The Impact of Business Intelligence Systems on Profitability and Risks of Firms

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Abstract

Researchers in the field of operations management (OM) have long advocated fact-based decision-making. The use of business intelligence (BI) systems represents a great opportunity for manufacturers to improve profitability and reduce firm risks. However, the actual business value of BI systems has remained highly controversial because integrating BI systems into production and manufacturing operations is difficult. In particular, the informational sources and operational use of BI systems require substantial internal support from employees and institutionalized incorporation of BI into operations. Using a sample of 278 manufacturing firms in the US that had used BI systems from 2005 to 2014, we examine the impact of BI systems on firms' profitability and risks. We show that firms improve their profitability and reduce risks in profit returns directly after the operational use of BI systems. Firms with superior employee relationships and higher process institutionalization (i.e., firms that are ISO 9000 certified) benefit more from the operational use of BI systems. We provide a resource orchestration perspective (ROP) of the resource-based view (RBV) of firms for the competitive advantage derived from the operational use of BI systems; and we ascertain the circumstances in which manufacturers are more likely to benefit from BI systems.

Keywords: business intelligence systems; profitability; firm risks; process institutionalization

1. Introduction

Founded on "scientific management," the field of operations management (OM) bears the hallmark of fact-based decision-making. Business intelligence (BI) systems present a great opportunity for firms to improve profitability and reduce risks. In general, firms make use of BI systems in daily operations to analyse economic and market trends as well as internal operational data such as process efficiency and productivity. Proponents of BI systems believe they can dramatically improve a firm's ability to make better-informed decisions, thus improving their intellectual and risk management capabilities (Popovič et al. 2012; Shollo and Galliers 2016). Recent research has shown that US firms continue to invest substantially in BI systems (Arnott et al. 2017; Schermann et al. 2014). Firms equipped with BI systems are better at aligning resources, which improves operational capabilities and performance outcomes.

Although BI software licenses are widely available in the market, the operational use and integration of BI systems into production and manufacturing operations presented a great challenge to firms (Gunasekaran et al. 2018; Matthias et al. 2017; Yusof and Yusof 2013). In particular, the operational use of a BI system requires substantial internal employee support. Moreover, although BI systems are useful for analysing and integrating data, their actual benefits require them to be integrated into daily operational routines. Using BI systems operationally means more than putting business analytical tools into the hands of users: it means making them routine processes and organisational cultures (Choo 2013; Yoon et al. 2017). Incorporating BI systems into manufacturing processes and operations requires good employee relationships and internal trust among employees while gathering and using operational data (Visinescu et al. 2017; Williams and Williams 2010).

Although many organisations are exploring the business potential of operationalizing BI systems, and anecdotal evidence suggests that BI systems deliver great value to firms, there is a need to examine their actual performance implications through rigorous academic research (Agarwal and Dhar 2014; Trieu 2017). This study takes the theoretical lens of resource orchestration perspective (ROP) of firms' resource-based view (RBV; Koufteros et al. 2014) to explore the business value of BI systems and seek to understand the organisational and managerial factors critical for integrating BI systems into production and manufacturing operations. The ROP of RBV theory emphasises coordination and synchronization strategic resources such as big data assets of firms across different organisational layers, functions, and units to create a significant competitive advantage (Sirmon et al. 2011). By selecting control firms and analysing the profitability and risks of 278 manufacturing firms in the US that had used BI systems between 2005 and 2014, we provide empirical evidence of the potential benefits derived from the operational use of BI systems. We further explore the moderating effects of employee relationships and process institutionalization (i.e., ISO 9000 certification) on the operational use of a BI system. Our findings show that BI systems simultaneously improve profitability and mitigate risks. Furthermore, the strong employee relationships and high process institutionalization that follow BI integration can further enhance firms' profitability and reduce risks. Our overall contribution is the deriving of ROP for the competitive advantage resulting from the operational use of a BI system.

2. Theoretical Foundations and Research Hypotheses

2.1. Literature Review

Researchers in production and operations management have long been interested in the roles of enterprise systems (ES) in improving performance outcomes. Several scholars have examined the impact of ES on firm performance but have achieved mixed results. Dehning et al. (2007) examined the impact of IT-based supply chain management (SCM) systems on the financial performances of manufacturing firms. They found that although SCM systems increase inventory turnover and gross margin and reduce selling and general administrative expenses, they do not lead to higher returns on assets (ROA) as a whole. Similarly, Hendricks et al.'s (2007) studies on the impacts of enterprise resource planning (ERP), customer relationship management (CRM), and SCM systems on firm performance also yielded mixed findings: they found no consistent positive associations between ES investments and performance outcomes.

Another stream of research has examined the impact of performance measurement systems (PMS) on firm performance. Chenhall (2005) showed that using PMS leads to a strategic alignment of manufacturing, which influences quality and productivity. Similarly, Koufteros et al. (2014) demonstrated that PMS leads to improved capabilities; however, contrary to the extant literature, they found that using PMS for reporting and control purposes leads to declining financial returns. Instead, interactive use of PMS enhances communication and stimulates new initiatives and ideas, enhances responses to environmental uncertainty, and leads to more positive outcomes.

With the exception of a few studies that examined the performance impacts of ES and PMS, little research has looked at the impact of the operational use of BI systems on firms' returns and risks. The current state of the art in business analytics mainly focuses on the impact of BI or business analytics systems on firms' returns (e.g., Chae et al. 2014; Ji-fan Ren et al. 2017; Gawankar et al. 2019). Other studies have focused on moderating or mediating factors in the relationship between BI or business analytics and firm performance. For example, Raguseo and Vitari (2018) demonstrated that big data analytics leads to better profitability through better customer satisfaction and higher market performance. Vitari and Raguseo (2019) studied the moderating effect of environmental features on the relationship between big data analytics and firm performance. Srinivasan and Swink (2018) focused on supply and demand visibility in the development of analytical capability as well as the influence of market conditions. They also found that analytic capability leads to better firm performance when a firm has higher flexibility. However, the moderating effects of employee relationships and process institutionalization have not been studied. In addition, previous studies primarily used perceptual survey data rather than public announcements and objective accounting data to measure BI and firm performance. Sangari and Razmi (2015) showed that firms' BI competences are related to agile capabilities and agile performances in the supply chain, but their research was limited to a single-respondent survey. Gunasekaran et al. (2018) conducted multiple case studies to examine the role of big data and business analytics in agile manufacturing.

BI systems enable more advanced, interactive, and innovative use of organisational information in generating insights for capability building (Popovič et al. 2019; Shollo and Galliers 2016). This is particularly true regarding the RBV and ROP (Hitt et al. 2016), which

posit that the coordination capability achieved with information systems enhances a firm's competitive advantage. Previous studies (e.g., Ji-fan Ren et al. 2017; Raguseo and Vitari 2018) have widely used the RBV to highlight the roles of firms' heterogeneous data resources and BI capabilities in achieving better performance. However, the RBV does not specify how firm-specific resources can be used to generate competitive advantages (Liu et al. 2016), whereas the ROP is an extension of the RBV and suggests that coordinating and synchronizing strategic resources, capabilities, and management leads to significant competitive advantages (Liu et al. 2016). Trieu (2017) reviewed hundreds of BI studies published from 2000 to 2015 and found that most studies focused on the impact of BI on firm performance; however, there is a lack of understanding of the specific operational initiatives and contexts in which the competitive advantages from resource orchestration in the use of BI systems.

2.2. BI Systems and Competitive Advantage from RBV and ROP

BI systems are equipped with a range of capabilities that help consolidate, link, organise, and analyse data originating from different sources such as customers', supply chains', and competitors' activities, and convey data as knowledge for managerial actions (Liu et al. 2016; Popovič et al. 2012; Trieu 2017). Through BI systems, firms can understand the current operational conditions, marketing performance, and external factors necessary to achieve better planning and coordination of management efforts (Koufteros et al. 2014). BI systems enable firms to make use of management data beyond routine reports, generating novel views and organisational insights (Li et al. 2013; Shollo and Galliers 2016). The primary purpose of BI systems is to improve organisational capability using information and data (Shollo and Galliers 2016). The operational use of a BI system can empower an organisation with timely and insightful market and

organisational information, leading to unique time-compressed, path-dependent competitive advantages.

RBV theory posits that a heterogeneous use of valuable, rare, inimitable, and non-substitutable resources leads to a significant competitive advantage (Hitt et al. 2016). A firm's strategic resources include tangible and intangible assets, firm attributes, organisational processes, and information and knowledge for envisioning and deploying organisational strategies. The common objectives for the deployment of BI systems are to improve performance management and support corporate strategy (Li et al. 2013). Specifically, BI systems are often used to monitor and achieve strategic business and corporate objectives. BI systems empower organisations by providing the most current insights derived from organisational information and data to help better formulate organisational strategies, thus synchronizing and aligning management efforts (Koufteros et al. 2014). Embedding BI within firms' process routines and thus building an organisational culture among employees can significantly enhance those firms' operational capabilities, leading to a competitive advantage that is difficult to imitate.

