# Big data investments in knowledge and non-knowledge intensive firms: what the market tells us

Tingting Zhang, William Yu Chung Wang and David J. Pauleen

**Abstract**

**Purpose** – *This paper aims to investigate the value of big data investments by examining the market reaction to company announcements of big data investments and tests the effect for firms that are either knowledge intensive or not.*

**Design/methodology/approach** – *This study is based on an event study using data from two stock markets in China.*

**Findings** – *The stock market sees an overall index increase in stock prices when announcements of big data investments are revealed by grouping all the listed firms included in the sample. Increased stock prices are also the case for non-knowledge intensive firms. However, the stock market does not seem to react to big data investment announcements by testing the knowledge intensive firms along.*

**Research limitations/implications** – *This study contributes to the literature on assessing the economic value of big data investments from the perspective of big data information value chain by taking an unexpected change in stock price as the measure of the financial performance of the investment and by comparing market reactions between knowledge intensive firms and non-knowledge intensive firms. Findings of this study can be used to refine practitioners' understanding of the economic value of big data investments to different firms and provide guidance to their future investments in knowledge management to maximize the benefits along the big data information value chain. However, findings of study should be interpreted carefully when applying them to companies that are not publicly traded on the stock market or listed on other financial markets.*

**Originality/value** – *Based on the concept of big data information value chain, this study advances research on the economic value of big data investments. Taking the perspective of stock market investors, this study investigates how the stock market reacts to big data investments by comparing the reactions to knowledge-intensive firms and non-knowledge-intensive firms. The results may be particularly interesting to those publicly traded companies that have not previously invested in knowledge management systems. The findings imply that stock investors tend to believe that big data investment could possibly increase the future returns for non-knowledge-intensive firms.*

**Keywords** *Knowledge-intensive firm, Event study, Market value, Big data investment*

**Paper type** *Research paper*

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## Introduction

The big data phenomenon is widespread and presents great investment potential. It is predicted that global organizations will spend roughly US$48.6bn on big data analytics and relevant services by 2019 (International Data Corporation, 2015). Meanwhile, interest grows in understanding the potential economic impact of investment in "big data" (Tambe, 2014). For instance, a McKinsey report estimates that using big data in the area of healthcare, energy, education, transportation and consumer finance could have a potential annual value of US$3tn (Manyika *et al.*, 2011). Columbus (2016) also reports that increased efficiency, improved decision-making and improved customer experience and engagement are the top three

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benefits of enterprise-wide big data implementation, as they could lead to positive economic returns.

Nonetheless, there are also different signals regarding the actual return value of big data investments. In a McAfee *et al*. (2012) study, big data investments do not bring significant value to the industry, especially in the European market. Coleman *et al*. (2016) also shares similar observation that firms in UK and Germany are unsure whether they are going to gain benefits from big data investments.

Moreover, controversial or inconsistent results are found in the literature. For example, both Min and Bae (2015) and Huang *et al*. (2016) investigated the value of big data investments using the same financial measures (i.e. changes in stock prices). While the former found positive impact brought by big data investment, the latter concluded there was no impact. Consequently, despite the trend of big data adoption, companies may choose to retain the status quo until the benefits are explicitly observed in more cases. There is a need to see more evidence of the actual economic value that big data might bring to a company.

In fact, the surge of big data brings knowledge management to a new era, as big data can provide value in extracting and managing knowledge (Côrte-Real *et al*., 2017). Therefore, it is important to know whether big data investment is perceived to have potential economic value for firms where knowledge is viewed as a crucial organizational asset (Erickson and Rothberg, 2014). These types of firms are classified in the literature as knowledge-intensive firms, "whose primary value-added activities consist of the accumulation, creation or dissemination of knowledge for the purpose of developing customized products and services" (Millar *et al*., 2016, p. 844). Recently, a few studies which investigate the impact of big data investments have looked into the characteristics of firms such as firm size and whether the firm is an IT firm (Min and Bae, 2015; Huang *et al*., 2016). However, there is a shortage of research focusing on whether there would be any difference in the value of big data investments between knowledge-intensive firms and other firms.

Adopting an event study approach, this study examines whether and in what way stock market investors recognize the value of big data investments. Specifically, this study investigates how firm stock prices react to big data investment announcements as direct evidence as to whether such an investment has perceived value for the firm. Such a reaction is further assessed to examine whether the reaction differs for knowledge intensive firms and non-knowledge-intensive firms. This study contributes to the literature on assessing the economic value of big data investments from the perspective of big data information value chain and from the viewpoint of stock market investors. Findings of this study can be useful for decision makers in deciding on big data investments depending on their firm's knowledge-intensive nature.

