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BIG DATA RESOURCES, MARKETING CAPABILITIES, AND FIRM PERFORMANCE: THE MODERATING EFFECT OF CHOICE OF BUSINESS STRATEGY

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BIG DATA RESOURCES, MARKETING CAPABILITIES, AND FIRM PERFORMANCE: THE MODERATING EFFECT OF CHOICE OF BUSINESS STRATEGY

If the resources that a firm possesses and exploits are critical in competitive settings, then what is being referred to as "big data" is surely one of the most important resources to be held up for scrutiny in decades. No doubt big data resources include the ability to collect, sanitize, standardize, and analyze these data, but they also include the ability to utilize them in an effective manner and ahead of rivals. Studies to date suggest that in spite of universal acknowledgement that these resources could be critical in a variety of mission-critical firm activities, they are currently under-deployed. Why is this the case? We argue that, because of the lack of prior, definitive theoretical/empirical studies, managers do not realize that the management of big data has a major influence on marketing capabilities and subsequently on firm performance. Using the resource-based view of the firm (RBV) as our primary theory base, we go on to theorize that business strategy (low cost or differentiating) has a moderating impact on these mainstream effects. Our approach was to find empirical evidence for this mediated-moderated relationship via a field study of 301 large firms across a wide variety of industries, capturing our constructs through previously-developed and new instrumentation. Findings are generally supportive of our contentions, although the results of some moderation are counter-intuitive. A discussion of the value of this work for theory building and for IT managers, marketing managers, and general managers concludes the paper.

Keywords: big data resources; data analytics; non-relational databases; data warehousing; resource-based view of the firm (RBV); marketing capabilities; field study; low cost leadership and differentiation business strategies; firm performance; complementarities

BIG DATA RESOURCES, MARKETING CAPABILITIES, AND FIRM PERFORMANCE: THE MODERATING EFFECT OF CHOICE OF BUSINESS STRATEGY

"Big data" refers to techniques, technologies, systems, practices, methodologies, and applications related to the acquisition, storage, integration, analysis, and deployment of massive amounts of diverse data to support business decision-making (Chen et al. 2012, Jelinek and Bergey 2013; McAfee and Brynjolfsson 2012). Big data is touted as the next best thing to provide competitive advantage for firms, and even for whole economies, through improved efficiency, effectiveness, and innovativeness.

Given its promise, the vendor market for big data technologies has grown 40% annually, from $3.2 billion in 2010 to $16.9 billion in 2015 and this growth is expected to continue at a 23% rate over 2015-2019 with annual spending reaching $48.6 billion by 2019 (IDC 2015). As of 2011 and according to McKinsey Global Institute, the estimated value potential of big data resources was $300 billion for the US health care sector and €250 billion for Europe's public sector administration (Manyika et al. 2011). In addition, big data utilization is estimated to account for a 60% increase in retailers' operating margins while personal-location data is thought to be able to capture $600 billion in consumer surplus (Brown et al. 2012; Court 2015).

Recently, McKinsey Global Institute (Henke et al. 2016) published an updated report stating that the value potential of big data remains widely uncaptured and unexploited by firms today. According to their analysis, US retailing realized only 30-40% of big data's estimated value whereas the European public administration and US health care sector lagged even further behind with a modest 10-20% being captured. McKinsey's report (Henke et al. 2016) concluded that the main challenges that hinder firms from reaping greater rewards from big data are related to three major categories: (1) IT infrastructure; (2) strategy, leadership, and talent; and (3) organizational structure and processes. More specifically, many firms are unsure how to make use of big data, are cautious to invest into new information technologies, or simply find big data analytics too complicated (Barton and Court 2012; Einav and Levin 2013). To overcome these technological, skill-based and organizational challenges, firms need to acquire a diverse set of big data-related IT resources (Brown et al. 2012; Cap Gemini 2012; Day 2011; McAfee and Brynjolfsson 2012).

Despite these challenges, industry surveys reveal that an increasing number of firms regard big data as a major influence on corporate strategy (Brown et al. 2012; Cap Gemini 2012; Gartner 2013; Manyika et al. 2011). While no business function remains untouched by big data opportunities, the marketing function (marketing, sales and customer service) is the top driver of such initiatives (Gartner 2013). The combination of big data technologies and greater access to consumer data through web-based channels generates customer insight not previously possible (Chen et al. 2012; Day 2011; Nunan and DiDomenico 2013). By analyzing finely-grained data to identify subtle trends and patterns in individual customer attitudes and behavior, often in real-time, big data is moving firms from knowing their customers as a demographic segment to understanding them as individuals (Sluis 2014). Big data insights thus put managers in a superior position to design timely, automated, highly personalized offerings, with human expertise remaining critical but in a supporting role (Einav and Levin 2013; LaValle et al. 2011; McAfee and Brynjolfsson 2012).

Prior conceptual research emphasizes the role of industry in determining the value-creating potential of big data (e.g., Davenport 2014; Fosso Wamba et al. 2015). Certain industry sectors may offer fewer opportunities due to high entry barriers, limited access to data, and data privacy and protection concerns, as argued, for instance, by Brown et al. (2012), Cap Gemini (2012), and Manyika et al. (2011). Surprisingly, however, the role of firm strategy in fostering big data-driven competitive advantage has received little attention in extant literature. Since big data may enhance the firm's marketing capabilities through two distinct mechanisms, namely, by improving either the efficiency or the effectiveness of marketing activities, it is important to understand how the business impact of big data varies between firms pursuing either a cost leadership or a differentiation strategy (Porter 1980) as a means of achieving a competitive advantage.[2]

More specifically, some firms develop big data solutions to reduce operating costs by optimizing and automating marketing processes to gain a low cost advantage. For example, Walmart has dramatically reduced their response time between detecting a business problem to finding an actionable solution from an average of 2-3 weeks to 20 minutes across its 20,000 stores worldwide (Marr 2016). Other firms, in turn, focus on generating customer insights that present firms with market-based opportunities to achieve a differential advantage over competition (Brown et al. 2012; Cap Gemini 2012; Gartner 2013; Manyika et al. 2011). For instance, Apple collects multi-structured data about how, when, and where customers use their different products to predict future customer needs better than their rivals (Marr 2016).

As the preceding exposition suggests, there is an urgent need to understand how firms could gain returns from big data investment as part of a successful marketing strategy. Academic research has not examined how and to what extent big data impacts performance (McAfee and Brynjolfsson 2012). To begin to redress this knowledge gap, this paper concentrates on the

[2] Building on the strategic management literature, marketing research subsequent to Porter's (1980) ground-breaking work suggests that the actions undertaken by the marketing department and the role of market orientation/marketing capabilities to gain competitive advantage do depend on the firm's selected business strategy (e.g., Ketchen et al. 2007; Langerak 2003; Matsuno and Mentzer 2000, Olson et al. 2005). A major limitation of extant literature is that this cost versus differentiation advantage has yet to be examined when assessing the relationship between marketing capabilities and firm performance (Murray et al. 2011). Related marketing research asserts that the influence of marketing is greater in firms that adopt a differentiation strategy compared to a cost leadership strategy (Homburg et al. 1999; Verhoef and Leefland 2009).

impact of big data resources – defined here as a combination of complementary IT resources relevant to the utilization of big data – on firm marketing capabilities and, by extension, firm performance. In addition, we investigate whether these relationships differ as a function of the firm's chosen low-cost versus differentiation business strategy. Our research question, thus, combines these as:

> RQ: How can firms achieve competitive advantages from their big data-engendered marketing capabilities and how does the choice of corporate business strategy interact with these theoretical constructs?

In synthesizing knowledge from prior literature, we identify three primary sources as being most relevant to our research question: (1) big data conceptual contributions (Chen et al. 2012; McAfee and Brynjolfsson 2012), (2) the IT business value paradigm (Clemons and Row 1991; Hitt and Brynjolfsson 1996), and (3) marketing capabilities research (Day 1994, 2011; Krasnikov and Jayachandran 2008; Vorhies and Morgan 2005).

Undergirding these research streams, we focus on the theoretical resource-based view of the firm (RBV; Wernerfelt 1984) to posit that resource complementarity gives rise to a higher-order, strategic firm asset as represented by big data resources. When turned into powerful capabilities, these resources eventually can lead to competitive advantage (Melville et al. 2004). Indeed, we adopt marketing capabilities as the primary mechanism through which the firm leverages big data resources in organizational processes to create value (e.g., Barney and Hesterly 2012; Eisenhardt and Martin 2000). That is, we posit that big data resources, comprised of specified IT resources, influence firm performance by enhancing marketing capabilities.

Our research makes at least three important contributions. First, studies focusing on the business impact of big data are scarce. This study extends IS and marketing research by examining the extent to which certain big data resources enhance marketing capabilities, which in turn improve firm performance. The results show that despite the challenges associated with big data, firm performance increases 11-12% as a result of big data resources. Our finding suggests that even if firms have not learned how utilize big data to its fullest potential, the advantages are still double in comparison to traditional data analytics where we typically find 5-6% increases in firm performance (Brynjolfsson et al. 2011).

Second, this study sheds light on the actionable mechanisms through which specific big data-related IT resources, in combination, influence performance to capture the complexity inherent in such phenomena. The current paper thus extends the IT business value research by synthesizing knowledge from recent business analytics literature to formulate a parsimonious conceptualization of big data resources. Specifically, this study identifies and assesses the relative importance of three critical IT resources, namely: (1) big data-related technology; (2) analytics skills; and (3) organizational resources, all of which are confirmed as necessary and complementary dimensions for superior rents (Mata et al. 1995; Melville et al. 2004; Ross et al. 1996).

Last, but certainly not least, this study makes a contribution to big data research by highlighting the critical role of the firm's adopted business strategy in driving big data success. Contrary to the belief that industry characteristics largely determines the value potential of big data (Brown et al. 2012; Davenport 2014; Fosso Wamba et al. 2015), our findings provide some compelling albeit surprising evidence that differentiating firms are far more likely to benefit from big data than cost leadership firms.

THEORETICAL FRAMEWORK

To theoretically inform our study, we rely on the resource-based view of the firm (RBV) because of: (1) its applicability across IS research (Melville et al. 2004; Pavlou and El Sawy 2006); marketing (Day 1994; Srivastava et al. 2001), and strategy (Armstrong and Shimizu 2007; Crook et al. 2008); (2) its focus on the role of factors internal to the firm to explain organizational outcomes of interest (Conner 1991); and (3) its rich conceptualization of IT-related and marketing-related resources and capabilities (Kozlenkova et al. 2014; Wade and Hulland 2004).

Resource-Based View of the Firm

The theoretical arguments of RBV (Wernerfelt 1984) highlight the management of firm resources as the basic units of analysis and indicate that resource heterogeneity across firms accounts for differential performance (Barney 1991; Peteraf 1993). A *resource* refers to tangible and intangible assets, or any given strength or weakness of a firm that can be utilized to improve the efficiency and effectiveness of a firm or an available factor owned or controlled by the firm (Amit and Schoemaker 1993; Dierickx and Cool 1989).

RBV literature uses a set of criteria to determine whether resources can be combined and leveraged by a capability which then can be converted into sustainable competitive advantage. At least one of these resources must meet the criteria of: (1) valuable, (2) rare, (3) imperfectly imitable, and (4) organizational exploitable (VRIO) (Barney and Hesterly 2012; Peteraf 1993). For example, stand-alone resources may be valuable or rare but they are seldom inimitable since they can be freely traded in strategic factor markets, as in the case of technology or human resources (Barney 1991; Mata et al. 1995). However, resources seldom lead to differential performance in isolation; they nearly always have to be considered within their organizational context. RBV's resource complementarity argument posits that resources should be considered jointly rather than independently because the presence of one resource commonly enhances the value of another (Barney 1991). The value of a resource is thus ultimately determined by its contribution when combined with other resources into unique, higher-order resource bundles (Jüttner and Wehrli 1994). Such bundles form a *strategic resource* in accounting for a significant portion of the firm's investment base; moreover, this combination is not freely available in factor markets (Clemons and Row 1991).

