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Do shareholders favor business analytics announcements?

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ABSTRACT

Despite the growing acceptance of business analytics (BA) as a tool for making smarter business decisions, past research has rarely investigated shareholder reactions to BA announcements. We use signaling theory and resource-based theory (RBT) as our theoretical lens. The results show that BA announcements generate positive abnormal returns, thereby providing empirical evidence that shareholders view BA as beneficial. The results also suggest that characteristics that are more salient to shareholders are rewarded. Specifically, firms implementing BA systems from market-leading vendors obtain more positive stock market reactions compared with other firms. Announcements convey more benefits to overbought stocks than oversold stocks, and generate higher positive return in firms with high sales growth and high return on assets (ROA). Overall, empirical evidence favors signaling theory over RBT.

Introduction

The term "business analytics" (BA) is often used synonymously with "business intelligence" (BI)[1] which can be defined as methodologies, processes, architectures, and technologies that transform data into meaningful and useful information (Evelson, 2012). BA promises to enable faster reactions to a changing environment, provide new insights, and facilitate smarter decisions. BA systems have evolved into important systems for integrating structured and unstructured information (Sabherwal, 2007, 2008), giving managers access to timely and relevant information for making decisions (Hannula and Pirttimaki, 2006). Past literature has provided case studies of firms that successfully used BA (Davenport and Harris, 2007; Wixom et al., 2008) and explored the business value of BA systems based on accounting measures such as productivity, sales, return on equity (ROE), profit margin, and asset utilization (Aral et al., 2012; Brynjolfsson et al., 2011). Past research has also focused on decision support functionalities and technical aspects of BA (Chen et al., 2012).

Another stream of research uses the event study methodology (e.g. Dobija et al., 2012; Hendricks et al., 2007) to examine the impact of different types of technology investments. The underlying assumption is that market reaction to technology investment announcements is an important indication of how shareholders view the investment, which in turn could affect how corporate boards and executives decide on such investment. To our knowledge, only one study has applied event study in the context of BI. Specifically, Rubin and Rubin (2013) found that BI systems could help reduce a firm's stock volatility.

In contrast, we delve deeper into shareholder reactions to BA announcements and make several contributions. First, while Rubin and Rubin focus on stock return volatility, we focus on abnormal returns from BA announcements. By using an event

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[1] BI focuses more on reporting tools and dashboards, whereas analytics focuses more on answering predictive questions (Kassa, 2010).

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study method, we diverge from prior studies of BI systems value from the organizational performance perspective, which typically uses perceptual surveys (e.g., Popovič et al., 2012).

Investments in BA require a combination of technical and statistical skills compared to general IT investments that require technical skills. Further, BA focuses predominantly on accessing different data sources (structured data such as financial and operational performance, and unstructured data such as text, social media, and visual data) and tools to analyze them (Gartner, 2014). Conventional business management softwares such as Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) focus on relatively simple analysis and interpretation of data. Also, BA includes emerging approaches such as data visualization, process simulation, text and voice analytics, social media analysis, and predictive and prescriptive techniques (LaValle et al., 2011).

Theoretically, we contribute to the IS literature on the market value impact of IT announcements by comparing resource-based theory (RBT) with signaling theory. Specifically, we show that while RBT often suggest positive impacts of BA on market returns, signaling theory often suggest null impacts as investors fail to respond to various characteristics of BA announcements. Unlike past studies, which often used RBT to explain the impact of IT announcements, our empirical evidence suggests that such announcements are also signals for specific attributes. We also show that the specific characteristics of announcements as well as a firm's characteristics (individually as well as jointly) increase the strength of such signals.

Second, we examine whether the type of vendor (leading vendors vs non-leading vendors), the type of BA (basic vs advanced) and the extent of implementation (function-specific vs enterprise-wide) are associated with market returns. This is the first study that examines the effect of these variables on abnormal returns. Our results provide valuable insights by showing that the type of vendor is important, but the sophistication of BA adopted and the extent of implementation do not affect shareholder reactions.

Third, unlike past studies that rarely examined stock characteristics, we examine whether overbought and oversold stocks affect the value of BA announcements. Our results suggest that BA announcements convey more benefits to overbought stocks than normal or oversold stocks by mitigating market correction for overbought stocks. Further, our post hoc results provide valuable insights by showing that firm-specific characteristics such as sales growth and ROA complement each other, and generate high positive returns. Thus, attributes of the signaler affect the strength of the signal.

The rest of the paper is organized as follows. We present our theory and hypotheses, then describe our dataset and analysis procedures, and finally we provide results, discussion, limitations, and implications for research and practice.

Theory and hypotheses

Resource-based theory (RBT) and signaling theory

Reviews of IS event studies (see Appendix A) have highlighted that past studies have examined market reaction to IT investment as well as specific technologies (Roztocki and Weistroffer, 2009), and have often used RBT to explain the business value of IT (Konchitchki and O'Leary, 2011). According to RBT, firms potentially derive competitive advantage from resources that are valuable (V), rare (R), inimitable (I) and nonsubstitutable (N) (Chatterjee et al., 2002; Doherty and Terry, 2009).[2] RBT also considers the importance of managerial strategies for developing new capabilities. Because they are the owners of such resources, firms could lower their costs and thus realize higher returns relative to their peers (Seddon, 2014).

IS literature has often emphasized a firm's capabilities rather than IT assets as a source of competitive advantage (Wade and Hulland, 2004). IT assets are often imitable, and therefore unlikely to be source of competitive advantage. But IT assets coupled with savvy IT managerial skills could provide the capabilities essential for sustained competitive advantage. Past research suggests that information assets that emerged from firms' digitization could provide insights after analysis, thereby enabling firms to compete more effectively (Kohli and Grover, 2008). Such information assets include BA solutions that could identify trends and patterns in the firm's data. Further, Davenport and Harris (2007) show that BA could be a source of competitive advantage as capabilities such as evidence-based management could eliminate authority-based and ad-hoc decision-making, and facilitate data-driven decision-making. Such specific capabilities are valuable (V) as they improve decision-making and reveal previously unobserved facets of firms' performance to management.

Firms could purchase or develop in-house BA solutions. Vendor implementation capabilities are important in helping firms to better leverage BA for competitive advantage. The specific manner in which firms transform data to create high quality and integrated data, and utilize insights make BA capability rare (R). Further, such capabilities are not easy to acquire and require change management, flexibility and agility in firms, as well as having the firm's BA well embedded within its social fabric (Cosic et al., 2012). Since such capabilities are firmly embedded in a firm's context, they cannot be easily imitated (I). Conventional IT assets such as CRM and ERP cannot substitute BA, as they primarily emphasize collecting rather than analyzing data to deliver strategic insights. Advanced capabilities such as predictive analytics are unique to BA solutions and hence are difficult to substitute (nonsubstitutable (N)). Thus, BA announcements could indicate the acquisition of IT assets and capabilities that are potentially valuable, possibly rare, difficult to imitate and difficult to substitute (VRIN).

[2] IS studies such as Aral and Weill (2007) define resources as the combination of IT assets (hardware and software) and capabilities (practices, skills and competencies to use IT).

BA capabilities tend to evolve over time and are not static resources, rather, they could reflect dynamic capabilities (defined as a firms' ability to respond to the dynamic business environment and renew competencies). It is important to note that dynamic capabilities can be viewed as an extension of RBT to dynamic environments rather than as a separate theory (Peteraf and Barney, 2003). Dynamic capabilities are categorized into adaptive capability, innovative capability and absorptive capability (Wang and Ahmed, 2007). Adaptive capability corresponds to firms' ability to identify changes in the environment and capitalize on emerging opportunities. BA that identify changes in consumer behavior and process performance could aid firms in identifying emerging opportunities. Innovative capability corresponds to firms' ability to develop new products or target new markets. Insights into consumer behavior using BA could help firms to identify the need for new products or an opportunity to penetrate new markets. Absorptive capability refers to the firm's ability to gather new, external information, realize its value, and assimilate it in its functioning. Firms could use BA to investigate external information such as consumers' reviews of their products posted on various social media sites, as well as to analyze data gathered from their suppliers. Consistent with RBT, firms develop resources such as BA that distinguish them from other firms and provide them with capabilities to respond quickly to any changes in the environment.

