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ABSTRACT

Measuring Information Systems (IS) value has been constantly attracting much attention and debate within the IS research community. Since information systems effects are often difficult to quantify, traditional payoff evaluation methods often yield conflicting results. In this paper we suggest that some information systems can be evaluated on the basis of their effect on stock return volatility. Systems which facilitate information sharing and decision-making can improve the quality of company information to stakeholders, thus reducing surprise levels in financial markets. Specifically, these systems can lead to more consistent and predictable company performance. Hence, we hypothesize that information systems can help to reduce a company's stock return volatility. To test this hypothesis, we have conducted an empirical analysis on a sample of firms that have deployed a Business Intelligence (BI) system. The results indicate a significant reduction in stock return volatility after BI deployment.

Keywords

Information systems evaluation, stock return volatility, decision support, information transparency, business intelligence

INTRODUCTION

During the last two decades the IS research community has reexamined the productivity gains resulting from IT investments. Motivated by the "productivity paradox of Information Technology" (Brynjolfsson 1993), numerous studies have researched this issue.

One popular line of research has examined the effects of IT investment on accounting performance measures, such as ROE and ROA. Early studies in this area of research have offered equivocal evidence. Indeed, some researches have indicated that IT contributes to productivity (e.g. Brynjolfsson and Hitt 1995). Yet, other researches have shown no correlation between the two (e.g. Landauer 1995).

Scholars have proposed several reasons for the conflicting results. Perhaps the most prominent reason has been using inadequate data (Dedrick et al. 2003). However, in subsequent research, with more adequate data, a new productivity paradox has emerged (Anderson et al. 2003). Rather than lack of productivity gains, highly abnormal returns on investment are found. For example, Brynjolfsson and Hitt (1996) find that the net returns from IT investments are more than 40% higher than those from non-IT investments. With such productivity gains, it suddenly appears that companies are underinvesting in IT.

Various reasons for the new paradox have been suggested. With respect to investment cost, it is noted that the true cost of IT may be underestimated (Brynjolfsson and Hitt 2000). Associated costs such as labor, training, and services are difficult to estimate. With respect to investment payoff, it is noted that since the timing of the payoff is not well known, payoff measurement may be inaccurate as well (Dedrick et al. 2003).

Seeking alternative measures for IT value, a more recent line of research has taken the "traditional event study" methodology[1] (e.g. Dehning et al. 2003). This methodology is based on the notion that IT value can be determined by analyzing market reactions to announcements on IT expenditures. Since rational investors are expected to value both tangible and intangible benefits associated with an investment, implications of system deployment can be captured in market reaction to an investment announcement.

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[1] As the empirical study of this paper can also be considered as an event study (on the return variance), we use the term "traditional event study" to refer to any event study that focuses on the return of a company's stock

In this paper we develop an approach related to this methodology. We suggest that an organization deploying a system directly related to information sharing or decision making likely reduces the risk associated with holding its stock. This effect originates from the capability of such systems to help generating comprehensive reports, both internally to the organization and externally to investors. Superior reporting abilities make the corporate information more available, which typically reduces surprise levels. Therefore, we propose that an event study measuring market reaction in terms of variance on returns may be a proper approach for analyzing such cases.

It is important to realize that an implicit assumption in *traditional* event studies is that the consequences of an IT initiative are effectively understood upon investment announcement. Since IT deployment is a complex process affected by many ambiguous factors, including management support, affiliation, and system acceptance, this assumption may raise some concerns.

Contrary to the limitation however, event studies on volatility[2] do not require the market to immediately understand the implications of the system. Rather, a lengthy event window may be defined; in essence, this allows the market to gradually adapt to the effect of the system. The advantage of studying volatility lies in its persistency. While event studies on returns work well when the event window is clearly defined over one or two days, the persistency of volatility makes possible testing effects that may take a longer period of time to be realized, and when the event date is not clearly defined in calendar time.

