger time window than ± 1 day around the event day.

Table A3
Regression Estimates of Equation (1) on CAR [-1, +2]

M1: Main effects only model; **M2:** Full model with interaction effects

<i>N</i> = 341		Dependent Variable: CAR [-1,+2]			
		(M1)		(M2)	
		β	SE	β	SE
Intercept		-2.87E-04	7.58E-03	1.49E-03	7.13E-03
RELMDP		1.21E-03*	5.53E-04	-2.81E-03*	1.17E-03
STAGE					
	Development (Vs Initiation)	8.55E-03*	3.97E-03	6.94E-03[†]	3.95E-03
	Commercialization (Vs Initiation)	1.39E-02**	3.91E-03	1.23E-02**	3.54E-03
ROUTE					
	Ally (Vs Make)	3.61E-03	3.54E-03	2.90E-03	3.22E-03
	Buy (Vs Make)	5.52E-03	4.25E-03	2.43E-03	4.23E-03
PLATFORM (Vs Component)		-2.03E-03	2.96E-03	-1.42E-03	2.69E-03
RELMDP * STAGE					
	Development (Vs Initiation)			2.48E-03*	1.18E-03
	Commercialization (Vs Initiation)			2.54E-03[†]	1.30E-03
RELMDP * ROUTE					
	Ally (Vs Make)			2.21E-03[†]	1.17E-03
	Buy (Vs Make)			4.97E-03**	1.46E-03
RELMDP * PLATFORM (Vs Component)				1.34E-03	1.05E-03
MARKET		1.06E-03	5.33E-03	2.58E-04	5.78E-03
LEV		9.11E-04	1.46E-03	4.98E-04	1.46E-03
STEMPH		-4.25E-04	4.30E-03	-2.78E-04	4.38E-03
SIZE		-6.85E-04	7.86E-04	-7.61E-04	7.82E-04
SGR		-4.76E-03**	1.37E-03	-5.38E-03**	1.34E-03
SLACK		7.97E-04	1.25E-03	6.88E-04	1.28E-03
HHI		-1.30E-02	1.11E-02	-1.33E-02	1.09E-02
INDSGR		6.45E-03	1.63E-02	4.67E-03	1.57E-02
MANF		-6.57E-03	4.13E-03	-6.37E-03	4.16E-03
F		3.03		4.19	
R ²		.10		.12	
[†] <i>p</i> < .1; * <i>p</i> < .05; ** <i>p</i> < .01					
Supported Hypotheses: H1, H2a, H2b (Marginal), H3a (Marginal), H3b					

Table A4
Regression Estimates of Equation (1) on CAR [-1, +1]

M1: Main effects only model; **M2:** Full model with interaction effects

<i>N</i> = 341		Dependent Variable: CAR [-1,+1]			
		(M1)		(M2)	
		β	SE	β	SE
Intercept		-7.45E-04	7.01E-03	6.68E-04	7.12E-03
RELMDP		8.79E-04[†]	4.74E-04	-1.76E-03	1.21E-03
STAGE					
	Development (Vs Initiation)	6.37E-03[†]	3.49E-03	5.63E-03	3.57E-03
	Commercialization (Vs Initiation)	8.90E-03*	3.45E-03	8.04E-03*	3.29E-03
ROUTE					
	Ally (Vs Make)	3.53E-03	3.37E-03	3.09E-03	3.08E-03
	Buy (Vs Make)	5.08E-03[†]	2.87E-03	3.59E-03	3.12E-03
PLATFORM (Vs Component)		-2.05E-03	2.41E-03	-1.76E-03	2.30E-03
RELMDP * STAGE					
	Development (Vs Initiation)			1.22E-03	1.19E-03
	Commercialization (Vs Initiation)			1.66E-03	1.23E-03
RELMDP * ROUTE					
	Ally (Vs Make)			2.06E-03*	1.03E-03
	Buy (Vs Make)			2.86E-03**	9.11E-04
RELMDP * PLATFORM (Vs Component)				8.00E-04	1.11E-03
MARKET		1.03E-03	5.70E-03	3.66E-04	5.98E-03
LEV		2.36E-04	1.13E-03	1.03E-05	1.16E-03
STEMPH		-1.52E-03	3.85E-03	-1.49E-03	3.93E-03
SIZE		-4.02E-04	7.24E-04	-4.52E-04	7.17E-04
SGR		-2.88E-03*	1.42E-03	-3.18E-03*	1.39E-03
SLACK		-1.53E-05	1.02E-03	-5.52E-05	1.04E-03
HHI		-1.01E-02	9.10E-03	-1.09E-02	9.33E-03
INDSGR		6.54E-03	1.37E-02	6.28E-03	1.36E-02
MANF		-4.51E-03	3.95E-03	-4.53E-03	4.15E-03
F		1.18		1.65	
R2		.06		.07	

[†] *p* < .1; * *p* < .05; ** *p* < .01

Supported Hypotheses: H1 (Marginal), H3a, H3b

Estimation using Winsorized variables: To ensure that our findings are not biased due to outliers, following extant literature (e.g., Lenz, Wetzel, and Hammerschmidt 2017; Warren and Sorescu 2017), we estimate the model after winsorizing the dependent variable (CAR [-2, +2]) and all continuous dependent variables at 5% level. Winsorizing the variables at 5% level sets observations below the 5th percentile to the level of the 5th percentile and observations above the 95th percentile to the level of the 95th percentile. We provide the results from model estimations using winsorized variables in Table A5 below. The findings from the estimation of the model suggest that our findings are not biased due to extreme observations in our data. Therefore, our findings are not influenced due to outliers.

Absolute measure of marketing department power: We re-examine the validity of the findings using the absolute measure of marketing department power used in prior literature (e.g., Feng et al 2015; Srinivasan and Ramani 2019), rather than the industry relative measure. All other control variables are also included in their absolute values to be consistent with the focal measure of marketing department power. Results from the re-estimated model are similar to that of the main model results reported in Table 3, except we find partial support for H2. Readers can review the results of the model estimations in the Table A6.

Estimation without observations with single announcements per industry: There are 7 announcements which are the only announcements for their respective industries (two-digits SIC code). To ensure that our findings are not influenced due to the presence of these events, we re-estimate the model excluding these 7 observations. Results (see Table A7) confirm that the findings from the main model reported in Table 3, except for H2 are still supported. We find partial support for H2 with marginally significant effects of marketing department power on investor response during commercialization stage ($\beta = .0026$, $t = 1.76$),

compared to initiation stage. However, the effects of marketing department power on investor response are not significantly different between initiation and development stages.

Table A5
Regression Estimates of Equation (1) using 5% Winsorized Variables

M1: Main effects only model; **M2:** Full model with interaction effects

<i>N</i> = 341		Dependent Variable: CAR [-2,+2]			
		(M1)		(M2)	
		β	SE	β	SE
Intercept		-1.86E-03	9.04E-03	9.98E-04	7.94E-03
RELMDP		1.69E-03**	6.22E-04	-4.32E-03**	1.17E-03
STAGE					
	Development (Vs Initiation)	5.57E-03	4.65E-03	4.28E-03	4.72E-03
	Commercialization (Vs Initiation)	1.15E-02*	4.68E-03	9.67E-03*	4.16E-03
ROUTE					
	Ally (Vs Make)	2.20E-03	3.93E-03	1.37E-03	3.50E-03
	Buy (Vs Make)	1.34E-03	4.99E-03	-1.56E-03	4.90E-03
PLATFORM (Vs Component)		-1.77E-03	3.72E-03	-1.15E-03	3.29E-03
RELMDP * STAGE					
	Development (Vs Initiation)			2.28E-03[†]	1.19E-03
	Commercialization (Vs Initiation)			3.17E-03*	1.44E-03
RELMDP * ROUTE					
	Ally (Vs Make)			3.41E-03**	1.02E-03
	Buy (Vs Make)			5.85E-03**	1.58E-03
RELMDP * PLATFORM (Vs Component)				3.02E-03*	1.18E-03
MARKET		3.46E-03	5.15E-03	2.50E-03	5.27E-03
LEV		1.28E-03	1.39E-03	7.87E-04	1.41E-03
STEMPH		-3.41E-03	3.63E-03	-3.39E-03	3.73E-03
SIZE		-5.28E-04	9.81E-04	-6.59E-04	9.15E-04
SGR		-6.03E-03**	2.08E-03	-6.67E-03**	1.92E-03
SLACK		6.60E-04	1.84E-03	6.85E-04	1.87E-03
HHI		-1.40E-02	1.07E-02	-1.57E-02	1.04E-02
INDSGR		-1.62E-03	2.03E-02	-3.79E-03	1.87E-02
MANF		-2.63E-03	4.77E-03	-3.19E-03	4.72E-03
F		1.74		2.57	
R2		.09		.11	

[†] $p < .1$; * $p < .05$; ** $p < .01$

Supported Hypotheses: H1, H2a(Marginal), H2b, H3a, H3b, H4

Table A6

Regression Estimates of Equation (1) using Absolute Independent Variable Measures

M1: Main effects only model; **M2:** Full model with interaction effects

<i>N</i> = 341		Dependent Variable: CAR [-2,+2]			
		(M1)		(M2)	
		β	SE	β	SE
Intercept		-7.67E-03	1.12E-02	-2.59E-03	1.06E-02
MDP		1.83E-03*	7.82E-04	-5.18E-03**	1.41E-03
STAGE					
	Development (Vs Initiation)	5.70E-03	4.59E-03	4.44E-03	4.85E-03
	Commercialization (Vs Initiation)	1.22E-02*	4.65E-03	9.80E-03*	4.19E-03
ROUTE					
	Ally (Vs Make)	2.58E-03	3.92E-03	1.47E-03	3.54E-03
	Buy (Vs Make)	2.29E-03	4.84E-03	-1.71E-03	5.16E-03
PLATFORM (Vs Component)		-2.28E-03	3.82E-03	-1.94E-03	3.54E-03
MDP * STAGE					
	Development (Vs Initiation)			2.46E-03	1.50E-03
	Commercialization (Vs Initiation)			2.85E-03†	1.56E-03
MDP * ROUTE					
	Ally (Vs Make)			3.74E-03**	1.38E-03
	Buy (Vs Make)			7.38E-03**	1.76E-03
MDP * PLATFORM (Vs Component)				4.11E-03**	1.42E-03
MARKET		2.94E-03	5.21E-03	1.80E-03	5.18E-03
LEV		1.28E-02	1.10E-02	8.82E-03	1.14E-02
STEMPH		-1.44E-03	1.82E-02	-3.88E-03	1.84E-02
SIZE		-3.42E-09	1.76E-08	-6.50E-09	1.80E-08
SGR		-4.49E-02**	1.51E-02	-4.91E-02**	1.38E-02
SLACK		1.71E-03	3.85E-03	1.81E-03	3.91E-03
HHI		-9.31E-03	1.17E-02	-1.20E-02	1.12E-02
INDSGR		4.38E-02*	1.97E-02	4.30E-02*	1.88E-02
MANF		-2.34E-03	5.68E-03	-3.02E-03	5.63E-03
F		1.7		2.82	
R2		.08		.11	

† $p < .1$; * $p < .05$; ** $p < .01$

Supported Hypotheses: H1, H2b (Marginal), H3a, H3b, H4

Table A7

Regression Estimates of Equation (1) excluding single announcement industries**M1:** Main effects only model; **M2:** Full model with interaction effects

<i>N</i> = 334		Dependent Variable: CAR [-2,+2]			
		(M1)		(M2)	
		β	SE	β	SE
Intercept		-5.86E-04	8.84E-03	1.90E-03	8.06E-03
RELMDP		1.60E-03*	5.98E-04	-4.21E-03**	1.13E-03
STAGE					
	Development (Vs Initiation)	5.82E-03	4.75E-03	4.77E-03	4.86E-03
	Commercialization (Vs Initiation)	1.20E-02*	4.77E-03	1.03E-02*	4.28E-03
ROUTE					
	Ally (Vs Make)	2.19E-03	3.94E-03	1.51E-03	3.49E-03
	Buy (Vs Make)	1.95E-03	4.97E-03	-5.74E-04	4.96E-03
PLATFORM (Vs Component)		-9.76E-04	3.77E-03	-3.27E-04	3.29E-03
RELMDP * STAGE					
	Development (Vs Initiation)			1.73E-03	1.17E-03
	Commercialization (Vs Initiation)			2.48E-03†	1.38E-03
RELMDP * ROUTE					
	Ally (Vs Make)			3.11E-03**	1.01E-03
	Buy (Vs Make)			5.59E-03**	1.54E-03
RELMDP * PLATFORM (Vs Component)				3.39E-03**	1.22E-03
MARKET		1.56E-03	5.12E-03	7.42E-04	5.25E-03
LEV		8.39E-04	1.43E-03	3.94E-04	1.46E-03
STEMPH		-4.65E-03	3.89E-03	-4.95E-03	3.98E-03
SIZE		-4.50E-04	9.99E-04	-5.63E-04	9.06E-04
SGR		-6.31E-03**	2.10E-03	-6.86E-03**	1.93E-03
SLACK		7.59E-04	1.85E-03	8.87E-04	1.88E-03
HHI		-1.77E-02	1.14E-02	-1.92E-02†	1.09E-02
INDSGR		-2.93E-03	2.08E-02	-5.59E-03	1.90E-02
MANF		-2.24E-03	5.14E-03	-2.65E-03	5.02E-03
F		1.97		3.27	
R2		.09		.11	

† $p < .1$; * $p < .05$; ** $p < .01$ **Supported Hypotheses:** H1, H2b (Marginal), H3a, H3b, H4

Estimation without observations of companies from “Electronics & Electrical Equipment Manufacturing” (2-digit SIC = 36): Some may argue that AI is a familiar technology for companies from this industry segment (e.g., Apple and Intel). We re-estimate our model after excluding 111 observations from these companies. The results remain largely the same and we report the model estimation results in Table A8 below.

