Firms' Operational and Logistics Characteristics and Realisation of Business Analytics Benefits: Evidence from Stock Markets

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Abstract

The idea of "big data" provides practitioners in the logistics industry with valuable opportunities to improve their operational efficiency and economic performance. In fact, business analytics techniques are increasingly being used in international logistics, shipping, and supply chain management. We examine the impact of business intelligence (BI) system adoption on firms' market value and the influences of the operating characteristics and contexts of firms. Specifically, we examine whether the impacts of BI adoption is contingent on industry competitiveness, firms' operating cycle, and industry munificence. Using the event study methodology, we analyse 272 manufacturing firms in the United States that adopted BI systems from 2005 to 2014. We find that BI adoption does not have an immediate impact on firms' stock returns, but such impact is significantly enhanced for firms in highly competitive industries, and those with short operating cycles and high industry munificence, i.e., high-growth industries, suggesting that firms in fast-changing dynamic environments find BI systems much more useful.

Keywords: business intelligence systems; stock returns; industry competitiveness; operating cycle; industry munificence

1. Introduction

Digital technologies have been widely adopted in business, which has led to a rise in the use of big data analytics. With the widespread diffusion of internet technologies worldwide, a wide range of organisational and consumer data are available to manufacturers, wholesalers, and logistics firms (Baryannis et al., 2019). Indeed, many firms are under pressure to improve supply chain and operational performance through business analytics, machine learning, and artificial intelligence (AI) techniques (Baryannis et al., 2019; Chae et al., 2014; Waller and Fawcett, 2013). There are a large number of successful applications. For example, Proctor & Gamble and Walmart reported significant improvements in their logistics and shipping performance through the use of business analytics tools (Chae et al., 2014). In general, Business intelligence (BI) systems allow organisations to develop a critical capability to obtain value from vast amounts of data and create competitive advantage (Chen et al., 2012; Wamba et al., 2017). BI technologies are commonly adopted across industries to enable organisations to make better strategic decisions (Hagel, 2015). In manufacturing operations, organisations can benefit from BI in terms of real-time monitoring of processes, industrial automation, and supply chain visibility (Davenport et al., 2012; Rowe and Pournader, 2018).

Recent studies have shown that adopting BI systems can help leverage big data to significantly enhance organisational effectiveness and efficiency (Tiwari et al., 2018). In particular, logistics and supply chain managers in the manufacturing sector are more reliant on leveraging big data through BI systems to identify trends in operational costs and performance. BI techniques are also used to support process improvement and production optimisation, ensuring smooth and cost-effective operations (Hazen et al., 2014; Trkman et al., 2010). However, although many firms have made major investments in BI systems in the last decade (Arnott et al., 2017; Schermann et al., 2014), the competitive advantage of BI adoption is often hard to realise (Trivedi, 2018; Yeoh and Koronios, 2010). BI adoption is an extremely complex process that requires organisations to institutionalise operational processes and develop strong organisational culture (McAfee et al., 2012; Yoon et al., 2017). Also, the benefits from BI adoption may also depend on many other operational and contextual features. Accordingly, not all firms obtain the benefits of BI adoption equally. The firm-specific and industry-specific factors may play an important role.

In this study we empirically examine the impact of BI adoption on the stock returns of firms in the manufacturing sector. Because no single method is best for all the organisations, we adopt contingency theory (CT), which suggests that organisations should fit their management practices into their operating environments. As a result, understanding of the contingency factors is essential in reaping the full benefits of BI. We particularly focus on if the impact of BI adoption is contingent on industry competitiveness, operating cycle of firms and industry munificence. With the shipments and transactions handled every day between manufacturers and their supply chain partners, firms generate huge amounts of data (Tiwari et al., 2018; Wang et al., 2016). Such massive data need to be managed by logistics and supply chain managers in manufacturing firms with advanced methods. However, very little research has been conducted on the use of BI in the shipping and logistics sector. Through a contingency perspective, our study fills this research gap. By analysing 272 manufacturing firms in the United States that adopted BI systems from 2005 to 2014, we find that BI adoption does not have an immediate impact on stock returns, but its impact is significantly enhanced for firms operating in a highly competitive industry, and with short operating cycles and high industry munificence. In addition, we find that although the impact of BI adoption on short-term stock prices is limited, its influence on the long-term economic performance is significant. Our findings are important and relevant for firms operating in fast-changing, dynamic industries, guiding them to reap the benefits of BI adoption.

