LEADS US NOT INTO TEMPTATION: KNOWLEDGE WORKERS, BUSINESS INTELLIGENCE SYSTEMS, AND OCCUPATIONAL FRAUD

Completed Research Paper

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Abstract

This paper explores how uncertainty reduction due to increased forecasting accuracy, which is one of main benefits associated with the adoption of Business Intelligence (BI) systems, will affect the behavior of knowledge workers and how this change in their behavior will impact the appropriation of benefits from BI investments. The study uses a micro-economic model in order to show that higher forecasting accuracy is likely to create the conditions for knowledge workers to behave in a morally hazardous fashion. The result of this opportunistic behavior is that knowledge workers can appropriate for themselves a relatively larger portion of the firm’s rents from BI investments that should accrue to firm and ultimately to external stakeholders. Studies that measure the payoffs from IT investments that enable more accurate forecasts, such as BI, are likely to underestimate the total benefits by the portion that knowledge workers will appropriate for themselves through their opportunistic behavior.

Keywords: Knowledge workers, Business Intelligence, Occupational Fraud, IT value, IS models, Agency Theory, Moral hazard
Introduction

Globalization and hypercompetitive markets require organizations to react quickly to changes in the marketplace. This requires evaluating and responding to changes in market conditions faster, thus making information accuracy and uncertainty reduction a critical competence for competitive advantage. In response, firms are making substantial investments in a variety of applications to analyze, mine, query and process firm-owned and external data. These applications, known as business intelligence (hereafter BI), help managers, among others, predict changes in competitive environment and develop response plans. The justification for these investments are readily supported by the numerous success stories (e.g., Harrah’s, Capital One, and Boston Red Sox) reported in the popular press and trade journals. In addition, empirical evidence supports the link between uncertainty reduction and improved resource allocation, decision timeliness, decision quality (Cyert and March 1992; Devaraj and Kohli 2003; Galbraith 1973; Stiglitz 2000) and user productivity (Aral et al. 2006).

This proliferation of BI applications promotes a democratization of information (Duckers 2007; Henschen 2009), fueling the increasing need for knowledge workers (Apte and Nath 2007). Knowledge workers tend to be high-level employees with significant experience and/or expertise who acquire, manipulate, and interpret information in order to deal with complex problems. While the number of knowledge workers is increasing, we lack an understanding about how BI will affect knowledge workers’ habits and behaviors or how these changes may impact IT value creation, the organization, and organizational stakeholders (Aral et al. 2006). This study explores how forecasting accuracy, one of main benefits associated with the adoption of BI (Henschen 2009) and a proxy for uncertainty reduction, affects the behavior of knowledge workers and how these behavioral changes can create moral hazard and impact the appropriation of benefits from BI investments.

Given that BI projects are more likely to succeed if adopted by knowledge workers rewarded for their ability to achieve specific goals (Mulcahy 2007), we develop a micro-economic model in which knowledge workers are trying to maximize their expected payoff from meeting a performance related goal. In our setting, knowledge workers will leverage BI to produce more accurate forecasts (thus achieving higher certainty) of their expected performance and to know whether effort alone is likely to maximize their expected payoffs. In the event that these predictions indicate a shortfall, they can use the time advantage to increase the likelihood of achieving their goal through fraudulent action.

In addition, our analytical model demonstrates that knowledge workers can appropriate a relatively large portion of the firm’s rents from BI investments. In other words, there is a portion of BI benefits, which we refer to as ‘knowledge workers’ quasi surplus,’ that is not likely to manifest in firm level accounting or market performance metrics. Although from a welfare standpoint this may appear as a simple reallocation of benefits from firm stakeholders to knowledge workers, the ramifications of such opportunistic behavior on the firm, external stakeholders, and society in general are unknown. From an academic standpoint, this study provides an initial theoretical foundation for future work that seeks to understand user behavior and how it affects payoff appropriations from IT investments. From a professional standpoint it raises the need to couple investments in BI with more stringent internal controls.

The remainder of this paper is presented as follows. Section 2 provides background information about BI systems and occupational fraud. Section 3 develops and discusses the analytical model and related propositions. Section 4 concludes with a discussion of the implications and limitations of the analytical model and potential future research.