Table A8
Regression Estimates of Equation (1) excluding observations from SIC=36
M1: Main effects only model; **M2:** Full model with interaction effects

<i>N</i> = 230		Dependent Variable: CAR [-2,+2]			
		(M1)		(M2)	
		β	SE	β	SE
Intercept		-4.83E-03	9.95E-03	-3.68E-03	8.90E-03
RELMDP		1.12E-03[†]	5.88E-04	-5.28E-03**	1.56E-03
STAGE					
	Development (Vs Initiation)	5.39E-03	4.58E-03	5.71E-03	5.02E-03
	Commercialization (Vs Initiation)	6.85E-03	4.73E-03	6.87E-03	4.65E-03
ROUTE					
	Ally (Vs Make)	2.77E-03	4.51E-03	2.47E-03	4.02E-03
	Buy (Vs Make)	2.50E-03	5.02E-03	7.67E-04	5.88E-03
PLATFORM (Vs Component)		-6.14E-04	4.11E-03	-1.11E-03	3.52E-03
RELMDP * STAGE					
	Development (Vs Initiation)			2.84E-03[†]	1.60E-03
	Commercialization (Vs Initiation)			4.34E-03**	1.55E-03
RELMDP * ROUTE					
	Ally (Vs Make)			2.92E-03*	1.23E-03
	Buy (Vs Make)			4.84E-03*	1.98E-03
RELMDP * PLATFORM (Vs Component)				2.90E-03**	1.06E-03
MARKET		1.07E-02[†]	6.19E-03	1.05E-02	6.28E-03
LEV		1.93E-03	1.58E-03	1.45E-03	1.58E-03
STEMPH		-6.31E-03	4.33E-03	-5.61E-03	4.36E-03
SIZE		-1.28E-03	1.18E-03	-1.09E-03	1.10E-03
SGR		-4.91E-03[†]	2.56E-03	-5.58E-03*	2.53E-03
SLACK		3.22E-03	2.16E-03	3.13E-03	2.26E-03
HHI		-1.48E-02	1.19E-02	-1.58E-02	1.16E-02
INDSGR		-4.44E-03	2.64E-02	-3.58E-03	2.58E-02
MANF		-3.96E-03	5.25E-03	-4.57E-03	5.05E-03
F		1.41		6.26	
R2		.06		.09	

[†] *p* < .1; * *p* < .05; ** *p* < .01

Supported Hypotheses: H1, H2a(Marginal), H2b, H3a, H3b, H4

Including year fixed effects: Estimation of the models including year fixed effects yields similar results to those of the main models reported earlier in Table 3, in support of all the hypothesized effects. Therefore, our findings are robust after accounting for year fixed effects. The results of the model estimations with year fixed effects are provided in Table A9.

Table A9
Regression Estimates of Equation (1) with year fixed effects

M1: Main effects only model; **M2:** Full model with interaction effects

<i>N</i> = 341		Dependent Variable: CAR [-2,+2]			
		(M1)		(M2)	
		β	SE	β	SE
Intercept		-1.39E-03	9.76E-03	1.65E-03	8.65E-03
YEAR [Dummies]		✓		✓	
RELMDP		1.68E-03*	6.59E-04	-4.18E-03**	1.24E-03
STAGE					
Development (Vs Initiation)		5.65E-03	4.71E-03	4.30E-03	4.78E-03
Commercialization (Vs Initiation)		1.16E-02*	4.75E-03	9.80E-03*	4.25E-03
ROUTE					
Ally (Vs Make)		2.18E-03	4.15E-03	1.19E-03	3.67E-03
Buy (Vs Make)		1.78E-03	4.97E-03	-1.22E-03	4.76E-03
PLATFORM (Vs Component)		-1.94E-03	3.85E-03	-1.37E-03	3.36E-03
RELMDP * STAGE					
Development (Vs Initiation)				2.34E-03[†]	1.29E-03
Commercialization (Vs Initiation)				3.33E-03*	1.58E-03
RELMDP * ROUTE					
Ally (Vs Make)				3.29E-03**	9.95E-04
Buy (Vs Make)				5.66E-03**	1.65E-03
RELMDP * PLATFORM (Vs Component)				2.81E-03*	1.28E-03
MARKET		3.70E-03	5.29E-03	2.66E-03	5.35E-03
LEV		1.19E-03	1.41E-03	7.44E-04	1.43E-03
STEMPH		-3.52E-03	3.74E-03	-3.31E-03	3.82E-03
SIZE		-4.19E-04	1.11E-03	-5.86E-04	1.05E-03
SGR		-6.03E-03**	2.13E-03	-6.70E-03**	2.01E-03
SLACK		6.01E-04	1.93E-03	5.96E-04	1.99E-03
HHI		-1.50E-02	1.09E-02	-1.62E-02	1.06E-02
INDSGR		-4.82E-03	2.50E-02	-7.11E-03	2.36E-02
MANF		-2.22E-03	4.90E-03	-2.95E-03	4.83E-03
F		2.46		3.54	
R2		.09		.12	

[†] $p < .1$; * $p < .05$; ** $p < .01$

Supported Hypotheses: H1, H2a(Marginal), H2b, H3a, H3b, H4

Note: Further, although there has been an increase in the number of ETA announcements recently, compared to the baseline year of 2009, the returns to any of the subsequent years are not significantly different.

This page has been left blank on purpose.

Essay-2: When does Emerging Customer Orientation Affect Shareholder Value? Interactive Effects of Emerging Customer Orientation and Marketing Capabilities

Abstract

Emerging customer orientation, or the strategic predisposition of a firm to emphasise on small but fast-growing customer segments, has been deemed necessary by scholars for value creation. Yet, to date, no prior research has examined how emerging customer orientation affects shareholder value. Building on the theory of market-based assets, the authors argue and demonstrate that emerging customer orientation improves shareholder value, but only when complemented with the necessary marketing capabilities to build and leverage market-based assets. Using a panel data set (N=919) consisting of a sample of 127 U.S. retailers between 2009 to 2018, the authors find that the joint effects of emerging customer orientation and marketing capabilities (i.e., market-based asset building and leveraging capabilities) have a risk-reducing and return-enhancing effect on shareholder value. The results demonstrate the complementarity of emerging customer orientation and marketing capabilities in enhancing shareholder value.

Keywords: *emerging customer orientation, transformative marketing, marketing capabilities, market-based assets, marketing-finance interface*

Introduction

Markets are becoming demographically diverse and customer needs and expectations are becoming distinct and niche (Kumar 2018). To keep up with the changing nature of markets, firms are increasingly making strategic choices to appeal to emerging customer segments - i.e., small but fast growing customer segments whose needs are not met by the mainstream market offerings (Govindarajan, Kopalle, and Daneels 2011). For example, Beringer California Collection revamped its wine assortment and distribution strategies in a bid to appeal to emerging customer segments in North America who were willing to switch from consuming beer to wine if it was as affordable as beer (Sinha, Sehgal, and Mathur 2013). Likewise, Gillette introduced Gillette Direct, a direct-to-consumer subscription model, in view of emerging customer segments who demand basic, affordable, and hassle-free male grooming products (Arunachalam et al 2018). It is evident that firms are increasingly taking measures to focus on the needs of emerging customer segments – i.e., firms are improving their emerging customer orientation. But do firms with higher (vs lower) emerging customer orientation perform better and improve shareholder value? While emerging customer orientation may help firms to develop better understanding of unmet needs of emerging customer segments, to translate such knowledge into superior performance, firms must respond to such needs through appropriate marketing actions. To what extent then the relationship between emerging customer orientation and shareholder value is contingent on the firm's marketing capabilities?

To address such questions and investigate how emerging customer orientation affects shareholder value, we develop a conceptual framework based on emerging customer orientation literature (e.g., Chandy and Tellis 1998; Christensen and Raynor 2003; Govindarajan et al. 2011) and the theory of market-based assets (e.g., Feng, Morgan, and

Rego 2015; Srivastava, Shervani, and Fahey, 1998). We argue that although emerging customer orientation may stimulate firm growth by preventing it from inertia and consequently myopic decision-making (e.g., Chandy and Tellis, 1998; Christensen and Raynor 2003), the firm can achieve superior performance only when emerging customer orientation is complemented with the necessary marketing capabilities to build and leverage market-based assets (MBAs). This is because the needs of emerging customer segments are often ill-identified and evolving, and to improve emerging customer orientation, firms must make significant marketing investments for conducting elaborate search for new business opportunities beyond the scope of a firm's existing products, technologies, and customers (Govindarajan et al. 2011). Therefore, in the long run, the ability of a firm with higher emerging customer orientation to expend optimal marketing resources to develop relational and intellectual assets (i.e., MBAs) in the emerging customer segments should play an important role in helping the firm achieve superior performance. Similarly, the ability of a firm with higher emerging customer orientation to efficiently deploy its existing MBAs to capture and exploit evolving opportunities amidst market pressures should help the firm in improving its performance.

There are other similar, but different constructs discussed in prior marketing literature such as customer orientation and future-market-focus. While customer orientation helps a firm to be receptive to the expressed and latent needs of mainstream customers (e.g., Blocker et al. 2010; Narver and Slater 1990; Saboo and Grewal 2013), emerging customer orientation helps a firm to be receptive to the needs of emerging customer segments (e.g., Govindarajan et al. 2011). Further, emerging customer orientation and customer orientation can co-exist – i.e., firms don't need to trade-off between the two (Chandy and Tellis 1998; Govindarajan et al. 2011). Another construct that is similar to emerging customer orientation is the future-market-focus (Chandy and Tellis 1998). The difference between the two constructs is that

future-market-focus involves emphasis on latent needs of existing customers, unmet needs of emerging customer segments, and also future competitor focus. We present a summary of similarities and differences between these constructs in Table 1.

Insert Table 1 about here

Furthermore, emerging customer orientation and exploratory innovation are related but distinct constructs. While emerging customer orientation reflects the strategic predisposition of a firm to cater to the needs of emerging customer segments, exploratory innovations are technological innovations for entering new product-market domains. Thus, exploratory innovations, by definition, rely on technological innovations. In contrast, the needs of emerging customer segments may be resolved without technology innovations.

We focus on emerging customer orientation in our study because although it has long been implied that emerging customer orientation is an important strategic predisposition necessary for firms to improve shareholder value by ensuring growth (Christensen 1997, 2000; Chandy and Tellis 1998; Govindarajan and Kopalle 2006), surprisingly, to date, no prior study has examined this relationship (see Table 2 for a summary of past studies related to firm's emphasis on emerging customer segments). For example, Kopalle, Kumar, and Subramaniam (2020) argue that even legacy firms with digital customer orientation - i.e., emerging customer orientation specific to identification and pursuit of unmet needs of digital-native customers by embracing digital ecosystems, can potentially untap the benefits of digital ecosystems. Similarly, Kumar (2018) argues that one of the ways a firm can outperform competition through "transformative marketing" is by catering to emerging customer segments and bringing their unmet needs to the forefront of its innovation and marketing strategies. However, these propositions have not been tested before and given that firms are investing significant amount of resources to improve their emerging customer

orientation in response to the changing nature of market, a better understanding of how emerging customer orientation affects shareholder value is critical.

Insert Table 2 about here

Our study addresses this critical gap in the literature by examining how a high emerging customer orientation firm can improve shareholder value. Specifically, we argue that for a firm with higher emerging customer orientation, its marketing capabilities to build and leverage MBAs act as catalysts in improving shareholder value through a risk-reducing and return-enhancing mechanism. We test our predictions using an unbalanced panel data set of 919 firm-year observations consisting of 127 U.S. retail firms with an average of seven years of observations per firm over a period of ten years from 2009-2018. Our findings lend support to the predictions that firms with higher (vs lower) emerging customer orientation increase firm value when complemented with MBA-building and MBA-leveraging capabilities. Further, we find partial support to our prediction that joint effects of emerging customer orientation and marketing capabilities will lower the firm's risk. Specifically, the interaction between emerging customer orientation and MBA-building capability has a significant negative effect on risk (i.e., reduces firm risk), but interaction between emerging customer orientation and MBA-leveraging capability does not.

We contribute to marketing and innovation literature by (1) providing a framework to understand how firms with emerging customer orientation can succeed, (2) extending knowledge on MBA-building and MBA-leveraging capabilities (Feng et al. 2015; Srivastava et al 1998), and (3) providing empirical evidence that the implied positive relationship between emerging customer orientation and shareholder value is contingent on the firm's marketing capabilities. The remainder of the paper is organized as follows. Next, we develop our conceptual framework and hypotheses. We follow-up the discussion on conceptual

framework by describing the empirical methodology before presenting the findings from our analyses. Finally, we discuss the theoretical contribution and managerial implications of the present study, its limitations, and opportunities for further research.

Conceptual Framework

The central theme of our study is to examine the joint effects of a firm's emerging customer orientation and its marketing capabilities – i.e., MBA-building & MBA-leveraging capabilities – on shareholder value. We draw from the theory of market-based assets (Srivastava et al. 1998; Srivastava, Fahey, and Christensen 2001) which postulates that MBAs can function as financial hedging contracts when firms enter new markets to argue that firms must complement emerging customer orientation with necessary capabilities to build and leverage MBAs. Therefore, the effects of emerging customer orientation on shareholder value should be contingent on whether the firm possesses the required marketing capabilities. Accordingly, we predict that the joint effects of a firm's emerging customer orientation and its marketing capabilities to build and leverage MBAs will have a risk-reducing and return-enhancing effect on shareholder value.