The rest of the paper is structured as follows. In the next section, big data and its value are discussed. Then the use of signaling theory and efficient market hypothesis as theoretical foundations for the study are justified and two research hypotheses are proposed. This is followed by the research methodology, data collection and data analysis, as well as presentation and discussion of the results. Finally, implications for researchers and practitioners, limitations and future research directions are explained.

## Big data and its value

Big data represent great potential for businesses to gain competitive advantage. Big data make it possible to uncover hidden trends and provide insights into future business contexts so that organizations are able to not only deliver the best products or services but also anticipate the behavior of their customers, employees, vendors and partners (Baboo *et al*., 2013; Arora and Rahman, 2016). Consequently, organizations can take actions in advance to exceed the expectations of those they do business with (Baboo *et al*., 2013; World Economic Forum, 2012).



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### *Big data information value chain*

The extant literature presents a number of ways to understand the value of big data. The term big data is originally understood via the three "Vs", namely, volume, velocity and variety, where volume refers to the magnitude of data generated, velocity refers to the speed of data creation and collection and variety refers to the data sources in a data set (Gandomi and Haider, 2015). Another view of big date defines it as technologies that enable the collection, storage, management, processing and analysis of data that is too large for conventional tools (Tambe, 2014; Portela *et al.*, 2016). Others argue that, skills, expertise and management capabilities are necessary for defining and understanding the big data phenomenon and using technology and analyzing data in an effective way (Shim *et al.*, 2015; Coleman *et al.*, 2016). Although each of the aforementioned ways of defining big data offers a unique perspective to understand the value of big data, none of them captures the value of big data in a comprehensive manner.

It is argued that the big data information value chain provides a unique means to combine the aforementioned three perspectives for understanding the value of big data (Wamba *et al.*, 2015; Abbasi *et al.*, 2016). The information value chain:

> [. . .] is the cyclical set of activities necessary to convert data into information and, subsequently, to transform information into knowledge, which individuals use to make decisions and take action, which then result in outcomes such as business value and additional data (Abbasi *et al.*, 2016, p. 3).

According to Abbasi *et al.* (2016), essential components for each stage of the information value chain (i.e. people, processes and technology) can be used to interpret the role of big data along the value chain. The volume, velocity and variety of big data necessitate changes in how an organization stores and manages data. Traditionally, data are primarily stored in relational databases, whereas big data featured with larger volume, velocity in real-time applications and variety of unstructured data requires innovative data management approaches (Abbasi *et al.*, 2016). In addition, innovative technologies are needed in handling big data (Bhat and Quadri, 2015). For example, new data management systems, such as Hadoop and Spark, have been developed to store and manage big data. Moreover, the arrival of the big data age has generated an urgent need for data scientist and big data analysts (Tambe, 2014; Bughin, 2016).

Indeed, big data have imposed a disruptive impact on the traditional information value chain. In the context of big data, capitalizing data from internal and external sources could turn out to be valuable for accumulating business knowledge, and eventually for making organizational decisions (LaValle *et al.*, 2011; Kwon *et al.*, 2014). This is especially the case for data-intensive industries in which data are key strategic resource for production, such as in financial and IT-related services (Tambe, 2014). For instance, in the financial industry, organizations increasingly make decisions based on reliable insights supported by factual big data (Seth and Chaudhary, 2015). Likewise, appropriate knowledge management systems that communicate insights derived from big data within an organization are found to maximize the value of big data investments (Tormay, 2015). It is also argued that skills, expertise and management capabilities are necessary for understanding the big data phenomenon, using related technology and analyzing data effectively (Shim *et al.*, 2015; Coleman *et al.*, 2016). For example, better productivity performance is found when a company has employees with big data management and analytics skills (e.g. Hadoop skills) (Tambe, 2014).

Big data's impact on the information value chain is especially linked with the role of knowledge, which is at the core of the big data information value chain (Abbasi *et al.*, 2016). In the big data era, knowledge evolves quickly due to the availability of huge amounts of stored and real-time data, as well as the significant reduction of cost for data analytics. As a result, it is possible to openly share and fuse knowledge insights, leadings to the



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appearance of new knowledge (Xu *et al.*, 2016). When more knowledge is developed, managed and exploited, more value is created because knowledge is an important resource that helps firms to achieve a corporate goal and to sustain competitiveness (Cavaliere *et al.*, 2015). In other words, big data are clearly related to knowledge management. Not only does big data provide a tremendous resource for knowledge creation (Côrte-Real *et al.*, 2017) but also knowledge utilization and knowledge transfer are necessary for the effective communication of insights from big data within an organization to maximize the value of big data investments (Tormay, 2015).