However, it is important to note that while prior research often invokes RBT to understand shareholders' response to IT investment announcements (Konchitchki and O'Leary, 2011), the market reaction is conceptually distant from "competitive advantage" (Seddon, 2014). Market reaction reflects short-term response rather than a long-term effect such as sustained competitive advantage. Market valuation is driven by shareholders' perception of firms' capabilities. Consequently, we also use signaling theory to complement RBT in this paper. Signaling theory describes the phenomenon where one party signals a piece of information and the other party interprets the signal (Connelly et al., 2011; Negro et al., 2014). The underlying premise of signaling theory is information asymmetry. Information asymmetry implies that firms that signal and stakeholders (such as shareholders) that receive the signals have access to different sets of information. Consequently, shareholders interpret the signals positively or negatively on the basis of certain cues in the signal, and will reward or penalize such announcements accordingly.

Information asymmetry is significant for two distinct types of information: quality and intent (Connelly et al., 2011). Information about quality is relevant in cases where receivers are not aware of the characteristics of the signaler. When firms announce the adoption of BA, shareholders may or may not be conscious of the specific capabilities that firms require to leverage BA, and will respond accordingly. Consequently, we argue that receivers (shareholders) would respond to BA announcements on the basis of their perception of BA and a firm's characteristics. Information about intent refers to the context where receivers are concerned about signalers' intentions. Information asymmetry with regards to intention may be less of an issue as firms are publicly acknowledging the value of BA by announcing its adoption.

Since IT investment announcements could signal distinct characteristics, signaling theory could complement RBT in understanding the extent to which shareholders view BA announcements positively. Further, it is important to note that while BA appears to be a strategic capability (VRIN), it may not necessarily translate into superior market returns. Signaling theory could provide the linking mechanism between the internal capability and the shareholders' perception and subsequent market valuation.

Our research framework (Fig. 1) comprises two parts. First, using event study methodology, we examine the effect of BA announcements and the role of stock type (overbought vs oversold) in returns from BA announcements. Second, using robust regression, we examine three key factors related to market returns, namely, the type of vendor (leading vs non-leading vendors), the type of BA (basic vs advanced) and the extent of implementation (function-specific vs enterprise-wide). These factors are related to the different dynamic capabilities that firms could acquire due to BA and also conveys different signals to the market.

BA announcements

BA tools report on past performance, monitor the environment and predict future opportunities. They could help firms observe and manage their performance accurately and transparently (Aral et al., 2012). A recent survey reported that 23% of experienced BA users gained competitive advantage compared with the previous year (Kiron et al., 2011). Firms that emphasized data-driven decision-making experienced 5–6% productivity improvement (Brynjolfsson et al., 2011). Moreover, BA systems could help to improve the efficiency and effectiveness of business processes through reconfiguration of internal competencies and thus allow firms to outperform others in the same industry (Elbashir et al., 2008). BA capability is valuable (V) because it enables greater responsiveness to markets through better planning, forecasting, managing customer relationships, controlling risks, maintaining operations and operating supply chains (Loshin, 2012). Moreover, BA could facilitate the development of planning and management capabilities to anticipate future changes and the appropriate choice of platforms that accommodate changes (Daniel et al., 2014).

While firms could adopt the same BA solutions, there is no single approach to BA. Different approaches suit different firms depending on their situation (Watson, 2013). Thus, BA capability tends to be somewhat unique to each firm and could be relatively rare (R), not easily imitated (I) as it requires the mindset change from relying on managerial intuition to relying more on data analytics, and is not easily substitutable (N) with other non-analytics related technologies. Consequently,

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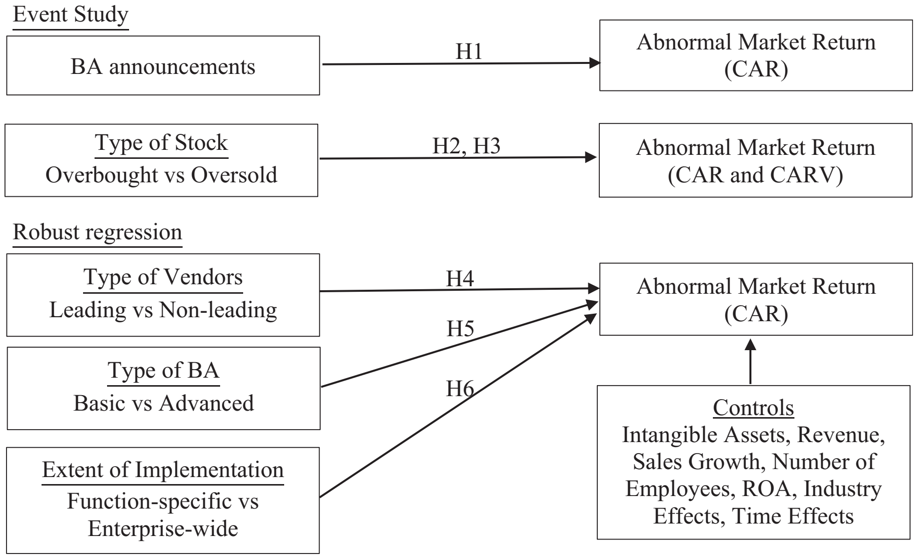

Fig. 1. Research framework.

BA has the potential to strengthen a firm's competitive position and makes it more sustainable in the long-term (Eckerson, 2011).

When firms announce that they are implementing BA, the announcement could implicitly signal that they would acquire future managerial capabilities for making sound judgments (Adner and Helfat, 2003). Recent studies such as Brynjolfsson et al. (2011) suggest that firms that implemented BA experienced appreciation in their market value and profitability. This empirical and anecdotal evidence in the media could shape shareholders' positive perception about BA.

Although shareholders may not be aware of the costs incurred and changes in business processes that are required to benefit from BA, they could be influenced by the positive sentiments surrounding BA. Thus, shareholders would reward BA announcements with an increase in stock prices, which is greater than the changes expected due to market conditions (referred to as positive abnormal return). Accordingly, RBT and signaling theory both agree on the positive consequence of BA announcements. Hence:

Hypothesis 1 (H1). Announcements of BA will yield positive abnormal returns.

The stocks of different firms exhibit different characteristics. Some stocks experience high appreciation in their price over a short time-frame. Such stocks are often referred to as overbought stocks as the demand unjustifiably pushes up the price to a level beyond the stock true value. In contrast, oversold stocks experience sharp depreciation in their prices to a level below their true value. Overbought stocks are due for a price correction, whereas oversold stocks are due for a price rally. As discussed, RBT focuses on capabilities and BA is a dynamic capability, irrespective of their stocks' characteristics. Therefore, the appreciation or depreciation in stock price should not influence the perception of BA. Thus, based on RBT, we propose:

Hypothesis 2a (H2a). Announcements of BA will yield positive abnormal returns for both overbought and oversold stocks.

Since overbought stocks appreciate in price in a short time-frame, shareholders might perceive overbought stocks to be due for a price correction. But, overbought stocks also tend to be associated with positive sentiments about the stock. This positive sentiment could be reinforced by BA announcements. Further, BA is a new technology that has the potential to improve firms' productivity, and may be interpreted as akin to a "technology shock" (events that affect industry or firm's productivity). Thus, BA announcement could be a strong signal for overbought stocks, since the overpricing of stocks could reinforce the shareholders' perceived positive impression. Consequently, positive abnormal returns could result despite the overpriced value of a firm's stocks.

Oversold stocks are due for a price rally, but they also tend to be associated with negative sentiments, which may or may not be mitigated by BA announcements. Past research based on prospect theory tends to suggest that negative sentiments are stronger than positive sentiments (Brown et al., 2012). However, it is unlikely that negative sentiments associated with oversold stocks will just "disappear" due to BA announcements. The negativity associated with such stocks might negate shareholders' positive impression of BA. Thus, due to negativity associated with oversold stocks, BA announcements might not be effective signals and would have insignificant impact on abnormal returns. Hence we hypothesize:

Hypothesis 2b (H2b). Announcements of BA will yield positive abnormal returns for overbought stock, but insignificant abnormal returns for oversold stock.