2. Theoretical Framework and Hypothesis Development

2.1. Big Data and BI Adoption from the Contingency Perspective

Big data refers to massive amounts of complex, structured, and unstructured data (Sanders, 2014; Younas, 2019). It is a high-volume, high-velocity, high-variety, high-veracity, and high-value information asset (White, 2012; Younas, 2019). From the management perspective, big data is beyond the ability of conventional software tools and requires specialised analytical tools to capture, store, manage, and analyse (Elgendy and Elragal, 2016; Sanders, 2014). Big data is an important driver of digital transformation for firms, bringing technological changes in knowledge assets (Davenport et al., 2012) and a new decision-making culture (McAfee et al., 2012).

Although many firms with enormous amounts of data are already using BI tools to transform their operations, many businesses are finding it hard to realise the benefits of big data (Trivedi, 2018; Yeoh and Koronios, 2010). BI systems are a set of technologies and software that help consolidate and analyse large volumes of data originating from various sources, such as buyers', suppliers', and competitors' activities, and leverage data to turn them into actionable insights (Bose, 2009; Trieu, 2017). Previous studies (e.g., McAfee et al., 2012; Trivedi, 2018; Yeoh and Popovič, 2016) have found some critical factors (e.g., a favourable organisational culture and strong employee commitment) for successful implementation of analytical systems. Moreover, we suggest that organisations also fit their BI infrastructure and implementation to their environment and operational characteristics from the contingency perspective to reap better benefits of big data. CT argues that no single method is best for all the organisations (Flynn et al., 2010; Morton and Hu, 2008). The environment influences organisations' structures and processes, and suppliers and buyers are important components of a manufacturer's environment (Flynn et al., 2010). Thus, CT posits that organisations should fit their structures and processes to contextual factors, including environmental uncertainties, firm-specific characteristics and industry-specific factors (Donaldson, 2001; Morton and Hu, 2008).

2.2. Hypothesis Development

2.2.1. BI Systems and the Market Value of Firms

We hypothesise that BI systems have a positive impact on the market value of firms. The primary objective of BI systems is to enhance the analytical capabilities of firms through improving data handling competence and timeliness in the decision-making process (Elbashir et al., 2008; Shollo and Galliers, 2016). BI systems enable firms to capture, store, discover, and analyse data to support organisational decision-making, leading to better operational performance (Elgendy and Elragal, 2016; Rubin and Rubin, 2013). Implementing a BI system leads to enterprise-wide change, and firms often undergo major transformations such as process re-engineering and core business re-structuring, thereby improving the firms' operational performance and stock returns (Rubin and Rubin, 2013).

By adopting BI systems, manufacturers can regularly analyse data collected from different sources and obtain a unified view of their supply chains, thus improving logistics and warehouse management (Langlois and Chauvel, 2017). Embarking on BI initiatives builds a culture of open communication and trust, where organisational members are encouraged to share and use information (Yoon et al., 2017). Firms can leverage BI systems to access updated sales reports, share information with stakeholders, and subsequently increase market responsiveness. With more information about buyers', suppliers', and competitors' activities, executives can make better strategic decisions (Chen et al., 2012; Negash and Gray, 2008). Overall, a BI-adopting firm is in a better position to manage its resources to achieve organisational goals, and business decisions are more reliable, resulting in better operating performance and higher stock returns.

H1. *The adoption of BI systems leads to higher stock prices of firms.*

2.2.2. The Contingency Factor of Industry Competitiveness

Industry competitiveness refers to an operating environment where there are many firms competing for the same group of customers without clear product/industry differentiation (Lo et al., 2013). Firms in a highly competitive environment must adopt new technologies to maintain their market positions, whereas non-adoption of technologies in such an environment might result in competitive disadvantage (Frambach and Schillewaert, 2002; Huang, 2011; Ramdani et al., 2013). Thus, a highly competitive environment influences firms' propensity to adopt new technologies such as BI systems (Huang, 2011).

BI technologies enable firms to keep up with the current industry trends, better understand the competitive environment, and make better use of available resources held throughout the organisation. Accordingly, their management can match the resources with the needs of the organisation to make better-informed operational decisions (Koufteros et al., 2014). BI is suggested as one of the most important technologies to facilitate coordination both inside and outside a firm in response to uncertainties (Sabherwal and Becerra-Fernandez, 2011). As such, through the fast information dissemination in BI systems, firms in highly competitive industries are more capable of discovering unfavourable market conditions, thus allowing them to take prompt actions to streamline structures, and bundle capabilities and resources to cope with intense competition (Chadwick et al., 2015). In accordance with CT, we argue that firms can obtain greater benefit from adopting BI systems in highly competitive industries, which in turn increases stock returns. In contrast, less competitive industries are usually dominated by fewer large firms, and less incentive exists for firms to implement BI systems because the firms have already been dominating the market.