### *Measuring the value of big data*

Given the multifaceted means of understanding big data, assessing the value of big data investments requires a comprehensive approach (Schryen, 2013). This is because when organizations view their big data as a type of business asset, assessing its value can be conducted from a traditional accounting perspective (Abbasi *et al.*, 2016). Big data, however, can be viewed as an innovative information system, such as big data storage capacity and grid technologies (Garlasu *et al.*, 2013) and cloud computing (Purcell, 2014). In this sense, the value of big data investments tends to be intangible and emerges over the long term, which can hardly be reflected on the balance sheet (Andoh-Baidoo *et al.*, 2012). Investments in big data can also involve acquiring big data experts (e.g. data scientists, data analytics staff) and other strategic management support (e.g. knowledge management strategies). Such investments are essential for maximizing the value of big data (Tambe, 2014; Tormay, 2015) but can be hardly assessed separately.

Prior studies in the information systems field have proposed a number of possible measures to assess the economic value of information system investments. Some example measures include accounting based measure such as return on investment, return on assets and return on equity (Schryen, 2013), Tobin's *Q* (Bharadwaj *et al.*, 1999; Bardhan *et al.*, 2013) and stock performance (Im *et al.*, 2001; Andoh-Baidoo *et al.*, 2012; Roztocki and Weistroffer, 2015). Among these measures, stock performance is likely to be appropriate for this study for the following three reasons.

First, the value of big data may be intangible. Hence, it is difficult to use common accounting measures to cover the hidden value of big data investments, such as cost reduction and improvement in products, services and decision-making (Huang *et al.*, 2016). Stock performance can reflect the overall trust of market investors in the ability of the firm to derive benefits from information system investments (Im *et al.*, 2001; Andoh-Baidoo *et al.*, 2012; Son *et al.*, 2014; Roztocki and Weistroffer, 2015).

Second, the value of big data may emerge in the long run. Accounting measures usually report on what has happened, not what will happen (Im *et al.*, 2001). Stock performance can serve as a reflection of the perception of the market investors on the present value of a firm's future benefits gained from an investment in both the short term and the long term (Im *et al.*, 2001; Andoh-Baidoo *et al.*, 2012).

Third, the stock performance can be viewed as a firm's ability to attract further capital on the financial markets when necessary (Roztocki and Weistroffer, 2015). It is important to take into account the perspective of the firms' investors, rather than that of the firms' decision makers, when considering a firm's big data investment for the development of a firm (Min and Bae, 2015).

For these reasons, this study adopts a stock performance measure to assess the economic value of big data investments. Specifically, the change in a firm's stock prices is used to evaluate the reaction of the market investors to its big data investment announcements.



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## How can an event influence the stock market?

The market reactions to a firm's big data investment announcements can be further explained by signaling theory (Spence, 1973) and the efficient market hypothesis (Fama *et al.*, 1993). Signaling theory holds that in the absence of complete and accurate information, decision makers will interpret observable factors or a signal revealed by a sender and adjust their purchasing behavior accordingly (Spence, 1973). Efficient market hypothesis implies that the revelation of information about an event can evoke an immediate stock price fluctuation (Fama *et al.*, 1993). Relating the influence of the signal sent by an event to a reaction of the stock market allows one to determine whether the event provides valuable information to stock market participants (Eastman *et al.*, 2010).

The announcement of a big data investment may send signals about information on the future profit of a firm (Filbeck *et al.*, 2009). For instance, investments in big data can help a firm to gain a better understanding of its internal and external business environment and to generate insights into business opportunities (Sharma *et al.*, 2014). It can also potentially reduce costs, improve products, service and decision-making (Huang *et al.*, 2016). The emergence of big data provides additional source for new knowledge, valuable insights and innovation, which is essential for a firm to gain competitive advantages. With a more holistic picture of the business environment, decision makers can make more informed decisions to improve firm performance. As reported by McAfee *et al.* (2012), data-driven firms perform better financially and operationally. Tambe (2014) also finds firms having invested in Hadoop to be associated with 3 per cent faster productivity growth.

When the big data investment signal is observed and understood by stock market participants, the cost and potential earning of the big data investment are justified (Filbeck *et al.*, 2009). Consequently, the investment signal will influence actions of market participants, which will be realized instantly on the stock market (Hannon and Milkovich, 1996). Thus, favorable big data investments may bring an unexpected increase in an organization's stock price (Hannon and Milkovich, 1996). Hence, based on big data investment announcements, investors would perceive that the investment would result in positive outcomes. This leads to the following hypothesis:

*H1*. The stock market reacts positively to big data investment announcements.