For strategic resources to become a source of competitive advantage, they must be leveraged by capabilities via organizational processes that create value for the firm (Barney and Hesterley 2012; Kozlenkova et al. 2014). A *capability* enables the firm to leverage bundles of resources advantageously in organizational processes to create value (e.g., Barney and Hesterly 2012; Eisenhardt and Martin 2000). Specifically, capabilities are a complex set of skills and routines deeply embedded in organizational processes (Day 1994). As such, capabilities are path-dependent (Kogut and Zander 1992), causally ambiguous (Lippman and Rumelt 1982; Reed and DeFillippi 1990), and contextually-embedded (Granovetter 1985), and therefore costly or impossible to trade, imitate, or substitute (Dierickx and Cool 1989; Peteraf 1993). Therefore, capabilities are a potential source of competitive advantage that when actualized can be called core competencies.

Big Data Resources

Building on the underpinning of RBV, IT business value research investigates the impact of information technology on firm performance (Clemons and Row 1991; Hitt and Brynjolfsson 1996; Melville et al. 2004). This discourse posits that diverse IT-related resources are combined into unique resource bundles that enhance firm performance and provide for competitive advantage (Bhatt and Grover 2005; Melville et al. 2004; Ross et al. 1996). As a strategic, firm-level IT resource, we define *big data resources* (hereafter referred to as BDR) as a combination of complementary IT resources necessary to utilize big data in enhancing firm performance.

IT business value research has identified three general types of IT resources: (1) technology resources, (2) human IT resources, and (3) organizational IT resources (Benjamin and Levinson 1993; Bharadwaj 2000; Mata et al. 1995; Ross et al. 1996). These resources represent necessary and complementary dimensions, and when combined appropriately, invoke superior performance (Melville et al. 2004; Pavlou and El Sawy 2006; Ross et al. 1996). Consistent with such overriding RBV rationale and based on a review of conceptual big data studies (e.g., Chen et al. 2012; McAfee and Brynjolfsson 2012), we identify three distinct IT business value resources that form firm-level, strategic BDR: (1) big data technology resources; (2) big data analytics skills; and (3) organizational big data resources.

Big data technology resources (1) refer to novel information technologies that are necessary to handle big data, i.e., various data formats and data types derived from interactions between people and machines beyond the ability of current relational databases and legacy systems (Chen et al. 2012; Manyika et al. 2011). Such technologies include non-relational databases, middleware, data warehousing, and analytic tools, all of which enable firms to capture and integrate big data in real-time; they likewise permit firms to deliver analytical results in accessible and understandable form to executives to support business decision-making (Chen et al. 2012; Jelinek and Bergey 2013; Nunan and DiDomenico 2013).

Once the technological infrastructure is in place, firms often struggle to make effective use of big data (Barton and Court 2012; Einav and Levin 2013). *Big data analytics skills (2)* refer to human resources acquired from internal or external partner sources, sources that have the knowledge to derive market insights from big data (Germann et al. 2013). Indeed, the big data skills gap is cited as the primary obstacle to the adoption of a big data-driven marketing strategy (Brown et al. 2012; Bloomberg 2012; Cap Gemini 2012; Manyika et al. 2011). In a nutshell, firms need “data scientists” who can find patterns in large quantities of multistructured data and transform these into useful and actionable insight (Davenport and Patil 2012; LaValle et al.

2011; McAfee and Brynjolfsson 2012). These people possess rare combinations of skills in mathematics, programming, business knowledge, interpersonal skills, and customer focus (Brown et al. 2012; Bloomberg 2012; Cap Gemini 2012).

Building a strategic big data resources requires a transformation in organizational culture to embed big data as part of daily operations (Barton and Court 2012; Brown et al. 2012; Bloomberg 2012; Cap Gemini 2012; Manyika et al. 2011; McAfee and Brynjolfsson 2012). *Organizational big data resources (3)* refer to top management and cultural support for big data. More specifically, big data culture encompasses shared values, beliefs and norms that encourage decision-makers to utilize big data-driven insights (Germann et al. 2013). A data-driven culture reflects an openness to systematically apply big data analytics to solve business problems (Brown et al. 2012). Top management support, in turn, provides leadership and vision that is crucial to ensure that managers are aligned to support big data, given that people are not naturally inclined to trust or understand data-based models (Barton and Court 2012; Bloomberg 2012). Effective users are almost always found in firms where top management highly values big data (Brown et al. 2012; Bloomberg 2012; Cap Gemini 2012; Manyika et al. 2011).

We posit that these stand-alone big data resources should be conceptualized holistically in this way in order to identify the combinations of IT resources required for achieving desired performance outcomes (Melville et al. 2004; Pavlou and El Sawy 2006). While big data-related resources can be purchased from strategic factor markets, higher-order BDR is difficult to copy and imitate. In fact, IT resources may even be co-specialized such that one resource has little or no value without the other; e.g., as occurs with hardware and software (Clemons and Row 1991). Thus, consistent with RBV's resource complementarity argument, we posit that these diverse resources act in a synergistic fashion.

Marketing Capabilities

RBV has become an influential theory in marketing research to examine the link between market-based resources and capabilities, firm performance and competitive advantage (Kozlenkova et al. 2014; Srivastava et al. 2001). Several typologies of marketing resources and capabilities have been proposed in extant literature (for an extensive review, see Kozlenkova et al. 2014). To inform our firm-level study, we chose the broadest classification that presents marketing capabilities as a strategic firm capability (Krasnikov and Jayachandran 2008; Morgan et al. 2009; Vorhies and Morgan 2005). As such, we define *marketing capabilities* (MC) as the firm's ability to understand and meet customer needs and deliver its products and services to customers (Day 1994; Krasnikov and Jayachandran 2008).

Firm-level, strategic MC encompasses eight distinct lower-level, operational marketing capabilities (Vorhies and Morgan 2005). Four of them are related to transforming resources into product and services based on the firm's marketing mix processes that include: (1) pricing, (2) product development, (3) channel management, and (4) marketing communications. Three others – (5) market information management, (6) marketing planning, and (7) marketing implementation) – help manage marketing mix capabilities and resource allocations related to their execution. Finally, selling capabilities (8) are processes carried out to encourage customer purchases (Vorhies and Morgan 2005).

These interdependent lower-level marketing capabilities work in a synergistic fashion (Morgan et al. 2009; Vorhies and Morgan 2005). Similar to BDR, we thus posit that MC should be conceptualized holistically to account for the joint effects of lower-level marketing capabilities on outcomes.

Business Strategy

While several conceptualizations of business strategy have been proposed in academic literature, the partially overlapping strategic typologies by Miles and Snow (1978) and Porter (1980) are best known. The former focuses on the rate of product-market change and the latter on customers and competitors (Homburg et al. 1999; Olson et al. 2005). We adopt Porter's 1980 typology as the most appropriate one for the current study. RBV scholars view it as complementary to RBV because of its emphasis on the firm's external environment; in this way, it offers an additional perspective to RBV's internal focus as the basis for achieving competitive advantage (Amit and Schoemaker 1993; Conner 1991; Foss 1997).

According to Porter (1980), business strategy refers to how the firm creates value compared to its competitors based on lower costs or differentiation, and based on the scope of its target market (i.e., entire market vs market focus). Firms that try to gain competitive advantage through a cost advantage (cost leadership strategy) are <u>internally oriented</u> and focus on efficiency gains by reducing costs across internal processes. Firms pursuing a differentiation advantage (differentiation strategy) employ an <u>external focus</u> to understand their market environment, i.e., customers, competitors and innovations (Porter 1980).

Building on the strategic management literature, marketing research suggests that the actions undertaken by the marketing department and the role of MC to gain competitive advantage depend on the firm's selected business strategy (Krasnikov and Jayachandran 2008; Olson et al. 2005). The firm's emphasis on cost advantage or differentiation advantage sets different requirements for MC and for its relative importance to achieve superior performance. For example, the contribution of MC relative to other strategic capabilities, such as operations or R&D capabilities, to firm performance may vary as a function of business strategy (Krasnikov and Jayachandran 2008). Compared to a cost leadership strategy, a differentiation strategy underscores the role of MC because marketing-related activities, and creating and acting on market intelligence, are critical to achieve a differentiation advantage. In sum, prior research asserts that the role of marketing is more important in firms that adopt a differentiation strategy compared to a cost leadership strategy (Homburg et al. 1999; Verhoef and Leefland 2009).

RESEARCH MODEL AND HYPOTHESES

To build on the IT business value paradigm and resource-based studies in marketing to advance a resource-based view (RBV) of how big data resources act to enhance marketing-related capabilities and, ultimately, firm performance, we propose the resource-based model depicted in Figure 1. As a newly-conceived construct in this nomology, big data resources (BDR) is critically important when firms are attempting to enhance marketing capabilities (MC). To succeed in this effort, firms need to acquire and combine different types of big data-related IT resources to achieve competitive advantage. BDR is modeled as antecedent to marketing capabilities (MC). The direct outcome of MC is firm performance. Specifically, we build on RBV to posit that BDR is leveraged by MC, which in turn provides for better firm performance, and is thus a source of a competitive advantage for the firm. That is, we expect that MC mediates the effects of BDR on firm performance. Furthermore, we anticipate that these constituent effects are contingent upon the business strategy pursued by the firm (Figure 1).

IT business value research (Hitt and Brynjolfsson 1996) has adopted resource complementarity arguments to explain the interactions between IT and non-IT resources and capabilities and how IT impacts performance (Melville et al. 2004). Strategic IT resources do not generally lead to superior firm performance, but those that influence other complementary strategic resources within business processes may yield competitive advantage (Bhatt and Grover 2005; Powell and Dent-Micallef 1997).

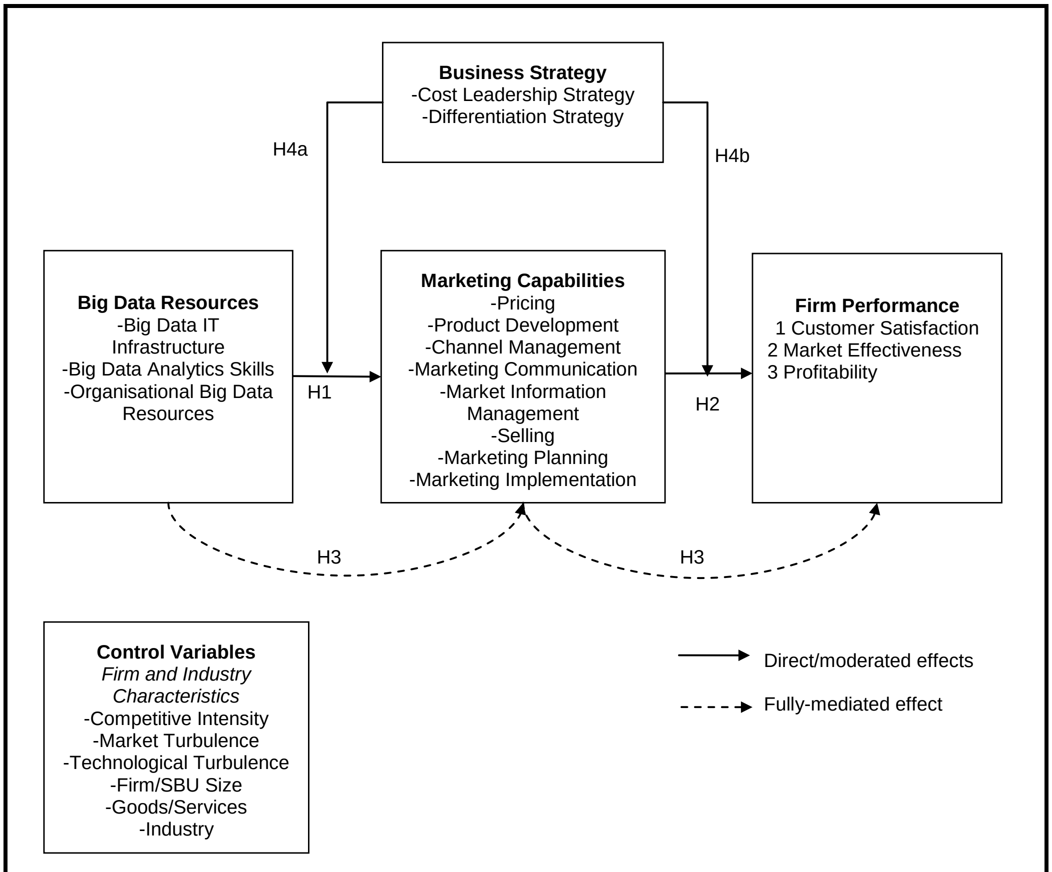

Figure 1. Research Model

Based on this logic, BDR is posited as an enabler of marketing-related capabilities. More specifically, BDR enables firms to gain market insights, continuously sense and act on market changes that are critical to execute marketing capabilities successfully (Day 2011). For example, big data resources enable firms to better innovate and optimize any given element of the marketing mix with big data-driven predictive models and experiments (Chen et al. 2012; Einav and Levin 2013; Jelinek 2013). Unlike traditional one-way marketing, firms are thus able to tap into customer opinions, understand customer behavior, and converse with customers (Chen et al. 2012; Day 2011). In addition, person-specific, context-specific, and location-specific offerings and communications can be tailored by big data-driven insights (Chaudhuri et al. 2011). Furthermore, data is available in real-time and at a significantly lower cost than traditional market research to tap into customer needs (Jelinek and Bergey 2013). Big data-driven marketing organizations thus find it easier, faster, and cheaper to orchestrate and experiment with the marketing mix to set optimal levels.