In light of this, the question deriving our research is whether the risk associated with holding a company's stock decreases once a company deploys a system, which directly facilitates information sharing. To answer this question, we analyze stock return volatilities of companies which have deployed BI systems, and hypothesize that BI deployment results in reduced stock return volatilities.

In this paper, Section 2 reviews the concept of BI systems. In Section 3, we provide the theoretical foundations leading to our hypothesis. The following sections provide details of the empirical analysis. Finally, we summarize with concluding remarks.

BUSINESS INTELLIGENCE SYSTEMS

Business Intelligence is a relatively new term that emerged in the enterprise systems domain during the early '90s. Broadly, the objective of BI tools is to improve the timeliness and quality of input to the decision process (Negash and Gray 2003). These systems help businesses store, find and analyze the information they need to make better decisions. Formally, Gray (2003) defines BI systems as those that:

"combine data gathering, data storage, and knowledge management with analytical tools to present complex corporate and competitive information to planners and decision-makers. The objective is to improve the timeliness and quality of the input to the decision process".

The BI software industry has begun to thrive in the last decade. Today BI tools are being incorporated into a steadily increasing number of businesses, and projected spending at many companies keeps rising (Whiting 2006). The most dominant users of such technology are financial managers, business executives, IT managers, and business analysts (Whiting 2006). The BI software market is poised for constant growth and is projected to reach $3 billion by 2009 (Gartner 2006).

However, the business value of these systems is hard to determine using traditional payoff measures. Since savings are only a small portion of the payoffs associated with BI deployment, it is rare that such systems pay for themselves through cost reductions alone (Gray 2003). Hence, both researchers and practitioners have called for better ways to evaluate the effect they have on organizations (Havenstein 2007; Gray 2003).

BUSINESS INTELLIGENCE AND VOLATILITY

BI systems reduce risk for two reasons. First, they facilitate information sharing and report generation (McMann 2004). The ability to generate comprehensive reports benefits many different groups of users - from specialists in controlling, financial reporting and finance to salespeople and board members (Rasmussen et al. 2002).Second, they reduce risk because they make the decision-making process more consistent. BI systems foster data based decision strategies and shift the emphasis in decision-making from intuition to data (Harding 2003; Brohman et al. 2000). Intuition based decisions are said to dismiss rational decision processes and are categorized as subconscious and emotion-based (Elsbach and Barr 1999; Sayegh et al. 2004). By demoting intuition based decisions, BI promotes consistent decisions.

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[2] The variance of the return is commonly referred to as volatility, or the second moment.

Reporting and Forecasting

For the last decade regulators and investors have pressured companies to provide more accurate guidance about the direction of their business, but fulfilling such demands has been difficult due to lack of technical support (McMann 2004). Now BI systems enable organizations to respond to these requests and proactively mange their own performance (McMann 2004). Therefore, it is no surprise that the finance function has been leading the adoption of business intelligence software in many organizations (Twentyman 2008). As much as a decade ago it was noticed that with BI CFOs were taking an increasingly central role in defining the organizations strategies as BI enabled them to "take the guess work out of decision making" (PriceWaterhouseCoopers p.210). However, initiation of system procurement directly from the office of the CFO flared in prominence shortly after Sarbanes-Oxley captured the attention of executives and boards of directors (Twentyman 2008).

Indeed, in a recent study (Myers and Knox 2004) noted better reporting and forecasting abilities among companies using a BI system. For example, 80% of BI users indicated that they were well-supported with the right technology. In contrast, only 19% using standalone point solutions indicated that they were well-supported technologically.

Consistent decision making

BI systems are the new generation of Decision Support Systems (DSS) (Gray 2003). As such, although they *enable* efficiencies to emerge, the *restrictive* aspects are just as important. More specifically, it appears that the deployment of a DSS within an organization may, either intentionally or unintentionally, foster specific decision strategies (Todd and Benbasat 1999).

Since DSS deployment implies specific decision strategies, decisions are likely to become more consistent in nature. Moreover, the decision strategy fostered by a DSS tends to rely on a well-understood process that is supported by coherent data. In other words, DSS will typically not support intuitive decision processes.