In an era of big data, the essential aspect of the big data value chain is to derive knowledge from big data (Abbasi *et al.*, 2016). It is, therefore, crucial for a firm to take advantage of big data for the acquisition, storage, organization, access and sharing of knowledge (Millar *et al.*, 2016). As firms may have different ranges of dependence on knowledge assets, the value of their big data investments will vary. For knowledge-intensive firms who rely heavily on knowledge for providing customized services and products (Millar *et al.*, 2016), the strategic importance of big data investments seems especially profound. This is because knowledge is more important than other business inputs for a knowledge-intensive firm (Cavaliere *et al.*, 2015). The application of superior knowledge is the main source of competitive advantages for this type of firm (Kärreman, 2010). Hence, investing in big data can have a profound impact on a set of activities associated with the transformation of data into information, and then into knowledge in knowledge-intensive firms (Abbasi *et al.*, 2016). Moreover, big data implementation could enhance knowledge acquisition and broaden the existing body of knowledge so as to derive more insightful knowledge for decision-making (Kabir and Carayannis, 2013; Abbasi *et al.*, 2016). Therefore, when knowledge-intensive firms announce their big data investments, the future return of the investments would be expected by stock market participants to be positive.

Non-knowledge intensive firms, on the other hand, are likely to depend heavily on other types of resources such as labor and capital, rather than knowledge (Kärreman, 2010). In this case, these firms may not have a mature system to derive knowledge from raw data or to disseminate the knowledge derived throughout the firm. As a result, it could be difficult



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for non-knowledge intensive firms to gain appropriate insight from big data and eventually to reap even limited economic benefits from big data investments (Tormay, 2015). Because of this, stock market participants would probably show little interest in big data investments made by non-knowledge-intensive firms. Hence, the following hypothesis is proposed:

*H2*. The stock market reacts more favorably toward big data investment announcements made by knowledge-intensive firms than those made by non-knowledge-intensive firms.

## Event study methodology

Event study methodology is considered appropriate for this study because it is a powerful means to examine how stock market participants assess the informativeness of an event (Konchitchki and O'Leary, 2011). The event study methodology was developed based on the efficient market hypothesis (Fama *et al*., 1993) to assess the effect of a specific event on the stock price of a firm (Andoh-Baidoo *et al*., 2012). Using this method, the current market value of a firm reflects investors' perception of the present value of all future benefits to the firm in both the long and short terms. Therefore, the effect of an event on the stock price of a firm can be determined by the difference between the actual and predicted returns, which is often termed "abnormal return" (Konchitchki and O'Leary, 2011, p. 102). Since Dos Santos *et al.*'s (1993) initial use of the event study methodology, it has become well established and accepted in the field of Information Systems (Meng and Lee, 2007; Andoh-Baidoo *et al*., 2012; Roztocki and Weistroffer, 2015). Table I provides a brief summary of research related to the big data value chain using event study methodology. Consistent with other studies that have examined the market value of Information Systems investments, this study followed standard event study methodology. Events of interest, event windows and target firms were first identified, followed by the measurement of abnormal returns for across time and firms.

### *Determining the event window*

This study used a three-day event window consisting of the day of the announcement, the preceding trading day and the trading day following the announcement day. It is believed that a three-day event window is likely to lead to reliable results. This is because, when the event window is increased beyond three days, the power of the estimation model decreases (Lin *et al*., 2007; Jacobs *et al*., 2010). Moreover, with a long-term event window, there might be confounding events affecting a firm's market value within the same period. Choosing a shorter event window can help to diminish the contamination of stock price data during the event window by confounding events such as dividend, earning, merge/acquisition and changes in top management (Lin *et al*., 2007; Jacobs *et al*., 2010).

In this study, a 250-day estimation period was used, starting 252 trading days and ending two trading days before the date of the announcement. In total, 250 days are roughly about the number of trading days in a calendar year. Using such a relatively long estimation period can lessen the influence of possible seasonal stock price movements (Corrado, 2010). In addition, a longer estimation period ensures adequate observations for estimating the parameters (Dobija *et al*., 2012).

### *Selecting big data investment announcements*

A procedure for sample selection used by Dos Santos *et al.* (1993) was followed in this study. Wind financial terminal database was used to identify announcements of big data investments until the end of July 2016. Search terms included "big data" together with action verbs (such as plan to purchase, install, develop, invest, implement and analyze) or corresponding nouns. An initial search yielded 501 available announcements. These were analyzed and evaluated for inclusion in further analysis based on the following sampling criteria:



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**Table I** Big data related event studies and some characteristics

| *Researchers* | *Topic* | *Period of announcements* | *Factors* | *Sample size* | *CAR window* | *Estimation window* | *Major findings* |
|---|---|---|---|---|---|---|---|
| Choi and Jong (2010) | Knowledge management strategy-related announcements | January 1, 1998-December 31, 2003 | Types of knowledge management strategy<br>Industry type | 79 | (−2, +2) | (−122, −3) | Positive reaction to knowledge management strategy announcements<br>Industry type determines the magnitude of market reaction |
| Huang *et al.* (2016) | Big data implementation | January 1, 2010-March 15, 2015 | Technology type<br>The objective of big data implementation<br>IT firms vs non-IT firms | 40 | (−1, +1)<br>(−3, +3)<br>(−5, +5)<br>(−10, +10) | (−180, −11) | No reaction to big data implementation announcements overall and regardless of the technology type, the objective, or IT firms or not |
| Huntgeburth *et al.* (2013) | Cloud computing adoption | January 2007 - June 2012 | Innovativeness<br>Firm size<br>Industry cluster<br>Industry sector<br>Strategic Intent<br>Timing | 65 | (−3, +3) | (−258, −4) | Positive reaction for innovative adoptions<br>Positive reaction for large firms<br>Positive reaction for firms in the services industry cluster<br>Positive reaction for firms in financial, health care and IT sector<br>Positive reaction for adoptions with automate and informate strategic roles<br>Positive reaction for adoptions made in earlier years |
| Min and Bae (2015) | Big data investment | July 2011-June 2014 | Firm size | 84 | (−5, +5) | (−260, −10) | Positive reaction on the event day and the day after<br>No evidence of firm size affecting market reaction |
| Sabherwal and Sabherwal (2005) | Knowledge management and business strategies | January 1, 1989-December 31, 2002 | Related experience<br>Time<br>Return on assets<br>Firm size | 89 | (−2, +2)<br>(−3, +3) | (−300, −46) | Positive reaction to knowledge management announcements with the (−3, +3) window greater than the (−2, +2) window<br>Positive reaction when there is an alignment between the knowledge management process and firm efficiency |

(*continued*)



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**Table I**

| Researchers | Topic | Period of announcements | Factors | Sample size | CAR window | Estimation window | Major findings |
|---|---|---|---|---|---|---|---|
| Sabherwal and Sabherwal (2007) | Knowledge management and business strategies | 1995 to 2001 | Firm size<br>Alignment<br>Time | 103 | (−2, +2) | (−300, −46) | Positive reaction to knowledge management announcements<br>The magnitude of positive reaction is affected by firm size over a 2-day CAR window<br>Greater positive reaction for firms with a higher level of alignment between the knowledge management effort and the business strategy over a 3-day CAR window |
| Son *et al.* (2011) | Cloud computing adoption | 2005 - 2010 | Strategic intention<br>Firm size<br>Industry<br>SaaS vs Non SaaS announcements | 183 | (−1, +1) | (−121, −2) | Greater positive reaction for adoption with internal focus than for external focus<br>Positive reaction for large and SME firms<br>Positive reaction for non-SaaS cloud computing adoption<br>Positive reaction for firms in the nonmanufacturing sector |
| Son *et al.* (2014) | Cloud computing initiatives | January 1, 2006-December 31, 2011 | Firm size<br>Prior experience<br>Cloud service type<br>Cloud implementation type<br>Cloud benefit<br>Vendor reputation | 212 | (−1, +1) | (−256, −2) | Positive reaction to the cloud computing initiatives<br>Positive reaction for smaller firms<br>Positive reaction for adoption with operational benefits<br>The magnitude of positive reaction is larger for initiatives integrated within a firm's existing systems |



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- Only announcements by firms that were traded on either the Shanghai Stock Exchange or Shenzhen Stock Exchange were included.
- Only announcements by firms whose stock price information was continuously listed over the three-day event period and the 250-day estimation period were included.
- If there were duplicate announcements describing the same big data investment, only the first announcement was included. If there were more than one announcement with the same date, only the one which provided the most details about the investment was included.
- Announcements which had confounding announcements during the event three-day event window were excluded, such as announcements about dividend, earning, merge/acquisition and changes in top management.

In total, 319 announcements were screened out during the sample selection period. Eighty-two announcements were excluded because the stock price information for corresponding firms was not complete over the 253 days included in this study. Sixty-seven duplicate announcements about the same big data investments and two different announcements on the same day were excluded. Another 168 announcements were excluded because of the existence of confounding announcements over the three-day event window period, including 72 for dividend or profit disclosures, 78 on merger, acquisition, investment and 18 on changes in top management and administrative policies. In the end, these sampling criteria resulted in a total of 182 big data investments announcements from 2012 to July 2016.

Another four announcements were further excluded during the process of calculating normal returns (the procedure is described in the *Calculating abnormal returns* sub-section). For these four announcements, the beta estimates derived from equation (3) (i.e. $\hat{\beta}$) were not statistically significant. Such results meant that the normal return on each particular day during the three-day window for the four announcements cannot be calculated by using equation (4) for subsequent analysis (Min and Bae, 2015).