In sum, prior RBV studies suggest that IT resources have a positive effect on non-IT organizational capabilities (Bharadwaj 2000; Feeny and Willcocks 1998; Ross et al. 1996). Consistent with this research, we expect that big data resources (BDR) will provide for more efficient and effective marketing capabilities (MC). Therefore:

H1: Big data resources will have a positive influence on marketing capabilities.

In contrast with the unexplored relationship between BDR and MC, the impact of MC on firm performance has received substantial support in prior research (Morgan et al. 2009; Vorhies and Morgan 2005). MC is crucial to understand customers and to deliver offerings that match their needs and to create firm-client relationships. It is therefore a key driver of superior value (Morgan and Hunt 1994; Zeithaml 1988). Marketing capabilities can be rare, valuable, non-substitutable, and imperfectly imitable and thus have potential for superior performance and competitive advantage (Day 1994; Vorhies and Morgan 2005).[3] A meta-analytic study found that MC influences superior firm performance more than other core firm capabilities, R&D and operational capabilities, which can be more easily imitated by competitors (Krasnikov and Jayachandran 2008). In sum, we anticipate that MC has a positive influence on firm outcomes (Morgan et al. 2009; Vorhies and Morgan 2005). Therefore:

H2: Marketing capabilities will have a positive influence on firm performance.

[3] Whereas it is usually resources that demonstrate these traits, some scholars transfer these criteria to capabilities.

IT business value studies have shown that the impact of IT resources and capabilities on firm performance is indirect, working through interactions with complementary non-IT resources and capabilities (Bharadwaj 2000; Ravichandran and Lertwongsatien 2005; Powell and Dent-Micallef 1997). In this study, we similarly anticipate that MC acts as the mechanism through which BDR is leveraged. Specifically, the first-order effects of IT are as a critical enabler of more efficient and effective organizational processes, which in turn lead to better firm performance (Kim et al. 2011; Kohli and Grover 2008; Mithas et al. 2011; Schwarz et al. 2012; Tallon et al. 2011). Stated differently, the impact of BDR on firm outcomes can be traced back to MC where efficiency and effectiveness gains would not be possible in the absence of BDR (Kohli and Grover 2008). As such, we argue that BDR does not affect firm performance directly but rather provides incremental value via MC (Mithas et al. 2011). Consistent with this line of theorizing, we anticipate that BDR influences firm performance indirectly via the mediating effect of MC. Thus we propose:

H3: Marketing capabilities will fully mediate the relationship between big data resources and firm performance.

We also anticipate that business strategy influences the relationship between BDR and MC. While no studies have specifically investigated whether strategic type moderates the effect of BDR on MC, related research has found that a cost leadership strategy has a weak negative moderating effect (at a 10% significance level) on the relationship between the firm's market orientation[4] (MO) and lower-level marketing capabilities, namely, new product development and marketing communications, but not on the MO $\rightarrow$ pricing capabilities link (Murray et al. 2011).

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[4] MO is conceptually similar to BDR as a strategic resource that generates market intelligence from the external environment that is leveraged by MC (Morgan et al. 2009).

Hence, prior research offers mixed evidence regarding the likely nature of the interaction between BDR and business strategic type in prediction of MC.

Furthermore, BDR can enhance MC through two distinct mechanisms, either by improving the efficiency or the effectiveness of marketing processes. First, cost and time efficiencies in MC may be achieved through the optimization and automation of marketing processes. Similarly, RBV scholars discuss the inside-out perspective as one that focuses on the optimal exploitation of internal processes and existing opportunities (Day 1994; March 1991). Cost leadership firms specifically pursue a big data-driven cost advantage that builds on this inside-out foundation to gain superior performance. Therefore, we expect the impact of BDR on enhancing MC efficiency to be stronger in cost leadership firms.

Conversely, gains in MC effectiveness are likely to be better achieved by firms pursuing a differentiation strategy. A differentiation advantage requires that firms focus on MC effectiveness by delivering better products and services to their customers. Big data-driven outside-in activities, such as market-sensing and customer-linking, enable the exploration of new business opportunities (Day 1994, 2011). Specifically, data-driven insights from the marketplace help firms better predict their customers' and competitors' behaviors and to innovate by personalizing their products and services as well as other aspects of marketing activities (Day 2011; Einav and Levin 2013; McAfee and Brynjolfsson 2012). Firms that emphasize a cost leadership strategy are thus less likely to improve MC effectiveness through market-based product innovation due to their inherent internal orientation.

In sum, we expect that BDR enhances MC through both efficiency and effectiveness mechanisms. As alluded to earlier, what is required of MC to achieve superior performance depends on whether the firm strives for low cost or differentiation over its rivals (Krasnikov and

Jayachandran 2008; Olson et al. 2005). In the context of big data, these opposing strategies would play out differently depending on whether BDR is primarily utilized to focus on improving MC efficiency or effectiveness. However, there is no empirical evidence that predicts which firm strategic type benefits more from big data-driven MC. Based on these considerations, we formally hypothesize that:

H4a: The positive influence of big data resources on marketing capabilities will be moderated by business strategy.

Prior research does suggest, however, that a differentiation strategy emphasizes the importance of MC as a driver of firm performance (Krasnikov and Jayachandran 2008). Prior work adopting the Miles-Snow (1978) typology has also shown the moderating effect of business strategy on the relationship between market-linking and other lower-level marketing capabilities on firm performance (Song et al. 2007), and between market orientation (MO) and firm performance (e.g., Langerak 2003; Matsuno and Mentzer 2000; Olson et al. 2005), respectively. For example, differentiating firms (i.e., the prospectors in the Miles-Snow typology) are in a better position to explore new market opportunities, develop new products and service innovations, and expand to more profitable market segments than defenders, i.e., firms focusing on cost efficiencies (Matsuno and Mentzer 2000).

Since MC is the MO deployment mechanism, it is reasonable to assume that prior findings on the MO $\rightarrow$ firm performance link may be extended to the MC $\rightarrow$ firm performance link (Morgan et al. 2009). As noted earlier, the role of the marketing department and MC are more important to achieve a differentiation advantage firms because marketing processes related to market intelligence generation and utilization are critical (Homburg et al. 1999; Olson et al. 2005; Verhoef and Leefland 2009). Cost leadership firms are likely to rely more on operational capabilities to gain superior performance by reducing costs (Krasnikov and Jayachandran 2008).

Based on the preceding exposition, we expect that a differentiation strategy strengthens the relationship between MC and firm performance. Therefore:

H4b: The positive influence of marketing capabilities on firm performance will be stronger for firms pursuing a differentiation strategy than for firms pursuing a cost leadership strategy.

Beyond the hypothesized effects, we control for a number of firm and industry characteristics that could influence the action mechanisms between the firm's big data resources, marketing capabilities, and firm performance. Widely adopted control variables, including (1) firm size, (2) goods versus services firms, (3) industry, (4) competitive intensity, (5) market turbulence, and (6) technological turbulence are included in our model to partial out noise in the variance (e.g., Menon et al. 1999; Verhoef and Leefland 2009; Vorhies and Morgan 2005).

Larger firms benefit from slack resources, and economies of scale and scope, that may positively influence the level of firm assets and performance (Menon et al. 1999; Vorhies et al. 2011). Firm/SBU size is controlled for by means of number of employees (Homburg et al. 1999). Differences between goods and services firms are controlled via a dummy variable (Homburg et al. 1999; Verhoef and Leefland 2009). Based on prior theory, no assumptions are made about the specific direction of potential variances between goods and service firms (Krasnikov and Jayachandran 2008). Industry is controlled to account for differences between industry sectors. Big data-driven industries could vary due to high entry barriers, limited access to data, and data privacy and protection concerns, among others (Brown et al. 2012; Cap Gemini 2012; Manyika et al. 2011). Three industry dummies are used to account for the three largest big data-driven industry sectors (with also the largest number of observations in our dataset), namely, B2C manufacturing, finance and insurance, and retail. Firms operating in markets with rapid technological change, aggressive competition, and volatile customer needs tend to build stronger marketing assets to cope with such contingencies (Homburg et al. 1999; Menon et al. 1999). Finally, prior research also shows environmental factors having direct effects on firm performance (e.g., Olson et al. 2005; Vorhies and Morgan 2005). Hence, competitive intensity, market turbulence and technological turbulence are accounted for using two-item scales (Kohli and Jaworski 1990).

METHODOLOGY

We employed a field study methodology and administered online questionnaires for data collection. Our sampling frame focused on strategic business units (SBUs) in large (>1000 employees), USA-based, B2C manufacturing and service firms who have invested in big data technologies. We set forth these sample criteria for the following reasons. Firstly, due to considerable initial investment, entry barriers and expertise required, large firms are more likely possess big data resources (Manyika et al. 2011). Second and similar to prior marketing studies, the focus of this study is at the SBU level (Homburg et al. 1999; Workman et al. 1998). If there were no distinct SBUs, respondents were instructed to answer at the firm level. Third, big data investment is more prevalent in the B2C sector because understanding the needs of a large customer base is more complicated than in B2B sectors where the number of customers is typically lower and the salesforce more knowledgeable about individual customers' needs.

Using a commercial research panel provider, we targeted senior marketing executives in SBUs across a range of B2C industries. Prior studies examining marketing capabilities have also adopted such a multi-industry approach (e.g., Song et al. 2007; Vorhies and Morgan 2005). The instrument was sent to senior marketing executives in 2497 SBUs, and after a rigorous screening process, 301 usable responses (12% response rate) were returned.[5] To ensure that the final informants possessed adequate knowledge, respondent competency was assessed through a separate question in the survey instrument (Kumar et al. 1993). Appendix A summarizes the sample characteristics.

The data were cleared for non-response biases, which included screening for possible differences in variable means between early and late responders. Specifically, an independent samples T-test was carried out to compare the differences of dependent variable (DV) means between early and late respondents (Armstrong and Overton 1977). In two-tailed tests with sufficiently high power (>.8), early and late respondent groups did not differ significantly (firm performance FP, t=.128, *p*=.898). Thus, non-response bias should not be a problem in generalizing to the sampling frame.

All of our measures are directly adopted from or based substantially on scales validated by prior studies (see Appendix B) and were measured on a 7-point Likert scale. Measures include first-order reflective and first-order formative scales and three higher-order constructs. Following established measurement model specification guidelines (Jarvis et al. 2003; Petter et al. 2007), we determined that some first-order scales modeled in prior studies as reflective were actually formative (Big Data Technology Resources, Big Data Analytics Skills, Organizational Big Data Resources). For the study's key second-order constructs, the decision rules by Wong et al. (2008) were also adopted for model specification purposes (see Appendix C for a detailed description)[6]. Based on these analyses, "Big Data Resources (BDR)" is modeled as a Type IV

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[5] Due to personal data protection laws, it was not possible to match the collected data with survey data from other informants or with objective financial data.