It is possible to argue that marketing capabilities of a firm may drive the firm's emerging customer orientation. While firms with higher marketing capabilities may be more aware of demand side changes in mainstream customer segments, it is not necessary that they may be aware of the emerging customer segments or their evolving needs. Prior literature demonstrates that managers tend to make myopic marketing investments to cater only to the needs of mainstream customer segments as such investments may lead to more certain, short-term returns, and thus are more justifiable (Chandy and Tellis, 1998; Christensen, 1997). Therefore, we do not anticipate marketing capabilities to drive a firm's emerging customer orientation.

In the following sections, we build upon extant literature to develop our conceptual framework and hypotheses.

Emerging Customer Orientation

Emerging customer orientation indicates a firm's focus on small but emerging customer segments (Chandy and Tellis 1998; Danneels 2003; Govindarajan et al. 2011). Emerging customer segments usually consist of low-end customers of mainstream market form whom existing products overshoot their performance requirement or a niche-market consisting of non-consuming customers with dramatically different needs relative to the mainstream customers (e.g., Christensen et al 2018; Tellis et al. 2009). Many firms, even those with higher customer orientation, may choose not to focus on these emerging customer segments due to organizational inertia and fear of cannibalizing their existing markets (Chandy and Tellis 1998; Christensen 1997; Christensen and Raynor 2003; Tellis 2006). In contrast, firms with higher (vs lower) emerging customer orientation have a higher (lower) willingness to cannibalize their existing offerings because emerging customer orientation broadens a firm's focus, alerts it to new opportunities, and prevents it from overly committing to its past investments (Chandy and Tellis 1998; Govindarajan et al. 2011). Firms with higher (vs lower) emerging customer orientation are better informed of- and more willing to exploit new market opportunities and therefore more likely to disturb the prevailing business models of an industry or ecosystem (Ansari et al., 2016; Chandy and Tellis 1998; Christensen, 2006).

Although these findings imply a positive relationship between emerging customer orientation and shareholder value, it is important to note that emerging customer orientation involves significant marketing investments for elaborate search for opportunities outside the firm's current scope of products, technologies, and customers (Govindarajan et al. 2011). This implies that effect of emerging customer orientation may be contingent upon other factors such as efficiency and effectiveness with which firms can translate such investments

into desirable outputs (i.e., marketing capability). Therefore, we do not make any formal predictions about the main effect of emerging customer orientation on shareholder value. Next, we discuss two key marketing capabilities – i.e., MBA-building and MBA-leveraging capabilities, and develop hypotheses about how they create shareholder value jointly with emerging customer orientation.

Market-based Assets (MBA) Building and Leveraging Capabilities

MBAs are intangible assets that a firm's marketing investments create and are principally of two types: relational and intellectual. Relational MBAs are outcomes of relationship between a firm and its key external stakeholders such as customers and partners. Intellectual MBAs are knowledge stocks developed by a firm about its external environment such as state of market conditions, ability to predict industry evolution path, understanding of evolving and emerging customer needs (Srivastava et al., 1998). A firm's capability to build MBAs efficiently through its marketing investments has been linked to improved long-term shareholder value whereas a firm's MBA leveraging capability has been linked to improved short-term financial outcome such as profitability (Feng et al. 2015).

Hypotheses

Joint Effects of Emerging Customer Orientation, and MBA- Building and Leveraging Capabilities on Firm Value

A firm with emerging customer orientation, rather than focusing only on the needs of its existing customers (i.e., mainstream customers), is also focused on serving to the needs of emerging customers segments – i.e., customer segments who are unable to afford, access, or use the existing products (Christensen and Michael, 2003, Christensen et al., 2004). In essence, a firm that is looking to exploit the market opportunities that exist by addressing the unmet needs of such emerging customer segments is looking to make inroads into a new market.

To gain foothold in any market, a firm must develop new MBAs (Srivastava et al., 1998). Examples of such MBAs include (1) knowledge about customer needs in that new market, (2) knowledge about suitable ways (e.g., product and business model innovations) to address the market needs, (3) establish relationships and communication channels with the new customers, and (4) form partner relationships and develop suitable distribution channels to provide product access to the new market. However, developing such MBAs in emerging customer segments maybe challenging because of the needs of these segments are often ill-identified and fast evolving (Govindarajan et al., 2011). Hence, in order to achieve superior performance, a firm with higher emerging customer orientation must not only invest in building MBAs to cater to the needs of emerging customer segments, but also be more efficient and effective in converting its marketing resources into MBAs. Therefore, we predict that firms with higher emerging customer orientation will improve firm value only when they also possess better marketing capability to build MBAs. Formally stated,

H1: Joint effects of a firm's emerging customer orientation and MBA-building capability on its abnormal stock returns will be positive such that the effects of emerging customer orientation on abnormal returns increases (decreases) as the firm's MBA-building capability increases (decreases).

The basic tenet of the theory of market-based assets is that MBAs can be leveraged via market-facing and core business processes to deliver superior corporate performance and shareholder value through superior customer value and competitive advantages (Srivastava, Fahey, and Christensen 2001). Leveraging is the process through which the existing MBAs are absorbed, transformed, and converted into desirable solutions for the market and generate economic value for the organization (Lehmann 1997; Srivastava et al. 1998). The value extraction through the MBA leveraging process in turn results in superior resources that can nurture MBAs and capabilities in the future (Srivastava et al 2001).

Extending this logic, while MBA-building capability may help a firm to create new intellectual and relational assets using marketing investments, it is the MBA-leveraging capability that helps the firm to deploy these intangible assets to gain market advantage (Srivastava et al. 1998). Indeed, resource-based theory stipulates that in order to gain sustainable competitive advantage, firms must “orchestrate” available resources - i.e., structure, bundle, and leverage firm resources (Barney et al. 2011; Simon et al. 2011). This view is also consistent with the dynamic capabilities literature that postulates that dynamic capabilities affect market outcomes by changing the focal firm’s resource base (Schilke et al. 2018). Thus, to successfully reap the benefits of emerging customer orientation, firms require capability to not only build and maintain MBAs, but also to combine, deploy, and mobilize MBAs (i.e., leverage the MBAs) in novel, meaningful and efficient ways for new uses. Formally stated,

H2: Joint effects of a firm’s emerging customer orientation and MBA-leveraging capability on its abnormal stock returns will be positive such that the effects of emerging customer orientation on abnormal returns increases (decreases) as the firm’s MBA-leveraging capability increases (decreases).

Joint Effects of Emerging Customer Orientation, MBA -Building and Leveraging Capabilities, on Firm Risk

Emerging customer orientation helps a firm to be more receptive to weak signals from the market (Govindarajan et al., 2011; Slater and Narver, 1998), and MBA-building capability helps the firm to develop the necessary MBAs required to effectively respond to these signals (Feng et al., 2015; Morgan, Slotegraaf, and Vorhies, 2009; Ramaswami, Srivastava, and Bhargava, 2009). A firm’s MBAs can generate greater receptiveness of consumers and distribution channel partners to its initiatives in a new market (Kaufman, Jayachandran, and Rose 2006). Further, MBAs such as brand equity can function as financial

hedging contracts when firms enter new markets by (1) creating loyalty among consumers and distribution-partners, (2) acting as a barrier to competition, and (3) providing bargaining power over channel partners (Srivastava et al., 1998). Moreover, firms focused on developing MBAs in an ignored market segment tend to minimize the threat of a competitive response from other players in the industry or ecosystem (Christensen 1997). Based on these findings from previous research, we predict that for a firm with higher emerging customer orientation, its MBA-building capability can prove crucial in insulating its performance from market downturns. Specifically, we expect that firms with high emerging customer orientation and high MBA-building capability can reduce their risk. Formally stated,

H3: Joint effects of a firm's emerging customer orientation and MBA-building capability on its risk will be negative such that a firm's emerging customer orientation reduces (increases) its risk as its MBA-building capability increases (decreases).

When a firm with higher emerging customer orientation leverages its MBAs effectively, not only does it develop desirable solutions for market segments with high growth potential but also improves the efficiency of its marketing activities (Srivastava et al. 1998) resulting in superior market penetration, adoption rates, customer loyalty and retention, and distribution power in the marketplace (Srivastava et al. 2001). Hence, the complementarity between emerging customer orientation and MBA-leveraging capability can enable a firm to maintain and grow future cash flows and reduce cash flow volatility. Similarly, prior research has demonstrated that MBAs such as brand equity can reduce a firm's risk by serving as a capital market information channel to firm's stockholders (Frieder and Subrahmanyam 2005; Grullon, Kanatas, and Weston 2004) and enabling it to adapt more efficiently to environmental changes (McAlister, Srinivasan, and Kim 2007; Miller and Bromiley 1990). As emerging customer orientation enables a firm to scan the environment for changes, MBA-leveraging capability can improve the firm's efficiency and flexibility

when responding to such changes. Therefore, we predict that emerging customer orientation, when complemented with MBA-leveraging capability, can help reduce firm's risk. Formally stated,

H4: Joint effects of a firm's emerging customer orientation and MBA-leveraging capability on its risk will be negative such that a firm's emerging customer orientation reduces (increases) its risk as its MBA- leveraging capability increases (decreases).

The conceptual framework of joint effects of simultaneous changes to emerging customer orientation, MBA -building and -leveraging capabilities is presented in Figure 1.

Insert Figure 1 about here

Methodology

Research Context, Design, and Data

Context: We use the U.S. retail domain to test our hypotheses. While no firm or industry is immune to risks of becoming obsolete due to lack of attention to emerging customer segments or the willingness to act upon the needs of such segments, investigating our research question within an industry that has arguably faced the most significant transformation due to changing customer landscape in recent years, allows us to extract meaningful insights. In the most recent Word Retail Congress summit, Ian McGarrigle, the event founder, highlighted that the retail landscape has seen significant changes in customer needs and has been in a state of evolution in recent years. Further, the changing industry landscape and heightened risks associated with such changes have evoked significant interest in the academic community to offer comprehensive assessments of the retail industry (e.g., Grewal, Roggeveen, and Nordfalt, 2017; Moreau, 2020; Verhoef, Kannan, and Inman, 2015). Many retailers, unable to cope with the changing customer landscape, have had to shut their

operations. For example, in 2017 alone, the U.S. retail industry witnessed more than 8,000 store closures and bankruptcy protection filing by 20 major retailers including prominent players such as Toys “R” Us, hhgregg, and RadioShack (Kahn, 2018). Hence, the retail industry provides a suitable context to investigate our research question.

Consistent with the American Customer Satisfaction Index (ACSI) convention and prior literature (e.g., Chaudhuri, Voorhees, and Beck 2018), we classified the following companies as part of the retail industry: department stores (Standard Industrial Classification [SIC]: 5311), shoe stores (SIC: 5661), drug stores (SIC: 5912), grocery stores (SIC: 5411), variety stores (SIC: 5331), general merchandise stores (SIC:5399), specialty retail stores (SIC 5700, 5940), consumer shipping (SIC: 4513), women’s apparel stores (SIC: 5621), Internet shopping (SIC: 5961), computer and computer software stores (SIC: 5734), game shops (SIC:5945), consumer electronics (SIC: 5731), and family clothing stores (SIC:5651).

Research Design

A secondary data-based approach is suitable to evaluate the joint effects of emerging customer orientation and marketing capabilities on the shareholder value. Despite its shortcomings (e.g., use of indirect indicators of constructs), using secondary data allows us to test the hypotheses for the sample firms over a long period of time.

Data

We assembled our dataset from several sources. We use: (1) firms’ stock information from the University of Chicago’s Center for Research in Security Prices and Kenneth French’s Data Library for the monthly risk factors (i.e., market, size, value, and momentum factor)⁶ to estimate our dependent variables (firm’s annualized abnormal stock returns and risk); (2) annual report text from U.S. Securities and Exchange Commission’s EDGAR

⁶ Factor data available from (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

database to measure firm-level emerging customer orientation; (3) firms' annual operational and financial information from the Standard & Poor's COMPUSTAT database used to estimate firm-level marketing capabilities along with data compiled from the United States Patent and Trademark Office database and Fortune's ranking database of World's Most Admired Companies and Fortune 500 companies. COMPUSTAT database is also used for estimating firm-specific control variables.

Combining all the data sources yields an unbalanced panel data set of 919 firm-year observations consisting of 127 U.S. retail firms from 2009 to 2018 with an average of approximately 7 observations per firm.

Variable Measurement

In the following sections, we describe how we measure the key variables of interest. First, we discuss the operationalization of our dependent variables (i.e., firm's annualized abnormal stock returns and risk) followed by key independent variables and other firm-level control variables. We provide a summary of data sources and operationalization of all the key variables in Table 3 and a summary of all the control variables in Table 4 below.

Dependent Variables: Abnormal Stock Returns and Firm Risk

To assess firm value, following extant literature (e.g., Srinivasan and Hanssens 2009), we use firm's annualized abnormal returns. Next, to assess risk, we use firm's systematic risk for two reasons. (1) Emergence of new customer segments is an external environmental phenomenon beyond the firm's control and the changes that such segments may bring upon are not specific to any one firm but the whole market. In other words, the risk facing the firms due to emerging customer segments is not idiosyncratic in nature. (2) Systematic risk is a critical risk factor for shareholders as it cannot be mitigated through asset portfolio diversification.