Overall, 178 announcements were included for further data analysis. The first announcements about big data investments were made in 2012. This is consistent with the big data phenomenon in China. Table II demonstrates the annual number of announcements about big data investment.

### *Data description*

The sample of this study consisted of 178 announcements made by126 firms listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The search for big data investment announcements was conducted using the Wind Financial Terminal Database, as was the retrieval of the daily stock returns of the individual firms. As a proxy for stock market returns, the daily return of the Shanghai Stock Comprehensive Index and the Shenzhen Stock Index was used.

The industry information of each firm was also obtained from the Wind Financial Terminal Database. The Wind Industry Classification Standard was adopted for categorizing the

**Table II** Annual numbers of announcements about investment in big data

| *Year* | *No. of observations* |
|---|---|
| 2012 | 2 |
| 2013 | 21 |
| 2014 | 41 |
| 2015 | 79 |
| 2016, till end of July | 35 |
| Total | 178 |



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selected firms. This standard is based on the Global Industry Classification Standard with minor justification to the characteristics of listed firms in China (Zhao, 2012). The Global Industry Classification Standard has been widely used in stock market research and is considered to be a better choice for financial analysts and investors than other industry classifications (Bhojraj *et al.*, 2003; Hrazdil *et al.*, 2013). Therefore, it is reasonable to believe that using the Wind Industry Classification Standard fits well with the purpose of this study, which is to understand investors' behavior in the stock market. In this sense, it can be argued that the findings from this study are likely to be comparable with findings from studies conducted in stock markets in other countries.

For the purposes of testing *H2*, the industries were further classified into knowledge-intensive firms and non-knowledge intensive firms by following the classification standard developed by the Organization for Economic Co-operation and Development. The reliability of such a classification approach has been testified in prior studies (Bonaccorsi *et al.*, 2014; Morariu, 2014). Table III provides an overview of sample description. In the sample, there were 84 announcements made by knowledge-intensive firms and 94 announcements by non-knowledge-intensive firms.

### *Calculating abnormal returns*

To measure the aforementioned change of a firm's financial performance triggered by the events of big data investment announcements, the normal rates of return were estimated by following the approach of Brown and Warner (1985). The stock return of firm *i* on day *t* (i.e. $R_{it}$) and the stock return of market portfolio on day *t* (i.e. $R_{mt}$) were first calculated using equations (1) and (2), respectively, where $P_{it}$ is the stock price of firm *i* on day *t* and $P_{mt}$ is the stock market price index on day *t*.

$$R_{it} = \frac{P_{it}}{P_{it-1}} - 1 \tag{1}$$

$$R_{mt} = \frac{P_{mt}}{P_{mt-1}} - 1 \tag{2}$$

Then, according to the efficient market hypothesis (Fama *et al.*, 1993), the return of a specific stock can be represented as a function of the market portfolio, as represented by equation (3), where $R_{it}$ represents return of stock *i* on day *t*; $R_{mt}$ is the return of the market portfolio on day *t*; $\alpha_i$, $\beta_i$ are the intercept and slope parameters, respectively, for firm *i*; and $\varepsilon_{it}$ is the disturbance term for stock *i* on day *t*. These parameters were estimated using stock price data observations over a 250 day-period ending two trading days before the events, i.e. day (−2). Then, regressions were run for $R_{it}$ on $R_{mt}$ as presented in equation (3) to derive $\hat{\alpha}$, and $\hat{\beta}$ in equation (4). Finally, the normal rate of return of firm *i* on day *t* (i.e. $\widehat{R_{it}}$) was calculated using equation (4).

**Table III** Industries of big data investment firms

| *Industries* | *No. of observations* | *Type of firm* |
|---|---|---|
| Energy | 1 | non-KIF |
| Materials | 10 | non-KIF |
| Industrials | 17 | non-KIF |
| Consumer discretionary | 33 | non-KIF |
| Consumer staples | 3 | non-KIF |
| Utilities | 30 | non-KIF |
| Healthcare | 5 | KIF |
| Financial | 9 | KIF |
| Information technology | 68 | KIF |
| Telecommunication Services | 2 | KIF |
| Total | 178 | |

**Notes:** KIF: knowledge intensive firms; non-KIF: non-knowledge intensive firms



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$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{3}$$

$$\widehat{R_{it}} = \widehat{\alpha_i} + \widehat{\beta_i} R_{mt} \tag{4}$$

Abnormal rate of return for firm *i* on day *t* within the three-day event window was derived using equation (5). Then, the cumulative abnormal return (CAR) for stock *i* over the event window was computed as Equation (6), while for a sample of *N* stocks the average CAR over the event window is represented by equation (7), where *N* is the number of observations included in the sample or subsample. Furthermore, the CARs were further tested for statistical significance using equation (8).