In a well-established body of research in psychology and the decision sciences, scholars have argued that intuition involves the use of heuristics, which can be defined as "mental shortcuts that reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations" (Dane and Prat 2007). However, rational processes for problem assessment are less subject to random inconsistencies and systematic distortions (Schoemaker and Russo 1993). Hence, the introduction of DSS stands out as a tool that can stabilize the decision-making process and thereby reduce instability in an organization's behavior.

EVENT STUDIES ON VOLOATILITY

Typically, in order to study the effect of an event on shareholders' wealth (i.e., the value of a firm's equity), a traditional event study methodology is used.

Unfortunately, there are many difficulties with the execution of traditional event studies that measure the effect of an event on a security's return. In order to measure the impact of the event on price, the researcher must have clear knowledge about the event window in calendar time. If the announcement itself reveals all necessary information to the market, the event window is well defined and will typically correspond to the next few days following the announcement.

However, if the researcher believes the effect will be reflected in prices after a longer period, the measurement of the event's effect on prices is more problematic. One problem that makes the event length in calendar time so crucial is the difficulty of measuring the security's normal return. Since financial theory suggests that investors are compensated for the risk they bear for holding risky securities, a certain asset pricing model must be used to measure the abnormal return due to the event. Furthermore, to estimate the statistical significance of the abnormal return, the researcher needs to know the distributional properties of the returns, which may also have changed due to the event (Savickas 2003; Aktas et al. 2007).

Many would argue that the effects of BI deployment are long-term and our theoretical arguments suggest that the effect will predominantly affect risk (i.e., the variance of the return) rather than the return itself. Fortunately, financial economics research has produced tools that allow us to test the effects on the variance of the return by adjusting the traditional event study methodology to include variance changes.

MEASURING THE EFFECT OF IS DEPLOYMENT ON VOLATILITY

When trying to estimate not only the return of a stock, but also its variance, heteroskedasticity becomes an important issue in the estimation procedure because of the persistency in stocks' variances (McQueen and Vorkink 2004). That is, the expected value of error terms at certain points of time is greater than at others. As a result, the econometric challenge is to specify how the information is used to estimate the mean and variance of the return, conditional on the past information. While there are different kinds of volatility models, one of the most popular and successful ways of modeling volatility is autoregressive conditional heteroscedasticity (ARCH) (Engle 1982), and its more general counterpart, generalized ARCH (GARCH) (Bollerslev 1986).

A simple GARCH model is a joint estimation procedure of two equations:

$$r_t = \alpha_0 + \varepsilon_t \qquad (1)$$

$$\sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 \qquad (2)$$

where r_t is the return at time t, ε_t is the error term at time t for the return equation, and σ^2_t is the variance of the return at time t. Equation (1) assumes a constant return process with noise, while eq. (2) specifies the variance of the return based on past information.

In order to control for general market effects and to examine the effect of BI on stock return volatility, we use a modified version of the simple GARCH in our analysis based on the following specification:

$$r_t = \alpha_0 + \alpha_1 m_t + \alpha_2 D_t + \varepsilon_t \qquad (3)$$

$$\sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 + \beta_3 m_t^2 + \beta_4 D_t \qquad (4)$$

where apart from the variables defined above, m_t (m_t^2) is the market return (market return squared) at time t, and D_t is a dummy variable that equals 0 for trading days prior to BI deployment and 1 for trading days following BI deployment.[3]

The specification in eqs. (3) and (4) controls for market effects. By including m_t, in eq. (3), we control for the component of the stock return that is correlated with the market. By incorporating m_t^2 in the eq. (4), we are controlling for market surprises that occurred at time t, over and above the information that is captured by the error (ε^2_{t-1}) and volatility (σ^2_{t-1}), which are based on the time $t-1$ information set. In the equations, it can also be seen that the coefficient of the dummy variable, α_2, in the return equation captures any possible effects of BI deployment on the return process, while the coefficient, β_4, in the variance equation captures any effects of BI deployment on volatility. Thus, our specification allows us to jointly test the long-term effects of BI deployment on the return and variance. As discussed previously, we expect that BI deployment will have no significant effect on the return, but that it will have a reducing effect on volatility.