Following Srinivasan and Hanssens (2009), we estimate abnormal stock returns and systematic risk using Carhart's (1997) four-factor model below:

$$(R_{im} - R_{fm}) = \alpha_i + \beta_{1i}(R_{mm} - R_{fm}) + \beta_{2i}SMB_m + \beta_{3i}HML_m + \beta_{4i}UMD_m + \epsilon_{it} \quad (1)$$

where, in the month m , R_{it} is the stock return for the firm i , R_{fm} is the risk-free return, R_{mm} is the market return, SMB_m is the size factor, HML_m is the value factor, and UMD_m is the momentum factor. Here, the parameter α_i serves as an estimate of the firm i 's *abnormal monthly returns* (i.e., AR_{im}), β_{1i} is an estimate of the firm's *systematic risk*. Therefore, for a firm i in year t , the annualized abnormal return (see equation 2) and systematic risk (see equation 3) are calculated as below:

$$AR_{it} = \ln \prod_{m=1}^{12} (1 + AR_{im}) \quad (2)$$

and,

$$SR_{it} = \frac{1}{12} \sum_{m=1}^{12} \beta_{1im} \quad (3)$$

Independent Variables

Emerging Customer Orientation

We use computer-aided text analysis (CATA) to content analyze firm annual reports to infer a firm's emerging customer orientation. Similar approaches have been used in prior research to measure other strategic variables such as market orientation, entrepreneurial orientation, and customer orientation (e.g., Bhattacharya, Misra, and Sardashti, 2019; Saboo and Grewal, 2013). Following Popping (2000), we developed a dictionary of phrases and words capturing high-level concepts of emerging customer orientation. We began with a set of "seed" words related to emerging customer orientation based on the previous literature. Next, we identified synonyms and phrases related to the seed words using a thesaurus. To

enhance validity, the dictionary was verified by three academic judges familiar with the strategy and innovation literature. Based on the judges' evaluation, we eliminated phrases that did not unambiguously capture emerging customer orientation. A representative sample of phrases from the dictionary is presented in Table 5.

Next, the frequencies of matching phrases and words from the verified dictionary in the company annual reports were obtained using the conventional CATA methodology. For ease of interpretation, we convert the matched text frequencies into 1-100 scores. A list of top 10 companies ranked based on their scores of emerging customer orientation in 2017 and 2018 is provided in the Appendix, Table W1.

MBA Building & Leveraging Capabilities

Following prior research to estimate firm capabilities using secondary data, we use the stochastic frontier estimation (SFE) methodology to estimate how efficient a firm is in converting a set of inputs to desirable outcomes. We follow Feng et al. (2015) to estimate a firm's *MBA-building & leveraging capabilities* as follows. First, we estimate a firm's MBAs as the portion of its Tobin's Q unexplained by its management quality and technology investments (e.g., R&D expenses & patents). To assess management quality of a firm, for each year, first we created two dummy variables to indicate whether the firm featured in "*Fortune 100 Most Admired Companies*" and "*Fortune 500 Companies*" lists. The two dummy variables were added to create a composite ordinal variable with a range of 0 to 2 to indicate management quality of a firm in a given year. So, in a given year, a firm's management quality would get a score of 0 if a firm featured in neither of the lists, a score of 1 if it featured in one of the lists, and a score of 2 if it featured in both the lists, respectively. Next, to obtain an estimate for the firm's *MBA-Building Capability*, we use SFE to measure the efficiency with which the firm converts its marketing resources (e.g., SG&A expenses and number of trademarks) into MBAs. Finally, to estimate a firm's *MBA-Leveraging*

Capability, we measure the efficiency with the firm converts its marketing resources and its MBAs into cash flows. For ease of interpretation, we convert both the capabilities measures into 1 to 100 scores.

Control Variables:

We include several firm-level covariates to control for other factors such as firm size, financial leverage, liquidity, sales growth, profits, company age, capital intensity, and a dummy variable to indicate firm's membership to non-store based retailers (i.e., SIC code = 596*) which may affect firm performance. In addition, we control for industry level factors such as competitive intensity, industry sales growth. Finally, we also include year dummies and sub-industry dummies to control for time-fixed effects and sub-industry fixed effects, respectively.

 Insert Table 4 about here

Model Specification

To test our hypotheses, in line with prior literature (e.g., Feng et al. 2015; Nath and Mahajan 2011; Saboo, Kumar, and Anand 2017) we specify the model using a one-year leading measure of dependent variables to incorporate the effects of past organizational actions and address concerns regarding reverse causality. Specifying the model with leading dependent variables result in loss of 71 observations. Further, we include year and sub-industry dummies to control for time and industry fixed effects. An autoregressive model controls for past levels of performance and factors such as inertia, persistence, and different initial conditions which can predict future performance (Saboo, Chakravarty, and Grewal 2016; Saboo et al. 2017). However, it may also introduce a dynamic panel bias. To address such concerns, we follow extant literature (e.g., Blundell and Bong 1998; Saboo et al. 2017) and use predicted value of the lagged dependent variables (i.e., $\widehat{AR}_{it}$ and $\widehat{SR}_{it}$) computed

using its lagged differences (i.e., ΔAR_{it} and ΔSR_{it}) as instrument to control for the past period performance. Further, the models are specified with robust standard errors to address potential issues in panel data related to serial correlation and heteroskedasticity and using random effects specification to account for unobserved heterogeneity.

Addressing Endogeneity: Reasons for management's decisions on market segment focus and resource allocation to various marketing activities are unobservable. Further, prior research suggests that managers may react to stock returns and volatility to adjust resource allocations to different activities (e.g., Chakravarty and Grewal 2011), which may influence MBA-building and leveraging capabilities. Such issues may raise concerns regarding endogeneity in our study. To address such concerns, we use the control function approach – which is more suitable for non-linear models (Papies, Ebbes, and van Heerde 2016). We use lagged values and industry averages of the respective endogenous variables (i.e., emerging customer orientation, MBA-building capability, and MBA-leveraging capability), and the lagged competitive intensity (HHI) as instruments to predict fitted residuals. Next, the control function parameters (i.e., fitted residuals of the endogenous variables from first stage) are used as control variables in the main estimated models. As recommended by Papies et al. (2016), we use a bootstrap approach to compute the fitted residuals. None of the control function terms are statistically significant ($p > .1$) in the model estimation with abnormal returns as the dependent variable, indicating that the uncorrected and endogeneity-corrected sets of estimates are statistically not different. Hence, we specify the model to estimate effects on abnormal returns as follows:

$$\begin{aligned}
 AR_{it+1} = & \beta_{0i}^{AR} + \beta_1^{AR} ECO_{it} + \beta_2^{AR} BUILDCAP_{it} + \beta_3^{AR} LEVCAP_{it} + \beta_4^{AR} ECO_{it} * \\
 & BUILDCAP_{it} + \beta_5^{AR} ECO_{it} * LEVCAP_{it} + \beta_6^{AR} CONTROLS_{it} + \beta_7^{AR} YEAR_t + \\
 & \beta_8^{AR} IND + \varepsilon_{it+1}^{AR} \quad (4)
 \end{aligned}$$

In the model estimating effects on systematic risk, although the control function parameters for emerging customer orientation and MBA-building capability are not significant, the control function parameter for MBA-leveraging capability is significant at 10% significance level. Therefore, we estimate the model using the vector of control function parameters for the three endogenous variables as additional control variables. Further, since we use lagged variables for estimation of control function parameters, we lose 23 observations more and the systematic risk model uses N=818 observations for estimation.

$$\begin{aligned}
SR_{it+1} = & \beta_{0i}^{SR} + \beta_1^{SR} ECO_{it} + \beta_2^{SR} BUILDCAP_{it} + \beta_3^{SR} LEVCAP_{it} + \beta_4^{SR} ECO_{it} * \\
& BUILDCAP_{it} + \beta_5^{SR} ECO_{it} * LEVCAP_{it} + \beta_6^{SR} CONTROLS_{ijt} + \beta_7^{SR} YEAR_t + \\
& \beta_8^{SR} IND + \beta_9^{SR} CF_{it} + \varepsilon_{it+1}^{SR} \quad (5)
\end{aligned}$$

Where, for the firm *i* in year *t*, AR is Abnormal Stock Returns; SR is Systematic risk; ECO is Emerging Customer Orientation; BUILDCAP is MBA-Building Capability; LEVCAP is MBA-Leveraging Capability; CONTROLS is vector of firm- and industry-level covariates including the predicted value of the past period performance. YEAR and IND represent vectors of year and sub-industry dummies to control for time and industry fixed effects. Finally, CF_{it} in model 5 is a vector of control-function parameters to correct for endogeneity.

Insert Table 5 about here

Results

Descriptive Statistics and Main Effects

Table 6 provides the summary statistics and bivariate correlation matrix of the variables. Variance inflation factors are less than the critical value of 10 indicating absence of collinearity issues. Further, we estimate the main effect models (M1) and the interaction models (M2) as specified in equations 4 and 5 and report the results in panel A and B of

Table 7. As reported in M1, we do not find a significant main effect of emerging customer orientation on firm-value or systematic risk. This lends support to our assumption that emerging customer orientation alone may not influence shareholder value significantly and that its effects may be contingent on other factors such as firm's execution capability (e.g., marketing capability). Next, we find a negative main effect of MBA-leveraging capability on firm-value. This is consistent with Feng et al. (2015), although they do not find support for their prediction that MBA-leveraging capability will have negative effect on long-term firm performance.

Insert Table 6 about here

Hypotheses Tests

We test our hypotheses based on the interaction model M2 in panels A and B of Table 7 with abnormal returns and systematic risk as dependent variables, respectively.

Joint effects of Emerging Customer Orientation and marketing Capabilities on abnormal returns (H1, H2):

According to H1, the joint effect of emerging customer orientation and MBA-building capability on firm's abnormal stock returns will be positive. As is evident in M2 of Table 7, Panel A, the interaction between emerging customer orientation and MBA-building capability is positive and statistically significant ($\beta = 9.74\text{E-}06$; $t = 3.68$). Similarly, H3 posits that the joint effect of emerging customer orientation and MBA-leveraging capability on firm performance will be positive. The model estimation supports H3 as we find a significant, positive interaction between emerging customer orientation and MBA-leveraging capability ($\beta = 4.12\text{E-}06$; $t = 2.34$).

Figure 2 shows the Johnson-Neyman plot to indicate the value of MBA-building capability at which the effect of emerging customer orientation on firm performance becomes

significant. The analysis indicates that the effect of emerging customer orientation on abnormal stock returns is (a) negative and statistically significant for values of MBA-building capability below 36; (b) positive and significant for values of MBA-building capability above 59. Similarly, figure 3 indicates that the effect of emerging customer orientation on firm performance is (a) negative and marginally significant for values of MBA-leveraging capability below the value of 32; (b) positive and marginally significant for values of MBA-leveraging capability above 90. These findings indicate the conditional effects of emerging customer orientation on firm value is significant only for extreme values of MBA-leveraging capability.

 Insert Table 7 about here

Overall, these findings lend support to the notion that in order to succeed, the complementarity between firm's strategic choice to focus on emerging customer segments and the firm's capabilities to use marketing resources efficiently to build and leverage market-based assets is crucial.

 Insert Figure 2 and 3 about here

Joint effects of Emerging Customer Orientation and marketing Capabilities on Systematic Risk (H3, H4)

Results of models estimating systematic risk are presented in M1 & M2 in Table 6, Panel B. In support of H2 (see M2), we find a significant negative interaction between emerging customer orientation and MBA-building capability ($\beta = -1.25E-04$; $t = -2.25$). We present the Johnson-Neyman plots for joint effects of emerging customer orientation and MBA-building capability on firm's systematic risk in Figure 4. As can be seen in Figure 4, conditional effect of emerging customer orientation on systematic risk for values of MBA-

building capability above 58 is negative and significant. The finding lends support to our prediction that the joint effects of emerging customer orientation and MBA-building capability have risk-reducing, return-enhancing effect on shareholder value.

Insert Figure 4 about here

On the other hand, we do not find support for H4, which predicts negative joint effects of emerging customer orientation and MBA- leveraging capabilities on firm's systematic risk. The interaction between emerging customer orientation and MBA-leveraging capability is not have statistically significant ($\beta = 3.56E-05$; $t = 0.66$).

Robustness Checks

We conducted additional analyses to verify whether the findings are robust to alternate measures of firm performance (e.g., Tobin's Q and ROA), risk (total risk), and marketing capability. The following subsections describe these additional analyses and report the findings. We report the findings in Web Appendix.

Alternate measure of firm-performance: Instead of abnormal returns as a measure of firm performance, we estimate model 4 with Tobin's Q as the dependent variable. We estimate Tobin's Q as the ratio of sum of market value of equity, total debt, and preferred stock value to total book value of assets. The interaction between emerging customer orientation and MBA-building capability is significant ($\beta = 2.30E-04$, $t = 2.01$). We find that (see Appendix, Table W2, Panel A for the results) The interaction between emerging customer orientation and MBA-building capability is positive, but statistically not significant ($\beta = 1.33E-04$, $t = 1.55$). Next, we also use return on assets (ROA), an accounting-based performance measure, as a proxy for firm performance. ROA is calculated as ratio of net income to average assets of the firm in the given year. We find that the interaction between

emerging customer orientation and MBA-leveraging capability is significant ($\beta = 3.26\text{E-}05$, $t = 3.09$), but the interaction between emerging customer orientation and MBA-building capability is not ($\beta = -9.72\text{E-}06$, $t = -0.57$). See Table W2, Panel B in the Appendix for the results of these analyses.