$$AR_{it} = R_{it} - \widehat{R_{it}} \tag{5}$$

$$CAR_i = \sum_{T1}^{T2} AR_{it} \tag{6}$$

$$CAR = \frac{1}{N}\sum_{T1}^{T2} CAR_{i(T1,T2)} \tag{7}$$

$$z = \frac{\text{average of CARi}}{\text{standard deviation}/\sqrt{N}} \tag{8}$$

## Findings and discussions

Table IV shows the CARs of all the firms obtained over a three-day event window. The generalized sign test is a comparison of the proportion of events with positive abnormal returns and that negative abnormal returns (Cowan, 1992). As shown in Table IV, there is a dramatic increase on day 0 and day (0,1) (i.e. from the announcement day to the day after). For day 0, the ratio of number of events with positive CARs to those with negative CARs is greater than 1 (107:71) with a generalized sign Z value indicating that the CAR for day 0 is positive and significant at the 1 per cent level. For the (0,1) event window, the ratio of number of events with positive CARs to those with negative CARs is greater than 1 (100:78) with a corresponding generalized sign Z value implying that the CAR for day (0,1) is positive and significant at the 1 per cent level. Therefore, *H1* is supported.

This finding aligns with Min and Bae's (2015) that big data investment announcements have positive impact on the stock prices of sample firms. Such a finding suggests that big data investments can enhance investors' beliefs that firm value will increase in the future.

The results of the CARs for knowledge intensive firms and non-knowledge intensive firms are presented in Table V. For knowledge intensive firms, none of the CARs on any day or

**Table IV** Cumulative abnormal return for all the firms

| *Event day(s)* | *Cumulative average abnormal return (%)* | *Z* | *Positive:negative* | *Generalized sign Z* |
|---|---|---|---|---|
| −1 | −0.70 | −1.397 | 78:100*** | 8.524 |
| 0 | 1.11*** | 3.428 | 107:71*** | 14.022 |
| 1 | −0.21 | −0.779 | 82:96*** | 14.751 |
| (−1,0) | 0.41 | 0.721 | 88:90*** | 11.297 |
| (0,1) | 0.90** | 2.084 | 100:78*** | 14.752 |
| (−1,+1) | 0.20 | 0.319 | 97:81*** | 12.017 |

**Notes:** ***Significant at the 1% level; **significant at the level of 5%

**Table V** Cumulative abnormal returns for knowledge-intensive firms and non-knowledge-intensive firms

| *Type of firm* | *No. of observations* | *− 1 (%)* | *Z* | *0 (%)* | *Z* | *1 (%)* | *Z* | *(− 1,0) (%)* | *Z* | *(0,1) (%)* | *Z* | *(− 1,1) (%)* | *Z* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| KIF | 84 | −0.70 | −0.928 | 0.90 | 1.929 | −0.20 | −0.395 | 0.20 | 0.208 | 0.70 | 1.239 | −0.30 | −0.295 |
| non-KIF | 94 | 0.50 | 1.421 | 0.40 | 1.081 | 0.20 | 0.779 | 1.50** | 2.529 | 0.90* | 1.925 | 1.80*** | 2.787 |

**Notes:** ***Significant at the 1% level; **significant at the level of 5%; *significant at the level of 10%



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any event window over the three-day event window period is found statistically significant. Statistically significant CARs are observed for non-knowledge-intensive firms during event windows (−1,0), (0,1) and (−1,1) at the significant level of 5, 10 and 1 per cent, respectively. This means that *H2* is not supported.

This is an interesting finding as it suggests that stock investors evaluate the future benefits of big data investments depending on whether the firm is knowledge intensive or not. Also, stock market investors would be more optimistic toward big data investments made by non-knowledge-intensive firms. Possible explanations for such a finding are as follows.

Big data investments publicly announced by non-knowledge-intensive firms could be seen as an initial step of exploratory investing in a large project intending to take advantage of data (Portela *et al.*, 2016). The announcement sends a message to investors that the organization is in the process of implementing an innovation. Prior studies on innovative information systems adoption have proved that this type of announcement invokes an increase in a firm's stock price (Konchitchki and O'Leary, 2011). Hence, announcements about big data investments probably signal increases in future benefits of the big data investment and investors would react positively accordingly.

On the contrary, for knowledge-intensive firms, big data are usually used as an extension of what already exists (Portela *et al.*, 2016). As some researchers have pointed out, a knowledge-intensive firm must devise appropriate knowledge management mechanisms such as strategies, policy, infrastructure and training that enable the company to maximize the value of their big data investments (Tormay, 2015). Without further investments to support the big data implementation, investors may perceive that the current big data implementation adds limited value to firms that may already have infrastructure or resources to conduct big data analytics.