Besides stock prices, stocks trading volume also indicate the value of announcements. For shareholders with limited information on firms' internal working, announcements help them form their beliefs about firms. Stock trading volume is positively associated with price movement and divergence in belief about firms among different shareholders (Kim and Verrecchia, 1991). Arguments based on RBT focus on firms' capabilities and consequently have internal orientation. Thus, they would not focus on divergence of beliefs among shareholders. Further, specific characteristics of stocks, such as overbought or oversold, would be inconsequential. Hence, arguments grounded in RBT would lead to the hypothesis of similar effects on BA announcements on overbought and oversold stocks. It follows that:

Hypothesis 3a (H3a). Announcements of BA will yield increase in stock trading volume for both overbought and oversold stocks.

But, arguments based on signaling theory take into account stock characteristics, which could result in a divergence in beliefs about firms posting similar announcements. Since overbought stocks are due for price correction, shareholders may resort to selling their stocks, thus increasing stock trading volume (Bondt and Thaler, 1987). Their behavior would be similar to profit booking observed in the stock market. Institutional and large investors with long-term focus could use this opportunity to increase their ownership of stocks, thereby also increasing trading volume (Campbell and Viceira, 2002). In contrast, while BA announcements alone could not change the negativity associated with oversold stocks, it might encourage shareholders to hold their stocks and wait to observe the outcome of BA implementation. Further, investors tend to be loss averse and might tend to hold on to their stocks with the hope that the price might increase in the future. Investors interested in purchasing such stock might also wait for change in negative sentiments in anticipation of a positive outcome of BA. Consequently, stock trading volume would remain stable. Hence, we hypothesize:

Hypothesis 3b (H3b). Announcements of BA will yield increase in stock trading volume for overbought stocks, but an insignificant effect for oversold stocks.

Besides signalers' characteristics, receivers also focus on the information contained in a signal to form their impression about the signal (Connelly et al., 2011). BA announcements could include vendor information, the type of BA solution implemented, and the different departments and functions inside the firm where BA would be implemented. Each piece of information could signal distinct characteristics and could be perceived differently by shareholders.

Vendor's capabilities in BA

Often, rather than developing their BA systems, firms partner with BA vendors or select solutions from BA vendors as part of their analytics portfolio. Selecting a BA vendor that matches their needs is an essential element of the implementation process. The selection process requires that management rely on their partner vendors for a significant part of the implementation (Feeny and Wilcocks, 1988). A Gartner Inc. research project defined market leaders as vendors who provide range and depth in BA capabilities, and who deliver enterprise-wide implementation supporting a broad BA vision. They also offer global operational capabilities that clients want (Sallam et al., 2011), in particular, solutions based on customer requirements, product capabilities and market responsiveness. Technological capability is a key strength of firms providing BA (Davenport, 2006). They invest considerable time and money developing systems that aggregate, integrate, store, present, and make data accessible from multiple sources. Leading vendors also "provide a variety of algorithms to use; allow data mining processes to be created, saved, and reused; and assist in exploring, preparing, and combining data to be used with the algorithms" (Watson, 2013: 23).

Thus, BA systems from leading vendors (compared to non-leading vendors) tend to be better-performing assets as such vendors often have more experience and are more able to provide a customized system to better cater to the firm's needs and support the firm's internal processes. A firm's processes (the way things are done inside the firm) and asset position (technology owned by the firm) determine its capabilities (Teece et al., 1997). Thus, BA systems from leading vendors may result in enhanced dynamic capabilities for the firm, which would be valuable (V) in enabling an effective response to changing environment. The leading vendor could also assist the firm in developing BA resources and capabilities that are rare (R) since solutions may be more effectively customized to a firm's operations, difficult to imitate (I) since customized internal BA processes are less visible to competitors, and also difficult to substitute (N) since the type of integrated data and its insights tend to be unique to the firm. Consequently, arguments grounded in RBT associate the positive relationship of announcements on engaging market-leading BA vendors with abnormal returns.

In terms of signal observability, leading vendors are often well-recognized in the market. When firms engage vendors that lead the market, they may signal assurance that the vendors could provide BA capabilities that support the firm's requirements, and better integrate current systems and processes. The strong capabilities of leading vendors could facilitate the extraction of valuable insights from the firm's data. In addition, selecting a leading vendor to match current and future requirements, and managing relationships with the vendor signals the development of capabilities to capture and analyze data for value creation. Thus, arguments based on signaling theory also support the positive relationship between abnormal returns and announcements on engaging market-leading BA vendors. In sum, both RBT and signaling theory converge on the positive relationship between abnormal returns and announcements regarding engaging market-leading BA vendors. Hence, we hypothesize:

Hypothesis 4 (H4). Firms that engage a market-leading BA vendor will generate higher positive abnormal returns than firms that engage a non-leading vendor.

Basic versus advanced BA

In general, basic BA includes capturing and storing data to provide historical information and knowledge. Advanced BA allows firms to embed analytical insights into the business to automate processes, optimize outcomes and ensure seamless actions; hence saving time on routine tasks, and allowing more time for applying insights to more strategic and tactical decisions (Kiron et al., 2011). Advanced BA, properly managed, is likely to be of greater value (V) to the firm than basic BA as it can potentially provide deeper insights into the data.

From the RBT perspective, advanced BA guides decision-making through insight creation, an intangible asset. Advanced BA captures intangible assets in areas such as achieving customer orientation, creating knowledge assets embedded in employee experiences, processes and policies, and synergizing across organizational functions and divisions (Bharadwaj, 2000). The creation of knowledge assets embedded in employee experiences, processes, policies, and synergies across functions could result in the development of dynamic capabilities that are rare (R) (since not many companies have the necessary knowledge and capabilities to leverage advanced BA effectively), difficult to imitate (I) (since embedded knowledge assets may not be easily visible to competitors), and difficult to substitute (N) with non-BA related technologies. Advanced BA go beyond historical analysis to include advanced modeling, simulation, and the use of predictive BA to enhance revenue and reduce operating costs. They also use complex algorithms to generate predictive insights to optimize activities and predict decision impacts. Mere capturing and reporting data (basic BA) is unlikely to result in significant business impact; such impact arises predominantly from models that predict and optimize business outcomes (advanced BA) (Barton and Court, 2012). Thus, advanced BA could enable firms to respond more quickly and effectively to a dynamic business environment compared to basic BA. It follows that:

Hypothesis 5a (H5a). Firms that use advanced BA will generate higher positive abnormal returns than firms that use basic BA.

However, shareholders might not be aware of the specific technological capabilities of different types of BA. They might not be able to distinguish between descriptive (basic) and predictive (advanced) BA as it is still quite novel to the average investor. As mentioned earlier, signaling theory focuses on receivers' interpretation and the significance they attach to various cues in the signals. Shareholders often reward announcements that signal potential for improved financial performance in the future (Connelly et al., 2011). If they are unable to differentiate between basic and advanced BA, then BA announcements are unlikely to result in different market returns for different cues. In other words, while advanced BA could result in better financial performance due to its advanced features, its underlying complex technological architecture might be difficult to decipher for shareholders. Shareholders might ignore information such as optimization and predictive BA, as such information tends to be technical in nature. In addition, although shareholders often get influenced by analysts' recommendation (Cohen et al., 2012), even analysts tend to focus on the underlying financial aspects. Thus, technological complexity in terms of basic versus advanced BA solutions may be an indistinguishable cue for shareholders. Hence:

Hypothesis 5b (H5b). Firms that use advanced BA will not generate higher positive abnormal returns than firms that use basic BA.