Alternate measure of firm-risk: Our findings are robust when we use firm's total risk, calculated as square root of sum of systematic and idiosyncratic variances, instead of using systematic risk. Please note that the control function parameter effects are not significant and hence we estimate the model using total risk as the dependent variable without the fitted residuals of the endogenous variables. Therefore, the estimates are based on $N=841$ as in the case of abnormal returns model. Similar to our main findings, while the interaction between emerging customer orientation and MBA-building capability is negative and significant ($\beta = -1.41\text{E-}04$, $t = -2.81$), the interaction between emerging customer orientation and MBA-leveraging capability is not significant ($\beta = 1.30\text{E-}05$, $t = 0.77$). See Appendix, Table W2, Panel C for the results.

Overall, our findings are robust to use of alternate measures of firm performance and risk and suggest that emerging customer orientation improves shareholder value, but only when complemented with the necessary marketing capabilities to build and leverage MBAs.

General Discussion

Emerging customer orientation reflects the firm's emphasis on emerging customer segments whose needs are either overshot (i.e., low-end customers) or unmet (i.e., non-consuming market) by the existing offerings in the market (Govindarajan et al. 2011).

Previous research on emerging customer orientation has shown that it has a positive effect on firm's innovativeness (e.g., Chandy and Tellis 1998; Govindarajan et al. 2011). Emerging customer orientation requires significant investments to learn and respond to the needs of

these ignored market segments and such a strategic choice can have an impact on firm performance, and therefore on shareholder value. However, the relationship between emerging customer orientation and shareholder value is not clear.

We build on theory of market-based assets and argue that the effect of emerging customer orientation on shareholder value, measured as firm's annualized abnormal returns and systematic risk, are contingent upon the firm's capability to build and leverage MBAs. The results demonstrate that emerging customer orientation and marketing capability to efficiently build MBAs jointly increase firm-value and lower firm's systematic risk. Similarly, we find that joint effects of emerging customer orientation and marketing capability to efficiently leverage its MBAs on firm-value is also positive. However, the interaction between emerging customer orientation and MBA-leveraging capability did not significantly influence firm risk. Overall, our findings suggest that emerging customer orientation can improve shareholder value only when complemented with the necessary marketing capabilities to build and leverage market-based assets.

Theoretical Contribution

The present study contributes to marketing literature in the following three ways. First, to the best of our knowledge, the current study is the first to provide empirical evidence on the implied positive relationship between emerging customer orientation and shareholder value. Prior studies have implied that emerging customer orientation can affect shareholder value as it helps decision makers to allocate resources to closely match market evolution without overly committing to past investments (Chandy and Tellis 1998), and deemed it necessary for value creation through transformative marketing (Kumar 2018), digital customer orientation (Kopalle et al 2020), and creation of new market opportunities for the firm through innovations targeted to attract the non-consuming customer segments (Chandy and Tellis 1998; Govindarajan et al 2011; Sorescu and Spanjol 2008). Therefore, an

examination of how it affects firm performance helps in developing a deeper understanding of this critical orientation that firms must develop to succeed in the new business environment. We find that emerging customer orientation by itself does not lead to superior shareholder value and its effect on shareholder value are contingent upon the necessary marketing capabilities to build and leverage MBAs.

Second, other than playing the odds, literature on emerging customer orientation provides no guidance about how firms with higher emerging customer orientation can achieve superior performance (Christensen et al 2015). Similarly, Hopp et al. (2018) note that the link to organizational capabilities remains “strikingly absent” in the literature. The current research overcomes these limitations and provides a framework to understand how firms with emerging customer orientation can succeed.

Finally, we extend the work of Feng et al. (2015) who distinguish between two types of marketing capabilities, namely MBA building & MBA leveraging capabilities. Moorman and Day (2016) note that investigating the effects of MBA-building and leveraging capabilities presents an important avenue for research. We add to the knowledge of when and how these different marketing capabilities affect shareholder value. Further, much of prior literature on marketing capability has viewed it as an overall capability of a firm to convert marketing inputs (e.g., SG&A expenses) to desirable marketing outputs (e.g., sales). Thus, we contribute to the scant stream of literature which recognizes different types of marketing capabilities a firm may possess (e.g., Arunachalam et al. 2018; Feng et al. 2015; Voohries et al. 2009) by demonstrating that a dynamic strategic fit between marketing capabilities and strategic choices (e.g., focus on emerging customer segments) is necessary to positively influence shareholder value.

Implications

Firms are increasingly looking to appeal to emerging customer segments. For example, Macy's opened "Backstage" brand to appeal to "treasure-hunters" (Macy's 2015). However, it is not clear how marketing investments should complement such firm choices. Further, in highly competitive industries such as retail, the role of marketing departments is typically directed towards pricing, promotions, and sales (i.e., MBA-leveraging). Findings from the present study can help managers to make informed decision on how to re-align marketing activities and investments when focusing emerging customer segments.

Our findings demonstrate that developing relevant marketing capabilities along with focus on emerging customer segments is necessary. Specifically, we highlight the importance of both MBA-building and MBA-leveraging capabilities to succeed when a firm has higher emerging customer orientation. Given the average market capitalization of \$11.52 billion among our sample firms, our results indicate that a unit increase in scores of both emerging customer orientation and MBA-building capability can improve firm value by approximately \$112,000. Similarly, a joint increase in scores of emerging customer orientation and MBA-leveraging capability by one unit each can increase firm value by approximately \$47,000.

On a scale of 1 to 100, an average firm in our sample scored 15 on emerging customer orientation, 51 on MBA-building capability, and 67 on MBA-leveraging capability. Hence, there is scope and significant incentive for managers to improve on both these aspects. For example, when an average firm jointly increases its emerging customer orientation and MBA-building capability by 10 units each, it can improve its market value by more than \$11.2 million. Similarly, joint increase in emerging customer orientation and MBA-leveraging capability by 10 units can improve firm value by approximately \$4.7 million. Beyond improving firm-performance, our finding also indicates that the emerging customer orientation and MBA-building capability jointly reduce firm risk. Therefore, we conjecture

that complementarity between emerging customer orientation and marketing capabilities has risk-lowering and return-enhancing effects on shareholder value.

The findings from the present study will provide guidance to managers on how to win with emerging customer orientation and allocate necessary resources to build and leverage market-based assets. Finally, investors will benefit from our research as the findings can help them optimize their portfolio with assets that can provide higher returns at lower risk.

Limitations and future research

Our study has a few limitations which can provide avenues for future research. First, the research context is set within the U.S. retail industry. While the U.S. retail industry provides a suitable context to investigate our research question as it is arguably one of the industries facing significant risks of changing in customer landscape, a validation of our results in other industries across different countries is an important area research in the future. Specifically, in emerging economies, where several firms may inherently be more focused on catering to the low end of the market, an investigation of marketing's role in helping such firms deliver shareholder value would help advance our knowledge in this domain further. Next, we only examine the interplay between firm's emerging customer orientation and its marketing capabilities. An investigation of interactive effects of emerging customer orientation and other firm-level capabilities such as technological capability and operational capability may provide a more holistic understanding of the effects of emerging customer orientation on shareholder value. Finally, despite our best efforts to minimize measurement related issues, it is possible that the findings of the study may be driven by the operationalization of the measures due to the nature of analyses using proxy measures based on secondary data. This may be of higher concern for the newly develop measure of emerging customer orientation in this study. Although we developed the dictionary based on the theory, validated it using expert judges, and provide face validation by providing

examples of firms scoring high on this construct, future research can replicate the findings using other measurements (e.g., survey instruments developed by Govindarajan et al., 2011).

References

- Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic management journal*, 14(1), 33-46.
- Ansari, S., Garud, R., & Kumaraswamy, A. (2016). The disruptor's dilemma: TiVo and the US television ecosystem. *Strategic Management Journal*, 37(9), 1829-1853.
- Arunachalam, S., Ramaswami, S.N., Herrmann, P. and Walker, D. (2018). Innovation pathway to profitability: the role of entrepreneurial orientation and marketing capabilities. *Journal of the Academy of Marketing Science* 46(4), 744-766.
- Bhattacharya, A., Misra, S. and Sardashti, H. (2019). Strategic orientation and firm risk. *International Journal of Research in Marketing* 36(4), 509-527.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1), 57-82.
- Chandy, R. K., & Tellis, G. J. (1998). Organizing for radical product innovation: The overlooked role of willingness to cannibalize. *Journal of marketing research*, 35(4), 474-487.
- Chandy, R. K., & Tellis, G. J. (2000). The incumbent's curse? Incumbency, size, and radical product innovation. *Journal of marketing*, 64(3), 1-17.
- Chaudhuri, M., Voorhees, C. M., & Beck, J. M. (2019). The effects of loyalty program introduction and design on short-and long-term sales and gross profits. *Journal of the Academy of Marketing Science*, 47(4), 640-658.
- Christensen Clayton, M. and Raynor Michael, E. (2003). *The Innovator's Solution, Creating and Sustaining Successful Growth*. Harvard Business School Press, Boston, MA.
- Christensen, C. M., McDonald, R., Altman, E. J., & Palmer, J. E. (2018). Disruptive innovation: An intellectual history and directions for future research. *Journal of Management Studies*, 55(7), 1043-1078.
- Christensen, C.M. (1997). *The Innovator's Dilemma*. Harvard Business School Press. Boston, MA.
- Christensen, C.M. (2006). The ongoing process of building a theory of disruption. *Journal of Product Innovation Management* 23(1), 39-55.
- Christensen, C.M. and Tedlow, R.S. (2000). Patterns of disruption in retailing. *Harvard Business Review* 78(1), 42-42.
- Christensen, C.M., Anthony, S.D. and Roth, E.A. (2004). *Seeing what's next: Using the theories of innovation to predict industry change*: Harvard Business Press.
- Christensen, C.M., Raynor, M.E. and McDonald, R. (2015). What is disruptive innovation. *Harvard Business Review* 93(12), 44-53.
- Danneels, E. (2004). Disruptive technology reconsidered: A critique and research agenda. *Journal of Product Innovation Management* 21(4), 246-258.
- Ebbes, P., Papies, D., & van Heerde, H. J. (2016). Dealing with endogeneity: A nontechnical guide for marketing researchers. *Handbook of market research*.
- Feng, H., Morgan, N.A. and Rego, L.L. (2015). Marketing department power and firm performance. *Journal of marketing* 79(5), 1-20.
- Frieder, L., & Subrahmanyam, A. (2005). Brand perceptions and the market for common stock. *Journal of financial and Quantitative Analysis*, 57-85.
- Govindarajan, V. and Kopalle, P.K. (2006). The usefulness of measuring disruptiveness of innovations ex post in making ex ante predictions. *Journal of Product Innovation Management* 23(1), 12-18.
- Govindarajan, V., Kopalle, P.K. and Danneels, E. (2011). The effects of mainstream and emerging customer orientations on radical and disruptive innovations. *Journal of Product Innovation Management* 28(s1), 121-132.
- Grewal, D., Roggeveen, A.L. and Nordfält, J. (2017). The Future of Retailing. *Journal of Retailing* 93(1), 1-6.
- Grullon, G., Kanatas, G., & Weston, J. P. (2004). Advertising, breadth of ownership, and liquidity. *The Review of Financial Studies*, 17(2), 439-461.
- Hopp, C., Antons, D., Kaminski, J. and Oliver Salge, T. (2018). Disruptive innovation: Conceptual foundations, empirical evidence, and research opportunities in the digital age. *Journal of Product Innovation Management* 35(3), 446-457.
- Hunt, S. D., & Morgan, R. M. (1995). The comparative advantage theory of competition. *Journal of marketing*, 59(2), 1-15.
- Kahn, B.E. (2018). *The shopping revolution: how successful retailers win customers in an era of endless disruption*: Wharton School Press.

Kaufman, P., Jayachandran, S., & Rose, R. L. (2006). The role of relational embeddedness in retail buyers' selection of new products. *Journal of Marketing Research*, 43(4), 580-587.

Kumar, V. (2018). Transformative Marketing: The Next 20 Years. *Journal of Marketing*, 82(4), 1-12.

Kopalle, P. K., Kumar, V., & Subramaniam, M. (2020). How legacy firms can embrace the digital ecosystem via digital customer orientation. *Journal of the Academy of Marketing Science*, 48(1), 114-131.

Macy's. (2015). It's Showtime for Macy's Backstage. Retrieved from <https://www.macysinc.com/investors/news-events/press-releases/detail/594/its-showtime-for-macys-backstage>

McAlister, L., Srinivasan, R., & Kim, M. (2007). Advertising, research and development, and systematic risk of the firm. *Journal of Marketing*, 71(1), 35-48.

Miller, K. D., & Bromiley, P. (1990). Strategic risk and corporate performance: An analysis of alternative risk measures. *Academy of Management journal*, 33(4), 756-779.

Moorman, C., & Day, G. S. (2016). Organizing for marketing excellence. *Journal of Marketing*, 80(6), 6-35.

Moreau, C.P. (2020). Brand Building on the Doorstep: The Importance of the First (Physical) Impression. *Journal of Retailing*.

Morgan, N. A., Slotegraaf, R. J., & Vorhies, D. W. (2009). Linking marketing capabilities with profit growth. *International Journal of Research in Marketing*, 26(4), 284-293.

Nath, P., & Mahajan, V. (2011). Marketing in the C-suite: a study of chief marketing officer power in firms' top management teams. *Journal of Marketing*, 75(1), 60-77.