[6] We carried out additional tests following Chwelos et al. (2001) to test whether measurement model specification affects structural model results. We tested two other versions of the model (one with all constructs formative (Mode B) and another with all constructs reflective (Mode A). The results of the structural model (path coefficients between research constructs BDR, MC, FP) were qualitatively similar with no path coefficients gaining or losing statistical significance, and no significant paths changed in sign. In sum, measurement model specification decisions, which are always judgment calls made by authors, do not affect the results of the study.

(second-order formative, first-order formative) formative composite construct, and "Marketing Capabilities (MC)" and "Firm Performance (FP)" as Type I second-order reflective, first-order reflective) reflective composite constructs, respectively. Constructs, measurement types, item contents, sources of measures, formative item weights and reflective item loadings are summarized in Appendix B.

RESULTS

General Approach

Measurement model validation included reliability and validity analyses for reflective measures and validity analyses for formative measures. After interpreting the measurement model, we estimated the structural model (Anderson and Gerbing 1988). Partial Least Squares (PLS) structural equation modeling (Wold 1982) was utilized because the model is complex, includes formative measures, and our objective was to test novel theory (Hair et al. 2011). Furthermore, PLS is less demanding with respect to sample size and is adaptable for conducting multigroup analyses with smaller sub-samples (Chin 1998). The version used was SmartPLS 3 (Ringle et al. 2015) with 5000 resample bootstraps to estimate the p-values of measurement properties (Hair et al. 2011; Hair et al. 2017).

We modeled our key second-order constructs Big Data Resources (BDR), Marketing Capabilities (MC) and Firm Performance using a hierarchical component model with repeated indicators (Wold 1982; Lohmöller 1989; see Appendix C). A Mode A (path-weighting scheme) was adopted for the reflectively-measured repeated indicators of MC and firm performance, respectively. A Mode B was selected for BDR's formatively- measured repeated indicators, an approach that produces the most reliable results for structural models including formative higher-order constructs (Becker et al. 2012).

Prior to multigroup analyses (MGA), the measurement invariance of composite models (MICOM) procedure assessed measurement model invariance across predefined groups (see Appendix F for a detailed description; Henseler et al. 2016). MICOM is regarded as the best method to test for measurement invariance of reflective and formative latent constructs (composites) between different groups in PLS-SEM (Henseler et al. 2016; Hair et al. 2017). Following this was multigroup analyses using the PLS-MGA method with 5000 resample bootstraps to test for observed heterogeneities in the total sample by comparing structural models across groups (Sarstedt et al. 2011; Henseler et al. 2009).

Because of the complexity of our structural model (number of repeated indicators in higher-order constructs), we treated the second-order factors Big Data Resources (BDR), Marketing Capabilities (MC) and Firm Performance (FP) as composite scores for MICOM and PLS-MGA analyses. The adoption of composite scores is appropriate in our case because: (1) the validity of the three higher-order scales is established in measurement model testing with the pooled sample (N=301; Zhou et al. 2005; Matsuno et al. 2002); (2) measurement invariance can still be established in MICOM testing across subsamples for the higher-order composites (Henseler et al. 2016); and (3) given the size of subsamples, using composite scores helps meet the minimum sample requirements recommended by PLS scholars to ensure structural model stability and valid results (Barclay et al. 1995; Hair et al. 2017).

Measurement Model

Reflectively-measured constructs were assessed in terms of item-level reliability (Appendix B), construct reliability, and convergent and discriminant validity (Appendix D) for both 1st and 2nd order measurement models. All item loadings, composite reliability, and average variance extracted (AVE) exceeded acceptable reliability criteria (Hair et al. 2011) and all measures discriminated well[7] (Fornell and Larcker 1981). The 1st order and 2nd order formative measures were validated via multicollinearity (VIF values) and construct validity (item weights, loadings, and their significance levels) testing (MacKenzie et al. 2011; Petter et al. 2007). All VIF values were below 2.3, which is under the recommended threshold of 3.3 (Diamantopoulos and Siguaw 2006). Formative indicator weights and their significances (Appendix A) and loadings (>.70) also showed acceptable psychometric properties for structural model assessment.

Common Method Bias

Since both independent and dependent measures were obtained from the same source, we first used CFA and Harman's single-factor test to assess CMB or common method bias (Podsakoff et al. 2003). Eight factors had eigenvalues greater than one, and together they accounted for 59% of the total variance; the first factor accounted for 37% of the total variance.

In that the Harman test does not completely rule out the risk of common method bias, we carried out additional common method tests with a marker variable (Lindell and Whitney 2001). This test proved to be acceptable for the testing of CMB by Schwarz et al. (2017). Ideally, the marker variable should be theoretically unrelated to other substantive variables in the study, chosen a priori, and similar to the substantive variables in content and format, i.e., in this case latent variables, perceptual/subjective measures (Richardson et al. 2009; Simmering et al. 2015). To provide a plausible *a priori* assumption of a zero correlation between the marker and other study variables, the marker variable was adopted from another discipline. Following these criteria, the 4-item perceptual "Astrology interest (Mowen et al. 2009)" scale was chosen *a priori*

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[7] Item-to construct correlations of higher-order (first-order reflective, second-order reflective) constructs Marketing Capabilities (MC) and Firm Performance (FP) did not meet Fornell and Larcker's (1981) AVE criterion. In other words, some first-order factors (indicators) of MC and FP do not have discriminant validity with respect to their underlying second-order construct. In first-order reflective, second-order reflective constructs, all variances are assumed to be positively inter-correlated (Diamantopoulos et al. 2008). Therefore, discriminant validity between first-order factors and the underlying second-order construct is not assumed. At second-order construct level, MC and FP discriminated well from other study constructs. It is also worth noting that the high correlation between MC and FP (.82) was expected. In Vorhies and Morgan's (2005) study, the latent variable correlations between higher-order MC and FP was not reported but the standardized beta coefficient MC → FP was .67. We expect that the stronger correlation between MC and FP can be at least partially explained by enhanced MC attributable to big data resources.

and included in the instrument. Pearson correlations and significance levels between the marker and substantive variables are shown in Appendix E.

The correlations between all predictor and criterion variables are highly significant. “Astrology interest,” in turn, has a nonsignificant correlation of .085 with our DV “Firm Performance.” This correlation of the marker with the criterion scale is then used to partial out the common method effect from other correlations to assess the extent of method bias. The partial correlations between all predictor and criterion variables remain highly significant, indicating that correlations in the model are not heavily biased by a common method (Lindell and Whitney 2001). In sum, CMB is not likely to be a concern.

Measurement Invariance

The three-step MICOM approach (cf. Appendix F) is adopted to test for measurement model invariance between firm groups with cost leadership and differentiation strategies (Henseler et al. 2016). Configural invariance (Step 1) was established by employing identical measurement and structural models for each group that were estimated using identical data treatment and analysis specifications.

The permutation test was used to assess compositional invariance (Step 2) and the equality of means values and variance (Step 3). Permutation is a non-parametric procedure that compares group-specific bootstrap estimates to produce confidence intervals (percentiles). Permutation establishes whether pre-defined groups have statistically significant differences in measurement model parameter estimates between groups. We employed tests with 5000 permutations to examine whether correlations *c* of composite scores significantly differ (different from 1) across groups. In Step 2, correlations with *p*-values lower than .05 leads to the rejection of compositional invariance (Henseler et al. 2016).

Compositional invariance is a prerequisite to test for the equality of mean values and variances (Step 3). In Step 3, the permutation test calculates two-tailed confidence intervals (percentiles) of differences in mean values and variances. If the original differences between inter-group composite scores are within the confidence interval, measurement invariance is confirmed (Henseler et al. 2016). If all composites have equal means and variances across groups, full measurement invariance is confirmed. If composite means and variances are not equal, partial measurement invariance is established. The results are shown in Appendix G.

In comparing the two business strategy groups, differentiation and cost leadership, compositional invariance (Step 2) is confirmed with the exception of the 1st order composites of Selling and Profitability. Since compositional invariance is established for their respective higher-order composites MC and Firm Performance, and due to the low number of violations (2 out of 25 composites), it is still permissible to proceed to Step 3 (Henseler et al. 2016; Hsieh et al. 2008). The equality of mean values is established (Step 3a). In the final step, two composites showed inequality of variances (Step 3b). Second-order composite MC and its first-order composite (indicator) Market Information Management have significantly different variances between groups. Partial measurement invariance is thus confirmed and multigroup analysis is permissible for comparing group-specific differences of standardized path coefficients in the structural model (Hair et al. 2017).

Structural Model

Main Effects Model

We assessed the main effects model with explained variances, standardized beta coefficients, and significance levels with 5000 bootstrap iterations (Hair et al. 2011; Hair et al. 2017). The results are summarized in Table 1.

Table 1. Results

Predictor variables	Dependent variable: Marketing Capabilities	Dependent variable: Firm Performance	Hypothesis	Supported?
Big Data Resources	.50** (7.65)		H1	Yes
Marketing Capabilities		.72** (10.82)	H2	Yes
Control variables				
Competitive Intensity	.05 (.73)	.04 (.72)		
Market Turbulence	.17** (2.94)	.14** (2.96)		
Technological Turbulence	.02 (.29)	.07 (1.25)		
Firm/SBU Size	-.05 (1.16)	-.04 (1.20)		
Good vs Service Firm	-.13* (2.19)	.00 (.09)		
Industry: Finance & Insurance	.02 (.37)	.05 (1.61)		
Industry: B2C Manufacturing	.10 (1.76)	.04 (1.02)		
Industry: Retail	.04 (.84)	.04 (1.11)		
Explained variance R2	**.423**	**.715**		

*p<.05 ** p<.01

The results reveal that Big Data Resources (BDR) has a significant effect (b = .50, *p*<.01) on Marketing Capabilities (MC), thus supporting H1. In addition, all three dimensions forming BDR make a significant contribution to the underlying second-order construct. Big Data Analytics Skills make the strongest contribution to BDR (weight = .48, *p*<.01) in our model, followed by Big Data Technology Resources (weight = .39, *p*<.01) and Organizational Big Data Resources (weight = .26, *p*<.05).

As expected, the results confirm that MC (b = .72, *p<.01*) is a strong predictor of Firm Performance (FP). H2 is thus supported. Since MC is formally hypothesized (H3) to fully mediate the relationship between BDR and FP, we tested for indirect effects separately using the bootstrapping method with 5000 bootstrap resamples (see Appendix H, Edwards and Lambert 2007; Kenny 2008; Preacher and Hayes 2008). The results of the mediation hypothesis (Table 2) are interpreted by examining the standardized regression coefficients, the significance levels, the bias-corrected 99% confidence intervals, and the standard errors of the indirect effect *ab* (Preacher and Hayes 2008; Shrout and Bolger 2002; Zhao et al. 2010).

Table 2. Mediation Bootstrapping Results

Mediation path	**BDR→MC→FP**	
a	.50**	
b	.68**	
c	.43**	
c'	0.09	
ab	**.34****	
SE	.056	
Bias-C. CI 99% Lower	.242	
Bias-C. CI 99% Upper	.461	
R^2	.719	
Controls	**Control→MC**	**Control→FP**
Competitive Intensity	.05	.02
Market Turbulence	.17**	.13**
Technological Turbulence	.02	.04
Firm/SBU Size	-.05	-.04
Good vs Service Firm	-.13*	.01
Industry: Finance & Insurance	.02	.06
Industry: B2C Manufacturing	.10	.04
Industry: Retail	.04	.03

** p<.01; * p<.05
Legend: BDR: Big Data Resources, MC: Marketing Capabilities, FP: Firm Performance
Path a: from independent variable to mediator.
Path b: from mediator to dependent variable.
Path c: direct effect.
Path ab: indirect effect.
Path c': direct effect when ab is controlled for

The indirect relationship between BDR and FP (ab = .34, *p<.01*) is highly significant, thus supporting H3. When the indirect effect is controlled for, the direct effect of BDR → FP turns insignificant (b = .09, *p=.07*), suggesting a complete mediation by MC on the link between BDR and FP (Baron and Kenny 1986; Zhao et al. 2010).