Extent of the implementation of BA

Firms that implement BA enterprise-wide may gradually develop a data-oriented culture crucial for attaining the full value of BA (Kiron et al., 2011). By data-oriented culture, we mean that employees at all levels accept the critical role that data plays in the firm's success. Such firms value BA (V) as a strategic asset and integrate data-based insights into every organizational process (Watson, 2013). They imbibe fact-based decision making rather than intuition or supposition-based decision making. Further, firms that develop a data-oriented culture use BA more broadly and effectively across functions so that all units and functions achieve comparable and synergistic BA capabilities. Also, a data-oriented culture is not easily replicable (R). Firms that adopt fact-based decision making can continuously experiment to find what works or what does not, e.g., Harrah conducts experiments to test customers' response to different promotional offers (Watson, 2013). Findings from such experiments are integrated into marketing campaigns to cater better to customers' changing needs. In such firms, disparate data from functions or units are integrated into a common platform for sharing across the firm (Kiron and Shockley, 2011).

Fostering a data-oriented culture requires analytical capabilities of organizational human resources, effective integration of IT and business planning processes, conceiving and developing reliable and cost-effective applications, effective communication among business units, anticipation of future business needs and innovation of new product features before competitors (Bharadwaj, 2000). Thus, firms develop better processes due to their extensive deployment of BA. Capabilities are also embedded in different ways depending on how BA and organizations' functions are integrated in firms. Therefore, there is a

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seamless integration between technological assets and organizational processes. In such firms, the managerial capabilities, a result of implementing enterprise-wide BA systems, is highly path dependent and evolves uniquely for each firm. They are also complex and cannot be acquired easily, making them difficult to imitate (I). Firms may also find it difficult to find a strategically substitutable resource (N) for the managerial capabilities that have become ingrained into an enterprise-wide culture over time. Conversely, when firms implement BA for a single function, managerial capabilities would be confined mainly to that function, thereby hindering the sharing of insights across functions. Without an enterprise-wide data-oriented culture, collaboration and integration across functions might be difficult, as would aligning different functions to overall firm strategic objectives. Thus, enterprise-wide implementation aids the development of BA as a dynamic capability. Hence, predicated on RBT, we propose:

Hypothesis 6a (H6a). Firms that implement function-specific BA will generate lower positive abnormal returns than firms that implement enterprise-wide BA.

Unlike RBT, signaling theory focuses on the shareholders' perceptions. Information on adoption of BA in a specific unit or specific department provides the cue that firms do not implement BA enterprise-wide. Since enterprise-wide adoption is costly, it could be an effective signal (Connelly et al., 2011), provided it is considered significant information by shareholders. However, in the context of BA, such information might not improve signal strength. Signal strength reflects how readily a signal can be detected by shareholders. While implementation of BA due to the current hype surrounding it makes it an effective signal, other pieces of information such as the extent of implementation might not be a critical piece of information for shareholders. They might ignore such information and focus solely on BA implementation. Thus:

Hypothesis 6b (H6b). Firms that implement function-specific BA will not generate lower positive abnormal returns than firms that implement enterprise-wide BA.

Method

Sample and data

Using the Factiva database, we obtained a sample of publicly traded firms using BA from January 2004 (when interest in BA began to increase) to December 2012. We eliminated firms with insufficient information on CRSP, announcements involving product launches by vendors of BA tools (not related to the implementation of BA within a firm), and confounding announcements such as financial earnings release during the event window (Konchitchki and O'Leary, 2011). The articles we identified during the search concerned the implementation of BA, including software solutions and tools, the engagement of BA vendor to provide customized BA solutions, the acquisition of another firm (BA vendor) to build an in-house BA division, and the appointment of key executives to spearhead BA initiatives in the firm. A second party compiled, reviewed, and verified more than 25% of announcements to ensure consistency in coding before we coded the rest of the data (see Appendix B for illustration of announcements). The final sample comprised 156 announcements.

Event study methodology

We used the event study methodology to examine market reaction to the announcement of BA news or events. Stock market reaction is captured through abnormal returns in the event window following the event. It provides an estimate of how stock price deviates from its expected value during the event window. We used the two-day event window of $[-1, 0]$ and conducted several robustness checks. In addition, we used the calendar-time portfolio approach, or Jensen alpha approach, to estimate abnormal returns (Jaffe, 1974; Mandelker, 1974). This method is better than basic event study methods mainly because it controls for cross-sectional dependence in the data. Cross-sectional dependence in data occurs for many reasons such as clustering of event period, the different degrees to which firms anticipate each event, and the effects of insiders' information (Kothari and Warner, 2007). Ignoring cross-sectional dependence in panel data may bias results because of systematic underestimation of the variance of mean excess returns, causing the null hypothesis to be rejected too often (see Appendix C for details on calendar-time portfolio approach).

The estimation period began on Day -210 and ended on Day -11, i.e., ending 10 days before the event to shield the estimates from the announcement effect. The abnormal return A_{it} for the firm i on Day t was computed as the difference between the actual return and the expected return. The mean abnormal return on Day t for N stocks is given by: $AR_t = \frac{1}{N}\sum_{i=1}^{N} A_{it}$. The cumulative abnormal return (CAR) is then calculated to estimate the performance over a period of interest through the sum of the average abnormal performance and the statistical significance of CAR is tested using the t-test. We also computed the cumulative abnormal return volume (CARV).

Cross-sectional analysis

To further understand the drivers of abnormal returns, we performed a cross-sectional analysis relating the CAR to various firm and event characteristics. The specification for regression for the cross-sectional analysis is:

$$CAR_{it} = \alpha_0 + \alpha_1 Leader_{it} + \alpha_2 Advanced_{it} + \alpha_3 Business\ Function_{it} + \alpha_4 Revenue_{it} + \alpha_5 Employees_{it} + \alpha_6 ROA_{it} + \alpha_7 SalesGrowth_{it} + \alpha_8 Intangibles_{it} + \alpha_{9-15} Year + \alpha_{16-34} IDUM_i + \varepsilon_{it}$$

where CAR_{it} is the individual cumulative abnormal return for firm i in two-day event window $[-1,0]$. $Revenue_{it}$ is calculated from log(total revenue) of firm i, $Employees_{it}$ is calculated from log (number of employees), ROA_{it} is the profitability measure of return on assets which is calculated as (net income/total assets), $SalesGrowth_{it}$ is a control variable representing the growth of the firm, and $Intangibles_{it}$ is calculated from log (intangible assets). Dummy variables were used to control for year (Year) and industry specific effects ($IDUM_i$).

Firm-level control variables are total revenue, number of employees, profitability based on return on assets (ROA), sales growth, and intangible assets of the firm. The total revenue and number of employees are used to indicate the firm size. ROA indicates how efficiently the firm uses its resources to generate additional value for shareholders. Sales growth indicates the firm's growth rate. The firm's intangible assets include assets that are not physical in nature such as patents, copyrights, licenses and trademarks. These controls have been often used in past research (Konchitchki and O'Leary, 2011). We used the Standard and Poor's Compustat database to obtain these variables, using information from the previous fiscal year. To reduce skewness, we used the logarithm of total revenue, number of employees, and intangible assets. We included dummy variables for time effects to account for non-stationarity of technology over time and the possibility of occurrence of "meta-events," which are major macroeconomic events that systematically affect any firm (Konchitchki and O'Leary, 2011). We used the two-digit SIC industry identifiers in creating industry dummy variables.

We classified announcements according to whether the vendors of BA solutions were market leaders. We obtained the list of market-leading vendors from the Leaders Quadrant of the Gartner's Magic Quadrant for Business Intelligence Platforms (Appendix D). We also classified the types of BA described in the announcements. According to SAS (2008), BA solutions generally fall into eight categories (Appendix E). We categorized firms in the first four categories of standard reports, ad-hoc reports, query drilldown and alerts, as using basic analytical tools, while firms in the next four categories of statistical analysis, forecasting, predictive modeling and optimization were categorized as using advanced analytical tools. We classified announcements into firms that implement BA solutions enterprise-wide or only in a specific business function (e.g., human resource, finance). Function-specific BA solutions include marketing campaign tools, trade promotion and optimization tools, and financial reporting. Enterprise-wide implementation includes BA solutions implemented across functions.

We performed robust regression as well as OLS regression with clustered robust errors. Robust regression is robust against outliers. The clustered robust errors method avoids misspecification or biased estimates associated with a standard error model because of the assumptions of homoskedasticity, even for data generated from a heteroskedastic model (Thompson, 2011). In addition, we used clustered robust errors to adjust for correlations among error terms over time. We also conducted panel data regression as robustness checks. We tested the robustness of our estimates using bootstrapping to address potential concern related to small sample size. Table 1 shows the summary statistics and correlations among the variables.