H2. *Firms operating in highly competitive industries obtain greater benefit from the* *adoption of BI systems than firms in less competitive industries.*

2.2.3. The Contingency Factor of Operating Cycle

An operating cycle is considered as a contingency factor in adopting BI systems. It is related to the processes that businesses undertake to acquire raw materials from suppliers, turning raw materials into finished products, and delivering products to customers (Greer and Theuri, 2012; Lo et al., 2009). The operating cycle time of firms affects the ways that they manage the flows of materials, products, and supply chain transactions (Ngai et al., 2011). In particular, firms with shorter operating cycles require a faster information flow with their supply chain partners to achieve high coordination and flexibility to meet market changes.

With the support of BI, the flow of information becomes much faster, enabling a timely response to the market. In particular, executives can use the insights generated from the BI systems to provide directions to the entire supply chain. From the CT perspective, firms should adopt BI systems that are compatible with their operating characteristics to generate greater business value. With the synergistic effect of BI systems matching firms' short operating cycle, the entire organisation can quickly move towards a common goal. In addition, BI helps firms improve their process visibility (Davenport et al., 2012; Rowe and Pournader, 2018) and attain faster information dissemination. Therefore, BI adoption is more important for firms characterised by shorter operating cycles rather than firms characterised by longer operating cycles in terms of achieving speedy information flow that helps manage material flows, product sales, and supply chain transactions.

H3. *Firms characterised by shorter operating cycles obtain greater benefit from the adoption of BI systems than firms with longer operating cycles.*

2.2.4. The Contingency Factor of Industry Munificence

Industry munificence refers to the availability, abundance and richness of external resources, particularly when firms are operating in a high-growth market (Anderson and Tushman, 2001). As a firm's operating and contextual characteristic, a munificent industrial environment supports the adoption of BI systems in many ways. First, a fast-growing environment suggests that there are abundant market opportunities, providing firms with operational and financial resources for the implementation of BI systems. Second, a munificent environment, as compared to a hostile situation with limited prospects, motivates firms to carry out strategic investments on IT capability, building long-term BI competence (Stoel and Muhanna, 2009). More generally, in contrast to an operating context with limited market prospects, industry munificence provides a favourable environment for organisation innovation and efficiency enhancements (Chen et al., 2017).

More importantly, industry munificence also implies that the operating environment is more dynamic, vibrant and fast-changing, making the use of BI systems more critical (Lo et al., 2013). With fast developments in the industry, many other players may also enter the market, leading to competition risk and uncertainty (Qi et al., 2014; Chen et al., 2017). Also, in a dynamic and fast-developing environment, firms need to develop better product and market knowledge, rendering timely data related to operations, supply chain and customers more important. The adoption of BI systems enables firms to sensibly explore, analyse and share operational and market information (Stoel and Muhanna, 2009). In addition, a munificent environment also implies that logistics, supply chain and inventory requirements are more dynamic and difficult to predict, making the use of BI systems more critical for efficient operations. Accordingly, we develop the fourth hypothesis:

H4. *Firms operating in the context of high industry munificence obtain greater benefit from the adoption of BI systems than firms with low industry munificence.*

3. Methodology

3.1. Data Collection

We focus on US-listed manufacturing firms (SIC codes: 2000–3999) that have adopted BI systems (Chen et al., 2012; Yiu et al., 2020a). The sample is from the period between 2005 and 2014, when BI technologies were more developed (Chen et al., 2012; Teo et al., 2016). We collect BI adoption news announcements in Factiva, which combines the Reuters Business Briefing and Dow Jones Interactive databases to provide comprehensive global business news (Gnyawali et al., 2010; Yiu et al., 2020b). We focus on BI platforms provided by leading and niche BI service providers. Following prior studies on BI (e.g., Rubin and Rubin, 2013; Teo et al., 2016), we identify BI-adopting firms by searching for news announcements containing the names of leading and niche BI service providers, together with the names of the firms (Yiu et al., 2020a), using the keywords 'business intelligence systems' or 'BI systems' with 'adoption', 'introduce', or 'implementation'.

We identified 323 sample firms with BI adoption. We removed 14 sample firms that had implemented their BI systems with other enterprise systems. In the event-study analysis, we examine the impact of BI system adoption on firms' stock returns. Among the remaining sample firms, 272 BI-adopting firms have enough data on stock returns in the estimation period of 120 trading days and the three-day event window. So, we had the final sample of 272 firms to conduct the event-study analysis

In the cross-sectional regression analysis, we consider the impacts of three contingency factors, namely *industry competitiveness*, *operating cycle*, and *industry munificence*, on the cumulative abnormal return (CA) of a firm. As mentioned above, 272 BI-adopting firms have enough data on stock returns to support the measurement of CA. However, only 219 out of the 272 sample firms have enough data to measure the contingency variables and control variables. So, we had the final sample of 219 firms to conduct the regression analysis.