An important benefit of examining change in volatility using a GARCH model is the statistical power of the analysis. As opposed to the many cross sectional differences that typically exist between companies, a single company does not typically undergo many dramatic changes over time. Hence, the probability of not rejecting the null hypothesis due to other conflicting spurious differences is reduced. While a cross-sectional analysis will typically require a large sample size in order to increase the statistical power of the test, in a time series GARCH analysis a small sample provides sufficient statistical power. Typically, samples of ten to twenty firms are used in studies analyzing stock behavior using the GARCH model (e.g. Lamoureux and Lastrapes 1994).

DATA

We test our hypothesis by analyzing volatility measures in companies that have undergone a BI initiative. Our sample is derived from a collection of press releases associated with the implementation of a range of Cognos BI solutions. Cognos is recognized as one of the top three market leaders in BI solutions (e.g. http://www.olapreport.com/Market.htm) and routinely reports on selected BI deployments through a single media source: PRNewswire. From the list of customers released to the press via PRNewswire, we have extracted all companies that are publicly traded on either the NYSE or NASDAQ.

From this sample, we have excluded any subsidiaries of publicly-traded companies unless they are significant subsidiaries of the parent company (i.e. incorporate at least 30% of the organizations' operating profit for the year 2006). These sampling criteria yielded a total of 22 firms that introduced BI systems during the years 1999-2004. The sample is listed in Appendix A. All BI applications deployed by companies in our sample provided functionality to facilitate at least two objectives: 1) provision of enhanced organizational reports, and 2) provision of company analytics to support the organizational decision-making process.

[3] We later modify the dummy variable to include an implementation period

In Table 1, we provide some descriptive statistics pertaining to these firms at the mid-point of our sampling period, i.e., the end of 2002.

	No.	Mean	Standard deviation	Percentile 5th	25th	50th	75th	95th
Exchange	22	14 stocks traded on NYSE, 8 stocks traded on NASDAQ						
Market value ($m)	22	3538	5918	119	646	1106	4427	10682
Price	22	28.97	21.45	6.60	12.74	26.45	35.45	59.40
Dollar volume ($m)	22	471.90	743.82	2.27	51.31	195.31	458.20	1831.55
Employees	22	25.10	39.92	1.22	5.25	10.77	20.44	109.60
Common shareholder	19	18.59	32.20	0.07	1.31	6.40	25.23	138.00
R&D to sales ratio	10	0.05	0.07	0.00	0.00	0.03	0.11	0.20
Income ($m)	22	159.69	797.22	-27.00	29.29	83.87	324.64	976.00
Leverage	22	0.31	0.28	0.01	0.07	0.24	0.51	0.77

Table 1: Distribution of Variables.

For the sample of firms, we compare stock return volatilities before and after the implementation of the BI system. PRNewswire announcements are typically made during system deployment. However, deployment itself is a lengthy process, which in extreme cases can span more than a year (Pendse 2006). In the analysis phase we account for this by also allowing for an implementation period and comparing volatility between the pre- and post-implementation periods.

RESULTS

Figure 1 illustrates how return volatility changed around the time of BI deployment. The x-axis corresponds to the number of trading weeks from the announcement date. The measure plotted is the equal-weighted excess return volatility. To calculate this measure, we compute the weekly standard deviation of excess return for each of the firms; and averaged standard deviation corresponding to the same week number across firms.

We measure excess-return volatility, as opposed to return volatility, to mitigate the effect of market changes. In general, market effects should be averaged out in our sample as the announcement on deployment is at different calendar times across firms. However, because all BI deployment announcements occurred during the years 1999-2004, it may still be important to control for general shifts in the market concerning volatility (Campbell et al. 2001).

Figure 1 shows that the equal-weighted measure is mostly between 2% and 4% in the period of 75 weeks prior to deployment to around 30 weeks after deployment. Afterwards, there is a sizeable reduction in excess volatility. Not surprisingly, the effect of BI on volatility does not appear to be immediate one; rather, the reduction in volatility starts at a period that corresponds to approximately 30 weeks after deployment.