Results

Hypotheses testing

We used the calendar-time portfolio analysis to control for event clustering and cross-sectional correlation. Table 2 indicated that shareholders reacted positively to BA announcements, but returns were relatively small. The average CAR over the 2-day event window period was 0.45% ($t = 2.67$, $p < 0.01$) and the mean cumulative abnormal return volume (CARV) was positive and significant (62.18%, $p < 0.05$). The non-parametric sign test indicated 91 positive CAR vs. 65 negative CAR, and was significant ($z = 3.09$). Although the mean CAR for window $[-6,-2]$ was relatively high at 0.68, its median value was low (0.09). Also, the ratio of positive to negative was quite similar at 79:77, resulting in insignificant mean CAR. The results confirmed that intervals before and after the 2-day event window yielded insignificant CARs, thereby verifying that the result was not driven by other unrelated events beyond the event window of $[-1,0]$. Hence, H1 was supported. We also used the market-adjusted returns method for calculating excess returns to verify the results obtained from the market model (Appendix F).

Williams' %R is a technical indicator showing whether the stock is overbought or oversold; 0% to −20% indicates overbought stocks and −80% to −100% indicate oversold stocks (Investopedia, 2013). About 25% were overbought stocks, 14% were oversold stocks and the rest were normal stocks. We examined the price trend data for overbought stock and found support for high CAR (1.40%, $p < 0.05$). 77% of overbought stocks experienced positive CAR. The high CAR indicates much higher return on the day of announcement relative to the expected return based on the relationship between market indices and prior returns. Thus, BA announcements are effective signals that provide impetus to continue the bull run. However, the average CAR for the oversold stocks is negative but insignificant (−0.37%, $p > 0.05$), hence supporting H2b, but rejecting H2a. BA announcement as signals mitigate price correction and augment the positive sentiments about such firms. For oversold stocks, BA announcements could not change negative sentiments or create strong positive sentiments. For overbought stocks, CARV increased by 55.27% ($p < 0.05$), whereas for oversold stocks, CARV increased by only 0.41% ($p > 0.05$). This

Table 1
Descriptive statistics and correlations.

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1	CAR [−1,0]	0.004	0.021	1.00							
2	Leader	0.204	0.404	0.19	1.00						
3	Advanced	0.526	0.501	0.00	0.16	1.00					
4	Function-specific	0.507	0.502	−0.03	−0.10	0.27	1.00				
5	Intangibles[a]	2.350	1.468	0.17	−0.05	0.01	0.10	1.00			
6	Revenue[a]	3.441	0.826	0.10	−0.05	0.07	0.14	0.73[*]	1.00		
7	Employees[a]	3.867	0.943	0.05	0.01	0.07	0.20	0.65[*]	0.79[*]	1.00	
8	ROA	0.030	0.138	−0.07	−0.01	0.02	−0.04	0.10	0.20	0.06	1.00
9	Sales growth	0.133	0.312	0.05	−0.06	0.03	0.04	−0.11	−0.16	−0.04	−0.31[*]

Notes: Bonferroni adjusted, correlation for categorical variables are tetrachoric correlations.
[a] Natural logarithm.
[*] $p < 0.05$ (two-tail).

Table 2
CARs over various event windows.

Event period (days)	Event span (in days)	N	Mean CAR (%)	Median CAR (%)	*t*-stat	Positive: negative	Rank test *Z*
[−6,−2]	5	156	0.68	0.09	0.653	79:77	0.994
[−1,0]	2	156	0.45[**]	0.50	2.671	91:65[**]	3.087
[+1,+5]	5	156	−0.37	−0.07	−0.546	76:80	0.554

Notes: Estimation period ends 11 days before event and length is 200 days.
[**] $p < 0.01$ (two-tail).

indicates that the impact of BA announcements increases trading volume on overbought stocks, but has no effect on oversold stock, thus supporting H3b, and rejecting H3a.

To assess the effect of BA announcements, we performed a cross-sectional analysis using different estimation methods. Control variables, industry effects, and time effects were also included (Table 3). The Durbin–Watson statistic for the full model is 2.2, thereby indicating that serial correlation is not an issue. Note that Durbin Watson statistic ranges from 0 to 4. Value close to 0 indicates positive serial correlation, value close to 4 indicates negative serial correlation, and value close to 2 indicates no serial correlation (Allbright et al., 1999).

Our data exhibited unbalanced panel structure (1.10 announcements per firm). However, majority of announcements were single announcements by unique firms. We computed estimation using robust regression (Model 1, main model) since CAR values might have some outliers and might not meet some of the assumptions for OLS. As a robustness check, we also computed estimates using OLS regression with clustered robust standard errors (Model 2). Next, we computed estimates using different panel data methods to ensure that our estimates were robust (see Appendix G). The results suggested that BA announcements involving implementation of BA systems from market-leading vendors contributed to positive abnormal returns. Thus, H4 was supported. Other explanatory variables of interest *Advanced* (-0.004, $p > 0.05$) and *Function-specific* (0.001, $p > 0.05$) had no significant impact on abnormal returns. Therefore, H5a and H6a were not supported. But, H5b and H6b were supported.

Post hoc analysis

Besides announcements (signals) and signalers' stock characteristics, firms' financial performance could also influence CAR. Sales growth indicates the financial health of the firm in terms of revenue growth and is a proxy for growing firm. Another barometer for financial health is profitability or ROA. Sales growth can signal to shareholders how well the firm is performing, and growing firms could realize better market returns. Thus, sales growth would be positively associated with CAR, and our results (Table 3) partially support this conjecture. We suggest that the relationship between sales growth and CAR will be stronger for firms with high profitability (ROA), as positive indicators of performance tend to have a synergistic effect.

We tested the two-way complementarities between sales growth and ROA by including an interaction term in the full model (including controls such as intangible assets). To reduce multicollinearity, we centered the variables before computing their interaction terms. We had four subgroups of samples (combination of high and low sales growth and ROA), and adequate sample size to test the interaction effect. We used robust regression followed by various estimation techniques to ensure that our estimates were robust and unbiased. In addition, we checked and ruled out concerns such as omitted variable bias. The estimate for *ROA* ∗ *Sales Growth* ($\beta = 0.051$, $p < 0.05$) was significant, suggesting that sales growth and ROA were complements. The estimate for *ROA* ∗ *Sales Growth* using OLS regression with clustered robust standard errors ($\beta = 0.057$, $p < 0.01$), a random effect model ($\beta = 0.057$, $p < 0.05$) and a population average model ($\beta = 0.058$, $p < 0.01$) were consistently significant.

Table 3
Regression analyses.

Variable	Model 1 (Robust Regression) Main model			Model 2 (OLS regression with clustered robust error)
Leader	0.012**	0.010*	0.012**	0.01*
	{0.004}	{0.005}	{0.005}	{0.005}
Advanced	−0.002	−0.003	−0.004	−0.003
	{0.004}	{0.004}	{0.004}	{0.004}
Function-specific	1.67e−04	−8.7e−05	0.001	0.001
	{0.004}	{0.004}	{0.004}	{0.004}
Revenue	0.001	0.003	0.003	0.003
	{0.004}	{0.004}	{0.004}	{0.004}
Employees	−0.004	−0.004	−0.005	−0.005
	{0.003}	{0.003}	{0.003}	{0.003}
ROA	−0.007	−0.002	−4.6e−04	0.004
	{0.013}	{0.014}	{0.015}	{0.015}
Sales growth	0.005	*0.010*	*0.011*	0.012*
	{0.006}	*{0.006}*	*{0.006}*	{0.006}
Intangibles	0.004*	0.004*	0.004*	0.004*
	{0.002}	{0.002}	{0.002}	{0.002}
Constant	0.007	−0.008	0.009	−0.018
Industry dummies	No	No	Yes	Yes
Time dummies	No	Yes	Yes	Yes
N (sample size)	148	148	148	148
R^2	0.07	0.12	0.28	0.31

Notes: Italicized estimates are significant at $p < 0.05$ (one-tail). Standard errors for variables of interest are shown in parentheses. The estimates for variables of interest (Leader) are significant at both two-tail and one-tail level, Sales growth is not significant at two-tailed but significant at one-tailed level.
* $p < 0.05$.
** $p < 0.01$ (two-tail).