3.2. Event Study Analysis

We use the event study methodology to examine the impact the adoption of BI systems on a firm's stock return (*H1*). The event study methodology has been extensively used to estimate stock market reactions to corporate announcements of events (Xia et al., 2016). The event in this study is the adoption of BI systems.

Following previous studies using the event study methodology (Edmans, 2011; Xia et al., 2016), we estimate abnormal returns by using a four-factor model that includes Fama and French's (1993) three factors and the momentum factor identified by Carhart (1997). The model is as follows:

$$R_{it} = \alpha_i + R_{ft} + \beta_{i1}\left[R_{mt} - R_{ft}\right] + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}UMD_t + \varepsilon_{it}\ ,$$

where R_{it} is the stock return of firm *i* on day *t*, R_{ft} is the risk-free rate of return on day *t*, R_{mt} is the total market portfolio return on day *t*, SMB_t is the difference between the rates of return of small and big market capitalisation stocks, HML_t is the difference in returns between high and low book-to-market ratio stocks, UMD_t is the momentum factor that is the difference in returns between high and low previous stock performance, and ε_{it} is an error term.

We estimate $\hat{\alpha}_i$, $\hat{\beta}_{i1}$, $\hat{\beta}_{i2}$, $\hat{\beta}_{i3}$, and $\hat{\beta}_{i4}$ based on ordinary least squares regression over the estimation period of 120 trading days that starts on day –149 and ends on day –30 prior to a firm's BI adoption announcement. The abnormal return A_{it} of a firm *i* on day *t* is the difference between the firm's actual stock return R_{it} associated with the event regarding BI adoption and the expected stock return $E[R_{it}]$ without the occurrence of the event, i.e.,

$$A_{it} = R_{it} - E[R_{it}]\ = R_{it} - \left(\hat{\alpha}_i + R_{ft} + \hat{\beta}_{i1}R_{mt} + \hat{\beta}_{i2}SMB_t + \hat{\beta}_{i3}HML_t + \hat{\beta}_{i4}UMD_t\right).$$

We measure abnormal returns over an event window for three trading days from day –1 to day +1 (Ba et al., 2013; Xia et al., 2016). The announcement day on the adoption of BI systems is day 0, the next trading day is day +1 that captures the impact of the announcement made after the market closes, and the trading day before the announcement day is day –1 that accounts for the possibility that the information about BI adoptions has been released before the announcement (Xia et al., 2016). Following this approach, the cumulative abnormal return (CA) of firm i is $CA_i = \sum_{t=-1}^{+1} A_{it}$. To minimise the confounding effects from other applications, we eliminate 14 BI-adopting firms with multiple implementations and other systems such as enterprise resource planning and customer relationship management systems in the event window. We further drop 37 firms to obtain the final sample size of 272 firms that have available data on stock returns in the estimation period of 120 trading days and the three-day event window. The 272 firms are from 18 industries based on two-digit SIC codes. Table 1 shows that the top five industries are (a) chemicals and allied products, (b) electronics and other electric equipment, (c) instruments and related products, (d) industrial machinery and equipment, and (e) food and kindred products, representing 72.06% of the total sample.

Insert Table 1 about here

Barber and Lyon (1996) suggested that non-parametric statistical methods such as the Wilcoxon signed-rank (WSR) and sign tests are more appropriate than the parametric *t*-test for event studies with financial data. WSR also takes the magnitude of abnormal returns into account (Yeung et al., 2011). Specifically, WSR is the preferred method for our analysis because the distributions of abnormal returns and cumulative abnormal returns are non-normal and symmetric, according to both the Kolmogorov-Smirnov and Shapiro-Wilk normality tests, with *p*-values less than 0.05 and the absolute values of the skewness less than 1, respectively. To reduce the influence of the outliers, we also supplement the *t*-test with the WSR test (Xia et al., 2016).

3.3. Cross-Sectional Regression Analysis

To examine the impacts (Hendricks and Singhal, 2008) of the contingency factors of industry competitiveness (*H2*), operating cycle (*H3*), and industry munificence (*H4*) on CA, we use a cross-sectional regression model as follows:

$$CA_i = \beta_0 + \beta_1 Industry\ Competitiveness_i + \beta_2 Operating\ Cycle_i + \beta_3 Industry\ Munificence_i + \beta_4 Firm\ Age_i + \beta_5 Market\ Share_i + \beta_6 Firm\ Profitability_i + \beta_7 Firm\ Size_i + Year\ Dummies + Industry\ Dummies + \varepsilon_i.$$

We employ the reverse Herfindahl index as a proxy for *industry competitiveness* (Hendricks and Singhal, 1997; Modi and Mabert, 2010). That is, the higher the reversed index is, the higher the industry competition will be. The Herfindahl index is calculated as the squared sum of firms' market shares in the same industry based on two-digit SIC codes (Modi and Mabert, 2010; Vomberg et al., 2015).