Interactive BI systems enable manufacturers to synchronize processes, optimise resource allocations, and improve decision-making capabilities (Koufteros et al. 2014; Li et al. 2013). The ROP of RBV theory pinpoints management's role in coordinating and synchronizing strategic resources across different organisational layers, functions, and units, which helps derive a significant competitive advantage (Sirmon et al. 2011). Sirmon et al. (2007) argued that the possession of valuable, rare, inimitable, and non-substitutable resources by themselves is not enough for organisations to yield a competitive advantage. Instead, firms must possess the skills to orchestrate their resources, bundle them to create capabilities, and then leverage them to achieve competitive priorities (Chadwick et al. 2015; Liu et al. 2016). Comprehensive use of BI systems

can put firms in a better position to strategically deploy their resources, thus orchestrating their management efforts across organisational functions and combining operational capacities and managerial information that ultimately lead to superior performance (Chadwick et al. 2015). BI enables firms to proactively explore management information and organisational data in the interests of performance improvement.

2.3. Hypothesis Development

2.3.1. BI Systems and Firm Profitability

ROP emphasises how the firm's resources are deployed, aligned, and synchronized to generate competitive outcomes (Liu et al. 2016). Manufacturers who use BI systems are in a better position to align and orchestrate resources, reducing transactional inefficiency and creating strategic benefits. BI systems often improve sales forecasting, leading to better sales and operations planning, which in turn results in better production planning and scheduling and ensures optimal lot sizing and production timing while minimizing unnecessary setups and changeovers. BI systems help employees access information from a single dashboard, which enables their different divisions to synchronize planning and improve efficiency. Timely operational data leads to early identification of quality problems, bottlenecks, and process inefficiencies, enhancing production competency. ROP advocates that firms must develop competency in structuring, bundling, and leveraging their resources so as to generate new capabilities (Sirmon et al. 2007; Sirmon et al. 2011) such as leveraging current organisational data for improvements and identifying unique opportunities for capability building. BI systems are important in enhancing managerial acumen, synchronizing resources, and developing competency. Overall, BI systems enable manufacturing

firms to transform data into useful information, thus allowing them to better structure and bundle their resources, resulting in higher firm profitability.

H1. The operational use of BI systems leads to higher firm profitability.

2.3.2. BI Systems and Firm Risks

Firm risks related to operations include production and supply chain disruptions, inventory shortages, and quality crises, which lead to profit volatility (Merriman and Nam 2015; Ruefli et al. 1999). A greater risk implies that firms are more vulnerable and have cash flow uncertainty (Luo and Bhattacharya 2009). Following ROP, we argue that BI systems enhance manufacturers' capability to leverage and orchestrate strategic resources, thus reducing associated operational risks (Thornhill and Amit 2003). A comprehensive BI enables firms to stay current with the latest developments, survive in a competitive environment, and access the available resources held in different functions, thus enabling them to optimise resources and reach more informed operational decisions (Koufteros et al. 2014). With speedy information dissemination, firms are more likely to detect unfavourable economic conditions, orchestrate management efforts, and correct errors (Chadwick et al. 2015). BI systems help generate informative reports, enabling proactive management of business performance (Rubin and Rubin 2013). With more internal and external information, executives need to rely less on their own intuitions in making judgments, thus increasing decision quality and reducing associated risk to the firm.

H2. The operational use of BI systems leads to lower firm risks (i.e., lower volatility in profits).

2.3.3. The Moderating Effect of Employee Relationships

Employees are largely responsible for orchestrating resources through BI, so firms employing BI should have good employee relationships. BI is a complex undertaking requiring significant commitment from both management and employees. Several cases have reported that successful BI integration into production and manufacturing operations requires a favourable organisational culture with significant employee commitments (e.g., Yeoh and Popovič 2016). Embarking on a BI initiative changes the way in which organisational members access and use information; it requires superior employee relationships and a culture of trust (Williams and Williams 2010; Yoon et al. 2017), which affects employees' willingness to disclose and exchange internal and external data. Previous research has shown that employees' resistance to providing and sharing data is often a critical obstacle to the operational use of BI systems. Organisations with a culture that emphasises employee cooperation and consensus building are in a better position to realise the benefits of BI systems (Watts et al. 2008). Firms must secure strong employee commitment and support to enhance the effectiveness of their BI systems (Shehzad and Khan 2013).

> *H3a. The positive impact of BI systems on profitability is strengthened through superior employee relationships.*

> *H3b. The positive impact of BI systems on reduction of risk to firms is strengthened through superior employee relationships.*

2.3.4. The Moderating Effect of Process Institutionalization

Process institutionalization is likely to strengthen management efforts that promote resource orchestration (Popovič et al. 2012). Specifically, firms need established process systems

and procedures for developing and bundling strategic resources and for orchestrating organisational activities (Hitt et al. 2016). Accordingly, successful BI integration into production and manufacturing operations requires formal, established, and routine organisational processes. Firms with formal processes and procedures are more likely to make use of the information in daily operations, assimilating BI systems into the organisational fabric. Particularly, ISO 9000 certified firms are in a better position to integrate BI systems into the entire organisation. The ISO 9000 series is based on quality management principles that advocate leadership, employee involvement, and a process management approach (Naveh et al. 2004; Singh et al. 2011). Previous research has shown that ISO 9000 adoption enhances knowledge codification and accumulation within firms (Bénézech et al. 2001; Su and Chen 2013) and facilitates the implementation of management information systems (Yoo et al. 2006).

Process institutionalization through ISO 9000 ensures that BI systems are bundled into the operational systems, structuralizing the use of BI systems within the organisation. Over time, firms can get embedded in an organisational system with formal procedures for the use of the BI systems (Crossan et al. 1999). Peng et al. (2008) asserted that organisational routines developed through process institutionalization provide a facilitating factor that enhances firms' profitability or mitigates uncertainties (Wu et al. 2010).

> *H4a. The positive impact of BI systems on profitability is strengthened in ISO 9000 certified firms.*

> *H4b. The positive impact of BI systems on reducing firm risks is strengthened in ISO 9000 certified firms.*

3. Methodology

3.1. Sample and Data Collection

We have focused on the publicly owned manufacturing firms listed in the US (SIC code: 2000-3999) because BI systems are commonly used in the manufacturing sector (Chen et al. 2012; Empie 2016; Sarkar 2018; Yosof et al. 2013). We sampled a period from 2005 to 2014. Internet technology has matured since the early 2000s (Chen et al. 2012), advancing the development of BI systems to enable firms to carry out text and web analytics (Chen et al. 2012; Yosof et al., 2013). Through BI system text and web-mining, firms can gather, organise, and visualize an immense amount of information related to industries, products, and customers. As the importance of knowledge assets has increased, BI systems have achieved substantial acceptance in the market during our research period (Teo et al. 2016).

To identify firms that have used BI systems, we focused on leading and niche BI vendors. According to Gartner Inc., the world's primary IT research and advisory body, leading BI vendors include Business Objects, Cognos, Hyperion Solutions, IBM, Information Builders, Microsoft, MicroStrategy, Oracle, Qlik, SAP, SAS, Tableau, and Tibco, whereas niche providers of BI systems include firms such as Alteryx and Applix. Together, these providers of comprehensive BI systems occupy nearly two-thirds of the BI tools market (Sallam et al. 2011; Teo et al. 2016). The other third comprises several thousands of small BI solution providers (Forrester 2014). However, about 93% of our sample firms selected the leading BI providers, whereas the remaining sample firms selected BI solutions from the niche players, making BI solution providers less likely to be selected. Table 1 presents the types of BI vendors and their BI platforms. Vendors such as SAP and Microsoft, whose product portfolios are broad, offer general BI platforms (i.e., general BI)

that can integrate into other ES more easily (Woods 2011). Conversely, vendors such as Qlik and Pentaho are more likely to provide single, specialized BI platforms (i.e., specialized BI).

Insert Table 1 about here

We identified the firms using BI systems through the names of leading providers and niche players of BI platforms. We searched for news releases containing the names of leading and niche BI players together with the names of the US-listed manufacturing firms, using keywords such as "business intelligence systems" or "BI systems" in conjunction with "adoption," "introduce," or "implementation" through publicly available articles in the Factiva database. Factiva combines the *Dow Jones Interactive* and *Reuters Business Briefing* databases, providing an extensive coverage of the news from leading business resources such as the *Wall Street Journal* and *New York Times* (Gnyawali et al. 2010; Jiang et al. 2006). Through such articles, we identified 323 firms that use BI systems.