Moreover, when a big data investment is viewed as an extension of the existing resources and systems, knowledge-intensive firms may overlook the real business need of such investments (Lavastorm Analytics, 2014). When investors are unable to see a clear objective of a big data investment, they probably perceive that the investment would not lead to future benefits or may even bring negative effect on future profit as the big data investment can be a risk investment (Portela *et al.*, 2016). Huang *et al.*'s (2016) study provides some evidence for this suspicion. They (Huang *et al.*, 2016) found that announcements made by firms whose news coverage mentioning the objective of big data investments have a positive impact on the firms' CARs over a 21-day event window. Whereas, announcements not mentioning the objective of big data investments have negative impact on firms' CARs over an 11-day and a 21-day event windows (Huang *et al.*, 2016).

## Conclusions

Based on signaling theory and the efficient market hypothesis, this study investigated how the stock market recognizes the value of big data investments by checking the relationships between investment announcements and the variation of stock prices. The results show that big data investment announcements bring increases in a firm's stock price in general and in non-knowledge-intensive firms in particular. These findings have implications for research and practice.

This study makes an effort to answer the calls for assessing the economic value that big data investments can bring to a firm (Abbasi *et al.*, 2016; Côrte-Real *et al.*, 2017). By viewing market reactions, this study suggests that market reaction can serve as a comprehensive measure for understanding the economic value of big data investment. Building upon the big data information value chain, this study also points out a relationship between big data and knowledge management.



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In addition, the current paper addresses the questions that how return on investment in big data can be perceived and when a firm should invest in big data using an event study approach. Although few prior studies have specifically focused on the impact of big data investment announcements on firms' stock prices, they have generated controversial or inconsistent results. For example, Min and Bae (2015) find positive impact of big data investment news on firm stock prices based on data from 84 firms. However, Huang *et al.* (2016) find no impact using a sample consisting of 40 big data investment announcements. This paper contributes another empirical study to the literature on examining the economic value of big data investments from the perspective of stock market investors using a larger sample size of 178 from a major stock market compared to the extant literature.

Moreover, this study takes an innovative perspective to understand the association between big data investments and the market's perception of the investment under different firm conditions. Prior studies have compared the market reactions to big data investment news between firms of different sizes (Min and Bae, 2015) and between IT firms and non-IT firms (Huang *et al.*, 2016). This study looks into the differences in the market reaction toward big data investment announcements made by knowledge-intensive firms and non-knowledge-intensive firms. Given that data are the fundamental element from which to derive knowledge (Abbasi *et al.*, 2016), it is important to understand investors' attitudes toward big data investments in both knowledge-intensive firms and in non-knowledge-intensive firms.

For practitioners (including executives and managers), this study provides support to justify big data investments. The results that stock markets react positively to big data investments announcements indicate that investors tend to believe that firms will gain significant earnings from big data investments in the future based on their interpretation of the investment announcements. Therefore, this study can be used to refine these practitioners' understanding and thinking about their investors' expectations about the future earnings from big data investments. In addition, results of this study suggest that decision makers can use the possible perceived value of big data investments by the stock market to prepare or adjust the implementation of their big data investments. This would optimize their investment decisions.

In particular, this study suggests that practitioners from firms with different levels of knowledge intensiveness need to consider big data investments with caution. Practitioners of non-knowledge-intensive firms may particularly consider making or increasing investments in big data as the investments would enhance investors' trust in the future performance of the firm. However, the expansion of big data implementation imposes challenges for knowledge-intensive firms. These firms might need to focus mainly on how to align their knowledge management strategies with big data implementation (Kabir and Carayannis, 2013). Alternatively, knowledge-intensive firms may need to upgrade their knowledge management systems to make full use of big data for strategic and competitive advantage (Kabir and Carayannis, 2013).

Some limitations and future research are noted here. Firms that are not listed on the stock market may need to interpret the results of this study with caution because the event study methodology only allows for the investigation of firms with stock prices available. Hence, further studies can try different approaches to examine the economic value of big data investments for firms that are not publicly traded on the stock market. In addition, although results of this study indicate that the stock market is more favorable toward big data investments made by non-knowledge-intensive firms, further research is needed to confirm the reasons leading to such results. Moreover, as a common challenge for event studies, there might be additional factors affecting stock performance, which were not considered in this study; for example, whether big data investments are innovative or follow-up investments may affect a firm's market performance (Dos Santos *et al.*, 1993). Similarly, the amount of big data investment expenditure might result in variation in stock price



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fluctuation. Therefore, future studies could consider investment-related features to capture the market performance of big data investment in more detail.

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