Pauwels, K., Silva-Risso, J., Srinivasan, S. and Hanssens, D.M. (2004). New products, sales promotions, and firm value: The case of the automobile industry. *Journal of marketing* 68(4), 142-156.

Popping, R. (2000). Computer-assisted text analysis: Sage.

Ramaswami, S. N., Srivastava, R. K., & Bhargava, M. (2009). Market-based capabilities and financial performance of firms: insights into marketing's contribution to firm value. *Journal of the Academy of Marketing Science*, 37(2), 97.

Saboo, A. R., Kumar, V., & Anand, A. (2017). Assessing the impact of customer concentration on initial public offering and balance sheet-Based outcomes. *Journal of Marketing*, 81(6), 42-61.

Saboo, A.R. and Grewal, R. (2013). Stock market reactions to customer and competitor orientations: the case of initial public offerings. *Marketing Science* 32(1), 70-88.

Schmidt, G.M. and Druehl, C.T. (2008). When is a disruptive innovation disruptive? *Journal of Product Innovation Management* 25(4), 347-369.

Sinha, A., Sahgal, A., & Mathur, S. K. (2013). Practice prize paper—category optimizer: A dynamic-assortment, new-product-introduction, mix-optimization, and demand-planning system. *Marketing Science*, 32(2), 221-228.

Slater, S. F., & Narver, J. C. (1998). Customer-led and market-oriented: let's not confuse the two. *Strategic management journal*, 19(10), 1001-1006.

Sood, A. and Tellis, G.J. (2005). Technological evolution and radical innovation. *Journal of marketing* 69(3), 152-168.

Sood, A. and Tellis, G.J. (2011). Demystifying disruption: A new model for understanding and predicting disruptive technologies. *Marketing Science* 30(2), 339-354.

Sorescu, A. B., & Spanjol, J. (2008). Innovation's effect on firm value and risk: Insights from consumer packaged goods. *Journal of Marketing*, 72(2), 114-132.

Srinivasan, S. and Hanssens, D.M. (2009). Marketing and firm value: Metrics, methods, findings, and future directions. *Journal of Marketing Research* 46(3), 293-312.

Srivastava, R.K. and Reibstein, D.J. (2005). Metrics for linking marketing to financial performance.

Srivastava, R. K., Fahey, L., & Christensen, H. K. (2001). The resource-based view and marketing: The role of market-based assets in gaining competitive advantage. *Journal of management*, 27(6), 777-802.

Srivastava, R.K., Shervani, T.A. and Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of marketing* 62(1), 2-18.

Tellis, G. J. (2006). Disruptive technology or visionary leadership?. *Journal of Product Innovation Management*, 23(1), 34-38.

Tellis, G. J., Prabhu, J. C., & Chandy, R. K. (2009). Radical innovation across nations: The preeminence of corporate culture. *Journal of marketing*, 73(1), 3-23.

Verhoef, P.C., Kannan, P.K. and Inman, J.J. (2015). From multi-channel retailing to omni-channel retailing: introduction to the special issue on multi-channel retailing. *Journal of Retailing* 91(2), 174-181.

Vorhies, D. W., Morgan, R. E., & Autry, C. W. (2009). Product-market strategy and the marketing capabilities of the firm: impact on market effectiveness and cash flow performance. *Strategic Management Journal*, 30(12), 1310-1334.

Lists of Tables and Figures

Table 1.
Similarities and Differences between Emerging Customer Orientation (ECO), Customer Orientation (CO), and Future-Market-Focus (FMF).

Focus on	ECO	CO	FMF
Needs of emerging customer segments	✓	✗	✓
Willingness to Cannibalize?	✓	✗	✓
Current needs of existing customers	✗	✓	✗
Latent needs of existing customers	✗	✓	✓
Current competitor focus	✗	✗	✗
Future competitor focus	✗	✗	✓

Table 2.

Representative studies in marketing and innovation literature on Emerging Customer Orientation (ECO) and related constructs.

Study	ECO related construct used in the study	Definition	Research Type / Data Source	Moderators	Findings	Effect on Shareholder Value
Chandy and Tellis (1998)	Future-market focus (FMF)	Degree to which a firm emphasizes on needs of emerging customer segments, latent needs of existing customers, and future competitors in its innovation and marketing strategies	Empirical / Survey data	-	FMF positively influences willingness to cannibalize (WTC) existing products & markets and radical innovations	Implied but not tested
Tellis, Prabhu, and Chandy (2009)	FMF	Same as Chandy and Tellis (1998)	Empirical / Survey & Archival data	-	FMF and WTC positively influence radical innovations	Implied but not tested
Govindarajan et al (2011)	ECO	Degree to which a firm emphasizes on needs of emerging customer segments in its innovation and marketing strategies	Empirical / Survey data	-	ECO positively correlated with WTC, disruptive, and radical innovations.	Implied but not tested
Kumar (2018)	Transformative marketing	Marketing response to marketplace changes and future trends* to leapfrog customers with superior value offerings and benefits all stakeholders	Conceptual / No data	Implies potential catalytic role of marketing capabilities	-	Implied but not tested

Table 2. Continued.						
Study	ECO related construct used in the study	Definition	Research Type / Data Source	Moderators	Findings	Effect on Shareholder Value
Kopalle, Kumar, and Subramaniam (2020)	Digital Customer Orientation (DCO)	ECO specific to identification and pursuit of unmet needs of digital-native customers by embracing digital eco-systems. †	Conceptual [£]	-	-	Implied but not tested
Present Study	ECO	Same as Govindarajan et al. (2011)	Empirical / Secondary data	Marketing Capabilities	Effect of ECO on firm value is contingent on marketing capabilities	Tested with supporting evidence

* marketplace changes & future trends requires an emerging customer orientation to identify changes in customer preferences;

† Authors note that DCO and ECO are similar in spirit; £ Authors pre-test using survey data and use ECO as a proxy for DCO

Table 3.
Summary of measures, literature sources, and data sources.

Variable	Sample of previous studies	Data sources	Operationalization
Dependent Variables			
Abnormal Stock Returns (AR)	Bharadwaj, Tuli, and Bonfrer (2011); Frennea, Han, and Mittal (2019)	CRSP, Kenneth French website	Annualized monthly excess stock returns
Systematic Risk (SR)	Bharadwaj et al. (2011); McAlister, Srinivasan, and Kim (2007)	CRSP, Kenneth French website	Beta: coefficient of the market returns factor in the four-factor model
Emerging Customer Orientation (ECO)	Govindarajan et al. (2011) used survey measure	10-K filings from SEC Edgar	Scores obtained from frequencies of matching words & phrases calculated using computer-aided text analysis
MBA-building Capability (BUILDCAP)	Feng, Morgan, and Rego (2015)	COMPUSTAT, USPTO	Efficiency scores computed using SFE in converting marketing inputs to MBAs.
MBA-leveraging Capability (LEVCAP)	Feng et al. (2015)	COMPUSTAT, USPTO	Efficiency scores computed using SFE in converting marketing inputs and MBAs into cash-flow.

Table 4.
Summary of Control Variables

Variable	Data sources	Operationalization
Firm Size (SIZE)	COMPUSTAT	Logged value of firm's total assets
Capital Intensity (CAPINT)	COMPUSTAT	Ratio of firm's property, plant, & equipment expenses to total assets
Firm Age (AGE)	COMPUSTAT	Number of years since IPO
Firm Sales Growth (SGR)	COMPUSTAT	Change in YoY sales relative to previous year sales
Firm Leverage (FIN LEV)	COMPUSTAT	Ratio of long-term debt to total assets
Firm Liquidity (LQD)	COMPUSTAT	Ratio of working capital to total assets
Firm Profits (PROFITS)	COMPUSTAT	Ratio of net income to sales
Dividend (DIV)	COMPUSTAT	Dividend paid in \$
Non-store-based operator (NONSTORE)	COMPUSTAT	Dummy variable to indicate whether the firm is non-store-based operator – i.e., if the firm belongs to SIC = 5961 (catalogue and mail-order house), 5962 (automatic merchandising machine operator), or 5963 (direct selling establishment).
Competitive Intensity (HHI)	COMPUSTAT	Sum of square of market share
Industry Sales Growth (indSGR)	COMPUSTAT	% of Year on Year industry-level sales growth

Table 5.

Sample words and phrases shortlisted in the final dictionary used to measure Emerging Customer Orientation using text analysis.

Emerging Customer Segment Type	Segment Description	Dictionary Phrases
Low-end	Price-sensitive, lower tier customers of an established market who are willing to trade-off full-service or other complex functionalities for a more affordable and simple product/ service.	<i>low price, budget price, affordable to customer, everyday low price, simple product, save money, basic product, essentials, generics</i>
New-market	Non-consumers of mainstream offerings due to dramatically different needs compared to the mainstream segment.	<i>new market, new value, new benefits, emerging segment, emerging needs, evolving needs, change customer behavior, niche market, novel product, pioneer, one and only, unlike any other, open source</i>

Table 6.
Summary Statistics & Correlation Matrix

Summary Statistics			Correlation Matrix															
Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
AR	0.001	0.026	1.000															
SR	0.954	0.490	-0.105*	1.000														
ECO	15.716	17.266	-0.045	-0.046	1.000													
BUILDCAP	51.268	19.389	0.002	0.079*	0.007	1.000												
LEVCAP	70.937	25.385	-0.042	0.019	-0.008	-0.162*	1.000											
SIZE	8508.480	25268.440	0.007	-0.033	0.150*	0.049	0.065*	1.000										
CAPINT	0.707	0.351	-0.025	0.049	0.0764*	0.1563*	0.239*	-0.048	1.000									
AGE	15.584	5.577	-0.071*	0.024	0.013	-0.096*	0.456*	0.096*	0.228*	1.000								
SGR	0.039	0.122	0.103*	-0.028	0.088*	0.262*	-0.213*	0.087*	-0.247*	-0.155*	1.000							
FIN LEV	0.134	0.158	-0.007	0.007	0.168*	-0.127*	0.035	0.196*	0.008	0.034	0.003	1.000						
LQD	0.239	0.181	0.016	-0.014	-0.237*	0.021	0.037	-0.340*	-0.287*	-0.032	-0.073*	-0.233*	1.000					
PROFITS	0.015	0.059	0.139*	0.076*	0.026	0.316*	-0.076*	0.077*	-0.086*	0.058	0.302*	-0.071*	0.210*	1.000				
DIV	158.368	655.543	0.000	-0.056	0.110*	0.062	0.068*	0.864*	0.049	0.099*	0.006	0.107*	-0.252*	0.080*	1.000			
NONSTORI	0.161	0.368	0.013	-0.041	-0.080*	0.106*	-0.120*	-0.049	-0.299*	-0.216*	0.105*	-0.099*	0.012	-0.156*	-0.101*	1.000		
HHI	0.242	0.147	-0.059	-0.040	0.250*	-0.022	-0.019	0.124*	0.145*	0.004	-0.005	0.290*	-0.272*	0.025	0.126*	-0.228*	1.000	
INDSGR	0.043	0.048	0.043	-0.082*	-0.039	-0.084*	-0.012	-0.002	-0.284*	-0.105*	0.080*	-0.071*	0.091*	-0.053	-0.059	0.384*	-0.453*	1.000

N=919; * indicates $p < .05$

Table 7.

The Joint-effects of Emerging Customer Orientation and Marketing Capabilities on Firm Shareholder Value

Panel A: Effects on AR(it+1)				
	M1		M2	
	Coef.	SE	Coef.	SE
Intercept	-1.59E-02	1.03E-02	-4.36E-03	1.12E-02
ECO (Emerging Customer Orientation)	4.73E-05	5.26E-05	-7.73E-04***	1.96E-04
BUILDCAP (Marketing Capability to Build MBAs)	3.98E-05	5.80E-05	-8.32E-05	7.33E-05
LEVCAP (Marketing Capability to Leverage MBAs)	-1.05E-04**	4.53E-05	-1.61E-04	5.95E-05
H1:				
ECO x BUILDCAP			9.74E-06***	2.65E-06
H2:				
ECO x LEVCAP			4.12E-06**	1.76E-06
AR_HAT (Predicted Abnormal Returns)	4.49E-01	9.73E-01	4.31E-01	9.68E-01
SIZE (Firm Size)	2.21E-08	5.30E-08	3.93E-08	5.44E-08
CAPINT (Capital Intensity)	9.05E-06	4.48E-03	-1.20E-03	4.52E-03
PROF (Profits)	3.78E-02	3.28E-02	3.98E-02	3.18E-02
DIV (Dividends Paid)	3.36E-07	1.62E-06	-6.35E-07	1.69E-06
AGE (Firm Age)	2.94E-04	2.18E-04	2.72E-04	2.14E-04
SGR (Firm Sales Growth)	-4.08E-03	8.57E-03	-4.05E-03	8.42E-03
LEV (Financial Leverage)	6.27E-03	7.03E-03	6.80E-03	6.97E-03
LQD (Liquidity)	2.55E-03	6.44E-03	1.20E-03	6.62E-03
indSGR (Industry Sales Growth)	2.18E-02	3.16E-02	2.26E-02	3.16E-02
HHI (Industry Competitive Index)	2.94E-02	2.13E-02	3.16E-02	2.04E-02
NOSTORE (Dummy for firms with no physical stores)	-1.45E-03	3.68E-03	-1.24E-03	3.68E-03
Year (Dummies)		✓		✓
Sub-Industries (Dummies)		✓		✓
R ² (N=841)		0.051		0.063

*p<.1; **p<.05; ***p<.01;

Panel B: Effects on SR (it+1)					
	M1		M2		
	Coef.	SE	Coef.	SE	
Intercept	-1.62E+01	1.13E+01	-1.70E+01	1.13E+01	
ECO	-4.02E-04	8.98E-04	2.69E-03	4.42E-03	
BUILDCAP	2.23E-03	1.44E-03	3.72E-03**	1.51E-03	
LEVCAP	-1.32E-03	1.29E-03	-2.06E-03	1.60E-03	
H3:					
ECO x BUILDCAP			-1.14E-04**	5.67E-05	
H4:					
ECO x LEVCAP			3.68E-05	3.96E-05	
SR_HAT	1.92E+01	1.27E+01	2.01E+01	1.27E+01	
SIZE	3.81E-09	1.02E-06	-1.55E-07	1.00E-06	
CAPINT	3.22E-02	7.96E-02	3.82E-02	8.08E-02	
PROF	7.51E-01	5.33E-01	7.26E-01	5.35E-01	
DIV	-4.95E-05	3.08E-05	-4.41E-05	3.04E-05	
AGE	5.88E-03	5.20E-03	5.74E-03	5.16E-03	
SGR	1.34E-01	1.48E-01	1.25E-01	1.51E-01	
LEV	3.97E-01**	1.54E-01	3.96E-01**	1.53E-01	
LQD	-1.62E-01	1.58E-01	-1.59E-01	1.56E-01	
indSGR	-8.82E-01*	5.22E-01	-8.90E-01*	5.22E-01	
HHI	-3.44E-01**	1.73E-01	-3.40E-01*	1.73E-01	
NOSTORE	-2.75E-02	7.19E-02	-2.81E-02	7.23E-02	
Year (Dummies)		✓		✓	
Sub-Industries (Dummies)		✓		✓	
Control Function Parameters		✓		✓	
<i>N=818, Bootstrap replications=1000</i>					
Wald χ^2		99.06		103.4	
*p<.1; **p<.05; ***p<.01;					

Figure1.
Conceptual Framework.