Business Intelligence Systems and Occupational Fraud

Each day, knowledge workers make decisions that can impact the future of a firm; thus, reducing uncertainty, concerning how current and short-term actions will impact future performance, is an ongoing concern. Traditional approaches to uncertainty reduction include the use of consultants, developing end-user decision support systems or knowledge repositories, and development and application of performance metrics.

Each of these traditional approaches can enhance uncertainty reduction; however, BI offers several advantages over more traditional methods. BI is pervasive. Data contained in the BI crosses traditional intra-firm boundaries such as departments or divisions and can incorporate data from external sources.
such as trade groups allowing industry dynamics to be incorporated into decision analysis. The
pervasiveness of the information contained in the BI ensures analysis is complete and considers the firm
in totality.

Data contained in the BI are the most current available. Unlike traditional performance metrics generated
using dated historical information, performance metrics generated with BI will reflect the most current
information concerning the results of prior firm actions. BI also eliminates reporting backlogs by
providing a single access point for information that enables on-demand generation of the reports and
metrics used to evaluate performance as well as ad-hoc creation of new metrics.

Finally, analysis and decision-making utilizing BI are not subject to heuristics, biases, and cognitive load
limitations inherent in human decision processes. Nor is the information and analysis incorporated in the
BI tacit. The explicit information and decision algorithms contained in the BI facilitate post-hoc decision
analysis and adjustment. In addition, the ability to quickly and easily alter decision parameters allows
faster and more complete analysis of alternate decision scenarios. Traditional methods, such as end-user
decision support systems (e.g., an Excel decision support systems), are difficult to develop, somewhat static
as to input variables, subject to programming error, and frequently unavailable firm wide.

While the benefits of BI use explain its rapid adoption by firms, there is a lack of anecdotal information
and academic investigation concerning the potential negative effects of BI use on firms and the knowledge
workers they employ. This paper investigates one potential negative effect, an increase in temptation to
commit occupational fraud, attributable to the use of BI by knowledge workers. We define temptation as a
condition leading to an increase in knowledge worker’s utility level, which is attributed to a fraud driven
increase in reward without a corresponding increase in risk.

Occupational fraud is an international problem costing firms approximately 5% of their annual sales
of one’s occupation for personal enrichment through the deliberate misuse or misapplication of the
employing organization’s resources or assets” Thus, in addition to theft of corporate assets and financial
statement fraud, occupational fraud includes such activities as intentionally adding slack to a budget to
ensure a satisfactory performance appraisal or adjusting performance, when such adjustment is
detrimental to the firm, to achieve a bonus.

According to classical fraud literature, all fraud incidents contain three elements: motivation,
rationalization, and opportunity. These three elements are interactive and form what is known as the fraud
triangle. Motivation refers to the incentive facing managers and executives to commit a fraud, such as
greed (financial incentives) and pressure (to meet expectations) (Albrecht et al. 2010). Rationalization
refers to the reason (e.g., I’m underpaid) fraud perpetrators use to justify committing fraud (Albrecht et al.
2010). Opportunity refers to the situations or conditions that allow a person to commit a fraud, such as
ineffective internal controls or insider information. Fraud perpetrators must have a perceived opportunity
or they will not commit fraud (Albrecht et al. 2010).

There is a growing body of literature on IT related unethical behavior (e.g., use of Internet for phishing;
software piracy; hacking and denial of service attacks of e-commerce sites), but attention to occupational
fraud is relatively limited. In most studies, technology is either the target or the vehicle for perpetrating
occupational fraud. The objective of our study is to propose that an undesired side effect of IT, particularly
business intelligence and business analytics, is to create an environment conducive to occupational fraud
(hereafter fraud). More specifically, we argue that BI systems provide knowledge workers with private
information (i.e., increased certainty regarding the accuracy of forecasts) that can be used to appropriate
BI investment benefits that should accrue to the firm. We are not suggesting that the increased temptation
to commit fraud will result in the actual occurrence of fraud, as fraud requires motivation, rationalization,
and opportunity. However, an increase in the temptation to commit fraud will, ceteris paribus, increase
the probability of fraud occurring.