BI system implementation comprises two stages: the vendor contract stage and the full operational use stage. During the vendor contract stage, a firm enters a contract with a BI solution provider to install BI platforms. Once the contract has been signed, firms must install the BI software, develop prototypes, and merge data from separate systems (Gangadharan and Swami 2004; Zeng et al. 2006). They must also provide user training and system adjustment (Olexová 2014; Zeng et al. 2006). This process normally takes about 6–18 months (with an average of about a year; Horakova and Skalska 2013; Olexová 2014). Thus, it takes about one year after the *vendor contract stage* to reach the full operational use stage. Out of the 323 sample firms announcing their adoption of BI systems, a total of 186 (57.6%) firms did so in the first stage and 134 (41.5%) in the second. In three cases (0.9%), the firms made their announcements during other stages of BI system implementation. For example, a firm might announce in 2011 that it had fully employed a

BI system in 2009. In this case, we counted 2009, rather than 2011, as the first year of full operational use.

We designated the year of full operational use of BI systems (i.e., the second stage) as year t. One year immediately prior to the full operational use of a BI system (i.e., the vendor contract stage) is taken as year t–1. We considered the two years preceding the operational use of a BI system (year t–2) as the base year for determining the control group because firms should be free from the impact of the BI system. Overall, we examined the abnormal firm profitability and abnormal firm risks from years t–2 to t+1, which is the year after the first year of full operational BI system use. Table 2 lists some examples of the announcements.

Insert Table 2 about here

Panel A in Table 3 presents the distribution of the sample firms based on year t. During our sample period, most firms used BI systems in the early years of our sample period, 2005–2007. The figure remains stable after that period. Panel B of Table 3 presents the distribution of the sample firms based on their 3-digit SIC codes. Note that most sample firms are in industries related to drugs, electronic components, and medical instruments. Panel C reports some information related to the sample firms that use BI systems operationally.

Insert Table 3 about here

3.2. Measurements

Firm profitability. Firm profitability refers to a firm's ability to make use of its total assets to generate net operating income (Nath et al. 2010; Terjesen et al. 2011). We use ROA as a proxy

for firm profitability. ROA is measured as the ratio of operating income before interest, taxes, depreciation, and amortization to total assets (Guthrie and Datta 2008).

Firm risks. Firm risks refer to the profit volatility (Merriman and Nam 2015; Ruefli et al. 1999). In our study, firm risks related to operations include production and supply chain disruptions, inventory shortages, and quality crises that lead to profit volatility. We captured the real risks in business that can be reflected in the firm's income deviations (i.e., ROA deviations associated with the operational use and integration of BI systems into production and manufacturing processes).

Empirical measures of firm risk generally fall into four camps, as stated below. In the following firm risk measures, the first measure reflects the volatility of firm's profitability. The second stock-based measure is basically derived from investor behaviour in response to firm and market information. The third measure concerns variability in analyst forecast. The fourth measure is closely related to firm investment decisions on the risk-related activity. Thus, profit volatility is the most appropriate proxy for firm risk in this study. Because a five-year period is standard in the literature (e.g., Andersen and Bettis 2015; Bromiley et al. 2017; Core et al. 1999; Faccio et al. 2016, Kim et al. 1993; Vithessonthi 2016), we used the standard deviation of ROA over a five-year period up to the current year to measure firm risks.

Previous studies based firm risk on four factors. First, the firm risk measure is based on accounting returns such as variability in return on assets (ROA; Andersen and Bettis 2015; Bromiley et al. 2017; Dewan and Ren 2011; Faccio et al. 2016). Second, the firm risk measure is based on stock price variations (e.g., Lenard et al. 2014; Ngoc Hung et al. 2019; Owiredu et al. 2014). This measurement reflects systematic and unsystematic risk for the stock price variation associated with stock market variation and the residual stock price variation, respectively

(Bromiley et al. 2017). Besides, beta is a measure of a stock's volatility (e.g., Albuquerque et al. 2019; Kwok and Reeb 2000). Third, the firm risk measure is based on variability in analyst forecasts of firm income (Bromiley 1991) to reflect the uncertainty of income (Bromiley et al. 2017). Fourth, the firm risk measure is based on levels of discretionary firm activity such as R&D (i.e., R&D intensity or R&D spending as a risk-taking activity; Chen and Miller 2007; Devers et al. 2008; Li and Tang 2010).

Employee relationships. We used items such as employee involvement, human capital development, and labour–management relations from the employee relational dimensions (Hillman and Keim 2001) of the Kinder, Lydenberg, Domini & Company, Inc. (KLD), data to construct the employee relationships measure. The KLD database covers approximately 1,100 publicly traded firms (McPeak and Dai 2011; Wong et al. 2011) and is based on multiple sources such as SEC filings and press releases (Entine 2003; Wong et al. 2011). To create a comprehensive employee relationships construct, we focused on both strengths and concerns to consider the items on which a firm performed well or otherwise by subtracting the total number of concerns from the total number of strengths (Choi and Wang 2009; Wong et al. 2011).

Process institutionalization. We used ISO 9000 certification as a proxy for process institutionalization because firms pursuing the ISO 9000 quality standard must define and plan their operational processes with supporting documentation and audits to ensure steady process improvement (Naveh et al. 2004; Singh et al. 2011). ISO 9000 facilitates institutionalization of organisational routines for management practices. Firms with ISO 9000 certifications are considered to have a high level of process institutionalization. We assigned 1 to firms with ISO 9000 certifications and 0 to firms without ISO 9000 certifications. We collected ISO 9000 registration data through the *Quality Digest*, *Who's Registered*, and the *IAAR Directory of*

Registered Companies, which are among the most comprehensive databases on ISO 9000 certified firms (Anderson et al. 1999; Yeung et al. 2011).

Table 4 summarizes all the variables along with their sources used in this study.

Insert Table 4 about here

3.3. Identifying Control Firms and Estimating Abnormal Performance

We employed Barber and Lyon's (1996) matching method to pair each sample firm with a portfolio of similar control firms. We matched each sample firm to control firms within 50%–200% of the sample firms' size in terms of total assets, controlling for firm size and performance in terms of prior profitability and prior profit volatility in the matching groups according to the following steps (Corbett et al. 2005; Hendricks and Singhal 2008; Narasimhan et al. 2015; Naveh and Marcus 2005; Orzes et al. 2017; Treacy et al. 2019):

Step 1. We used the three-digit SIC code for industry matching (Hendricks and Singhal 2001). Also, we required that the control firms' performance in the base year (year t–2) be within 90%–110% of their sample firms (Swink and Jacobs 2012).

Step 2. If no firm was obtained in a three-digit SIC code in Step 1, we then found a control firm with the same two-digit SIC code in the same prior performance range.

Step 3. If some sample firms did not get paired, we determined a control firm with the same one-digit SIC code within the same prior performance range.

Step 4. For any remaining sample firms, we found a control firm within the same prior performance range regardless of SIC code.

We dropped firms that did not provide enough information for us to compute the profitability and risks in the base year (year t–2). This reduced the sample size to 287 for firm profitability and 259 for firm risks. Analysing firm risks involved fewer firms because some firms did not have enough financial data for five consecutive years to measure profit volatility. Of the remaining 287 and 259 firms, we obtained comparison groups for 90.24% (259 out of 287) and 91.12% (236 out of 259) of the sample firms in Step 1 for profitability and risks, respectively. We applied Step 2 for 15 and 21 firms, and Step 3 is applied for 7 and 2 firms, for profitability and risks, respectively, and used Step 4 for four firms for profitability only. Two sample firms did not match any control firms with similar (90%–110%) pre-event profitability. The matched sample of 285 for profitability and 259 for risks, on average, paired with 39.82 and 34.43 control firms. Figures for about 88% (252 out of 285) of the sample of profitability and 85% (220 out of 259) of the sample of risks matched with five or more control firms.

After completing the matching process, we used event study methodology to measure the abnormal performance of firms associated with the event. This methodology is widely used in finance, accounting, and management strategy studies and has been applied in recent production research (e.g., Duan et al. 2014; Ni et al. 2016) to assess the stock price reaction to corporate announcements of certain events such as the implementation of enterprise systems. This study applied a long-term event study methodology widely employed in finance research (Antoniadis et al. 2019; Boubakri et al. 2012; Huson et al. 2004; Nohel and Tarhan 1998) to examine the impact of the operational use of BI systems on the abnormal firm profitability and abnormal firm risks on a year-to-year basis and over aggregated multiperiod performance, from year t–2 to year t–1 and from year t–2 to year t, respectively. We first estimated the expected performance (i.e., firm

profitability or firm risks) and then measured abnormal firm profitability or abnormal firm risks (Hendricks and Singhal 2008; Swink and Jacobs 2012):

Expected performance of a sample firm if the operational use of BI has not occurred

$$= \quad \begin{matrix} \textit{A sample firm's} \\ \textit{performance} \\ \textit{in the base year} \end{matrix} \quad + \quad \begin{matrix} \textit{The change in median performance} \\ \textit{of the control firms over time} \end{matrix} \quad (1)$$

Abnormal performance of a sample firm

$$= \quad \begin{matrix} \textit{A sample firm's actual} \\ \textit{performance with the} \\ \textit{operational use of BI} \end{matrix} \quad - \quad \begin{matrix} \textit{A sample firm's expected performance} \\ \textit{if the operational use of BI has not} \\ \textit{occurred} \end{matrix} \quad (2)$$

We followed Hendricks and Singhal (2008) and Swink and Jacobs (2012) in deleting data falling in the outlier regions, resulting in the final samples of 278 and 257 for firm profitability and risks, respectively.