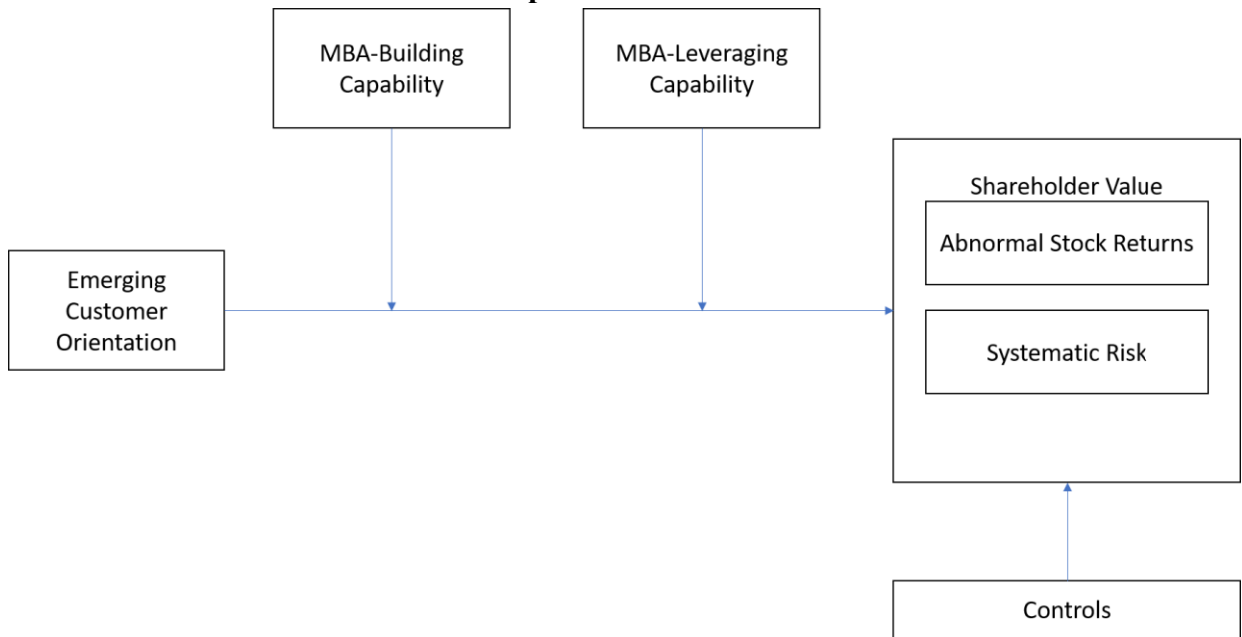


Figure 2.
Interactive effects of ECO and MBA-building capability on AR

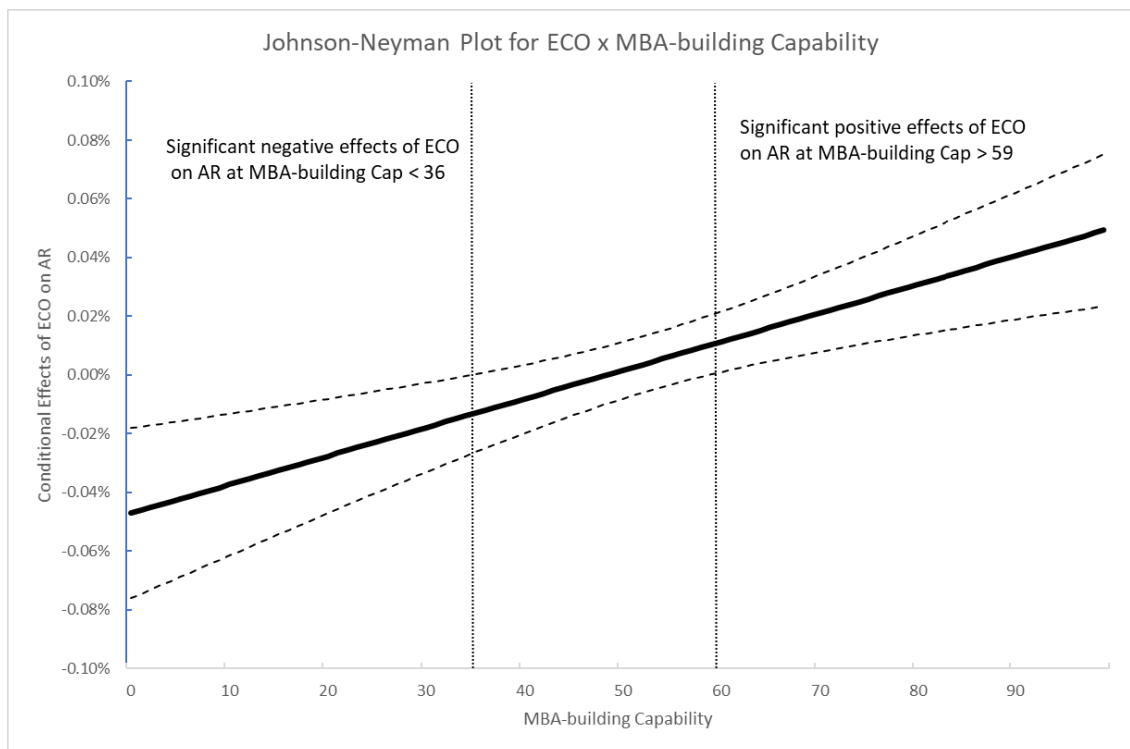


Figure 3.
Interactive effects of ECO and MBA-leveraging capability on AR

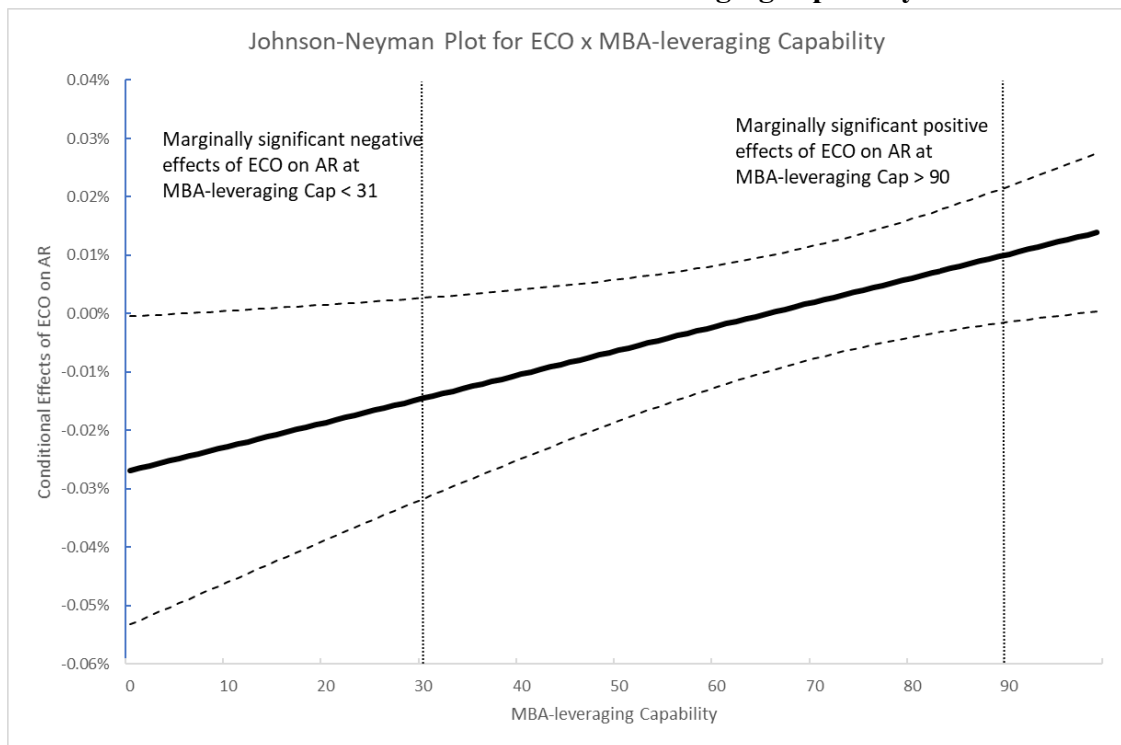
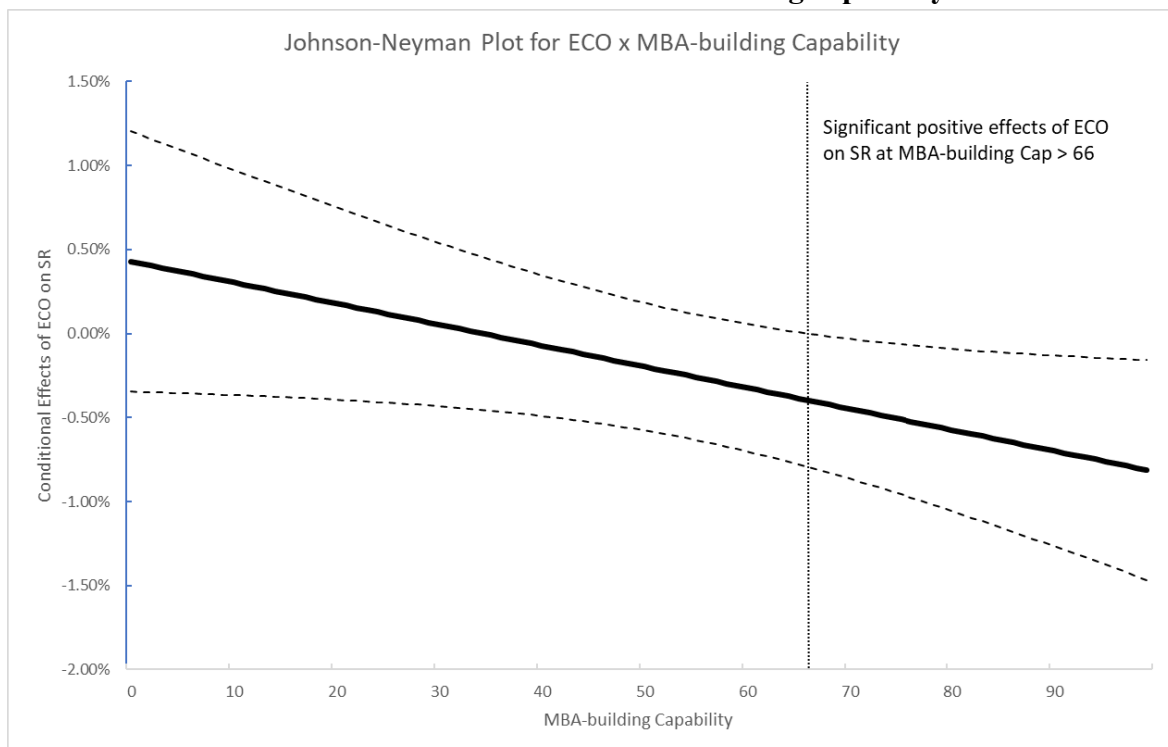


Figure 4.
Interactive effects of ECO and MBA-building capability on SR



Appendix

Table W1

Top 15 Companies Ranked on Emerging Customer Orientation Scores (2017 and 2018)