The control variables Firm/SBU Size, Industry Sector, and Environmental Turbulence had no significant direct influence on structural model variables with the exception of Market Turbulence on MC (b = .17, *p<.01*) and FP (b = .14, *p<.01*). The Goods/Services dummy also had a negative effect on MC (b = -.13, *p*<.05), suggesting that goods firms have higher levels of MC than services firms.

Multigroup Analyses

We formally hypothesized (H4a-b) that structural model relationships would differ depending on the firm's business strategy, namely, cost leadership or differentiation. We carried out multigroup analyses following the PLS-MGA method (Appendix F, Sarstedt et al. 2011; Henseler et al. 2016) to test for observed heterogeneities in the total sample. This was done by comparing structural models for significant differences in standardized path coefficients across groups. The results of PLS-MGA analyses are summarized in Table 3.

PLS-MGA analyses (one-tailed test) show that both constituent paths BDR → MC and MC → FP are significantly different between the cost leadership and differentiation strategy groups. In firms pursuing a differentiation strategy, the standardized path from BDR to MC is .62 compared to .37 for the cost leadership strategy group (difference = .25, $p=.021$). Thus, H4a received empirical support. It is worth noting that the relative importance of the three dimensions forming BDR did not change significantly across the groups. The relationship between MC and FP, in turn, is significantly stronger (difference = .22, $p=.028$) for firms with a differentiation strategy (.69) than for firms with a cost leadership strategy (.47). Hypothesis H4b is thus supported.

Cost leadership and differentiation groups showed no significant differences in control variable paths with the exception of the link between Competitive Intensity and MC (CTURB → MC difference = .38, $p=.012$). In stark contrast with the differentiation strategy group (.02, *ns*), Competitive Intensity remarkably has an even stronger positive effect on MC (.41, $p<.01$) than BDR in cost leadership firms.

As an additional test, we also calculated the conditional indirect effect (moderated mediation) of BDR on FP through MC between the two strategy groups (Table 4). The multigroup comparison shows that the indirect effect of BDR on FP is more than two times stronger (.36 vs .17) when the firm pursues a differentiation strategy than when it pursues a cost leadership strategy.

Table 3. Multigroup Analysis Results (PLS-MGA)

Path	Path by group		Difference in path	
Main Effects	**Cost leadership strategy (n=79)**	**Differentiation strategy (n=205)**	**Difference**	**p-value**
H1: BDR→MC	.37**	.62**	.25	.02*
H2: MC→FP	.47**	.69**	.22	.03*
Controls				
CTURB→MC	.41**	.02	.38	.01*
CTURB→FP	.17	.00	.17	.07
MTURB→MC	.08	.14	.05	.68
MTURB→CPERF	.17*	.17**	.00	.52
TTURB→MC	.08	.01	.08	.30
TTURB→FP	.23*	.07	.17	.08
SIZ→MC	-.07	-.04	.03	.63
SIZ→FP	-.10	-.01	.09	.90
GOODSERV→MC	-.17	-.16**	.01	.54
GOODSERV→FP	-.05	-.02	.03	.66
IND-F&I→MC	.03	.02	.01	.47
IND-F&I→FP	.08	.07	.01	.44
IND-MNF→MC	.08	.15*	.07	.72
IND-MNF→FP	.14*	.04	.10	.12
IND-RET→MC	.10	.07	.03	.38
IND-RET→FP	.04	.07	.03	.68

** p<.01 *p<.05 (one-tailed)
Legend: BDR: Big Data Resources, MC: Marketing Capabilities, FP: Firm Performance, CTURB: Competitive Intensity, MTURB: Market Turbulence, TTURB: Technological Turbulence, SIZ: Firm/SBU Size, GOODSERV: Good/Service, IND-F&I: Finance & Insurance Industry, IND-MNF: B2C Manufacturing Industry, IND-RET: Retail Industry

In sum, PLS-MGA analyses showed a significant degree of structural variance in the main effects across cost leadership and differentiation strategy groups. In addition, structural model differences between the two business strategy groups remained robust to control variable paths with the exception the direct effect of competitive intensity on MC.

Table 4. Conditional Indirect Effects as a Function of Business Strategy

Indirect path *ab*	Moderator	Conditional path *ab*	SE	LLCI 95%	ULCI 95%
BDR→MC→FP	Cost Leadership strategy	.17 (2.87)**	0.060	0.080	0.311
BDR→MC→FP	Differentiation strategy	.36 (6.23)**	0.069	0.297	0.563

** p<.01 (p-value of indirect path *ab* was also assessed at bias-corrected 99% confidence intervals)
Legend: LLCI: Lower level bias-corrected confidence interval. ULCI: Upper level bias-corrected confidence interval

Additional Multigroup Analyses

We carried out additional measurement invariance and PLS-MGA multigroup analyses for the grouping control variables, namely, good versus services and the three main industry sectors of B2C manufacturing, finance and insurance (F&I), and retail (see Appendix I for detailed analysis). The results suggest that the structural model is generalizable across both goods and services firms. In comparing the three industry sectors, differences in path BDR → MC were insignificant. In a similar vein, the weights of BDR dimensions remained robust across all multigroup analyses.

B2C manufacturing firms had a significantly stronger MC → FP relationship than firms in F&I (.80 vs .44, difference = .36, p<.01) and retail (.80 vs .56, difference = .24, p<.05 one-tailed test). The two-tailed permutation test confirmed that MC → FP in the B2C manufacturing industry is significantly different from F&I (p<.01) and retail (p<.05). Thus, the results suggest that data-driven MC in the B2C manufacturing industry is associated with higher firm performance than in other industries.

In conclusion, all three hypotheses in the main effects model received strong empirical support (p<.01). Moderation hypotheses H4a-b were also supported (p<.05) by our data.

DISCUSSION

This study offers numerous novel contributions to the IS, marketing, and data sciences literatures. These are highlighted in Table 5 and discussed in greater depth next.

Research Implications

This study builds on RBV theory to answer how and to what extent big data resources (BDR) acts to enhance marketing capabilities (MC), which in turn leads to better firm performance. In so doing, this study makes important contributions to resource-based research in IS and marketing.

The study makes several important theoretical contributions. First, our study improves understanding of the ways in which BDR impacts firm performance. Consistent with RBV logic and based on study findings, BDR can be inferred to be a valuable, rare, and costly-to-imitate resource (Amit and Schoemaker 1993; Dierickx and Cool 1989; Peteraf 1993) that can be a source of strategic advantage when its value-creating potential is capitalized via marketing processes (Barney and Hesterly 2012; Kohli and Grover 2008; Nevo and Wade 2010). Specifically, the results show that MC fully mediates the relationship between BDR and firm performance. This study thus lends support to recent RBV-based marketing/IS studies asserting that strategic IT resources only have value *potential* but realizing this value requires alignment with other complementary IT –enabled organizational capabilities (Kohli and Grover 2008; Mithas et al. 2011; Morgan et al. 2009).

Table 5. Key Contributions of this Study

	Novel Contribution	Theoretical Implication	Practical Implication
1	Offers insights into how use of big data resources can improve marketing capabilities and thereby firm performance (a fully	Lends support to recent RBV studies which argue that strategic IT resources only have value *potential*, and thus can only influence	Proof that the business benefits of big data depend on its ability to support (and thus align with) marketing processes.

	mediated linkage).	firm outcomes through their effect on more granular organizational capabilities.	
2	Makes the case that effective BDR requires a set of critical, complementary big data-related IT resources exerting a joint influence on MC.	Empirical evidence supports RBV's resource complementarity argument in the totally unexplored domain of big data.	A balance of IT infrastructure, human capital, and cultural resources are all necessary for effective BDR.
3	Empirically tests competing predictions regarding how firm strategy (cost leadership versus differentiation) influences the business impact of big data.	RBV predictions about the sustainable competitive advantage afforded by resources must account for "how" those resources are deployed (i.e., must account for business strategy).	Firms that choose to pursue a differentiation strategy will get an added boost offered by the impact of big data resources on marketing capabilities and marketing capabilities on firm performance.
4	Shows that firm strategy – above and beyond industry characteristics and product mix (goods versus services) – determines BDR success.	Unlike other theoretical tests of RBV, industry effects and product mix characteristics were not important whenever big data resources are concerned.	Managers have greater control over their BDR despite their given industry characteristics and product mix. In brief, decisions about deploying big data resources are not contingent on type of industry or whether a firm predominantly sells goods or services. This opens up degrees of freedom for managers.

Even more specifically, the findings show that the indirect effect of BDR on firm performance being leveraged in firm marketing processes is substantial (coefficient = .34, $p<.01$). This suggests that an 11-12% increase in firm performance may be attributed to strategic investments in BDR. By way of contrast, prior IT business value research has found that IT investment into business intelligence (BI) resources, before the emergence of big data technologies, improves firm performance by only 5-6% beyond what can be explained by other factors (Brynjolfsson et al. 2011). Our results thus confirm the expectation that BDR has greater potential for differential performance and competitive advantage than prior data-driven IT (Chen et al. 2012; McAfee and Brynjolfsson 2012).

Second, this study makes a novel theoretical contribution with its parsimonious conceptualization of big data resources (BDR). Consistent with RBV theory, the results suggest that effective BDR requires a set of critical, complementary big data-related IT resources exerting a joint influence on MC. As informed by qualitative big data literature, our empirical analyses indicate that all three dimensions (big data technology resources, big data analytics skills, and organizational big data resources) represent statistically significant, conceptually distinct domains of BDR.

Furthermore, the BDR construct captures the relative importance of BDR dimensions in predicting MC and firm performance. The results suggest that specialized human resources, i.e., big data analytics skills (weight = .48, p<.01), is the most important facet of BDR. The empirical results thus confirm concerns raised by scholars that the lack of human talent to develop predictive models and algorithms that support corresponding business decisions and organizational processes is the greatest impediment to big data success (Davenport and Patil 2012; McAfee and Brynjolfsson 2012). We emphasize, however, that big data-driven IT infrastructure (weight = .39, p<.01) (including non-relational databases and warehousing technologies, which are the analytics platform and applications), and organizational resources (weight = .26, p<.05) that foster big data utilization (e.g., top management support and organizational culture), are also key dimensions of strategic BDR. It is worth noting that the relative importance and significance of the three BDR dimensions remained unchanged across firm and industry characteristics, lending support for the generalizability of the novel BDR construct.

Third, the findings underline that the business impact of big data is contingent on firm strategy, i.e., whether the firm pursues a cost leadership or a differentiation advantage over its rivals. The multigroup analyses suggest that when mediated by MC (.62, $p<.01$), BDR's indirect contribution to the explained variance of firm performance is 13% (.36, $p<.01$) in differentiating firms. In stark contrast, firms competing on the basis of cost leadership achieve only a 3% increase in performance attributable to BDR (indirect effect .17, $p<.01$).

The most likely explanation for these highly divergent effects between differentiation and low cost leader firms is that the predictive properties of big data analytics outweigh the efficiency advantages achieved through the automation and optimization of marketing processes. The findings thus underscore how firms seeking to differentiate themselves from competition need to understand what their customers want and, by offering new products and services accordingly, will then be poised to reap greater rewards from a big data-driven marketing strategy than will cost-focused firms. That is, big data particularly enhances marketing capabilities by helping them become more adaptive to continuous changes in the market (Day 2011). We offer another possible explanation in that big data may also be utilized to enhance MC efficiency by differentiating firms to maintain relative cost parity in their quest for competitive advantage (Olson et al. 2005; Porter 1985). Cost leadership firms, in turn, may not be able to exploit big data's full potential to improve MC effectiveness through a better understanding of customer needs and new product and service innovations.

These findings are also intriguing because prior research has emphasized the critical role of industry rather than firm characteristics in determining the value-creating potential of big data (e.g., Davenport 2014; Gartner 2013). While the results show that industry sector, goods versus services, and environmental turbulence demonstrate minor effects on business impact, our findings strongly suggest that firm strategy, above and beyond industry characteristics, determines BDR success. The multigroup analyses further indicate, however, that the role of industry characteristics may be more important for cost leadership firms. Competitive intensity notably exerts a greater influence on the levels of MC (.41, $p<.01$) than BDR (.37, $p<.01$), implying that cost leaders are more likely to build better marketing capabilities as response to competitive pressures, rather than as a result of big data investment.