3.4. Estimating Moderating Effects Using Hierarchical Linear Model

We used a hierarchical linear model (HLM) to examine moderating factors, employee relationships (*H3a* and *H3b*), and process institutionalization (*H4a* and *H4b*) on the abnormal firm profitability and firm risks as expressed in the following equations (Liu et al. 2014; Naor et al. 2010):

Level 1 regression equation:

$$CAPS_{ij} = \beta_{0j} + \beta_{1j}(Previous\ performance_{ij})$$
$$+ \beta_{2j}(Multiple\ implementations_{ij})$$
$$+ \beta_{3j}(General\ or\ specialized\ BI\ platform_{ij})$$
$$+ \beta_{4j}(Year\ of\ adoption_{ij}) + \beta_{5j}(Firm\ size_{ij})$$
$$+ \beta_{6j}(Sales\ growth_{ij}) + \beta_{7j}(R\&D\ intensity_{ij})$$
$$+ \beta_{8j}(Labor\ intensity_{ij}) + \beta_{9j}(Capital\ intensity_{ij})$$
$$+ \beta_{10j}(Industry\ size_{ij})$$
$$+ \beta_{11j}(Industry\ technology\ intensity_{ij})$$
$$+ \beta_{12j}(Employee\ relationships_{ij})$$
$$+ \beta_{13j}(Process\ institutionalization_{ij}) + \varepsilon_{ij} \tag{3}$$

Level 2 regression equation:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(Industry\ size_j) + \gamma_{02}(Industry\ technology\ intensity_j) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}(Industry\ size_j) + \gamma_{12}(Industry\ technology\ intensity_j) + u_{1j}$$
$$......$$
$$\beta_{13j} = \gamma_{130} + \gamma_{131}(Industry\ size_j) + \gamma_{132}(Industry\ technology\ intensity_j)$$
$$+ u_{13j} \tag{4}$$

where i refers to the ith sample firm and j refers to the j industry. Previous performance is either the previous firm profitability or previous firm risks in year t–2. All the control variables are in year t–2. Employee relationships and process institutionalization are in year t. $CAPS_{ij}$ is a cumulative *abnormal performance of sample* in industry j from t–2 to t+1.

We included dummy, firm-specific, and industry-specific variables that might potentially affect the benefits of BI systems. We included *multiple implementations* as the control variable to indicate that in the announcement a firm has used other ES together with the implementation of BI systems (assigned 1). *Single implementation* indicates that only the BI system implementation has been mentioned in the announcement (assigned 0). Only a total of 14 (4.33%) of our announcements were found to involve multiple software implementations. Also, we controlled for

BI platforms that have major portfolios of software solutions such as SAP and Oracle (assigned 1) versus other BI vendors with single BI solutions that must integrate with other ES platforms (assigned 0); please refer to the variable of "*general or specialized BI platform*" and the list of "*general or specialized BI platform*" in Table 1. A total of 203 (62.85%) firms use general BI platforms and 120 (37.15%) firms use specialized BI platforms.

As for firm-specific factors, we considered firm R&D intensity and sales growth, both of which indicate the dynamism of a firm. The business environment of fast-growing and high-technology industries requires a higher BI and faster response to market changes (Mendelson 2000). We also included firm size and labour intensity. The size affects the firms' capability to exploit the potential of BI applications. Larger firms might easily obtain more benefits from the operational use of BI systems because they are more complex and have wide-reaching organisational data (Dutta and Bose 2015; Popovič et al. 2016). Labour-intensive firms may also find BI systems more important because members' different roles often require diversified organisational data (Hendricks and Singhal 2008). Capital-intensive firms are usually characterized by high capital layouts and high investment risks, making the use of BI systems more important in capacity planning and decision analysis (Ramamurthy et al. 2008). Additionally, our models included prior profitability and prior firm risks to control for their persistent influence over time (Vandaie and Zaheer 2014). We included operational use of a BI system year as a control for the unobserved time-dependent effect. All the firm-specific control variables were in year t–2.

Based on the two-digit SIC codes, we included industry size and industry technology intensity. Larger industries are likely to have more complex supply chains, requiring more industrial data and market intelligence (Brunnermeier and Cohen 2003). The pace of change in the

high-technology industry is faster, making real-time data more important for decision-making (Trieu 2017; Watson et al. 2006). Table 4 provides details about the variable measurements.

4. Results

Table 5 reports the descriptive statistics related to firm profitability and firm risks for the sample and control firms before the operational use of BI systems. We conducted t-tests on the sample and control firms' profitability and risks, and the statistical results show no significant difference ($p > 0.1$) in profitability and risks between the sample and control firms in the base year (i.e., year t–2).

Insert Table 5 about here

4.1. Analysis of Results

We examined the impact of the operational use of BI systems on profitability and firm risks. Tables 6 and 7 present the corresponding statistical results, along with details concerning the patterns of abnormal firm profitability and abnormal firm risks over time. Note that the sample size (i.e., *N)* progressively decreases because of the unavailability of longitudinal data. Barber and Lyon (1996) pointed out that in the test of financial data, the non-parametric Wilcoxon signed-rank (WSR) test is more powerful than the parametric t-test. The WSR test takes the magnitude of changes into consideration without being seriously affected by outliers (Lo et al. 2014; Yeung et al. 2011). Our discussion below will be mainly based on WSR test results. However, for completeness, we also report the t-test and sign test results in the table. They provide consistent results.

Table 6 reveals no abnormal increase in profitability in the initial BI implementation period—the contract stage (i.e., year $t–2$ to year $t–1$ [$p > 0.1$]). However, the abnormal value of firm profitability significantly increases just after the firms have fully integrated BI systems into production and manufacturing operations in the year t (i.e., year $t–1$ to year t [$p < 0.05$]), as well as the year immediately after the operational implementation of BI systems (i.e., year t to year $t+1$ [$p < 0.05$]). Thus, *H1* is supported. The cumulative results indicate that from the base year to the year of the operational use of BI systems (i.e., year $t–2$ to year t), the abnormal increase in profitability is significant ($p < 0.05$). Moreover, when we compare the base year with the year after the operational use of BI systems (i.e., year $t–2$ to year $t+1$, [$p < 0.05$]), we detect a significant increase in abnormal firm profitability. Together with the yearly figures, this suggests that firms achieve significant abnormal improvement in profitability with the operational use of BI systems.

Insert Table 6 about here

Table 7 shows the abnormal changes present in the values of firm risks. We find a significant decrease in abnormal firm risks just after firms have used BI systems in year t (i.e., year $t–1$ to year t [$p < 0.05$]) as well as in the subsequent year (i.e., year t to year $t+1$ [$p < 0.01$]). The cumulative abnormal decrease in firm risks appears to be strongly significant from the base year to the year of the operational use of BI systems (i.e., year $t–2$ to year t [$p < 0.01$]) and in the period between the base year and a year immediately after the operational use of BI systems (i.e., year $t–2$ to year $t+1$ [$p < 0.01$]). These results indicate a significant abnormal decrease in firm risks after the full operational use of BI systems. Thus, *H2* is supported.

Insert Table 7 about here

4.2. HLM Estimations Results

Because KLD mainly covers major publicly traded firms, our final sample with enough information about employee relationships contained a sample of 125 out of 192 firms for cumulative abnormal profitability and a sample of 137 out of 197 firms for cumulative abnormal risks.

Table 8 reports the correlation results for the study variables and Tables 9 and 10 present the HLM estimations results. In our analysis, we have four models. Model 1 reports the estimation with control variables. Models 2A and 2B consider the moderating roles of employee relationships and process institutionalization, respectively. Model 2C reports the full model.

In Table 9, the moderating effect of employee relationships is significantly positive for abnormal firm profitability in Models 2A and 2C ($p < 0.01$), suggesting that the impact of the operational use of a BI system on abnormal profitability is more positive when firms have superior employee relationships. Thus, *H3a* is supported. Furthermore, the impact of employee relationships is significantly negative for abnormal firm risks in Models 2A and 2C ($p < 0.05$), as Table 10 shows, indicating that firms with superior employee relationships better alleviate volatility in profit for firms with operational BI systems. Thus, *H3b* is supported. As with the inclusion of employee relationships, the values of -2 log-likelihood (deviance) in Model 2A decrease (chi-square > 7.38 with df=1, $p < 0.01$ for abnormal firm profitability in Table 9; chi-square > 2.89 with df=1, $p < 0.1$ for abnormal firm risks in Table 10), indicating that the model fits better.