Theoretical Model and Propositions

The theoretical model developed in this section is generalizable to numerous principal agent scenarios
both internal and external to the firm. In the following subsections, we develop and present the

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1 The term ‘fraud triangle’ was introduced by D. Cressey in his seminal work, “Other People’s Money” (1953).
Model Assumptions

We consider a two-person, single period $t \in [0,1]$, principal agent model. The agent takes some action (selects a level of effort) $\alpha \in [a, \overline{a}] \subseteq \mathbb{R}$ that is not directly observable by the principal. The agent may or may not commit fraud. The principal will not knowingly employ an agent that has been detected committing fraud. The probability that a fraud will be observable is a function of $C$, the effectiveness of the firm’s internal controls ($C \in \mathbb{R} | C \geq 0$) and the magnitude of manipulation ($m$), that is $p = p(m, C) \in [0,1]$ with $p_m > 0$ and $p_C > 0$.

Agent’s effort-based and fraud-based actions along with a random unobservable state of nature ($\theta$) generate a signal $x = x(a, \theta, m)$ that is observable by the principal at the end of the period. While the signal is observable, unless fraud has been investigated and detected, the principal cannot make the distinction between $x(a, \theta|m = 0)$ and $x(a, \theta|m \neq 0)$. Assuming that state of nature ($\theta$) is uniformly distributed, i.e., $\theta \in [\theta, \overline{\theta}]$, and agent’s effort ($\alpha$) has a multiplicative effect on $\theta$, while magnitude of manipulation ($m$) is simply additive, the signal ($x$) will be uniformly distributed, i.e., $x \in [\underline{x}, \overline{x}] \subseteq \mathbb{R}$.\(^2\)

The agent’s compensation $\psi \in [\underline{\psi}, \overline{\psi}] \subseteq \mathbb{R}$ is a function of the observed signal. In order to motivate the agent to achieve the desired goal (e.g., contain cost or raise revenues) firms tend to link compensation to performance by providing incentives to agents to achieve task goal ($G$). For example, the principal selects the performance goal ($x - G \geq 0$ for a revenue related goal or $x - G \leq 0$ for a cost related goal) in the beginning of the period ($t = 0$). A commonly used compensation form, associated with a revenue related goal, is an option-like contract such as $\psi = \psi + \beta \max(x - G, 0)$.\(^3\) This corresponds to a salary of $\psi$ and $\beta$ options that have an exercise price of $G$. This can be viewed as a bonus $R = \beta \max(x - G, 0)$ that kicks in once a target level of performance (which corresponds to the option’s exercise price) is achieved. This contract means that the agent’s compensation will be equal to base salary ($\overline{\psi} = \underline{\psi}$) if the agent fails to meet the pre-specified performance goal ($x - G < 0$) and the compensation will be the base salary plus the reward ($\psi = \underline{\psi} + R = \overline{\psi}$) if the agent meets or exceeds the performance goal ($x - G \geq 0$).

The residual $x - \psi (x)$ will accrue to the principal who is trying to maximize the following utility function: $W [x(a, m, \theta) - \psi (x)]$ with $W' > 0$ and $W'' < 0$. On the other hand, agents are trying to maximize their own utility function, which is assumed to be additive and separable in terms of compensation ($\psi$) and selected level of effort ($\alpha$). Additionally, the agent is assumed to be risk neutral and ‘upper bound’ work seeking. The former means that the agent will be willing to take an extra risk if there is a proportional increase in the reward. The latter means that the agent places high value in achieving that maximum reward $\psi = \overline{\psi}$ and, in order to secure this level of reward, is willing to apply the maximum possible level of effort towards achieving the necessary performance related goal. In other words, if a level of performance $x - G \geq 0$ can be achieved with effort $\alpha \in [a, \overline{a}]$ the agent will choose to apply the maximum level of effort ($\alpha = \overline{a}$) towards achieving the performance goal. Therefore the agent’s utility function is given by $U = U(\psi) - V(\overline{a})$ with $U'(\cdot) > 0$ and $U''(\cdot) < 0$. While recognizing neo-classical economic theory posits that agents will exert only the effort necessary to maximize their individual utility function, we adopt the assumption of maximum effort to simplify model presentation. The propositions and associated corollaries derived from the model, while more computationally complex, remain unchanged when the assumption of maximum effort is relaxed.