2017		2018	
Rank	Company	Rank	Company
1	Kroger Co. (The)	1	Weis Markets Inc.
2	Weis Markets Inc.	2	Kroger Co. (The)
3	TJX Companies Inc (The)	3	TJX Companies Inc (The)
4	J.C. Penney Company Inc.	4	Village Super Market Inc
5	Ascena Retail Group Inc	5	J.C. Penney Company Inc.
6	Smart & Final Stores Inc	6	Tile Shop Holdings Inc
7	Village Super Market Inc	7	Smart & Final Stores Inc
8	Tile Shop Holdings Inc	8	CVS Health Corp
9	CVS Health Corp	9	Abercrombie & Fitch Co.
10	Abercrombie & Fitch Co.	10	Ascena Retail Group Inc
11	RTW Retailwinds Inc	11	Dollar Tree Inc
12	Ross Stores Inc	12	Stage Stores Inc
13	Walmart Inc	13	Ross Stores Inc
14	Shoe Carnival Inc	14	RTW Retailwinds Inc
15	Fred's Inc	15	Shoe Carnival Inc

Table W2. The Joint effects of Emerging Customer Orientation and Marketing Capabilities on Firm Shareholder Value

Panel A: Effects on Tobin's Q (it+1)				
	M1		M2	
	Coef.	SE	Coef.	SE
Intercept	-1.24E+00**	5.07E-01	-9.53E-01[†]	5.33E-01
ECO	6.59E-04	2.23E-03	-2.08E-02***	7.60E-03
BUILDCAP	3.55E-02***	2.76E-03	3.29E-02***	2.74E-03
LEVCAP	-2.74E-03	2.32E-03	-4.70E-03[†]	2.49E-03
H1:				
ECO x BUILDCAP			2.29E-04**	1.14E-04
H2:				
ECO x LEVCAP			1.33E-04	8.59E-05
SIZE	-1.71E-01	1.91E-01	-3.55E-08	7.08E-06
CAPINT	2.79E-07	6.91E-06	-1.98E-01	1.94E-01
PROF	1.86E+00***	6.67E-01	1.86E+00***	6.51E-01
DIV	1.10E-04	1.69E-04	1.05E-04	1.74E-04
AGE	1.34E-03	1.14E-02	8.30E-04	1.16E-02
SGR	8.71E-01**	3.70E-01	9.01E-01**	3.59E-01
LEV	-2.50E-01	3.27E-01	-2.17E-01	3.24E-01
LQD	-5.36E-01	3.71E-01	-5.75E-01	3.75E-01
indSGR	1.26E+00	8.59E-01	1.25E+00	8.55E-01
HHI	2.31E-01	3.10E-01	2.25E-01	3.01E-01
NOSTORE	2.85E-02	1.76E-01	2.06E-02	1.76E-01
Q_HAT	6.38E-01**	2.91E-01	6.61E-01**	2.94E-01
Year (Dummies)		✓		✓
R2 (N=782)		0.596		0.604
*p<.1; **p<.05; ***p<.01;				

Table W2. Panel B: Effects on ROA (it+1)				
	M1		M2	
	Coef.	SE	Coef.	SE
Intercept	-9.64E-02***	3.10E-02	-5.89E-02	3.86E-02
ECO	5.62E-04**	2.33E-04	-1.37E-03	1.14E-03
BUILDCAP	1.32E-03***	3.78E-04	1.46E-03***	3.93E-04
LEVCAP	-3.67E-04	2.56E-04	-9.00E-04***	3.28E-04
H3:				
ECO x BUILDCAP			-9.72E-06	1.72E-05
H4:				
ECO x LEVCAP			3.26E-05***	1.06E-05
SR_HAT	5.01E-02	9.93E-02	4.69E-02	9.86E-02
SIZE	3.67E-08	2.05E-07	-4.43E-08	2.02E-07
CAPINT	5.99E-03	1.58E-02	4.17E-03	1.47E-02
PROF	8.91E-01***	2.02E-01	9.13E-01***	1.92E-01
DIV	8.38E-06	6.46E-06	9.69E-06	6.46E-06
AGE	3.12E-03***	1.02E-03	2.90E-03***	9.56E-04
SGR	6.09E-02	3.77E-02	6.06E-02	3.69E-02
LEV	6.27E-03	2.50E-02	9.12E-03	2.36E-02
LQD	7.72E-02**	3.21E-02	7.37E-02**	3.18E-02
indSGR	1.01E-01	7.62E-02	9.29E-02	7.68E-02
HHI	7.42E-02**	3.03E-02	7.61E-02**	3.01E-02
NOSTORE	-2.72E-02	2.09E-02	-2.62E-02	1.99E-02
Year (Dummies)	✓		✓	
R2 (N=776)	0.452		0.464	
*p<.1; **p<.05; ***p<.01; Note: Year-specific dummies are included in both M1 and M2.				

Table W2. Panel C: Effects on Total Risk (it+1)				
	M1		M2	
	Coef.	SE	Coef.	SE
Intercept	9.23E-01***	1.43E-01	8.46E-01***	1.64E-01
ECO	-5.29E-04	7.98E-04	6.36E-03	3.68E-03
BUILDCAP	1.87E-03	1.21E-03	3.66E-03	1.38E-03
LEVCAP	-8.54E-04	1.08E-03	-1.07E-03	1.36E-03
H3:				
ECO x BUILDCAP			-1.39E-04***	4.96E-05
H4:				
ECO x LEVCAP			4.05E-06	3.35E-05
TR_HAT	-1.55E-02	7.19E-02	-1.87E-02	7.20E-02
SIZE	1.04E-07	1.02E-06	-6.66E-08	9.86E-07
CAPINT	1.79E-02	6.81E-02	2.71E-02	6.96E-02
PROF	-1.09E-01	3.50E-01	-1.35E-01	3.49E-01
DIV	-4.84E-05	3.11E-05	-4.06E-05	3.03E-05
AGE	5.82E-03	4.68E-03	5.87E-03	4.65E-03
SGR	4.07E-02	1.38E-01	3.07E-02	1.40E-01
LEV	2.42E-01**	1.23E-01	2.38E-01**	1.21E-01
LQD	-5.44E-02	1.33E-01	-4.57E-02	1.31E-01
indSGR	-5.49E-01	4.61E-01	-5.51E-01	4.62E-01
HHI	-2.76E-01*	1.55E-01	-2.78E-01*	1.56E-01
NOSTORE	-9.60E-03	6.37E-02	-1.01E-02	6.45E-02
Year (Dummies)	✓		✓	
R2 (N=841)	0.076		0.083	
*p<.1; **p<.05; ***p<.01; Note: Year-specific dummies are included in both M1 and M2.				

This page has been left blank on purpose.

Thesis Conclusion

The present doctoral thesis, over the passage of two essays, is aimed at exploring the strategic value implications of transformative marketing. According to Kumar (2018), we are primed for the era of transformative marketing which could last over the next two decades. Through transformative marketing, firms have the potential to create and sustain value for all parties involved by keeping customers at the centre of the organization and therefore significantly strengthen their interactions with all stakeholders. As defined previously in the preface section, transformative marketing is a firm's response to one of the seven identified forces demanding a transformation in its marketing strategies – i.e., technology, customer preferences, environmental resources, economic forces, competitive forces, and government regulations (Kumar 2018). Naturally, the firm's response outcome to these forces is in the form of innovations to uncover growth opportunities and / or improve efficiencies and effectiveness by unlocking the full potential of its assets and resources.

Accordingly, the central theme of our exploration of strategic value of transformative marketing involves uncovering the impact of innovations in response to (1) emerging technologies and (2) emerging customer segments. As we are concerned with strategic value implications of transformative marketing, we study the impact on firm value which have significant implications for shareholders – arguably one of the key stakeholders of a firm. Specifically, in the first essay we study the investor response to emerging technology adoption or ETA, which we define as new product innovations where the application and originating domains of the emerging technology being adopted are different. Further, in the second essay, we investigate when and how emerging customer orientation – i.e., the degree to which a firm is focused on the needs of emerging customer segments (Govindarajan et al. 2011), affects shareholder value.

Findings from our investigations imply that shareholder value creation from transformative marketing, specifically from innovations in response to emerging technologies and emerging customer segments, is contingent upon the marketing department's ability to attract and allocate the necessary resources. For example, in the first essay, we find that investor response to emerging technology adoption is positive only when the adopting firm has a powerful marketing department. Further, the positive effect of marketing department power on investor response is positively moderated by the fit between resources and competences managed by the marketing department and those required by the different innovation characteristics such as stage of the innovation (i.e., *initiation*, *development*, and *commercialization*), route to innovation (i.e., *make*, *ally*, or *buy*), and level of adoption (i.e., *platform-level* Vs *component-level adoption*).

The first essay makes the following three contributions to innovation and marketing literature. First, we extend new product innovation literature by developing a comprehensive framework to analyze investor response to ETA. To the best of our knowledge, no previous study has investigated the strategic value implications of ETA. Confirming our assumption that impact of ETA and the mechanisms through which it affects firm value may be different, in contrast to extant literature on RBI which finds a positive stock market response to RBI announcement (e.g., Chandy et al. 2006; Sood and Tellis 2009; Sorescu, Chandy, and Prabhu 2003), we find that investor response to ETA announcements is not significantly different from zero. This finding further provides us with the impetus to examine the drivers of investor response to ETAs.

Second, we extend the scant literature on the effects of marketing department power on firm outcomes (Feng, Morgan, and Rego 2015; Srinivasan and Ramani 2019) by uncovering an additional mechanism through which powerful marketing departments can boost firm value – by acting as a confidence-boosting firm-level characteristic for investors to

assess the firm's prospects through expensive and risky ETAs. The role of TMT, and particularly that of marketing department, in investor's assessment of future firm performance from innovation initiatives is unexplored in the prior literature although recent studies suggest that marketing department plays an important role in innovation outcomes (e.g., Stock and Reiferscheid 2014; Kashmiri, Nicol, and Arora 2017; Arunachalam et al 2018). Our study addresses this critical gap in the literature and demonstrate that investors rely on firm's marketing department power to update their beliefs about a firm's prospects from its new product innovation.

Finally, we extend the literature exploring the effects of innovation characteristics on firm value (e.g., Borah and Tellis 2014; Sood and Tellis 2009; Sawhney 1998). We demonstrate that the fit between innovation characteristics (i.e., innovation stage, route to innovation, and adoption level) and the firm indicator of interest (i.e., marketing department power) can positively affect investor response to the signal.

Similarly, in the second essay, we find the emerging customer orientation creates shareholder value only when the firm possesses the required marketing capabilities to build and leverage marketing-based assets. This essay contributes to both marketing and innovation literature by (1) providing a framework to understand how firms with emerging customer orientation can succeed, (2) extending knowledge on MBA-building and MBA-leveraging capabilities (Feng et al. 2015; Srivastava et al 1998), and (3) providing empirical evidence that the implied positive relationship between emerging customer orientation and shareholder value is more nuanced than previously thought as it is contingent on the firm's marketing capabilities.

These findings have significant implications for managers and make several key contributions to the literature on transformative marketing. While the specific theoretical contributions and managerial implications are discussed in the specific essays, at a broader

level, to the best of our knowledge, this thesis is the first to explore the strategic value implications of transformative marketing. While Kumar's (2018) editorial paper provides an overarching framework to study transformative marketing, no prior studies have investigated the effect of innovations in response to the specific forces behind transformative marketing on shareholder value. Overall, our findings call for stronger emphasis on the marketing department's power and capabilities to attract and allocate the necessary resources and assets when embarking on transformative marketing initiatives, and we hope that our investigation into strategic value implications of transformative marketing in this doctoral thesis will lay the foundation for future research in this area.

References

- Arunachalam, S., Ramaswami, S.N., Herrmann, P. and Walker, D. (2018). Innovation pathway to profitability: the role of entrepreneurial orientation and marketing capabilities. *Journal of the Academy of Marketing Science* 46(4), 744-766.
- Borah, A., & Tellis, G. J. (2014). Make, buy, or ally? Choice of and payoff from announcements of alternate strategies for innovations. *Marketing Science*, 33(1), 114-133.
- Chandy, R., Hopstaken, B., Narasimhan, O., & Prabhu, J. (2006). From invention to innovation: Conversion ability in product development. *Journal of Marketing Research*, 43(3), 494-508.
- Feng, H., Morgan, N. A., & Rego, L. L. (2015). Marketing department power and firm performance. *Journal of Marketing*, 79(5), 1-20.
- Govindarajan, V., Kopalle, P. K., & Danneels, E. (2011). The effects of mainstream and emerging customer orientations on radical and disruptive innovations. *Journal of Product Innovation Management*, 28(s1), 121-132.
- Kashmiri, S., Nicol, C. D., & Arora, S. (2017). Me, myself, and I: influence of CEO narcissism on firms' innovation strategy and the likelihood of product-harm crises. *Journal of the Academy of Marketing Science*, 45(5), 633-656.
- Kumar, V. (2018). Transformative Marketing: The Next 20 Years. *Journal of Marketing*, 82(4), 1-12.
- Sawhney, M. S. (1998). Leveraged high-variety strategies: From portfolio thinking to platform thinking. *Journal of the academy of marketing Science*, 26(1), 54-61.
- Sood, A., & Tellis, G. J. (2009). Do innovations really pay off? Total stock market returns to innovation. *Marketing Science*, 28(3), 442-456.
- Sorescu, A. B., & Spanjol, J. (2008). Innovation's effect on firm value and risk: Insights from consumer packaged goods. *Journal of Marketing*, 72(2), 114-132.
- Srinivasan, R., & Ramani, N. (2019). With power comes responsibility: How powerful marketing departments can help prevent myopic management. *Journal of Marketing*, 83(3), 108-125.
- Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of marketing*, 62(1), 2-18.
- Stock, R. M., & Reiferscheid, I. (2014). Who should be in power to encourage product program innovativeness, R&D or marketing?. *Journal of the Academy of Marketing Science*, 42(3), 264-276.