Operating cycle is considered a process that a business undertakes to acquire inventory, deliver finished products from manufacturers to buyers, and realise cash from sales. It is measured as the sum of inventory days and accounts receivable days (Greer and Theuri, 2012; Lo et al., 2009).

Industry munificence in a specific year is measured as the slope coefficient obtained by regressing industry sales (log transformed; two-digit SIC code) over a five-year period prior to this year (Wales et al., 2013; Lam et al., 2019).

We also consider four control variables and dummies that might potentially affect changes in firms' market values. We include *firm age*, measured as the natural logarithm of the number of years since a firm's incorporation (Loderer et al., 2016). Because an older firm provides more information, the market knows more about the intrinsic quality of the firm (e.g., business trend, financial condition, and the quality of top management) (Dasgupta et al., 2010). An older firm is more likely to have a stable abnormal stock return. Thus, firm age can capture changes in stock returns (Zhang, 2006). We also include *market share*, measured as firm sales divided by industry sales (two-digit SIC codes), to capture a firm's bargaining power (Vomberg et al., 2015). A firm in a stronger bargaining position is more likely to gain more favourable terms from stakeholders to enhance its stock returns. In addition, we use return on sales to measure *firm profitability* (Bharadwaj, 2000) because the stock returns of less profitable firms are more sensitive to business environment changes than more profitable firms (Hao et al., 2011). Finally, we control for *firm size*, which is measured as the natural logarithm of a firm's sales (Hendricks and Singhal, 2014), as large firms may have more resources to adopt BI systems.

The final sample includes 219 BI-adopting firms with enough data for measuring all the contingency factors and control variables.

4. Results

We examine the impact of BI systems adoption on firms' stock returns. Table 2 presents the statistical results. As mentioned in Section 3.2., our analysis will focus on the WSR test results. Yet, for completeness, we also supplement the WSR test with *t*-test.

Table 2 shows that there is no significant abnormal change in returns ($p > 0.1$) on the day of announcing BI adoption, i.e., day 0, and the trading day before the announcement day, i.e., day –1. In addition, the abnormal returns insignificantly increase ($p > 0.1$) on the next trading day after the announcement is made, i.e., day +1, according to the WSR results, whereas the increase in abnormal returns is marginally significant ($p < 0.1$), according to the *t*-test results. The cumulative results indicate that the abnormal returns over the three different event windows, i.e., day –1 to day 0, day 0 to day +1, and day –1 to day +1 are insignificant ($p > 0.1$). Thus, *H1* is not supported.

Insert Table 2 about here

We further study the effects of the contingency factors of industry competitiveness, operating cycle, and industry munificence on the cumulative abnormal returns (CA) from day –1 to day +1. Table 3 shows the descriptive statistics and correlations of the research variables. Table 4 reports the regression results. We have four models in our analysis. Model 1 is a basic model including all control variables, and Models 2, 3, and 4 add the three moderating variables to Model 1, respectively. Model 1 is insignificant ($F = 1.022$, $p > 0.1$), but Models 2 to 4 are significant ($F \geq 1.520$, $p < 0.05$).

The coefficient of industry competitiveness is significantly positive in Models 2 to 4 ($p < 0.01$), suggesting that the impact of BI systems adoption on abnormal returns is more pronounced for firms operating in more competitive industries. Thus, *H2* is supported. Models 3 and 4 show that the coefficient of operating cycles is significantly negative ($p < 0.05$), meaning that firms with shorter operating cycles can obtain greater benefits from the adoption of BI systems than firms with longer operating cycles. Thus, *H3* is supported. Finally, the coefficient of industry munificence is significantly positive ($p < 0.1$) as shown in Model 4. This suggests that firms operating in more munificent industries gain higher stock returns from their BI adoptions, supporting *H4*.