Given that the agent’s level of effort is not directly observable, the principal’s problem is described as follows:

\[^2\] For simplicity we assume that $x$ is the actual monetary outcome of interest to the principal. An alternative might have been to assume that agent’s actions affect a vector of $x$ signals, which in turn affect the variable of interest to the principal via $y = y(x) \in Y \subseteq \mathbb{R}$ and $y_C \geq 0$. However, this assumption adds complexity without altering the main results of this study.

\[^3\] Given the symmetric nature of the $x$-distribution, the overall results will not be altered if we were to introduce a cost-related goal.
\[
\max_{\psi, \alpha} \int [W [x (\alpha, m, \theta) - \psi (x)]] \, dx
\]
subject to the following constraints:
\[
\int [U [\psi (x)]] \, dx - V (\alpha) \geq U
\]
\[
\alpha \in \arg \max \int [U [\psi (x)]] \, dx - V (\alpha)
\]

However, given that the agent is risk neutral and ‘upper bound’ work seeking, the solution that the principal will select is such that the agent will always adopt an upper bound border solution in terms of \(\alpha\).

To demonstrate the model assumptions discussed above, we create a simple hypothetical inventory management scenario. Our knowledge worker is the inventory manager (hereafter manager) for a distributor. The manager is responsible for predicting customer demand, ordering and storing merchandise sufficient to meet customer demand, and shipping merchandise to customers. Thus, one of the manager’s key responsibilities is to accurately anticipate customer demand and obtain sufficient merchandise to meet the anticipated demand while simultaneously minimizing inventory holding costs and controlling the number of stock outs. The manager has developed an Excel based decision support system (DSS) to calculate inventory orders. The DSS determines the amount of inventory to order using prior year same week sales scaled by prior months sales.

The manager’s compensation is comprised of a yearly base salary plus a quarterly bonus. The owner (i.e. principal) instituted the bonus program to minimize inventory holding costs while ensuring customers do not become dissatisfied because of stock outs. For the manager to achieve the quarterly bonus, inventory holding costs and number of stock outs must be below an amount determined by the owner. The owner sets the bonus targets at the beginning of each quarter. To date, the owner is satisfied with the manager’s performance. However, bonus target levels are not always achieved. There is no evidence of fraud by the inventory manager.

**Forecasting Accuracy and Temptation to Commit Fraud**

During the period \(t \in (0, 1)\) the agent can leverage BI tools to update predictions regarding the likelihood of achieving the desired level of compensation given the state of nature and the chosen level of effort. At some point \(t \in (0 + l, 1 - k)\), with \(l, k \in \mathbb{R}^+\), such that \(l\) and \(k\) are long enough to allow the agent to observe the result of his/her effort but not close enough to the end of period when the signal is observed by the principal, the rational agent will have to make the following choices. What is the likelihood that the selected level of effort will deliver the maximum and desired level of compensation? If this likelihood is diminishing, what is the smallest possible amount of error that could lead to the maximum level of compensation? Therefore, the agent will try to achieve

\[
\max_m E (\psi) = E \left[ \psi + \beta \max [x (\alpha, \theta, m) - G, 0] \right] \tag{1a}
\]

Given that the effect of \(m\) on \(x\) is simply additive and using the law of total expectations this is written as follows:

\[
\max_m E (\psi) = \psi + R (1 - p) \, \text{Prob} [x + m \geq G] - p \, (m; C) P \tag{1b}
\]

Given that \(\psi\) is fixed during the current period, the agent’s problem becomes that of maximizing the following expected incremental compensation function:

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4 In our analysis we have been looking at examples when the magnitude of fraud is entering incrementally in the final value of the signal in order to contribute to the knowledge worker effort to maximize some performance measure (e.g., generate sales above historical average or increase customer satisfaction or customer retention). However, one can easily reverse this to include cases when the fraud reduces the value of the reported signal in order to minimize another performance related measure (e.g., reduce production cost, inventory holding cost, or budgeted expenses below historical average). In such an example the contract will be written as \(\psi = \psi + \beta \max (G - x, 0)\) and the agent’s
\[
\max_{m} B(m) = R (1 - p) \text{Prob}[x + m \geq G] - p P
\]  