We plotted the interaction effects (Fig. 2) as recommended by Cohen and Cohen (1983).

The slopes for both high ROA and low ROA lines were significantly different from zero [($t = 3.499$, $p < 0.01$), ($t = 1.998$, $p < 0.05$)]. Fig. 2 shows that there is a substantial difference in CAR values between firms with high ROA and low ROA in favor of firms with both high sales growth and high ROA. Table 4 shows the summary of results of hypotheses testing.

Discussion

We used an event study approach to investigate the value of BA, which can also be considered a firm's strategic technology investment. Using the RBT and signaling lens as our theoretical framework, we conceptualized the capabilities that firms could leverage from the implementation of BA and the signals which acquisition of such capabilities disseminate to the market. Our empirical findings are consistent with previous event studies on technology infrastructure investments (Roztocki and Weistroffer, 2011), and with empirical research on the business value of BI to business processes and organizational performance (Popovič et al., 2012). Specifically, our findings indicate that shareholders favor BA announcements. Short-term positive abnormal returns occur when firms make announcements related to BA, with an average CAR value of 0.45%. The results also show that leveraging the capabilities of a leading vendor brings more positive shareholder response than engaging a non-leading vendor, suggesting that shareholders consider the market position when assessing a firm's investment in BA. This finding is consistent with previous event studies that focused on vendor characteristics (Dobija et al., 2012). Leading vendors are recognized for their execution ability as well as future planning (Gartner, 2015). The plausible reason for our finding is the perception that a strong leading vendor with recognized expertise will lead to successful implementation. Further, leading vendors may be more able to assist firms in deriving business value from BA in a more timely and focused manner. Thus, announcements about engaging leading vendors are strong signals.

Our finding that technology characteristics were not rewarded by shareholders differs from several IS event studies, where IT investment type was salient in shareholders' response (Roztocki and Weistroffer, 2009). Our results suggest that shareholders are indifferent to the level of sophistication of BA solutions adopted and the scale of implementation, thereby supporting signaling theory rather than RBT. One key reason is that the average investor may have difficulty in distinguishing between basic and advanced BA. Further, since firms usually develop BA capabilities at unit or business levels before diffusing enterprise-wide (Hopkins et al., 2010), shareholders may expect that BA will eventually be deployed throughout the firm, after successful experimentation. Thus, shareholders may be indifferent as to whether BA are implemented in a single business function or enterprise-wide. Another reason why our results differ from earlier studies (of more established type of technologies) is that BA is still relatively new and many investors do not understand its details. As the phenomenon becomes more widespread and entrenched, and investors also learn more about it, they may then have the ability to appreciate the details of BA characteristics.

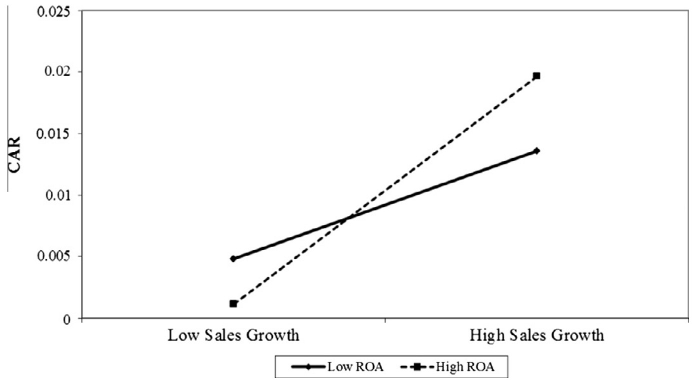

Fig. 2. Two-way interaction plot.

Table 4
Summary of results of hypotheses testing.

Hypothesis	Theoretical lens	Effect of BA announcements	Supported
H1	RBT, ST	Positive CAR	Yes
H2a	RBT	Positive CAR for overbought and oversold stock	No
H2b	ST	Positive CAR for overbought stock, no effect on oversold stock	Yes
H3a	RBT	Positive CARV for overbought stock and oversold stock	No
H3b	ST	Positive CARV for overbought stock, no effect for oversold stock	Yes
H4	ST, RBT	CAR with market-leading vendor > CAR with non-leading vendor	Yes
H5a	RBT	CAR with advanced BA > CAR with basic BA	No
H5b	ST	CAR with advanced BA similar to CAR with basic BA	Yes
H6a	RBT	CAR with function-specific BA < CAR with enterprise-wide BA	No
H6b	ST	CAR with function-specific BA similar to CAR with enterprise-wide BA	Yes

Note: ST = signaling theory, RBT = resource-based theory.

Moreover, past IS studies have rarely focused on stock characteristics. Our findings suggest that BA announcements reinforce the positive sentiments associated with overbought stocks, but have no effect on returns for oversold stocks. Hence, BA announcements are strong signals for firms that are enjoying a bull-run in the market as they mitigate any downward price correction, thereby extending the bull-run.

Our interaction plot (Fig. 2) also reveals several interesting patterns. Firms with low sales growth and low ROA experience higher CAR from BA announcements relative to firms with low sales growth and high ROA. Perhaps, for shareholders, low sales growth and low profitability signals that firms should take initiatives to improve their performance, and therefore they reward BA announcements. Firms with high sales growth and high ROA benefit most from BA as their high sales growth and high ROA could signal better growth prospects as well as sound financial fundamentals that could be further enhanced through BA. Shareholders might consider BA as a tool to manage and sustain the growth, and therefore reward announcements on BA. As sales growth increases, returns from BA increase. The empirical evidence therefore suggests that firms' characteristics could define the quality of signalers. However, firms' characteristics in isolation could have different consequences relative to their joint impact. While low sales growth in isolation could be construed as an indicator of the poor quality of the signaler, in conjunction with low ROA, it could signal the need for firms to consider adopting BA initiatives to improve performance. Similarly, ROA in itself is insignificant as an indicator of a signaler's quality. Nevertheless, together with sales growth, it enhances the strength of a signal.

To summarize, our study suggests that while RBT and signaling theory agree on certain relationships, empirical evidence supports signaling theory when it diverges from RBT. Past research (Dobija et al., 2012) postulates that the factors that could explain market response are announcement characteristics (BA), IT type (advanced vs basic BA), firm characteristics (sales growth, ROA), vendor characteristics (leading vs non-leading vendors) and the economic condition (time dummies).

Our results provide some insights into the importance of these factors in affecting CAR (Fig. 3). Broadly, our results suggest that the characteristics that are more salient to shareholders evoke market response. Other less salient characteristics, despite their potential contributions to dynamic capability development are often ignored. Unlike some past studies, economic conditions (reflected in estimates for time dummies) did not matter. Perhaps, due to the hype surrounding BA, shareholders ignored macro-economic conditions. But, they did not ignore firms' recent stock performance (overbought/oversold), perhaps due to the negativity or positivity associated with such stocks. Individually, sales growth, but not ROA affect CAR. While sales growth and ROA are reflected in financial statements, sales growth significantly strengthens the signal. Perhaps, sales growth is a more significant cue to shareholders. But, together, they act as complements to affect CAR.