Since the impact of BI adoption on stock price reaction is insignificant, we also conduct a long-term event study to investigate the impact of BI adoptions on long-term economic performance, which is a composite measure representing the average of ROA, ROE and ROS and better capturing a firm's overall performance (Staw and Epstein, 2000). We first employ propensity score matching (Austin, 2011; Lam et al., 2019) to match each BI adopting firm (sample firm) with a control firm who has a similar propensity or probability as the sample firm to adopt BI but eventually did not adopt BI. Specifically, we construct a logit regression model with a dummy variable as the dependent variable (coded 1 for BI adopting firms and 0 for other manufacturing firms) while independent variables include various firm characteristics such as firm age, firm size, firm profitability, market share, and operating cycle (all measured in the year prior to BI adoption), as well as industry and year fixed effects. After running the logit regression model, we obtain the propensity score for each firm and select a BI non-adopting firm as a control firm if its propensity score is similar to that of a BI adopting firm (sample firm). This matching process can reduce the self-selection bias and the corresponding endogeneity concern (Austin, 2011). We then compute the difference in difference results as the differences between the sample and control firms in the changes of economic performance from the pre-BI adoption period (year *t-1*) to the post-BI adoption periods (years *t*, *t*+1, *t*+2). The test results as shown in Table 5 suggest that although BI adoption does not have a significant impact on firms' economic performance in the adoption year and one year after adoption, the impact becomes significantly positive two years after adoption, demonstrating BI adoption's ability to improve firms' long-term performance. This finding also suggests that investors' short-term reactions may under-estimate BI adoption's long-term performance benefit to the adopting firms.

We also further explore how firms operating in different industries may benefit differently from BI adoptions. In fact we have included industry dummies in our regression analysis as shown in Table 4, now we further display the specific test result for each industry in Table 6. We find that while firms operating in the Lumber and Wood Products industry (two-digit SIC code = 24) are able to gain more positive stock returns from their BI adaptions ($p < 0.1$), investors react less positively (or more negatively) to the BI adaptions of firms operating in the Fabricated Metal Products industry (two-digit SIC code = 34) ($p < 0.05$). On the other hand, there are no significant results ($p > 0.1$) for firms operating in other industries. These findings suggest that BI adoption is not a one-size-fits-all solution as its benefit varies across industries.

Insert Table 3 about here

Insert Table 4 about here

Insert Table 5 about here

Insert Table 6 about here

5. Discussion

This study investigates the short-term impact of BI adoption on firms' stock returns while previous studies focus on the long-term impact (e.g., Yiu et al., 2020a). We find that BI adoption does not have an immediate impact on firms' stock returns. Although the BI literature (e.g., Chae et al., 2014; Ji-fan Ren et al., 2017) has largely focused on the impact of BI adoption on operational performance, Rubin and Rubin (2013) showed that the implementation of BI systems influences a company's stock price in terms of reducing stock variation.

Previous studies also examine the moderating and mediating factors of BI adoption such as culture and human factors on operational performance (e.g., Yeoh and Koronios, 2010; Yeoh, and Popovič, 2016). In contrast, our study considers firms' operational and logistics characteristics as contingency factors that could affect the impact of BI adoption on firms' stock returns. The operational and logistics characteristics of firms such as operating cycle and industry munificence have not been investigated in the previous studies. Specifically, our study is guided by the literature that firms should fit their BI implementation to their operational characteristics from the contingency perspective (e.g., Davenport et al., 2012).

Our additional analysis with propensity-score matching of sample and control firms further shows that while investors do not react positively to the adoption announcements of BI systems, the impact of BI adoption on the long-term economic performance of firms is indeed positive and significant. This shows that investors might underestimate the operational benefit of BI systems. Specifically, our empirical data show that it may take up to two years for firms to realise the economic benefit of BI adoption. Zajac and Westphal (2004) show that stock market is not always efficient in estimating the benefits of organisational innovation, particularly when there is a lack of research that provides scientific and rigour evidence on the real benefits of the organisational innovation (Staw and Epstein, 2000). Also, market evaluation of an organisational innovation is also governed by many social and institutional factors, not economic reasons alone (Lam et al., 2016; Westphal et al., 2001; Yeung et al., 2011).

5.1. Theoretical Implications

BI systems provide critical functions that enable firms to improve their decision-making processes and performance. Even though BI capabilities have been largely studied from the organisational perspective (e.g., Wamba et al., 2017), many organisations have found it difficult to obtain significant value from their BI system implementations (Trivedi, 2018; Yeoh and Koronios, 2010). We take the CT perspective on BI systems adoption in the manufacturing sector. Our findings show that adopting BI systems has an insignificant impact on enhancing stock returns for BI-adopting firms in general. This is consistent with CT's suggestion that no single strategy fits all the organisations to improve all aspects of business performance (Flynn et al., 2010).