(1c)

Where \( P \) is the penalty for committing fraud, \( p = p(m, C) \) is the fraud detection probability, and \( C \) is a parameter and proxy for effectiveness of existing internal controls. The probability of detection \( p \) is an increasing function of \( m \) and when \( m \) is sufficiently large \( p \) will approach 1. Values of \( C \) approaching zero indicate that internal controls are very effective and as a result, the probability of detection is very high. While there are business intelligence tools that could be used to detect fraud, the principal does not have an incentive to make such an investment in the current period. Recall that the principal will not knowingly employ an agent that has been previously detected committing a fraudulent act. Absent evidence of fraud, the cost of additional controls exceeds the potential benefits derived from the introduction of new internal controls.

For tractability, we will assume that the functional form of \( p = \frac{m}{m + C} \). This functional form meets the conditions \( p_m' > 0 \) and \( p_c' > 0 \). Therefore, we can compute the expected incremental compensation as:

\[
B(m) = \begin{cases} 
\frac{CR + \frac{mP}{C + m}}{C + m} & \text{if } G - m \leq \bar{x} \\
\frac{CR(\bar{x} - G + m)}{(C + m)(\bar{x} - \bar{x})} - \frac{mP}{C + m} & \text{if } \bar{x} \leq G - m < \bar{x} \\
\frac{-mP}{C + m} & \text{if } \bar{x} \leq G - m 
\end{cases}
\]

(1d)

In order to find the optimum value of the compensation, we take the first derivative of (1d) with respect to \( m \) and find the value of \( m \) at which this is equal to zero \([B'(m) = 0]\) and see if the second derivative of (1d) is less than zero \([B''(m) < 0]\). If we let \( m^* \) denote the global optimum solution, from (1d) it is clear \( m^* > G - \bar{x} \) since \( B(m) < 0 \) for \( m < G - \bar{x} \). It is also clear that \( B(m) \) is decreasing when \( m > G - \bar{x} \), so we also have \( m^* < G - \bar{x} \). Therefore if there is a positive optimal solution \( m^* \), it must be in the range \([G - \bar{x}, G - \bar{x}]\).

Assuming that \( m \) is in the range \((G - \bar{x}, G - \bar{x})\), we have that

\[
B'(m) = \frac{CR(C - \bar{x} + G)}{(C - \bar{x})(C + m)^2} - \frac{CP}{(C + m)^2} = \frac{CR}{(C + m)^2} \left( \frac{C - \bar{x} + G}{\bar{x} - \bar{x}} \cdot \frac{P}{R} \right)
\]

(2)

If the following condition is met

\[
\frac{C - \bar{x} + G}{\bar{x} - \bar{x}} \geq \frac{P}{R}
\]

(3)

then \( B(m) \) is increasing and it gets the maximum at \( m = G - \bar{x} \), that is \( m^* > G - \bar{x} \). Otherwise \( B(m) \) is decreasing and it gets the maximum at \( m^* = G - \bar{x} \). However, \( B(G - \bar{x}) \) is a negative value, therefore there exists no positive optimal solution in this case. Therefore, there is a positive optimal solution \( m^* > G - \bar{x} \) if and only if \( G > \bar{x} \) and (3) is true. If there is an optimum solution \( m^* \) then

\[
B(m^*) = \frac{CR(G - m^*)}{(C + m^*)(\bar{x} - \bar{x})} - \frac{m^*P}{C + m^*}
\]

(4)

If we replace \( m^* = G - \bar{x} \) then (4) will become

\[
B(G - \bar{x}) = \frac{CR - GP + xP}{(C + G - \bar{x})}
\]

(5)