The results for Models 2B and 2C presented in Tables 9 and 10 show that process institutionalization in firms using a BI system is significantly related to abnormal profitability ($p < 0.05$) and abnormal firm risks ($p < 0.01$). This suggests that ISO 9000 certified firms can obtain

higher profitability and lower firm risks than noncertified firms. Therefore, *H4a* and *H4b* are supported. The inclusion of process institutionalization (i.e., ISO 9000 certification) in Model 2B significantly improves model fitness with smaller -2 log-likelihood (deviance) values (chi-square > 4.45 with 1 *df*, $p < 0.05$ for abnormal firm profitability; chi-square > 5.31 with 1 *df*, $p < 0.05$ for abnormal firm risks).

The results also show that, as with both employee relationships and process institutionalization in Model 2C, the values of -2 log-likelihood (deviance) significantly decrease (chi-square > 10.76 with 2 *df*, $p < 0.01$ for abnormal firm profitability; chi-square > 8.46 with 2 *df*, $p < 0.05$ for abnormal firm risks), indicating that Model 2C has yielded better model fitness. The results presented in Tables 9 and 10 suggest that, as control variables, a firm's prior firm profitability is insignificantly related to abnormal profitability ($p > 0.1$), whereas a firm's prior volatility in profit is significantly negatively related to abnormal firm risks ($p < 0.1$ in Models 1 and 2A; $p < 0.05$ in Model 2B), indicating that firms with higher prior risks obtain more benefit (i.e., more reduction in abnormal firm risks) after the operational use of BI systems.

As Table 9 makes evident, firms with higher sales growth and R&D intensity achieve higher profitability in generating operational incomes (sales growth: $p < 0.05$ in Models 1 and 2B; $p < 0.01$ in Models 2A and 2C; R&D intensity: $p < 0.05$ in Models 1 and 2B; and $p < 0.1$ in Model 2C). Labour intensity is a significantly positive predictor of a firm's abnormal profitability ($p < 0.05$ in Model 2A). However, size is related less to profitability improvement with BI use because this relationship is only weakly significant ($p < 0.1$ in Models 2A and 2C). Firms with higher R&D intensity and capital intensity reduce firm risks to a greater extent (Firm R&D intensity: $p < 0.1$ in Models 1 and 2A; $p < 0.05$ in Models 2B and 2C; and Capital intensity: $p < 0.01$ in Models 1 to

2C). Yet bigger firms have less risk reduction with BI use ($p < 0.1$ in Model 1; $p < 0.05$ in Models 2A and 2B; and $p < 0.01$ in Model 2C).

Insert Table 8 about here

Insert Table 9 about here

Insert Table 10 about here

5. Discussion and Conclusions

Our results show that when a firm uses a BI system, its profitability increases and its risks are alleviated. Compared with control firms, sample firms attain significantly higher profitability just after the firms have implemented BI systems and in the year immediately after BI systems have become operational. As Table 6 shows, the median (mean) increase in profitability for the sample firms is 0.77% (0.83%), with nearly 52% of the firms experiencing improved profitability in the year of BI use (i.e., from year t–1 to t). Similarly, the median (mean) of changes in firm profitability is 0.76% (1.36%), with nearly 52% of the firms experiencing a positive change in profitability in the year after the BI system implementation (i.e., from year t to t+1). The median (mean) increase in firm profitability is 2.12% (3.44%), with nearly 55% of the firms experiencing improved profitability from the base year to the year after the operational use of BI systems (i.e., from t–2 to t+1.)

Similarly, as Table 7 shows, the sample firms significantly reduce risks in profit returns in the year of the operational use of BI systems and the subsequent year. In the year of BI system use (i.e., from year t–1 to t), the median (mean) abnormal decrease in the firm risks is 0.003 (0.004), with nearly 56% of sample firms experiencing a reduction in their financial risk. In the year after

BI system implementation (i.e., from year t to $t+1$), the median (mean) abnormal decrease in firm risks is 0.004 (0.006). Nearly 57% of sample firms experience a reduction in their financial risk from BI use. From the base year to the year after the operational use of BI systems (i.e., from $t–2$ to $t+1$), the median (mean) abnormal decrease in firm risks is 0.010 (0.011), with nearly 57% of sample firms experiencing less volatility in profit.

Our further analysis suggests that sample firms further enhance profitability and lower firm risk through better employee relationships and higher process institutionalization. The positive impact of BI use on risk reduction is stronger among firms with superior employee relationships. This might imply that superior employee relationships help a firm cultivate an open communication environment to acquire more reliable internal and external data, generating more insightful analysis through the BI systems. We also find that firms employing BI solutions in an institutionalized process environment enjoy stronger improvements in profitability and lower profit volatility to a greater extent. Process institutionalization provides a stable work environment with established procedures, streamlining the information collection process and facilitating BI system integration.

5.1. Theoretical Implications and Contribution to Production Research Literature

The operational use of BI systems related to big data and analytical support is a relevant and important topic for production research literature (Olson 2018). BI gives decision-makers the tools to analyse and make sense of the data originating from different sources (Olson 2019). The influx of big data has a significant impact on knowledge management, which has already received attention in the production research literature (Olson 2018; Yusof et al. 2013). Studies of the current state of the art in business analytics have examined the relationship between BI or business

analytics systems and firm performance (e.g., Chae et al. 2014; Ji-fan Ren et al. 2017; Gawankar et al. 2019). Some also examined moderating or mediating factors in the impact of BI systems on business performance (e.g., Srinivasan and Swink 2018; Vitari and Raguseo 2019). However, these studies mainly focus on the impact of BI tools on firm performance. Our study has examined the impact of the operational use of BI systems on firm risk and return in terms of financial volatility and profitability, respectively. It is important for practitioners and managers to understand both risk and return associated with their BI projects, especially given that the operational use of BI systems involves large investments and resources. Moreover, we examined the moderating influences of employee relationships and process institutionalization in the relationship between the operational use of BI systems and risk and return of firms. These two moderating factors have not been examined in the BI application, although the production and operations managers in the manufacturing firms are highly involved in managing relationships with employees and conducting quality standards to streamline operating processes. This research shows that stronger employee relationships and higher process institutionalization in firms may favour the operational use of BI systems.

We have provided ROP of RBV on the operational use of BI systems in the areas of production and manufacturing. In fact, two important theoretical and empirical questions in this manufacturing area are how using BI systems can enhance operational capabilities and what types of organisational and operational contexts promote the analytical capability to improve firm performance (Hendricks et al. 2007). The current study partially answers these questions. There is a lack of understanding of the specific organisational and operational contexts in which the competitive advantage from resource orchestration is realised. We contribute to the understanding of ROP by exploring the role of BI in aligning and orchestrating organisational resources, leading

to higher profitability and lower risk. We further demonstrate that the process of resource orchestration can be strengthened through superior employee relationships and a process of institutionalization. Our research, together with previous research in this area (e.g., Koufteros et al. 2014; Li et al. 2013; Vitari and Raguseo 2019), shows information systems that interactively support organisational goals and orchestrate organisational efforts, leading to stronger firm performance and a competitive edge. Specifically, we contribute to the research on BI in the manufacturing industry by considering the operational use of BI systems as a strategic operational initiative for orchestrating a firm's resources, improving goal alignment and resource orchestration capabilities for firms. From this perspective, a BI system can be used as an integral part of the production and operations strategy for manufacturers, leading to a stronger competitive advantage.

Academics in the area of production and operations management have long realised the importance of information and knowledge for enhancing organisational routines and capabilities. Yet the effects of BI systems on the risks and returns of firms have not been empirically examined. Scholars in strategic management traditionally believe that boosting financial returns through any innovations often entails risks to firms. There is a tradeoff between firm risks and returns (Mudambi and Swift 2014). However, our study provides substantial empirical evidence of the positive impact of BI systems on both profitability improvement and risk reduction for firms.

5.2. Applications for Production Systems and Logistics and the Implications for Managers

This study points out that the operational use and integration of BI systems into the production and manufacturing operations require substantial support from employees and an institutionalized process environment. This is of interest from a production system point of view

because productions and operations managers in the manufacturing industry are often involved in the use of BI systems for continuous improvements; they are also involved in building relationships between employees and in process formalization through ISO 9000 certification. Thus, production and operations managers must understand the factors in both the firm–employee relationship and the process institutionalization critical to the operational use and integration of BI systems into the area of production to lead to significant competitive advantages. Employee relationships affect the organisational culture in disclosing and exchanging data. Firms that can develop strong employee relationships for information sharing are in a much stronger position to integrate BI systems into production and manufacturing operations for enhancing profitability and reducing risk (Yli-Renko et al. 2001). Also, if firms effectively adopt the ISO 9000 practices, they might develop a structure with systematic routines to promote information flows, thus facilitating BI assimilation. Our research might help production and operations managers identify some factors critical to operational BI system use.