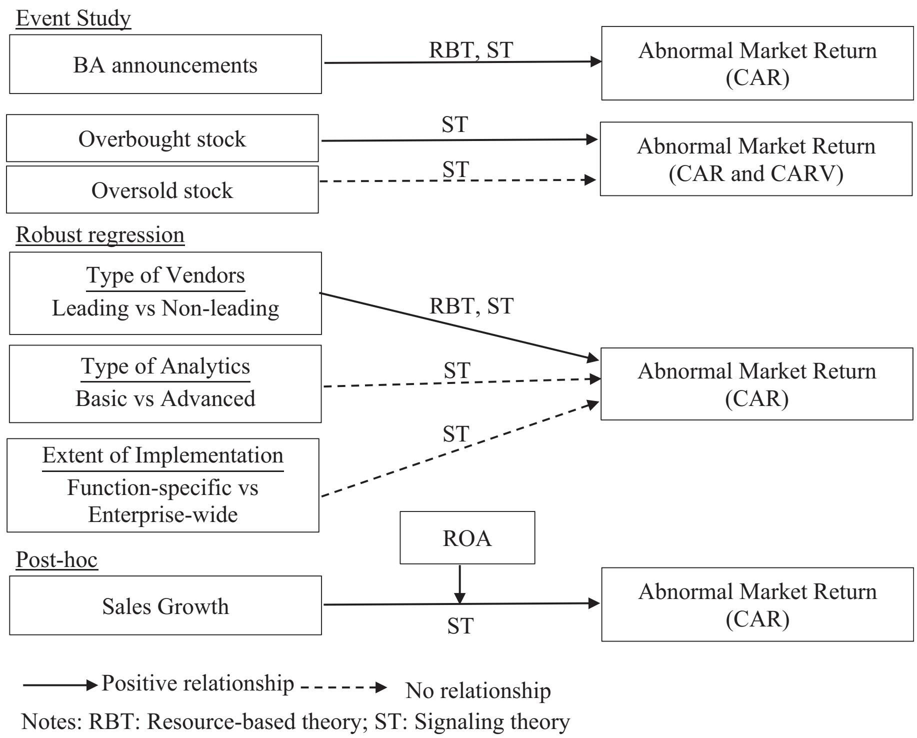

Fig. 3. Key results and supporting theories.

Limitations

There are several limitations to this study. First, while we controlled for variables such as firm size, other factors such as the competitive environment were not taken into account due to the lack of data. Environmental factors might affect the uncertainty in a firm's operating environment. Some environmental factors that might have moderating effects on a firm's resource capability include environmental turbulence, environmental munificence and environmental complexity (Wade and Hulland, 2004). Future research could include these variables that may potentially affect the strength of the signal.

Second, the event study methodology focuses on short-term returns from BA announcements. Consequently, the results might be more applicable to company management and speculators than long-term investors who invest mainly based on fundamentals than on firm announcements. It is also important to note that short-term returns might not be related to future improvements in firm performance. Hence, future studies could examine long-run measures of firm value (e.g., Tobin's Q) or conduct a long-horizon event study using the buy-and-hold abnormal returns (BHAR) approach since performance effects could primarily be observed in the long run.

Third, our sample size is small. However, it is consistent with previous event studies. We mitigate this limitation through the use of bootstrapping. With the increasing adoption of BA by firms, the availability of data should be less of a limitation in the future.

Fourth, our study did not examine the risk effects of implementing BA. Rubin and Rubin (2013) found that stock volatility (risks) associated with BI announcements were around 0.03–0.05%. They concluded that BI systems helped to reduce stock volatility since better data and analysis using BI resulted in more consistent firm behavior. Future research could examine which type of technology investments result in high risks in terms of stock volatility. Research could also attempt to integrate risk perspective with signaling theory to understand whether announcements as signals reduce or enhance market risks.

Implications

Implications for research

This study has several implications for research. First, past event study research often used the RBT. In this study, by combining RBT with signaling theory, we show that these two theories could complement each other in some instances and provide more holistic explanations of the results. Unlike RBT, signaling theory focus on the short-term impact. Short-term impact involves the immediate evaluation of IT investments. It is plausible that specific characteristics that make a resource VRIN in the long-term could not be observed by shareholders due to their inherent technological complexities. Thus, our findings suggest some differences between the RBT and signaling lens in terms of temporal orientation. Specifically, our empirical evidence related to the insignificant relationships of enterprise-wide adoption, and the sophistication of BA suggests that while IT assets could potentially be VRIN, future research focusing on immediate evaluation should also focus on its signaling potential. Past research using RBT to understand the market impact of IT announcements estimated CAR to range from 0.03% to 1.06% (Bharadwaj et al., 2009). This wide variation in the market impact could perhaps be also explained using the signaling power of IT initiatives in addition to their potential as VRIN.

In addition, our findings on the overbought stocks suggest that BA announcements are strong signals, mitigating any price correction due for such stocks. Past event studies often did not differentiate between overbought and oversold stocks. Our findings suggest that signals could influence the market value through different mechanisms such as enhancing price appreciation or mitigating price correction. Thus, future event studies could consider these distinctions, while evaluating the returns from announcements.

Second, we also examine the effects of certain characteristics (namely, market-leading vendor vs. non-leading vendor, basic vs. advanced BA, function-specific vs. enterprise-wide implementation) on returns from BA announcements. The results suggest the importance of market-leading vendors in market returns. However, there is no significant difference in CAR between basic and advanced BA, and between function-specific and enterprise-wide implementation. Future research could delve deeper into the reasons for the differences in the effect of different characteristics. In doing so, research could plausibly unravel the salient characteristics that determine whether signals are weak or strong.

Further, past research suggests that innovative and transformative technologies often generate positive market return for firms (Sood and Tellis, 2009). However, critics argue that innovation, being expensive, could generate negative returns for firms. In the present study, advanced BA represents more innovative and transformative technologies. Nevertheless, our findings on the sophistication of BA solutions suggest that shareholders are indifferent to advanced BA. Thus, market returns from innovative technologies require further exploration. Specifically, there is a need to examine the different contexts, where risks associated with them negate any positive payoffs in terms of market value.

Third, our complementarity analysis suggests that shareholders could perceive firm characteristics differently in isolation compared to their joint impact. Specifically, our results suggest that shareholders reward BA announcements when firms exhibit specific characteristics that complement each other. Future research could examine other firm characteristics as signals, in particular, whether these characteristics act as complements or substitutes. This could extend the research on BA beyond proverbial questions such as "whether BA results in positive pay-offs" by "digging deeper" into conditions where payoffs are likely to be enhanced or impaired.

Broad support for signaling theory, as well as the salience of perception in returns from announcements underlines the need to examine the short-term market value impact from a psychological perspective rather than organizational theory perspective. IS research on negative news that had strong market reactions such as IT failures had also used RBT (Bharadwaj et al., 2009). Perhaps, psychological theories such as prospect theory in conjunction with signaling theory could provide a new understanding of the phenomenon.

Fourth, future research could also seek to explain the differences between short-term and long-term impact using alternative approaches such as the paradox lens (Smith and Lewis, 2011). Reconciling the tension between short-term and long-term business value of IT would also contribute to existing debate on how firms can benefit from IT in both the short-term and long-term. In addition, such a reconciliation would further enhance our understanding of concepts specific to business value such as "productivity paradox". Future research could also examine other variables related to different capabilities that could affect the strength of the signal.

In addition, we did not examine the impact of BA on the accounting measures of firms' financial performance. Whether BA really improves firms' financial performance requires further exploration. This will extend the present discourse on BA beyond its signaling consequences to tangible payoffs from it.

While gathering data for analysis, we found that government organizations and private sector firms were also increasingly using BA. In such contexts, the market value cannot indicate the business value of technologies. Therefore, future research could explore different ways of measuring the business value of BA in the government and private sectors. Such research could explore approaches adopted in recent research, such as Kohli et al. (2012) to devise methods to compute the impact of BA in such contexts.

Implications for practice

There are also several implications for practitioners. First, this study provides empirical evidence to investors that BA announcements result in positive abnormal returns; specifically, resulting in an increase in stock price as well as stock volume. Such evidence should provide some assurance to top executive that investment in BA could have a positive impact on market value. However, they need to bear in mind that these effects are on overbought stocks rather than oversold stock. They could use this knowledge to extend the rally relating to overbought stocks.

Second, our results suggest that the market reacts more positively when the firm engages a market-leading vendor compared to a non-leading vendor. Thus, firms that are interested in positive payoffs in terms of market value should engage reputable vendors. Firms should also improve procedures for evaluating vendors, and manage external relations with them so that the firm, in partnership with a leading BA vendor, could facilitate smarter decisions through appropriate BA systems and infrastructure aligned with current and future needs. Therefore, assessment and selection of a leading vendor that could best cater to the firm's needs should be a key priority for BA implementation.