Managerial Implications

This study has important implications for firms because becoming a big data-driven marketing organization is inhibited by technological, human and organizational challenges. Study findings suggest, though, that firms that acquire appropriate big data resources (BDR) can indeed achieve competitive advantages over their rivals.

The key for praxis is for managers to understand what they can do to maximize the likelihood that their firms benefits from investments in big data resources. With this in mind, we stress that marketing capabilities are the critical link between big data resources and firm performance. Practitioners should ensure that big data resources are properly aligned with the firm's marketing processes. In practice, many marketing organisations fail to make full use of big data-driven insights to guide marketing decisions. We therefore recommend that managers assess the feasibility of big data resources in the context of their application to marketing capabilities. To do this, managers should regularly measure the impact of big data projects on different marketing processes in terms of efficiency, effectiveness, and innovativeness by identifying the most appropriate customer, market, and financial performance metrics.

Second, we advise managers to direct intensive effort to make sure that all aspects of the firm's overall big data asset are sufficient, if not perfectly balanced. Firms should not focus solely on their technological big data infrastructure or on their recruitment of data scientists. An organizational culture that discourages big data can seriously undermine its utilization and this lack cannot be compensated for by excelling in big data analytics skills, for example. We urge management to take immediate corrective action if inadequacies in any of these dimensions are observed.

Third, we recommend that managers carefully consider whether the potential of big data investment is being fully utilized in their respective firms. For example, Amazon.com's greatest competitive advantage is created through their outside-in orientation afforded by big data-driven customer insight (Day 2011). Yet Amazon.com also excels in minimizing the costs and time spent on pricing, distribution and communications with automated decision support engines. This study's findings similarly underline the point that managers working with differentiated products and services, regardless of the industry, should consider big data as a key component in building more efficient, effective, and innovative marketing capabilities to meet customer needs. B2C manufacturing firms should note that they may be in a particularly favorable position compared to other data-driven industry sectors. The advent of sensor-based analytics ("The Internet of Things") and the lower adoption of big data may represent opportunities in B2C manufacturing that are less evident in the retail, e-commerce, finance, and banking sectors (Brown et al. 2012; Cap Gemini 2012; Gartner 2013; Manyika et al. 2011).

Limitations

This study has several limitations, some of which point to opportunities for future research. First, the data in this research was gathered in a cross-sectional format and causal relationships between constructs cannot be asserted with complete confidence. We recommend that future studies adopt longitudinal research designs for confirming and extending our findings. Second, we used a single-informant design with self-reported subjective data that is conceivably a source of common method bias, although our numerous tests show that it should be not an issue. It needs to be noted that prior studies have found that subjective measures can slightly overestimate the MC → FP relationship (Krasnikov and Jayachandran 2008; Morgan et al. 2009). Third, the generalizability of results is restricted to large US-based firms/SBUs operating in B2C industries. Future studies might explore big data-driven marketing capabilities in SMEs, B2B sectors, and other cultural contexts. Fourth, this study focused solely on marketing capabilities. Future research may seek to improve understanding about how big data resources influence marketing capabilities once other firm capabilities such as R&D and operational capabilities are controlled for.

Conclusion

Strategic big data resources (BDR) play a vital role in improving the efficiency and effectiveness of strategic marketing capabilities (MC) to achieve competitive advantage. To the best of our knowledge, this study is the first large-scale empirical study to examine the action mechanism and impact of strategic big data investments on firm performance. As a foundation for future research, this study underscores the need to better understand the performance impacts of BDR. We hope that this contribution motivates more academic research to address the complementary, enabling role of BDR to enhance the effectiveness, efficiency and innovativeness of strategic organizational capabilities.

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APPENDIX A: ONLINE SUPPLEMENT

Sample Characteristics

Table A1. Sample Characteristics (N=301)

Industry	N	%
Finance & Insurance	68	22.6
B2C Manufacturing	60	19.9
Retail	52	17.3
IT	32	10.6
Hospitality	19	6.3
Wholesale	19	6.3
Professional services	18	6.0
Healthcare / Pharmaceuticals	11	3.7
Media & Advertising	10	3.3
Telecom	7	2.3
Other	5	1.7
Total	301	100

SBU revenue (m$)	N	%
less than 10	72	23.9
10-100	103	34.2
101-1000	62	20.6
over 1000	64	21.3
Total	301	100

Position of respondent	N	%
CMO	47	15.6
Marketing Director	67	22.2
Senior Marketing Manager	66	21.9
Marketing VP	29	9.6
CEO	24	7.8
CRM Director/Manager	68	22.6
Total	301	100

Tenure (years)	N	%
3-5 years	67	22
6-9 years	130	43
10-20 years	97	32
over 20 years	7	2.3
Total	301	100

Number of subordinates	N	%
10-20	89	30
21-50	140	47
51-100	41	14
over 100	31	10
Total	301	100

APPENDIX B: ONLINE SUPPLEMENT

Measure Descriptions and Item Reliability

Table B1. Measure Descriptions and Item Reliability

Measure / item		
Big Data Resources (2nd order formative) (new measure)	**Weight**	
Big Data Technology Resources	**0.39**	**
Big Data analytics skills	**0.48**	**
Organizational Big Data Resources	**0.26**	*
Big Data Technology Resources (1st order formative) (Germann et al. 2013)		
Our SBU has a state-of-art Big Data IT infrastructure.	**0.40**	**
Our SBU uses Big Data tools to gain a competitive advantage.	**0.41**	**
In general, our SBU collects more data than our primary competitors.	**0.51**	**
Big Data Analytics Skills (1st order formative) (Germann et al. 2013)		
Our analytics people are very good at identifying and employing the appropriate Big Data analysis tool given the problem at hand.	**0.49**	**
Our analytics people have the ability to use many different Big Data analysis tools and techniques.	**0.36**	**
Our analytics people can be considered as experts in Big Data analytics.	**0.47**	**
Organizational Big Data Resources (1st order formative) (Germann et al. 2013)		
If our SBU reduces its Big Data analytics activities, its profits will suffer.	**0.17**	*
The use of Big Data analytics improves our SBU's ability to satisfy its customers.	**0.37**	**
Most people in our SBU are skeptical of Big Data-based results and recommendations. (R)	**0.17**	*
Our SBU's top management has a favorable attitude towards Big Data analytics.	**0.24**	**
Our SBU's annual reports and other publications highlight our use of Big Data analytics as a core competitive advantage.	**0.34**	**
Our SBU's top management expects Big Data analyses be used to support important decisions.	**0.28**	**
Marketing Capabilities (2nd order reflective) (Vorhies and Morgan 2005)	**Loading**	
Pricing	0.86	**
Product development	0.86	**
Channel management	0.84	**
Marketing communication	0.85	**
Market Information Management	0.87	**
Selling	0.86	**
Marketing Planning	0.87	**
Marketing Implementation	0.86	**
In the most recent year, relative to your major competitors, how has your SBU performed with respect to:		
Pricing (1st order reflective) (Vorhies and Morgan 2005)		
Using pricing skills and systems to respond quickly to market changes.	0.82	**
Doing an effective job of pricing products/services.	0.81	**
Monitoring competitors' prices and price changes.	0.80	**
Product development (1st order reflective) (Vorhies and Morgan 2005)		
Ability to develop new products/services.	0.80	**
Successfully launching new products/services.	0.78	**
Ensuring that product/service development efforts are responsive to customer needs.	0.77	**
Channel management (1st order reflective) (Vorhies and Morgan 2005)		

Strength of relationships with distributors.	0.80	**
Attracting and retaining the best distributors.	0.76	**
Adding value to distributors' businesses.	0.81	**
Marketing communication (1st order reflective) (Vorhies and Morgan 2005)		
Developing and executing advertising programs.	0.75	**
Brand image management skills and processes.	0.79	**
Managing corporate image and reputation.	0.78	**
Market Information Management (1st order reflective) (Vorhies and Morgan 2005)		
Gathering information about customers and competitors.	0.80	**
Making full use of marketing research information.	0.79	**
Analyzing our market information.	0.81	**
Selling (1st order reflective) (Vorhies and Morgan 2005)		
Giving salespeople the training they need to be effective.	0.84	**
Sales management skills.	0.79	**
Providing effective sales support to the sales .	0.81	**
Marketing Planning (1st order reflective) (Vorhies and Morgan 2005)		
Marketing planning skills.	0.82	**
Marketing management skills and processes.	0.80	**
Thoroughness of marketing planning processes.	0.78	**
Marketing Implementation (1st order reflective) (Vorhies and Morgan 2005)		
Organizing to deliver marketing programs effectively.	0.78	**
Translating marketing strategies into action.	0.79	**
Executing marketing strategies quickly.	0.83	**
Firm Performance (2nd order reflective) (Vorhies and Morgan 2005)	**Loading**	
Customer Satisfaction	0.89	**
Market Effectiveness	0.88	**
Profitability	0.94	**
In the most recent year, relative to your major competitors, how has your SBU performed with respect to:		
Customer Satisfaction (1st order reflective) (Vorhies and Morgan 2005)		
Customer satisfaction	0.81	**
Delivering value to your customers	0.81	**
Delivering what your customers want	0.84	**
Market Effectiveness (1st order reflective) (Vorhies and Morgan 2005)		
Growth in sales revenue	0.76	**
Acquiring new customers	0.80	**
Increasing sales to existing customers	0.80	**
Profitability (1st order reflective) (Vorhies and Morgan 2005)		
Business unit profitability	0.76	**
Reaching financial goals	0.78	**
Return on investment (ROI)	0.76	**
Return on sales (ROS)	0.78	**
Competitive Intensity (1st order reflective) (Kohli and Jaworski 1990)		
Competition in our industry is cutthroat.	0.79	**
One hears of a new competitive move in our industry almost every day.	0.83	**
Market Turbulence (1st order reflective) (Kohli and Jaworski 1990)		
In our kind of business, customers' product preferences change quite a bit over time.	0.85	**
It is very difficult for our SBU to predict changes in the marketplace.	0.74	**

Technological Turbulence (1st order reflective) (Kohli and Jaworski 1990)		
A large number of new product ideas have been recently made possible through technological breakthroughs in our industry.	0.88	**
The technological changes in this industry are frequent.	0.81	**
Business Strategy (Verhoef and Leefland 2009)	NA	
Please indicate which of the following generic business strategies is most applicable for your firm: o Cost leadership: strategy to obtain the lowest costs in the market. o Differentiation: focusing on being better in different features of the product/service that are important to customers. o Cost focus: targeting a relative small segment in the market that is cost-conscious. o Differentiation focus: targeting a relative small segment in the market that desires a unique and good product and that is willing to pay a higher price for this.		
Firm Size (Homburg et al 1999)		
What is the total number of fulltime employees in your business unit (SBU)?	NA	
less than 500=1; 501-1,000=2; 1,001-5,000=3; 5,001-10,000=4; 10,001-50,000=5; 50,001-100,000=6; over 100,000=7		
Goods versus Services (Verhoef and Leefland 2009)		
Is your business unit's (SBU) offering primarily a good or service?	NA	
Industry		
What is business unit's (SBU) industry sector?	NA	
*p<.05 ** p<.01		
formative item weights in **bold**		