Manufacturing is an extensively data-intensive industry (Sarkar 2018). BI has been widely used in the manufacturing industry to solve organisational issues such as those in decision-making to enhance competitiveness; in particular, BI is commonly applied in manufacturing operations (Yosof et al. 2013). Managers may use BI to improve information visibility and make better-informed decisions, thus facilitating decision-making in supply chain logistics by evaluating daily performance and analysing data to ensure quality and delivery standards and providing remedial measures for reducing errors during production (Sarkar 2018; Yosof et al. 2013). However, the operational use of BI systems requires large investments in management infrastructure and resources, and integrating BI systems into production and manufacturing processes poses many challenges that have resulted in the failure of more than half of BI projects (Goasduff 2015; Yeoh

and Koronios 2010). Moreover, most data are often poorly utilized or lie idle with manufacturing firms (Sarkar 2018). Therefore, the model we have suggested enables those managers interested in using BI systems to extract the value of big data to understand how BI systems affect performance outcomes such as ROA and firm risks through integrating employee relationships and process institutionalization. For practitioners, this study shows that the business value of BI systems should be understood from the strategic production and operations management perspective. BI systems should be used as an integral part of the manufacturing industry's production and operations strategy for better resource orchestration, leading to competitive outcomes (Hendricks and Singhal 2008). BI systems should form part of a manufacturer's operations strategy for goal alignment and resource orchestration to improve operational capabilities. Particularly, previous research (Koufteros et al. 2014; Li et al. 2013) has shown that an interactive use of ES, such as those enabled by BI systems, leads to significant competitive advantages. The results indicate that BI systems enhance firms' profitability and reduce financial risk when firms can develop a stronger relationship with employees and establish an institutionalized process.

From this study, manufacturing firms struggling with their massive data from operational processes such as scheduling, assembly, and material planning (Yosof et al. 2013) and that have not yet used BI can gain a perspective of the benefits possible, in terms of ROA and firm risk, of integrating BI systems into production and manufacturing operations. Production and operation managers working in the manufacturing industry should consider the orchestrations between their use of BI systems and employee relationships as well as in the institutionalized process. Besides, manufacturers planning to increase investment in BI in their operations (Empie 2016; Sarkar 2018) should consider BI integral to their current and future strategies.

5.3. Limitations and Future Research

This study has some limitations that provide potential directions for future research. First, this research is limited in terms of its scope. We have no information regarding firms' motives for using BI systems. For example, Seddon and Constantinidis (2012) found that some firms have used BI systems for general purposes to analyse data for better decision-making, whereas others pursue strategic development through BI adoption. Future studies could extend this research by examining the motives of firms for using BI systems on firm performance. Second, we argue that ISO 9000 is a good proxy for process institutionalization; ISO 9000 certified firms are considered to have higher rates of process institutionalization. Although the adoption of ISO 9000 is iconic for instituting process-based management systems (Guler et al. 2002; Iden 2012), it is a perfect indicator, particularly because the construct of process institutionalization is multidimensional, and as in other research that uses secondary data, perfect metrics are not possible. Moreover, because the manufacturing industry is undergoing many changes and developments in the Industry 4.0 era, an interesting study might focus on the impact of operational use of BI systems with the integration of ISO 9000 adoption and employee relations in manufacturing firms. Practitioners may wish to understand how integrating BI applications into their production and manufacturing operations might provide a strategic approach to enhance competitiveness in the Industry 4.0 environment. Third, we consider firm profitability and risks as the two possible outcomes of the operational BI system use. Yet future studies can also focus on firm innovativeness because big data can be used to generate insights and innovation by providing timely measures and analyses based on more reliable and complete data, thus leading to better decisions (Manvika et al. 2011). Finally, the operational use of BI systems could consider other organisational contexts such as

environmental turbulence and complexity, which might affect the benefits derived from the BI application (Wade and Hulland 2004).

5.4. Conclusions

This study contributes to the understanding of the impact of the operational use of BI systems on profitability and firm risks and on integrating employee relationships and process institutionalization. We particularly enrich the research on production and operations strategy in the manufacturing industry through the theoretical lens of ROP of RBV of firms to suggest the operational use of BI as a strategic initiative for orchestrating a firm's resources, improving goal alignment and resource orchestration capabilities for firms. From this perspective, a BI system can provide an integral part of the production and operations strategy for manufacturers, leading to a sustainable competitive advantage.

Although several studies have examined the business value of ES, SCM, and CRM systems, they have led mostly to mixed findings. Furthermore, few studies have examined the business value of BI systems, particularly their impacts on firm profitability and firm risks. Moreover, little is known about the organisational environment most conducive to the operational use of BI systems. Based on our analysis of the operational use of BI systems in the United States, we demonstrate that BI systems provide firms with higher profitability while lowering firm risks. In addition, BI systems significantly improve profitability and reduce firm risk with better employee relationships and higher process institutionalization. This study offers evidence that the operational use of BI systems delivers higher business value when firms are able to develop better relationship with employees and increase their process institutionalization.

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Tables

Table 1. Types of BI vendors and their BI platforms.

BI vendors	Major providers	Niche players	General platforms	Specialised platforms
Actuate		✓	✓	
Alteryx		✓		✓
Applix		✓	✓	
Arcplan		✓		✓
Bitam		✓		✓
Board International		✓		✓
BusinessObjects	✓			✓
Cognos	✓			✓
Corda Technologies		✓	✓	
GoodData		✓		✓
Hyperion Solutions	✓			✓
IBM	✓		✓	
Infor		✓	✓	
Informatica		✓	✓	
Information Builders	✓			✓
Jaspersoft		✓		✓
Jinfonet Software		✓		✓
LogiXML (Logi Analytics)		✓		✓
Microsoft	✓		✓	
MicroStrategy	✓			✓
Oracle	✓		✓	
Panorama Software		✓		✓
Pentaho		✓		✓
ProClarity		✓		✓
Prognoz		✓		✓
Pyramid Analytics		✓		✓
Qlik	✓			✓
Salient Management		✓		✓
SAP	✓		✓	
SAS Institute	✓		✓	
Spotfire		✓		✓
Tableau	✓			✓
Targit		✓		✓
Tibco	✓			✓
Yellowfin		✓		✓

Table 2. Examples of the announcements about the operational of BI systems.

Announcement 1	
Company Name	Campbell Soup Company (NYSE: CPB)
Announced on	21 May 2007 (Operational use of BI systems i.e., year t in 2007)
Text extracted from Factiva	QlikTech, the world's leading provider of memory analysis and reporting solutions, announced today that Campbell Soup Company is using QlikView, its flagship business intelligence software solution, to improve its supply chain management. "QlikView's analytical power and simplicity enable our employees to more easily access critical information from disparate sources at a moment's notice," said Michael Mastroianni, vice president of North American planning, reliability and operations for Campbell's.
	In order to streamline operations and increase production efficiency, QlikTech and Terra Technology provide Campbell with the necessary tools to improve inventory analysis management and projections, sales and long-term forecasting analysis, demand planning, schedule compliance, transportation and warehouse scheduling. Today, members of the company's plant production, finance, and logistics departments use QlikView to make educated business decisions on a daily basis.
Announcement 2	
Company Name	Natus Medical Incorporated (NASDAQ: BABY)
Announced on	14 January 2013 (Operational use of BI systems i.e., year t in 2013)
Text extracted from Factiva	Working with NTT DATA, a Platinum-level member in the Oracle PartnerNetwork, and leveraging out-of-box, industry-specific Oracle Business Accelerators, Natus implemented the Oracle E-Business Suite 12.1, including Oracle Advanced Supply Chain Planning, Oracle's Demantra, Oracle E-Business Suite Financials, . . . and Oracle Service Management. Natus also implemented Oracle Customer Relationship Management, . . . and Oracle Business Intelligence in an aggressive 10-month implementation timeframe.
	With this integrated suite of Oracle Applications, Natus has been able to significantly reduce end-of-month reporting times, effectively meet increasing customer demand and establish a flexible and scalable platform to support future growth.
Announcement 3	
Company Name	Regal Beloit (NYSE: RBC)
Announced on	9 December 2008 (Operational use of BI systems i.e., year t in 2008)
Text extracted from Factiva	Regal Beloit Corporation, a leading manufacturer of electrical and mechanical motion control products serving markets throughout the world, has deployed Oracle Business Intelligence Applications to improve visibility into business operations and enhance decision-making enterprise wide, Oracle announced today.

Table 3. Sample description for firms with the operational use of BI systems.

Panel A: The Distribution of Sample Firms by Year of the Operational Use of BI Systems

Year	Number of Firms with Operational Use of BI systems	Percentage
2005	64	19.81
2006	56	17.34
2007	48	14.86
2008	32	9.91
2009	29	8.98
2010	25	7.74
2011	18	5.57
2012	17	5.26
2013	19	5.88
2014	15	4.64
Total	323	100

Panel B: Operational Use of BI Systems by Major Industries (Based on 3-digit SIC).