We extend the literature on BI by exploring the impact of BI systems adoption on the stock returns of firms in the presence of different contingency factors. According to CT, organisational effectiveness is contingent upon whether the business strategy fits the environment (Flynn et al., 2010; Morton and Hu, 2008). However, a lack of understanding persists regarding the deployment of BI systems to enhance organisational performance by matching the specific operating characteristics and contexts. Drawing on CT, we contribute to the theoretical development of BI adoption. We explore the adoption of BI systems matching the competitiveness of industries in the manufacturing sector. We further show that more benefits from BI adoptions can be realised by firms characterised by shorter operating cycle time and high industry munificence. Specifically, we contribute to research on BI by demonstrating the roles of operating characteristics and contexts as contingency factors, which lead to different benefits from BI systems adoption. In addition, our study contributes to the understanding of CT with respect to BI adoption in the areas of logistics and supply chain management. Firms in highly competitive industries or having shorter procurement, inventory, production, and logistics cycles should enhance their coordination with their suppliers and customers, thus ensuring timely communication.

5.2. Managerial Implications

Our study provides some important practical implications. Increasingly manufacturing firms are using and converting big data into insightful information through BI systems, many of which find it hard to realise the benefits of BI systems adoption. We demonstrate that a lack of fit between the adoption of BI systems and organisational operating characteristics and contexts can be a reason for not gaining competitive advantage through BI systems. To adapt to today's dynamic business environment, manufacturing firms must develop close relationships with their major business partners, such as suppliers and buyers. BI systems help ensure timely access to data, enhancing managerial decision-making processes, organisational agility, flexibility, and responsiveness (Sabberwal and Becerra-Fernandez, 2011; Trieu, 2017).

More importantly, logistics and supply chain managers in the manufacturing sector must manage a high volume of transactions every day with a tremendous amount of data highly related to different parties in the supply chain (Tiwari et al., 2018; Wang et al., 2016). According to our analysis, managers should consider whether their adoption of BI systems fits the industry competitiveness, and operating cycle time of firms and industry munificence, which are critical to ensure that adopting BI systems results in beneficial outcomes. Logistics and supply chain managers can obtain a clearer picture of the current operating condition through the help of BI technologies. Taking operating characteristics into consideration, BI systems assist managers in making decisions on sourcing, demand planning, inventory, and production, improving visibility and coordination in supply chains. This is particularly important in highly dynamic and competitive industries where timely access to relevant reports for decision-making is critical.

6. Conclusions and Limitations

Many studies have examined the value of BI systems from the organisational perspective. Successful adoption of BI systems enables organisations to derive value from their tremendous amounts of data, facilitating the delivery of better strategic decisions and providing benefits through improvements in operational processes (e.g., Tiwari et al., 2018; Wang et al., 2016). However, the benefits derived from the adoption of BI systems are not equally shared among firms (Trivedi, 2018). In addition, very few studies have investigated how BI technologies should fit the contingency factors inside and outside the firms. Based on the event-study analysis of the adoption of BI systems in the US manufacturing sector, we find that BI systems adoption does not have an immediate impact on the market value of firms, but such impact is significantly enhanced when firms are in highly competitive industries or characterised by shorter operating cycles and high munificence. We contribute to the literature by employing CT and linking BI adoption with the contingency factors associated with operating characteristics and contexts. Our research provides empirical evidence that fitting BI systems adoption to contingency factors is critical to enhancing the business value of BI systems. Specifically, firms in highly dynamic and competitive industries will find that their adoption of BI systems is extremely important.

Our findings may serve as a basis for a contingency perspective regarding BI adoption. However, this study is not without limitations. We consider stock returns as a possible outcome of BI systems adoption but do not examine other related factors such as the beta risk in the stock returns of firms. Furthermore, we focus on manufacturing firms with BI adoption between 2005 and 2014, whereas there have been recent advances in BI systems because of the cloud computing technology. Thus, future studies could be conducted to capture the impacts of BI adoption under continuous technological evolution and examine how firms can improve their performance outcomes to obtain more benefits. Finally, we only consider the contingency factors of industry competitiveness, operating cycles, and industry munificence, whereas further research could incorporate other factors, such as production capacity and supply chain complexity that might influence the benefits derived from BI systems adoption (Wade and Hulland, 2004; Wang et al., 2016).

The hallmark of the logistics industry is competitive, dynamic and fast-changing. This is in-line with operating and contextual characteristics we examine in this study. It is likely that the application of emerging technologies such as big data analytics, machine learning and AI techniques would be more important in technology-driven and rapid-changing sectors such as the logistics and supply chain industry (Baryannis et al., 2019; Chae et al., 2014; Wang et al., 2016). In fact, many global logistics firms such as UPS and FedEx have been increasingly investing on big data analytics. Future research should be carried out to examine the details as how logistics firms benefit from fast-developing AI and machine learning techniques, adopting different methods such as action research and case studies.

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Table 1. Distribution of sample firms across industries.