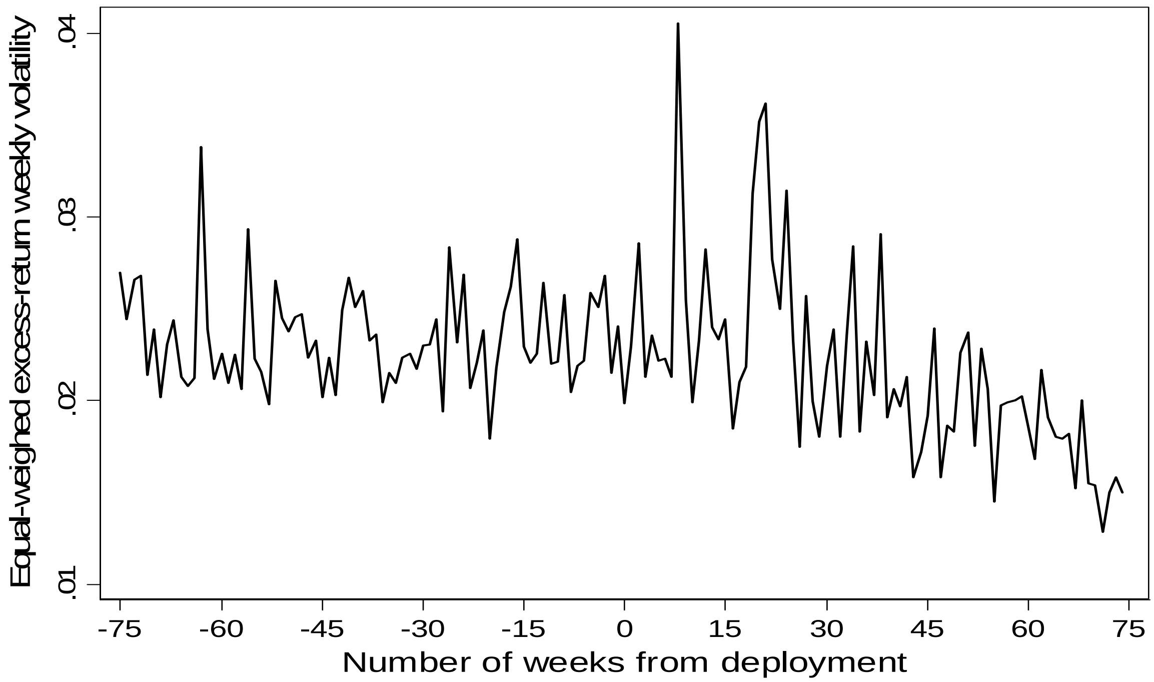

Figure 1: Equal-weighted excess-return weekly volatility

We next explore this observation by using the more robust GARCH specification, which accounts for the persistency in volatility and market effects, for modeling volatility. Figure 2 presents the average residuals of a pooled GARCH specification, which means that the parameters of the model are fixed for all firms. The residuals of the model capture the unpredictable part, or surprise, of volatility. In order to calculate the equal-weighted error, we first calculate the absolute value of the residual for each trading day for each firm. We then average this value across firms on their respective trading days compared to the deployment announcement days.