APPENDIX C: ONLINE SUPPLEMENT

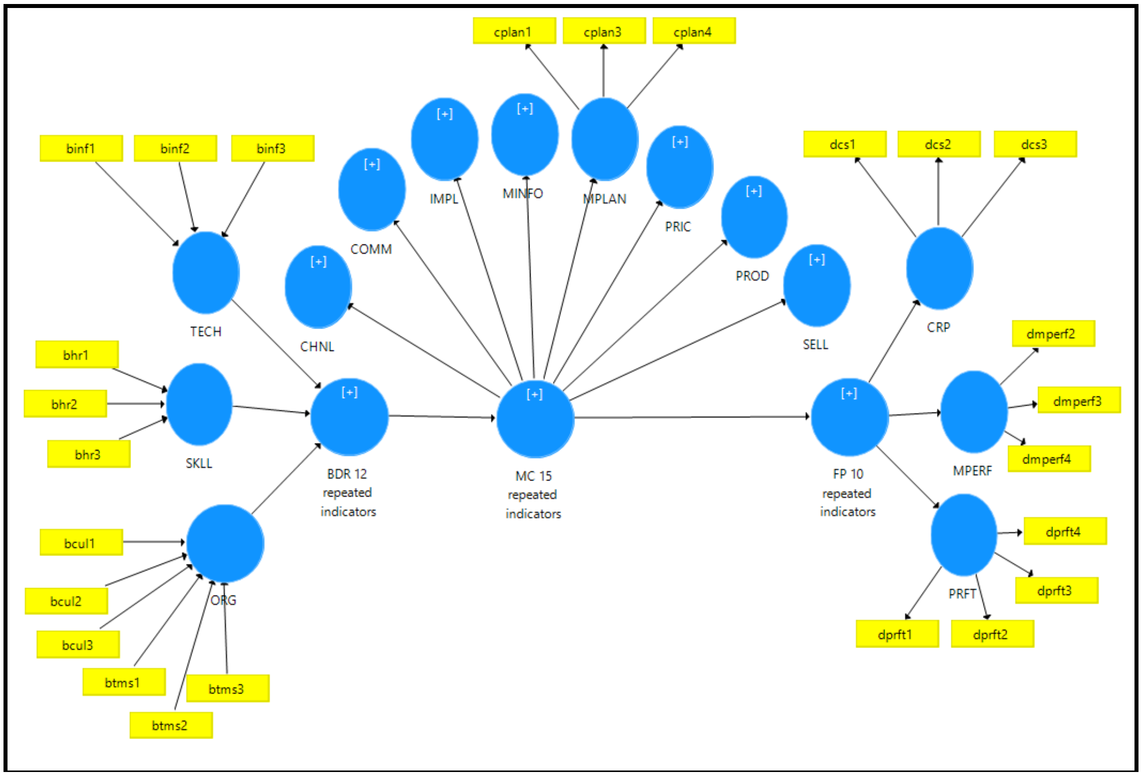
Higher-Order Construct Specification

Our measures include three higher-order constructs. We adopted "Marketing Capabilities (MC)" and "Firm Performance (FP)" from Vorhies and Morgan's (2005) study. Following established measurement model specification guidelines, we determined that both constructs are second-order reflective, first-order reflective (Type I) constructs, respectively (Petter et al. 2007; Jarvis et al. 2003).

Following the decision rules by Wong et al. (2008), we determined that the newly introduced "Big Data Resources (BDR)" is an aggregate model of a multidimensional construct (formative composite variable). Firstly, BDR's dimensions can be algebraically combined to form an overall representation of the construct. Second, BDR has a clear conceptual meaning as a strategic IT resource, and the relationships between BDR and its dimensions have been clearly established with resource complementarity arguments. Therefore, the overall construct and its dimensions do co-exist for theory building and empirical investigation to take place. Third, BDR's dimensions are unobservable, abstract constructs (unlike cause indicators of formative constructs) that can be measured and the overall construct can be operationalized from its dimensions. As for the implications for conducting analyses, the construct-level relationships of BDR can be deduced directly from theoretical arguments, hypotheses development, and empirical analyses at the dimension level. This argument is generalizable to multidimensional construct Y regardless of whether it is the predictor, mediator, or outcome variable (Wong et al. 2008).

In the PLS analyses, "Big Data Resources (BDR)" is thus treated as a Type IV formative composite, and "Marketing Capabilities (MC)" and "Firm Performance (FP)" as Type I reflective composites, respectively. More specifically, we modeled them using a hierarchical component model with repeated indicators (Wold 1982; Lohmöller 1989). A Mode B (path-weighting scheme) was selected for BDR's formatively-measured repeated indicators because this approach that produces the most reliable results (Becker et al. 2012). A Mode A (path-weighting scheme) was adopted for the reflectively-measured repeated indicators of MC and firm performance. The PLS structural model is illustrated in Figure A. For presentation purposes, the repeated indicators of BDR, MC and FP are not shown in the figure.

Figure C1. PLS Path Model



We carried out additional tests following Chwelos et al. (2001) to test whether measurement model specification affects structural model results. We tested two other versions of the model (one with all constructs formative (Mode B) and another with all constructs reflective (Mode A). The results of the structural model (path coefficients between research constructs BDR, MC, FP) were qualitatively similar with no path coefficients gaining or losing statistical significance and no significant paths changed in sign. In sum, measurement model specification decisions, which are always judgment calls made by authors, do not affect the overall empirical findings.

APPENDIX D: ONLINE SUPPLEMENT

Descriptive Statistics, Measure Validation, and Latent Variable Correlations

Table D1. Descriptive Statistics, Measure Validation, and Latent Variable Correlations

Construct	Mean	SD	CR	AVE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 Big Data Resources	5.41	.88	NA	NA	**NA**																				
2 Big Data Technology Resources	5.28	1.03	NA	NA	.88	**NA**																			
3 Big Data Analytics Skills	5.48	.98	NA	NA	.92	.69	**NA**																		
4 Organisational Big Data Resources	5.48	.92	NA	NA	.83	.64	.67	**NA**																	
5 Marketing Capabilitities	5.30	.97	.95	.93	.61	.53	.55	.50	**.96**																
6 Pricing	5.28	1.10	.85	.65	.50	.46	.42	.40	.86	**.81**															
7 Product Development	5.35	1.07	.83	.61	.56	.46	.52	.47	.86	.73	**.78**														
8 Channel Management	5.29	1.10	.83	.63	.47	.38	.45	.36	.84	.71	.66	**.79**													
9 Marketing Communication	5.32	1.08	.82	.60	.48	.43	.43	.37	.85	.71	.68	.70	**.78**												
10 Market Information Management	5.37	1.09	.84	.64	.52	.47	.45	.45	.87	.70	.70	.67	.71	**.80**											
11 Selling	5.33	1.13	.85	.66	.54	.48	.51	.41	.86	.68	.69	.66	.69	.74	**.81**										
12 Marketing Planning	5.25	1.09	.84	.64	.54	.46	.49	.45	.88	.72	.72	.69	.68	.73	.71	**.80**									
13 Marketing Implementation	5.18	1.15	.84	.64	.59	.50	.54	.51	.86	.69	.73	.67	.69	.70	.70	.75	**.80**								
14 Firm Performance	5.25	.99	.91	.95	.60	.55	.52	.49	.82	.73	.69	.68	.71	.71	.73	.73	.70	**.97**							
15 Customer Satisfaction	5.29	1.09	.86	.67	.54	.47	.47	.46	.72	.63	.59	.59	.63	.62	.65	.65	.59	.89	**.82**						
16 Market Effectiveness	5.26	1.09	.83	.62	.52	.47	.47	.38	.72	.65	.60	.60	.63	.61	.62	.64	.61	.88	.67	**.79**					
17 Profitability	5.20	1.05	.86	.60	.57	.54	.48	.47	.76	.69	.66	.65	.65	.68	.69	.68	.68	.94	.75	.74	**.77**				
18 Competitive Intensity	5.04	1.06	.79	.66	.42	.40	.33	.40	.33	.32	.26	.26	.25	.31	.34	.24	.28	.35	.32	.32	.31	**.81**			
19 Market Turbulence	4.84	.94	.78	.63	.49	.46	.43	.40	.44	.39	.36	.35	.33	.38	.42	.41	.38	.51	.44	.46	.48	.37	**.80**		
20 Technological Turbulence	4.95	1.04	.83	.71	.58	.52	.52	.50	.41	.36	.30	.38	.27	.37	.39	.38	.35	.45	.44	.37	.41	.42	.50	**.84**	
21 Firm Size	3.46	1.75	1.00	1.00	.01	-.04	.06	.00	-.06	-.03	.00	-.02	-.06	-.10	-.03	-.12	-.06	-.09	-.08	-.09	-.08	-.03	-.01	-.06	**1.00**

NA: not applicable for formative construct

√**AVE in bold**

APPENDIX E: ONLINE SUPPLEMENT

Marker Variable Analysis

Table E1. Marker Variable Analysis

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 Big Data Resources	1.00																	
2 Big Data Technology Resources	.882**	1.00																
3 Big Data Analytics Skills	.918**	.689**	1.00															
4 Organisational Big Data Resources	.828**	.641**	.671**	1.00														
5 Marketing Capabilitities	.612**	.531**	.553**	.499**	1.00													
6 Pricing	.496**	.462**	.420**	.400**	.864**	1.00												
7 Product Development	.559**	.462**	.520**	.469**	.859**	.728**	1.00											
8 Channel Management	.466**	.380**	.450**	.362**	.837**	.707**	.663**	1.00										
9 Marketing Communication	.483**	.434**	.426**	.370**	.849**	.708**	.680**	.698**	1.00									
10 Market Information Management	.524**	.469**	.448**	.452**	.866**	.695**	.698**	.672**	.713**	1.00								
11 Selling	.542**	.477**	.508**	.406**	.858**	.678**	.691**	.664**	.694**	.743**	1.00							
12 Marketing Planning	.536**	.457**	.485**	.452**	.875**	.721**	.716**	.693**	.677**	.731**	.708**	1.00						
13 Marketing Implementation	.592**	.503**	.539**	.512**	.863**	.691**	.730**	.666**	.685**	.696**	.704**	.752**	1.00					
14 Firm Performance	.603**	.548**	.522**	.489**	.824**	.729**	.686**	.678**	.705**	.710**	.725**	.728**	.697**	1.00				
15 Customer Satisfaction	.536**	.468**	.465**	.460**	.721**	.633**	.586**	.590**	.627**	.619**	.651**	.651**	.593**	.892**	1.00			
16 Market Effectiveness	.519**	.473**	.474**	.378**	.720**	.647**	.601**	.595**	.628**	.612**	.618**	.637**	.607**	.876**	.668**	1.00		
17 Profitability	.572**	.535**	.476**	.474**	.783**	.689**	.661**	.645**	.653**	.683**	.687**	.679**	.678**	.935**	.753**	.739**	1.00	
18 Astrology Interest	-.008	.006	-.023	-.051	.204**	.160**	.203**	.155**	.155**	.170**	.173**	.161**	.226**	.085	-.017	.091	.143*	1.00

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

APPENDIX F: ONLINE SUPPLEMENT

Measurement Invariance of Composite Models (MICOM) Procedure and PLS-MGA Multigroup Analysis

Measurement Invariance Assessment

Measurement invariance ensures that significant group differences in the structural model are not generated by different interpretations of measurement models across groups, which may lead to erroneous conclusions. The MICOM (measurement invariance of composite models) procedure was adopted to assess measurement model invariance (Henseler et al. 2016). MICOM is the recommended method to test for measurement invariance of reflective and formative latent constructs (composites) across different groups in variance-based PLS-SEM (Henseler et al. 2016; Hair et al. 2017). Regardless of measurement model specification as reflective (Mode A) or formative (Mode B), the latent variables in PLS-SEM are always modeled as composite constructs that do not contain an error term. Hence, MICOM focuses on detecting systematic measurement errors resulting from group membership (see Steps 2-3 below; Henseler et al. 2016).

MICOM is a three-step procedure to test: (1) configural invariance, (2) compositional invariance, and (3) the equality of composite means and variances (Henseler et al. 2016). Configural invariance is a qualitative step to ensure that an identical nomological net (the same constructs with the same number of items; the same structural), and identical data treatment and analysis (coding, missing values, weighting scheme, algorithm), is applied for model estimation for all groups (Hair et al. 2017; Henseler et al. 2016). Configural invariance is a precondition for carrying out Steps 2-3.

Step 2 tests for compositional invariance that occurs when composite (latent construct) scores between groups, as opposed to item loadings and weights, are not significantly different. For example, formative composite scores may have compositional invariance even if their indicator weights vary significantly across groups[8]. Studies have reported that lack of measurement invariance at item level does not affect structural model comparisons in PLS-SEM if composite scores are invariant (Dijkstra and Henseler 2011; Henseler et al. 2016). Permutation is adopted (as recommended) to test for compositional invariance. Permutation is a non-parametric procedure randomly assigns (permutes) observations to groups to compute correlations between inter-group composite scores. Correlations with p-values lower than .05 leads to the rejection of compositional invariance (Henseler et al. 2016).