Given that signal \( x \) is uniformly distributed in \( x \in [\bar{x}, \bar{x}] \), an increase in forecasting accuracy will be reflected in a smaller range for \( x \). Therefore the sensitivity of \( B(m^*) \) to an improvement in agent’s ability to forecast future performance with higher accuracy can be established as follows:

\[
\text{problem becomes that of maximizing the expected incremental compensation via } \max_{m, \bar{x}} B(m) = R (1 - p) \text{Prob}[G \geq x - m] - pP.
\]
Accordingly, the owner sets new bonus targets reflecting the investment in the new BI systems. After several ordering and delivery cycles are completed, the manager concludes that the forecasts produced by the new BI are more accurate and, when used, do decrease inventory holding costs while simultaneously minimizing stock outs. If the manager decides to commit fraud, there are several approaches available. Given that the cost of merchandise is one of the larger variable costs associated with holding inventory, the manager can attempt to reduce the amount of merchandise ordered from suppliers. However, this increases the potential for stock outs. If the owner has set the stock out bonus target to zero, the manager can intentionally short customer orders a small amount of merchandise, relying on the customer’s internal controls to miss the potential for fraudulent activity. Stated as the first proposition:

**Proposition 1:** Ceteris paribus, an increase in a knowledge worker’s ability to forecast future performance, i.e., smaller $x$ range, will increase the temptation to commit fraud.

Additionally, we have that $m^* = G - x = G - \mu + \sqrt{3}\sigma$ and from this we can easily see that $\frac{\partial m^*}{\partial \sigma} > 0$. This means that as a knowledge worker’s ability to produce more accurate forecasts increases ($\sigma$ is getting smaller) the fraud magnitude needed in order to achieve the maximum payoff is decreasing. Thus a logical corollary of the optimization process under increasing forecasting accuracy follows:

**Corollary:** Ceteris paribus, if there is an optimum solution, an increase in a knowledge worker’s ability to forecast future performance, i.e., smaller $x$ range, will lead to a lower level of fraud ($m^*$).

Taken together, Proposition 1 and its related corollary suggest that increased information accuracy, attributable to BI use, enhances agent temptation to commit fraud by reducing the magnitude of fraud necessary to achieve a desired result, which reduces the likelihood of detection.

To discuss the implications of Proposition 1 and its related corollary, we assume the owner has initiated a new BI system. Part of the functionality of this system is to improve the manager’s ability to forecast customer demand and decrease inventory-holding costs. To achieve these goals the BI systems use a sophisticated decision aid which incorporates yearly and monthly customer specific trend analysis, algorithms designed to detect whiplash ordering by customers, and advanced delivery and shipping scheduling software intended to minimize inventory holding time, as well as the information previously contained in the managers DSS. The owner believes the use of BI will improve the manager’s ability to accurately forecast customer demand, thus reduce inventory-holding costs while minimizing stock outs. Accordingly, the owner sets new bonus targets reflecting the investment in the new BI systems.

After several ordering and delivery cycles are completed, the manager concludes that the forecasts produced by the new BI are more accurate and, when used, do decrease inventory holding costs while simultaneously minimizing stock outs. The manager, using the increased predictive accuracy of BI, can calculate the probability of obtaining the current quarter performance bonus. The manager concludes that despite best efforts, the bonus target cannot be achieved.

Having expended the maximum amount of effort to achieve the bonus target, the manager may accept the impending bonus loss or choose to commit fraud to achieve the bonus target. If deciding to commit fraud, the increased forecasting accuracy of BI provides two advantages to the manager. First, because the manager can predict the failure to achieve the bonus earlier in the bonus period, more time is available to analyze, evaluate, and implement fraud schemes. Second, because the increased accuracy of BI forecasts provides a more precise estimate of fraud that must be committed to achieve the desired bonus target, the manager can minimize the level of fraud committed. Because the manager’s fraud activities can be smaller, potentially more frequent, and dispersed over a longer period of time, existing internal controls will be unable to detect anomalous activities indicative of fraud.

If the manager decides to commit fraud, there are several approaches available. Given that the cost of merchandise is one of the larger variable costs associated with holding inventory, the manager can attempt to reduce the amount of merchandise ordered from suppliers. However, this increases the potential for stock outs. If the owner has set the stock out bonus target to zero, the manager can intentionally short customer orders a small amount of merchandise, relying on the customer’s internal controls to miss the