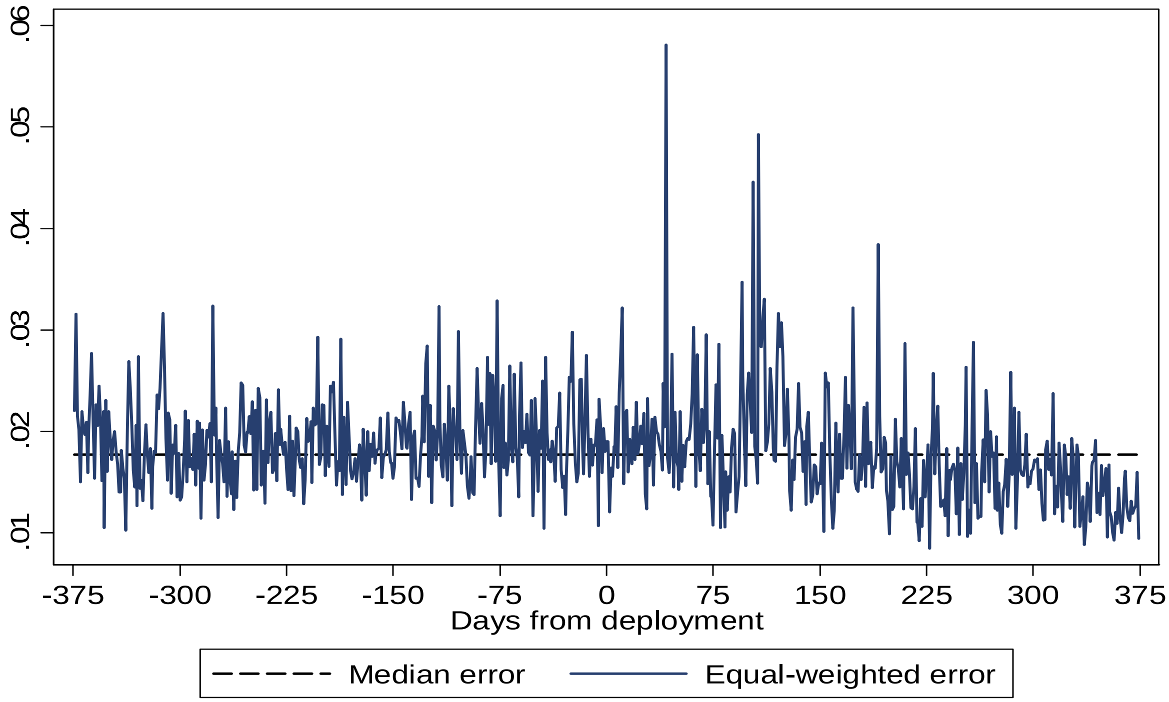

Figure 2: Absolute value of errors of the enhanced GARCH specification. Errors are averaged across firms on each trading day. The median sample error of the model is the straight dashed line.

It is noticeable in figure 2 that there are more observations beneath the dotted line after deployment than before deployment. The dotted line represents the median residual across the 748 trading days.[4] To check the robustness of these results, we conduct a difference of mean and median test (see Table 2). Clearly, a reduction in the GARCH's model residual occurs after deployment and the result are significant.

Difference of Means				
	N	Mean	Standard deviation	*t*-statistic
Prior to deployment	374	.0189901	.0002087	
After deployment	374	.0175786	.0002999	3.864
Difference of Medians				
	N	Smaller than median value	Larger than median value	Two-sample Wilcoxon rank-sum z- statistic
Prior to deployment	374	149	225	
After deployment	374	225	149	5.902

Table 2: Difference of Means and Median Tests - GARCH specification.

[4] Note that we lose two observations because (1) the GARCH model depends on past information, so the first point (-375) can not be estimated and (2) time 0 is discarded.

We next continue to provide a statistical analysis to quantify this effect. In Table 3, we use a dummy variable that equals one for the time period in which the BI system is assumed to become fully operational.[5] I.e., we conduct tests with an implementation period window. We present the results where the implementation period is assumed to be approximately one year, with the press release taking place at the 6-month mid-point (i.e., 125 trading days before the announcement to 125 trading days after the announcement).[6]

The table provides results for both a pooled estimation and for firm-specific estimations. In the pooled regression, the coefficients are the same for all sampled stocks; while in the firm-specific estimation, the GARCH model is run for each stock separately. For the firm-specific estimation, we use the Fama-McBeth (1973) procedure to calculate the standard errors. In the last two columns, we provide the number of positive and negative significant that are observed when the estimation is done separately for each stock.