3-Digit SIC Codes	Industries	Frequency	Percentage
283	Drugs	33	10.22
367	Electronic components and accessories	24	7.43
384	Medical instruments and supplies	22	6.81
357	Computer and office equipment	15	4.64
382	Measuring and controlling devices	13	4.02
366	Communications equipment	12	3.72
284	Soaps, cleaners and toilet goods	9	2.79
Others	Other industries	195	60.37
Total		323	100

Panel C: Information on Operational Use of BI Systems

	Number	Percentage
Firms using leading BI vendors	301	93.19
Firms using niche BI vendors	22	6.81
Firms using general BI platforms	203	62.85
Firms using specialised BI platforms	120	37.15
Firms with multiple implementations together with other systems	14	4.33
Firms without multiple implementations together with other systems	309	95.67

Table 4. Variable definition and operationalization.

Variable name	Definition	Variable operationalization	Data source	Reference
Firm profitability	Ability of a firm to use assets in generating profits (net operating income) in a certain year.	Return on assets $(ROA)_{it}$ $= {}^{\text{Operating income before interest, taxes, depreciation, and amortisation}_{it}}\!/_{\text{Total assets}_{it}}$	Compustat	Nath et al. 2010; Terjesen et al. 2011.
Firm risks	Unpredictable variability of a firm's financial returns (i.e. profit volatility).	Firm risks$_{it}$ = Standard deviation of ROA$_i$ over a five-year period up to the current period.	Compustat	Andersen and Bettis 2015; Bromiley et al. 2017; Faccio et al. 2016.
Abnormal performance	Discrepancy between a firm's actual performance and its expected performance over a period of time. The expected performance is determined based on the change in performance of the corresponding control firms during the same period.	Abnormal performance of a sample firm $(APS)_i$ $= $ A sample firm's actual performance with the operational use of BI $-$ A sample firm's expected performance if the operational use of BI has not occurred Expected performance of a sample firm if the operational use of BI has not occurred $= $ A sample firm's performance in the base year $+$ The change in median performance of the control firms over a period of time	Compustat	Barber and Lyon 1996; Hendricks and Singhal 2008; Swink and Jacobs 2012.
Cumulative abnormal performance	Sum of all of a firm's abnormal profitability and risks over an event period.	$$Cumulative\ abnormal\ performance\ (CAPS)_i = \sum_{k=-1}^{+1} APS_{i,t+k}$$ where $APS_{i,t+k}$ is the abnormal firm profitability or abnormal firm risks of sample firm i in period $t+k$.	Compustat	Barber and Lyon 1996; Swink and Jacobs 2012.

Employee relationships	Social relationship of a firm with employees in the year of operational use of BI systems (year t).	Employee relationships$_{it}$ $$= \frac{1}{2}\sum_{d=1}^{2}(\frac{\text{Sum of standardized strength score}_{idt} - \text{Sum of standardized concern score}_{idt} + \text{Max. no. of concern}_{dt}}{\text{Max. no. of strength}_{dt} + \text{Max. no. of concern}_{dt}})$$ where d = 1 and 2 represent the employee social relations dimension and social diversity dimensions in KLD, respectively.	KLD	Choi and Wang 2009; Hillman and Keim 2001; Jo and Na 2012; Mattingly and Berman 2006.
Process institutionalization	The process of embedding organisational policies, systems, structures, and procedures, and enhancing the maturity of organisational routines.	1 if a firm with ISO 9000 certification, 0 if a firm without ISO 9000 certification.	*Quality Digest*, *Who's Registered*, and the *IAAR Directory of Registered Companies*	Anderson et al. 1999; Yeung et al. 2011.
Previous firm profitability/ Previous firm risks	Previous firm profitability or risks in the base year (year t-2).	Previous performance$_{i,t-2}$ = ROA$_{i,t-2}$, or Previous performance$_{i,t-2}$ = Firm risks$_{i,t-2}$,	Compustat	Hendricks and Singhal, 2008; Lo et al., 2014.
Multiple implementations	Multiple implementations refer to an announcement in which a BI system is installed with other enterprise software (e.g., ERP) at the same time; single implementation refers to an announcement in which the operational use of a BI system is solely mentioned.	1 if multiple implementations; 0 if single implementation.	Factiva	N/A

General or specialized BI platform	General platform refers to BI vendors who have major portfolios of software solutions (e.g., SAP, Microsoft); specialized platform refers to a BI vendor which have a single BI solution (e.g., Qlik, Pentaho).	1 if general BI platform; 0 if specialized BI platform.	Corporate websites. Google search	N/A
Firm size	Size of a firm in terms of total assets (year t-2).	$\text{Firm size}_{i,t-2} = \text{Ln}(\text{Total assets}_{i,t-2})$	Compustat	Cheng et al. 2014; Hendrick and Singhal 2008.
Sales growth	The rate of growth in sales revenue in the base year (year t-2).	$\text{Firm sales growth}_{i,t-2} = {(\text{Sales}_{i,t-2} - \text{Sales}_{i,t-3})}/{\text{Sales}_{i,t-3}}\ \text{x100\%}$	Compustat	Montabon et al. 2007
R&D intensity	The percentage of R&D expenditure over sales of a firm in the base year (year t-2).	$\text{R\&D intensity}_{i,t-2} = {\text{R\&D expenses}_{i,t-2}}/{\text{Sales}_{i,t-2}}$	Compustat	Ba et al. 2013; Jacobs et al. 2015.
Labour intensity	The ratio of employee number over total assets of a firm in the base year (year t-2).	$\text{Firm labor intensity}_{i,t-2} = {\text{Number of employees}_{i,t-2}}/{\text{Total assets}_{i,t-2}}$	Compustat	Dewenter and Malatesta 2001; Lo et al. 2013.
Capital intensity	The ratio of fixed assets over total assets of a firm in the base year (year t-2).	$\text{Firm capital intensity}_{i,t-2} = {\text{Fixed assets}_{i,t-2}}/{\text{Total assets}_{i,t-2}}$	Compustat	Alam and Shah 2013; Chang et al. 2013.

Industry size	The total assets of the industry in which a firm belongs in the base year (year t-2).	Industry size$_{j,t-2}$ = Ln (Total assets$_{j,t-2}$) where j is industry based on 2-digit SIC codes.	Compustat	Lo et al. 2013.
Industry technology intensity	The ratio of the total R&D expenditure in an industry to which a firm belongs over the industry's total sales in the base year (year t-2).	Industry technology intensity$_{j,t-2}$ = Median ($R\&D\ expenses_{j,t-2} / Sales_{j,t-2}$) where j is industry based on 2-digit SIC codes.	Compustat	Liu et al. 2014; O'Brien and Jonathan 2014.

Table 5. Descriptive statistics of pre-event data for sample and control firms (year t-2).

	N	Mean	Median	Std. dev.	Min.	Max.
			Sample firms			
Firm profitability[a]	278	11.583	12.850	14.528	-94.282	50.333
Firm risks	257	0.044	0.029	0.050	0.004	0.462
			Control firms			
Firm profitability[a]	278	11.506	12.673	14.411	-94.582	50.317
Firm risks	257	0.044	0.030	0.050	0.004	0.457

[a] In percent

Table 6. Abnormal changes in firm profitability.

Period	N	Median (Statistics)	% Positive (Statistics)	Mean (Statistics)
Yearly abnormal change in firm profitability[a]				
Vendor contract stage	278	0.302	51.80	0.301
t-2 to *t*-1		(1.182)	(0.600)	(0.621)
Full operational use stage	265	0.771**	52.45	0.834**
t-1 to *t*		(1.964)	(0.800)	(1.881)
Full operational use stage	192	0.755**	52.08	1.355***
t to *t*+1		(1.770)	(0.578)	(2.484)
Cumulative abnormal change in firm profitability[a]				
Pre-BI operational use	265	1.230**	52.45	1.170*
t-2 to *t*		(1.938)	(0.800)	(1.453)
Full event window	192	2.119**	54.69*	3.436***
t-2 to *t*+1		(2.152)	(1.305)	(2.906)

Notes:

1. *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$. The *p*-values shown are those for the one-tailed test of the null hypothesis that there is no abnormal firm profitability, using the Wilcoxon signed-rank test, sign test, and *t*-test, respectively.

2. Wilcoxon signed-rank test Z-statistic for the median, binomial sign test Z-statistic for the percentage, and *t*-statistics for the mean.

3. % Positive indicates the percentage of firms achieving positive abnormal changes in firm profitability.

4. [a] In percent.

Table 7. Abnormal changes in firm risks.