Only if compositional invariance of all measurement models is supported can the equality of means and variances be assessed (Step 3). Permutation is adopted once again as the recommended approach. Specifically, the permutation test calculates two-tailed confidence intervals (percentiles) of differences in mean values and variances. If the original difference between inter-group composite scores are within the 95% confidence interval limits, the

---

[8] MICOM differs from multigroup confirmatory factor analysis (CFA) that assesses reflective common factor models in covariance-based SEM. The latter approach posits that only if item loadings are invariant across groups (metric invariance) can composite constructs be assumed to have the same meaning to all groups, thus allowing for a meaningful structural model comparison (Henseler et al. 2016).

construct mean values and variances may be considered to be statistically equal, i.e., measurement invariance is confirmed (Henseler et al. 2016).

In this case, the equality of means and variances of all composites supports *full measurement invariance*. Pooling the data for additional statistical power and more generalizable findings is permitted since no observed heterogeneity exists across pre-defined groups. However, if PLS-MGA analyses still reveal structural differences across groups, the model with pooled data should be extended by including moderators to account for such differences. If composite means and variances are not equal, *partial measurement invariance* is confirmed. In this case a multigroup comparison of standardized coefficients in the structural model is appropriate (Hair et al. 2017; Henseler et al. 2016).

PLS-MGA Multigroup Analysis

We carried out multigroup analyses following the PLS-MGA approach with 5000 resample bootstraps to test for observed heterogeneities in the total sample by comparing structural models across groups (Henseler et al. 2007; Sarstedt et al. 2011). PLS-MGA and permutation (Chin and Dibbern 2010; Henseler et al. 2009) are regarded as the most conservative methods that are least likely to render significant differences as is often the case with the parametric approach, for instance (Sarstedt et al. 2011). Permutation requires the groups under investigation to be of similar size (Hair et al. 2017). PLS-MGA was chosen as the most appropriate method since group sizes are considerably different for business strategy groups, namely, cost leadership (N=79) and differentiation (N=205).

Specifically, PLS-MGA is a non-parametric bootstrapping method that allows for testing when pre-defined data groups show significant differences in their group-specific path coefficients in the structural model. Specifically, PLS-MGA compares bootstrap estimates of the same parameters across groups to calculate one-tailed p-values for group differences (Hair et al. 2017). The results are based on composite scores obtained from pooled data that are then used in bootstrapping tests for each group, respectively.

APPENDIX G: ONLINE SUPPLEMENT

Measurement Invariance of Composite Models (MICOM) Results

Table G1. Measurement Invariance of Composite Models (MICOM) Results

	STEP 2					STEP 3a					STEP 3b				
	c value	95% CI		p-value	Compositional	Difference in	95% CI		p-value	Equal mean	Difference in	95% CI		p-value	Equal
Composite		low	high		invariance?	mean value	low	high		values?	variance	low	high		variances?
Big Data Resources	1.000	1.000	1.000	.192	Yes	-.003	-.271	.251	1.000	Yes	-.145	-.369	.367	.410	Yes
Big Data Technology Resources	.983	.969	1.000	.171	Yes	-.002	-.267	.248	1.000	Yes	-.097	-.385	.421	.575	Yes
Big Data Analytics Skills	.999	.977	1.000	.945	Yes	-.020	-.276	.260	.893	Yes	-.039	-.366	.339	.877	Yes
Organisational Big Data Resources	.975	.939	1.000	.493	Yes	.005	-.280	.251	.939	Yes	.006	-.533	.462	.917	Yes
Marketing Capabilitities	1.000	1.000	1.000	.068	Yes	.124	-.290	.260	.314	Yes	-.338	-.330	.301	.041*	No
Pricing	.999	.997	1.000	.204	Yes	.158	-.274	.280	.230	Yes	-.146	-.393	.344	.525	Yes
Product Development	.998	.995	1.000	.303	Yes	.137	-.278	.285	.300	Yes	-.291	-.360	.359	.108	Yes
Channel Management	.996	.994	1.000	.116	Yes	.003	-.253	.252	.943	Yes	-.112	-.411	.339	.579	Yes
Marketing Communication	.994	.992	1.000	.090	Yes	.121	-.260	.258	.346	Yes	-.144	-.376	.308	.422	Yes
Market Information Management	.998	.997	1.000	.184	Yes	.157	-.275	.245	.210	Yes	-.401	-.367	.344	.032*	No
Selling	.996	.997	1.000	.035*	No	-.027	-.272	.260	.879	Yes	-.101	-.389	.371	.631	Yes
Marketing Planning	.998	.998	1.000	.058	Yes	.159	-.282	.250	.210	Yes	-.134	-.387	.363	.531	Yes
Marketing Implementation	.999	.996	1.000	.584	Yes	.131	-.287	.249	.284	Yes	.022	-.372	.339	.947	Yes
Firm Performance	1.000	1.000	1.000	.171	Yes	.092	-.269	.256	.458	Yes	.040	-.381	.389	.833	Yes
Customer Satisfaction	1.000	.998	1.000	.634	Yes	.046	-.270	.255	.745	Yes	.226	-.394	.342	.204	Yes
Market Effectiveness	.996	.995	1.000	.123	Yes	.116	-.250	.235	.376	Yes	.093	-.434	.429	.683	Yes
Profitability	.996	.997	1.000	.042*	No	.083	-.271	.261	.496	Yes	-.032	-.397	.422	.855	Yes
Controls															
Competitive Intensity	.951	.931	1.000	.090	Yes	.124	-.270	.236	.330	Yes	.301	-.405	.381	.120	Yes
Market Turbulence	.994	.946	1.000	.513	Yes	.008	-.259	.263	.999	Yes	.034	-.388	.337	.773	Yes
Technological Turbulence	.999	.983	1.000	.651	Yes	-.090	-.271	.242	.541	Yes	.260	-.480	.449	.318	Yes
Firm Size	1.000	1.000	1.000	.169	Yes	.088	-.285	.270	.488	Yes	-.242	-.366	.308	.210	Yes
Good/Service	1.000	1.000	1.000	.131	Yes	-.212	-.227	.266	.094	Yes	-.059	-.059	.014	.068	Yes
Industry Finance & Insurance	1.000	1.000	1.000	.352	Yes	.250	-.284	.243	.132	Yes	-.303	-.356	.266	.080	Yes
Industry B2C Manufacturing	1.000	1.000	1.000	.184	Yes	-.155	-.242	.234	.196	Yes	.205	-.403	.306	.316	Yes
Industry Retail	1.000	1.000	1.000	.064	Yes	.051	-.280	.239	.837	Yes	-.094	-.526	.438	.773	Yes

APPENDIX H: ONLINE SUPPLEMENT

Mediation Testing Using the Bootstrapping Method

The most advanced method for examining indirect effects is bootstrapping (Edwards and Lambert 2007; Kenny 2008; Preacher and Hayes 2008; Zhao et al. 2010). Adopting Preacher and Hayes' (2008) bootstrapping macros for SPSS, each mediation path was assessed in the structural model. The bootstrapping procedure is a non-parametric test without normality assumptions which creates confidence intervals (CI) for the indirect effect. We used 5000 bootstrapping resamples with 95% bias-corrected confidence intervals to test our hypotheses.

Significant paths X→M (path a) and M→Y (path b) are necessary prerequisites for the indirect effect X→M→Y (path ab) to occur. In contrast with Baron and Kenny's (1986) third condition for mediation, a significant direct effect X→Y (path c) is not necessary to establish mediating effects. X→Y's direct effect c does not represent the effect to be mediated but the *total effect,* which is the zero-order effect of simultaneous direct and indirect effects c = c' + ab (c' is the direct path when ab is controlled for). If the direct effect c' is negative, the indirect effect ab may be significant when the total effect c is not. Thus, the indirect effect is assessed solely based on the strength of X→M→Y (path ab) (Edwards and Lambert 2007; Preacher and Hayes 2008; Shrout and Bolger 2002).

Zhao et al. (2010) refined Baron and Kenny's (1986) four tests of mediation. Following Zhao et al's (2010) classification of mediation and non-mediation types, we analyzed mediation effects as: (1) complementary (significant and positive ab and c'); (2) competitive (significant ab and c' with opposite signs); (3) indirect-only (significant ab , no direct effect c'); (4) direct-only non-mediation (significant c', no indirect effect ab); and (5) no-effect non-mediation (no direct or indirect effect exists). Baron and Kenny's (1996) third and fourth condition tests (significance of c and c' paths) are used to determine the type of mediation taking place, which provides additional information regarding the validity of mediators in the research model. Complementary mediation overlaps with partial mediation, indirect-only mediation with full mediation, and no-effect non-mediation with no mediation (Zhao et al. 2010). Competitive mediation, in turn, may be partial or full mediation where the opposite sign of direct effect c' indicates the possibility of alternative mediators.

APPENDIX I: ONLINE SUPPLEMENT

Additional Multigroup Analyses (PLS-MGA)

We carried out additional measurement invariance and PLS-MGA multigroup analyses for the grouping control variables, namely, good versus services, and three main industry sectors B2C manufacturing, finance and insurance, and retail. In comparing goods (N=165) and services (N=136) groups, compositional invariance (Step 2) was established. Inequality of means and variances (Step 3a-b) was detected at 10% confidence interval (CI) level (full measurement invariance at 5% CI). Similarly pairwise measurement invariance tests between B2C manufacturing (N=60), finance and insurance (N=68) and retail (N=52) sectors confirmed compositional invariance (Step 2) and partial invariance at a 10% significance level (Step 3a-b) in each pairwise comparison, respectively.

In PLS-MGA analyses, the relationship between BDR and MC did not differ significantly between goods and services firms (.52 vs .42, p=.25). It is also worth noting that the weights of all three BDR dimensions remained robust across all additional multigroup analyses. A weak significant difference (one-tailed test) was found in the standardized coefficient between MC and firm performance (.77 for manufacturing firms vs .59 for service firms; difference = .18, p =.054). Since there was no theory-based assumption regarding the direction of the moderating effect and with sub-sample sizes being relatively similar, we also carried out the permutation test for multigroup analysis (Hair et al. 2017). The two-tailed permutation test shows that the difference in MC→firm performance among goods vs services firms is non-significant (difference = .18, 10% confidence interval {-.193, .197}, p =.15). Therefore, the additional analyses suggest that the structural model is generalizable across goods and services firms. Full measurement invariance (with an alpha protection level of 5%) between goods and service firms suggests that pooling the data is permissible. The good/service dummy variable was thus tested as a moderating effect on the path between MC and firm performance in the structural model with pooled data (Hair et al. 2017; Henseler et al. 2016). The moderating effect was not significant (.06, *ns*).

In comparing cross-industry structural model paths, differences in BDR→MC were insignificant across the three industries. Overall, a pairwise multigroup analysis between F&I and retail revealed no significant heterogeneities in the structural model. However, B2C manufacturing firms had a significantly stronger relationship between MC and firm performance than F&I (.80 vs .44, difference = .36, $p < .01$) and retail (.80 vs .56, difference = .24, $p < .05$) firms (one-tailed test). The two-tailed permutation test confirmed that MC→firm performance link in the B2C manufacturing industry is significantly different from F&I ($p < .01$) and retail (p < .05).

Finally, we found that some direct impacts of environmental turbulence on MC and firm performance were significantly different in B2C manufacturing from the other two industries. Specifically, market turbulence had a significantly different ($p < .01$) positive influence on MC in B2C manufacturing compared with F&I and retail (.46 vs .05 vs -.03). Technological turbulence, in turn, had a significantly different ($p < .05$) negative influence on MC in B2C manufacturing than in F&I and retail (-.16 vs .12 vs .21). Finally, the effect of competitive intensity on firm performance was significantly different ($p < .01$) and reversed in sign in the B2C manufacturing industry (-.23 vs .34 vs .15). In sum, the results suggest that data-driven marketing capabilities in the B2C manufacturing industry perform better than other industries such as F&I and retail. In particular, B2C manufacturing firms operating in markets characterized by changing customer needs and few technological disruptions appear to develop high levels of MC.

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