2-digit SIC Code	Industry	Number	Percentage
28	Chemicals and allied products	61	22.43
36	Electronic and other electric equipment	46	16.91
38	Instruments and related products	35	12.87
35	Industrial machinery and equipment	33	12.13
20	Food and kindred products	21	7.72
37	Transportation equipment	16	5.88
26	Paper and allied products	10	3.68
23	Apparel and other finished products made from fabrics and similar materials	9	3.31
33	Primary metal industries	7	2.57
27	Printing, publishing, and allied industries	5	1.84
29	Petroleum refining and related industries	5	1.84
30	Rubber and miscellaneous plastics products	5	1.84
34	Fabricated metal products	5	1.84
25	Furniture and fixtures	4	1.47
31	Leather and leather products	4	1.47
Others	Other industries	6	2.21
Total		272	100

Table 2. Abnormal changes in returns.

Day	N	Median/Mean	WSR Test z-statistic	t-Test t-statistic
		Abnormal change in returns		
–1	272	–0.07%/–0.08%	–0.920	–0.685
0	272	–0.18%/–0.18%	–1.147	–0.973
+1	272	0.02%/0.21%	0.846	1.312*
		Cumulative abnormal change in returns		
–1, 0	272	–0.16%/–0.30%	–1.268	–1.276
0, +1	272	–0.24%/0.02%	–0.534	0.097
–1, +1	272	–0.15%/–0.06%	–0.935	–0.259

* $p < 0.1$ (one-tailed tests)

Table 3. Correlation matrix.

Variable	1	2	3	4	5	6	7	8
1. Cumulative abnormal return	1							
2. Firm age	0.069	1						
3. Market share	0.017	0.229***	1					
4. Firm profitability	-0.048	0.111*	0.049	1				
5. Firm size	0.016	0.382***	0.407***	0.391***	1			
6. Industry competitiveness	0.128*	-0.096	-0.770***	-0.011	-0.170**	1		
7. Operating cycle[#]	-0.056	-0.054	-0.123*	-0.158**	-.0321***	0.060	1	
8. Industry munificence	0.111*	0.076	0.007	0.044	0.098	-0.043	0.077	1
Mean	-0.003	3.783	0.017	0.126	7.635	0.997	145.608	1.061
Standard deviation	0.040	0.941	0.037	0.209	1.703	0.011	77.600	0.074

Notes:

1. *p < 0.1, **p < 0.05, and ***p < 0.01 (two-tailed tests).
2. [#] In days.

Table 4. Regression analysis results.

Variable	Model 1	Model 2	Model 3	Model 4
Firm age	-0.003 (-0.038)	0.014 (0.184)	0.030 (0.383)	0.031 (0.400)
Market share	0.085 (0.638)	0.392** (2.583)	0.415*** (2.738)	0.415*** (2.752)
Firm profitability	-0.055 (-0.713)	-0.037 (-0.490)	-0.040 (-0.544)	-0.047 (-0.639)
Firm size	0.002 (0.024)	-0.089 (-0.853)	-0.143 (-1.329)	-0.158 (1.465)
Industry competitiveness		0.607*** (3.828)	0.621*** (3.933)	0.631*** (4.010)
Operating cycle			-0.139** (-1.828)	-0.157** (2.050)
Industry munificence				0.124* (1.605)
Year dummies	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included
R-squared	0.145	0.207	0.221	0.232
Adjusted R-squared	0.003	0.071	0.083	0.090
F-value	1.022	1.520**	1.594**	1.636**

Notes:

1. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$ (two-tailed tests for control variables and one-tailed tests for hypothesised variables).
2. Standardised coefficients are shown.
3. t-statistics are in parentheses.
4. $N = 219$.

Table 5. Abnormal changes in economic performance.

Year changes	Difference in differences	Standard errors	*t*-statistics
-1 to 0	0.033	0.173	0.191
-1 to +1	0.108	0.166	0.651
-1 to +2	0.224	0.148	1.514*

Notes:
1. *$p < 0.10$ (one-tailed test).
2. $N = 237$.

Table 6. Test results across industries.

2-digit SIC Code	Standardised Coefficient	*t*-statistic	*p*-value
20	-0.014	-0.176	0.861
22	0.067	0.990	0.324
23	-0.066	-0.874	0.383
24	0.222	1.778	0.077*
25	-0.115	-1.580	0.116
26	-0.010	-0.138	0.890
27	0.022	0.310	0.757
28	-0.004	-0.050	0.961
29	0.062	0.791	0.430
30	0.056	0.648	0.518
31	-0.084	-1.064	0.289
33	-0.040	-0.557	0.578
34	-0.163	-2.324	0.021**
35	-0.045	-0.545	0.586
36	-0.121	-1.435	0.153
37	-0.009	-0.111	0.912
38	0.042	0.492	0.623

*$p < 0.10$ and **$p < 0.05$ (Two-tailed test).