Coefficient	Value (pooled)	*t*-statistics (pooled)	*t*-statistics Fama/McBeth	Number of coefficients significant and positive (1% level)	Number of coefficients significant and negative (1% level)
α_1	0.77082	50.27	49.49	22	0
α_2	1.17E-4	0.32	0.19	7	6
β_1	0.86485	299.25	49.26	18	2
β_2	0.12618	46.84	13.42	18	2
β_3	1320.29	73.42	15.94	18	1
β_4	-0.81440	-13.83	-13.28	5	14

Table 3: Volatility Changes and BI Deployment

The significance of the results is qualitatively similar for both types of estimation procedures. Both estimations reveal that a firm's return is highly correlated with the market, but it is not significantly correlated with BI deployment.

In the variance equation, both the coefficients of the variance (β_1) and error (β_2) are highly positively significant, as is the coefficient of the market surprise effect (β_3). Interestingly, we find a strong negative effect of BI deployment on volatility. In fact, the BI deployment coefficient (β_4) significance is similar in magnitude to the market surprise effect (β_3). This suggests that BI deployment has a substantial effect on volatility reduction.

CONCLUDING REMARKS

BI systems change the decision-making process and improve information transparency. In this paper we analyzed companies that implemented BI systems. The arguments reviewed in this paper suggest that the incorporation of BI systems will reduce stock return volatilities. Indeed, our results show that the volatility of stock returns after BI implementation is significantly lower.

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[5] As volatility is typically measured over a one-year period (for example, for the calculation of option values), we use 250 daily return observations, which approximately correspond to one year in calendar time. We also conduct the analysis with 375 trading days (approximately 1.5 years) and 500 trading days (approximately 2 years); the results are qualitatively similar.

[6] We conducted several robustness checks to see if our results are dependent on the implementation window. Using time intervals of 0 to 24 months, the results hold, but they are somewhat less significant for the very short implementation periods. Of course, the results with no implementation period collapse to the graphic illustration of Figure 2.

While BI systems are typically considered for their potential to increase profitability, we believe that important complementary aspects that should be considered are highlighted in this study - i.e. their risk reducing effects. CIOs should be aware of those aspects to better serve the needs of different stakeholders of the organization.

For example, it is clear that banks and other debt holders would be more interested in reducing the risk of the company than in increasing its productivity. In contrast, management and employees both gain and lose from a reduction in volatility. On the one hand, lower volatility enhances job security because stable cash flows reduce turnover levels. On the other hand, management and employees are often provided incentives in the form of stock options whose value increases with volatility. Thus, depending on the particular case, using the findings of this study CIOs could better evaluate the possible implications of deployment for different stakeholders.

We believe many new directions for research can be developed from this study. For example, it would be interesting to analyze how BI systems affect employee turnover levels, the value of a company's bond, and the amount of options given to employees. As this paper has introduced an important relationship between a well-studied financial measure and information systems' impact, we believe this work can prove relevant in many ways - both for practitioners and academics.

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Appendix A: Sampled companies and deployed systems.

Company	BI System Deployed
First Citizens Bancshares Inc	ReportNet
Dana Corporation	Impromptu Web Reports, PowerPlay Web, Visualizer
Popular incorporated	Impromptu Web Reports, PowerPlay, Cognos Query
Boeing	Impromptu Web Reports
American Airlines	CognosBI Series 7
Newmont Mining	CognosBI Series 7
Kennametal	CognosEnterpriseBI Series 7
Lesco	Impromptu Web Reports, PowerPlay
StorageTek	CognosBI Series 7
Key corporation	CognosBI Series 7
Bear sterns	ReportNet
Quick Silver	Cognos BI solution
AmeriCredit	PowerPlay, CognosQuery
Harrah's Entertainment	CognosBI for CRM solution
LandAmerica	CognosBI Series 7
Landstar	CognosBI Series 7
Eastman Chemical	Cognos Enterprise Reporting solution
American Eagle Outfitters	Cognos BI solution
Aspect Medical	DecisionStream
Otis	PowerPlay
Sygneta	ReportNet
Red Robin Gourmet Burgers	Cognos Enterprise Planning