Third, the results also highlight that advanced BA and enterprise-wide implementation might not affect returns from BA announcements. Hence, top executives and BA managers should be aware that perhaps evidence of capabilities in using BA effectively might be more important than a detailed announcement of BA adoption that emphasizes technological characteristics.

Fourth, our study empirically demonstrates that the presence of complementarities between sales growth and ROA could enhance market returns from BA announcements. As well, it suggests to top executives that when certain firm characteristics are lacking, returns from BA tend to be low. By understanding these boundary conditions and the firm-specific context, they can better plan BA announcements for greater impact on firm market value.

Appendix A. Summary of review papers on IS event studies

Review study	Insights on theoretical lens
Dehning et al. (2003)	Proposes firm value framework and suggests that market value depends on four factors namely industry, size, time period and IT role
Roztocki and Weistroffer (2009)	Lack of widely accepted theory to explain market response, but RBT was the most common theory
Zhang and Huang (2009)	RBT is the most common theory in IS event studies
Konchitchki and O'Leary (2011)	Focus on empirical method. RBT is the most common theory in reviewed articles
Roztocki and Weistroffer (2011)	RBT is the most common theory. other theories include transaction cost economies, absorptive capacity, information-cascade, information asymmetry

Appendix B. Sample announcements

- HP chooses Stone Bond's Enterprise Enabler to automate delivery of order-specific factory *information* to customers (Business Wire, 03 February 2010)
- Beckman Coulter selects Oco's Business Intelligence Solution; *Oco's Solution* helps drive operational improvements and customer satisfaction (Business Wire, 26 August 2008)
- Alaska Airlines selects *Siebel BA* to provide easy flying and caring service for all customers (Business Wire, 7 March 2005)
- Hormel Foods Extends Agreement with *SignalDemand for Predictive Analytics* (PR Newswire, 18 April 2011)

Notes: Complete announcements were used for classification.

Appendix C. Calendar-time portfolio approach

A portfolio is constructed for each month, comprising firms experiencing the event within the sample period. The number of firms included is not constant over time because the number of firms experiencing a particular event is unevenly distributed over the sample period. The equally weighted portfolio excess returns are calculated each month. The resulting time series of excess returns are regressed using a linear regression model (Hoechle and Zimmerman, 2007). The excess returns for each sample stock i for period time t is obtained based on the market model as:

$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$ where R_{it} is stock return of event firm i on Day t. R_{mt} is the market return on the CRSP equal-weighted market portfolio on Day t, α_i is the intercept of the relationship for stock i with respect to market return, and ε_{it} is the error term for portfolio i on Day t. The term $\beta_i R_{mt}$ is the portion of stock returns that can be attributed to market returns. ε_{it} is the portion of the return that cannot be explained by market movements and hence captures the effect of firm-specific information.

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Appendix D. Market-leading vendors

Year	List of vendors who are market leaders
2004	Business Objects; Cognos; Crystal Decisions
2005	Business Objects; Cognos; Information Builders
2007	Business Objects; Cognos; Hyperion Solutions; Oracle; SAS
2009	IBM; Information Builders; Microsoft; Microstrategy; Oracle; SAP; SAS
2011	IBM; Information Builders; Microsoft; Microstrategy; Oracle; Qliktech; SAP; SAS

Source: Dresner et al. (2003, 2004), Schlegel et al. (2007), Richardson et al. (2009) and Sallam et al. (2011).

Appendix E. Categories of analytics

No.	Category	Description	Classification
1	Standard reports	Reports generated on a regular basis which describe what has happened in a particular area	Basic BA
2	Ad-hoc reports	Custom reports that enable the user to request answers for some types of questions	
3	Query drilldown (or Online Analytical Processing (OLAP)	Enables the user to manipulate the data to allow some extent of discovery	
4	Alerts	Allows the user to be notified when a problem occurs	
5	Statistical analysis	Slightly more complex analytics including frequency models and regression analysis are used to examine trends in stored data	Advanced BA
6	Forecasting	Allows users to forecast and predict demand to ensure enough supply or inventory	
7	Predictive modeling	Predictive analytics that enable firms to predict what will happen next and how decisions will affect the business or how customers will respond	
8	Optimization	Enables firms to make decisions for complex problems based on resource constraints and available technology	

Source: Adapted from SAS (2008).

Appendix F. Robustness checks for event study

Models	Mean CAR (%)	*t*-value
Market-adjusted returns (MAR)	0.38*	2.408
GARCH	0.39*	2.396
Basic daily	0.45**	2.664
4 factor Fama-French	0.44**	2.646

* $p < 0.05$.
** $p < 0.01$ (two-tail).

Mean CAR was 0.38% ($p < 0.05$), which is in line with our earlier estimate. The presence of time dependence in stock return series, if not taken into account, might also give inefficient parameter estimates and hence misspecification of test statistics. Thus, the generalized autoregressive conditional heteroskedastic (GARCH) model allowing nonlinear intertemporal dependence in the residual series was used. The results provided support for the robustness of the OLS market model since the mean CAR obtained in the GARCH model was 0.39% ($p < 0.05$). We also used the four-factor model (Fama and French, 1993), which reflected other factors such as size, book-to-market ratio, and prior performance that might affect abnormal returns. The result showed CAR of 0.44% ($p < 0.01$). Overall, the results suggested positive market returns for BA announcements.

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Appendix G. Robustness checks

Variables	Random effect (MLE)	Between effect	Population average (GEE)	areg regression	Bootstrapping technique
Leader	0.011*	0.011*	0.010*	0.011*	0.011*
	{0.004}	{0.005}	{0.004}	{0.005}	{0.006}
Advanced	−0.003	−0.005	−0.003	−0.003	−0.004
	{0.003}	{0.004}	{0.003}	{0.004}	{0.004}
Function-specific	0.001	0.002	0.001	0.001	0.001
	{0.003}	{0.004}	{0.003}	{0.004}	{0.008}
Revenue	0.003	0.003	0.003	0.003	0.003
	{0.004}	{0.004}	{0.004}	{0.004}	{0.004}
Employees	*−0.005*	−0.005	*−0.005*	*−0.005*	−0.005
	{0.003}	{0.004}	*{0.003}*	*{0.003}*	{0.004}
ROA	0.004	0.012	0.004	0.004	4.6e−04
	{0.012}	{0.016}	{0.012}	{0.014}	{0.043}
Sales growth	0.012*	*0.010*	0.012*	0.012*	0.011
	{0.005}	*{0.006}*	{0.005}	{0.006}	{0.007}
Intangibles	0.004*	*0.003*	0.004*	0.004*	0.004*
	{0.002}	*{0.002}*	{0.002}	{0.002}	{0.002}
Constant	0.005	0.012	0.005	0.014	0.009
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
N (sample size)	148	148	148	148	148
R^2	Log likelihood (LL) = 392.847	0.33	$\chi^2 = 74.90$ ($p < .05$)	0.34	0.30

Notes: Estimates are rounded off to three decimal places. Estimates represented in scientific notation wherever required. Italicized estimates are significant at $p < 0.05$ (one-tailed).
* $p < 0.05$ (two-tailed).

We conducted the Hausman test to identify the best panel data model. The Hausman test statistics were insignificant ($p = 0.92$), thereby indicating the random effect model as the best model. We computed estimates using random effects maximum likelihood regression. Also, we conducted additional tests using other models such as the between effects model (which assumed variations occured only between groups, but did not consider variations within a group), and GEE population averaged model (which assumed only a marginal distribution).

Since our empirical model included many dummy variables, we also computed estimates using the bootstrap method and areg procedure. This ensured that our estimates were robust against concerns about sample size and degree of freedom. We also dropped controls such as intangible assets to check the robustness of our estimates. Although the results for significance of control variables differed in different models, the results suggested consistency in that the explanatory variable *Leader* was statistically significant and affected abnormal returns positively. We also reran the analysis by incorporating the type of stock in our regression model. The results remained the same, i.e., the coefficient for the market leader remained significant ($\beta = 0.01$, $p < 0.05$), thereby confirming the importance of engaging a market leader in BA adoption.

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