Period	N	Median (Statistics)	% Negative (Statistics)	Mean (Statistics)
Yearly abnormal change in firm risks				
Vendor contract stage	257	-0.001	53.31	-0.000
t-2 to t-1		(-1.264)	(-1.063)	(-0.105)
Full operational use stage	247	-0.003**	55.87**	-0.004**
t-1 to t		(-2.037)	(-1.858)	(-2.295)
Full operational use stage	197	-0.004***	57.36**	-0.006***
t to t+1		(-2.911)	(-2.089)	(-3.078)
Cumulative abnormal change in firm risks				
Pre-BI operational use	247	-0.005***	56.28**	-0.005**
t-2 to t		(-2.427)	(-1.988)	(-2.170)
Full event window	197	-0.010***	56.86**	-0.011***
t-2 to t+1		(-2.750)	(-1.942)	(-3.039)

Notes:

1. *p < 0.1, **p < 0.05 and ***p < 0.01. The *p*-values shown are those for the one-tailed test of the null hypothesis that there are no abnormal firm risks, using the Wilcoxon signed-rank test, sign test, and *t*-test, respectively.

2. Wilcoxon signed-rank test Z-statistic for the median, binomial sign test Z-statistic for the percentage, and *t*-statistics for the mean.

3. % Negative indicates the percentage of firms achieving negative abnormal changes in firm risks.

Table 8. Correlations matrix.

	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1.	Cumulative abnormal firm profitability	1													
2.	Cumulative abnormal firm risks	0.148*	1												
3.	Employee relationships	-0.112	-0.088	1											
4.	Process institutionalization[i]	0.089	-0.126	0.126	1										
5.	Multiple implementations[ii]	-0.027	-0.028	0.034	0.087	1									
6.	General or specialized BI platform[iii]	-0.046	-0.015	-0.111	-0.231***	-0.042	1								
7.	Year of operational use of BI systems	-0.029	0.019	0.082	-0.028	-0.086	0.150*	1							
8.	Firm size	-0.156*	0.112	0.325***	0.275***	0.053	-0.302***	-0.116	1						
9.	Sales growth	-0.016	0.036	-0.080	-0.129*	0.008	0.157**	-0.147*	-0.009	1					
10.	R&D intensity	-0.037	-0.189**	-0.011	-0.184**	0.012	0.120	-0.092	-0.228***	0.062	1				
11.	Labour intensity[iv]	0.169*	-0.040	-0.211***	0.168**	-0.003	-0.071	-0.030	0.114	-0.079	-0.221***	1			
12.	Capital intensity	-0.005	-0.061	0.041	0.099	-0.032	-0.116	-0.054	0.500***	-0.008	-0.272***	0.012	1		
13.	Industry size	0.088	-0.110	0.035	0.158**	0.039	-0.115	0.025	0.173**	0.033	0.141	-0.133	0.038	1	
14.	Industry technology intensity	0.111	-0.026	0.039	0.017	-0.083	-0.012	0.192**	-0.039	0.038	0.234***	-0.246***	-0.045	0.489***	1
	Mean	0.033	-0.012	0.496	0.599	0.054	0.641	2008.269	7.883	0.141	0.102	0.004	0.515	12.776	0.097
	Standard deviation	0.176	0.051	0.373	0.492	0.226	0.481	2.599	1.523	0.249	0.317	0.003	0.199	1.182	0.112
	Minimum	-0.316	-0.200	-0.296	0.000	0.000	0.000	2005.000	4.364	-0.631	0.000	0.000	0.077	12.776	0.056
	Maximum	0.868	0.188	1.977	1.000	1.000	1.000	2014.000	11.835	2.256	3.345	0.015	1.000	14.480	0.300

Notes:

1. $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$ (two-tail).
2. [i] 1 if firms with ISO 9000 certifications; 0 if firms without ISO 9000 certifications.
3. [ii] 1 if multiple implementations; 0 if single implementation.
4. [iii] 1 if general BI platform; 0 if specialised BI platform.
5. [iv] In thousands of employees/millions of dollars.

Table 9. HLM estimation for cumulative abnormal firm profitability (Year t-2 to Year t+1).

Variables	Model 1	Model 2A	Model 2B	Model 2C
Fixed effects				
Intercept	-6.764	-4.657	-3.151	-1.604
	(-0.547)	(-0.381)	(-0.251)	(-0.129)
Previous firm profitability	-0.063	-0.304	-0.103	-0.321
	(-0.291)	(-1.373)	(-0.485)	(-1.471)
Multiple implementations[i]	-0.015	0.025	-0.028	0.010
	(-0.177)	(0.289)	(-0.328)	(0.115)
General or specialized BI platform[ii]	-0.033	-0.037	-0.020	-0.025
	(-1.028)	(-1.186)	(-0.618)	(-0.805)
Year of operational use of BI systems	0.003	0.002	0.002	0.008
	(0.538)	(0.378)	(0.244)	(0.126)
Firm size	-0.007	-0.022*	-0.013	-0.025*
	(-0.557)	(-1.686)	(-1.039)	(-1.929)
Sales growth	0.207**	0.245***	0.211**	0.250***
	(2.370)	(2.906)	(2.453)	(2.999)
R&D intensity	0.138**	0.097	0.143**	0.105*
	(2.222)	(1.579)	(2.303)	(1.705)
Labour intensity	8.279	11.637**	4.760	8.771
	(1.466)	(2.104)	(0.849)	(1.570)
Capital intensity	0.019	0.055	0.022	0.045
	(0.203)	(0.600)	(0.238)	(0.500)
Industry size	0.012	0.010	0.011	0.010
	(0.677)	(0.552)	(0.703)	(0.590)
Industry technology intensity	0.049	0.104	-0.022	0.044
	(0.199)	(0.407)	(-0.097)	(0.186)
Employee relationships		0.116***		0.106***
		(2.863)		(2.615)
Process institutionalization[iii]			0.081**	0.067**
			(2.300)	(1.937)
Model fit				
-2 log-likelihood (deviance)	-96.8	-104.2	-101.3	-107.5
Change in chi-square		7.38***	4.45**	10.76***

Notes:

1. $^*p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$ (two-tailed tests for control variables and one-tailed test for the moderating variables).
2. t-statistics in parentheses.
3. [i] 1 if multiple implementations; 0 if single implementation.
4. [ii] 1 if general BI vendor; 0 if specialized BI vendor.
5. [iii] 1 if firms with ISO 9000 certifications; 0 if firms without ISO 9000 certifications.

Table 10. HLM estimation for cumulative abnormal firm risks (Year t-2 to Year t+1).

Variables	Model 1	Model 2A	Model 2B	Model 2C
Fixed effects				
Intercept	-0.238	-1.172	-0.327	-1.258
	(-0.065)	(-0.323)	(-0.092)	(-0.357)
Previous firm risks	-0.261*	-0.221*	-0.257**	-0.216
	(-1.954)	(-1.646)	(-1.960)	(-1.643)
Multiple implementations[i]	-0.009	-0.007	-0.010	-0.008
	(-0.513)	(-0.404)	(-0.546)	(-0.444)
General or specialized BI platform[ii]	0.005	0.004	0.002	-0.001
	(0.500)	(0.452)	(0.171)	(0.106)
Year of operational use of BI systems	0.000	0.001	0.000	0.001
	(0.085)	(0.343)	(0.106)	(0.370)
Firm size	0.006*	0.008**	0.008**	0.009***
	(1.754)	(2.214)	(2.203)	(2.677)
Sales growth	0.005	0.002	0.000	-0.003
	(0.290)	(0.136)	(0.007)	(-0.163)
R&D intensity	-0.042*	-0.045*	-0.050**	-0.052**
	(-1.735)	(-1.858)	(-2.068)	(-2.201)
Labour intensity	-1.040	-1.307	-0.276	-0.521
	(-0.634)	(-0.801)	(-0.171)	(-0.323)
Capital intensity	-0.085***	-0.089***	-0.089***	-0.093***
	(-3.209)	(-3.391)	(-3.419)	(-3.603)
Industry size	-0.006	-0.006	-0.004	-0.004
	(-1.166)	(-1.136)	(-0.740)	(-0.727)
Industry technology intensity	0.056	0.060	0.064	0.070
	(0.862)	(0.899)	(0.917)	(0.977)
Employee relationships		-0.021**		-0.021**
		(-1.717)		(-1.794)
Process institutionalization[iii]			-0.022***	-0.023***
			(-2.371)	(-2.435)
Model fit				
-2 log-likelihood (deviance)	-447.9	-450.8	-453.2	-456.4
Change in chi-square		2.89*	5.31**	8.46**

Notes:
1. $^*p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$ (two-tailed tests for control variables and one-tailed test for the moderating variables).
2. t-statistics in parentheses.
3. [i] 1 if multiple implementations; 0 if single implementation.
4. [ii] 1 if general BI vendor; 0 if specialized BI vendor.
5. [iii] 1 if firms with ISO 9000 certifications; 0 if firms without ISO 9000 certifications.