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5 One can arrive to the same conclusion by looking at the condition for manipulation (3). If in (3) we set $\bar{x} = \mu - \sqrt{3}\sigma$ and $\bar{\bar{x}} = \mu + \sqrt{3}\sigma$ then we have $\frac{\partial^2 B(m^*)}{\partial x^2} = \frac{PC + CR}{(C + G - x)^2} > 0$. Since an increase in $x$ leads to an increase in $B(m^*)$, in other words, as a knowledge worker’s ability to produce more accurate forecasts increases ($\sigma$ is getting smaller) the expected payoff is increasing, which provides a temptation for fraudulent activity. Stated as the first proposition:

\[
\frac{\partial B(m^*)}{\partial x} = \frac{PC + CR}{(C + G - x)^2} > 0
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\[
\frac{\partial B(m^*)}{\partial x} = \frac{PC + CR}{(C + G - x)^2} > 0
\]
small discrepancy. Using BI, the manager could further refine this approach by targeting customers that infrequently complain. While this approach may not eliminate customer complaints, the missing merchandise can be attributed to human error.

If the owner sets the stock out bonus target to 5 occurrences per 200 deliveries, the manager can use the superior forecasting accuracy of the BI to determine how many stock outs would occur naturally. If this number is below the bonus target (i.e., 6 more stock outs can occur without exceeding the bonus target for stock outs), the manager may intentionally order less merchandise to reduce inventory hold costs and allow 6 more stock outs to occur. In a refinement to this approach, the manager could accept the occurrence of the 6 stock outs, but, using BI to analyze customer profitability, target these stock outs to less profitable customers. If the owner questions the number of stock outs, the manager accepts the blame, but can point out that these customers are not highly profitable and should probably be dropped. Thus, the manager, while accepting blame for the stock outs, can achieve the performance bonus by committing fraud while, post hoc, engaging in impression management by appearing to serve the firm’s best interests.

**Forecasting Accuracy and Relative Magnitude of Fraud**

Up to this point we have assumed that the establishment of a goal is external. However it is more realistic that the goal will incorporate the more accurate forecasts that a suite of BI tools could produces. As a way of internalizing the goal within the model, we assume that the goal is set equal to the average of expected performance, i.e., \( G = (\bar{x} + \bar{x})/2 \). Based on the optimization conditions, if \( G = (\bar{x} + \bar{x})/2 \) then \( m^* = G - \bar{x} = (\bar{x} - \bar{x})^2/2 \). Therefore we can easily deduce the above corollary that as the forecasting accuracy level increases (i.e., \( \bar{x} - \bar{x} \) is getting smaller) the optimum level of manipulation is decreasing. Additionally, the payoff becomes

\[
B(m^*) = \left(2CR - P(\bar{x} - \bar{x})\right) / \left(2CR - (\bar{x} - \bar{x})\right)
\]

From this it is clear that as forecasting accuracy increases (\( \bar{x} - \bar{x} \) is getting smaller) the optimum payoff \( B(m^*) \) is increasing. Thus, the incentive and temptation to manipulate is higher. This confirms that our first proposition holds equally well under conditions when the knowledge worker is asked to maximize revenue (i.e., achieve sales above a certain level) or minimize costs (i.e., bring cost below a certain level).

While knowing that the magnitude of manipulation will decline as a result of the increased forecasting accuracy may be interesting, modeling is not needed as a proof.\(^6\) However, the model can be used to evaluate the relative size of optimum manipulation. Put another way, “Will the fraud magnitude, when expressed as percentage of the new mean \( m^*_\mu = m^*/\mu \), rise or fall?”

Recall that \( m^* = G - \bar{x} = G - \mu + \sqrt{3}\sigma \). If the goal is set equal to the mean of the expected performance, i.e., \( G = (\bar{x} + \bar{x})/2 \), then \( m^* = \sqrt{3}\sigma \) and \( m^*_\mu = \sqrt{3}\sigma / \mu \). Both sides, principal (owner) and agent (knowledge worker), understand that an investment in a new BI system is not only designed to reduce uncertainty (\( \sigma \)) but the expected value of the distribution (\( \mu \)) as well. Therefore, if we want to find the effect of an increase in forecasting accuracy on relative magnitude of fraud we need to consider the sign of the total differential of \( m^*_\mu \), which is given by

\[
d(m^*_\mu) = \left(\sqrt{3}/\mu\right) [\mu d\sigma - \sigma d\mu]
\]

\(^6\) Under the new distribution, more probability mass is “centered” in the middle, with only a little in the two ends. This is the assumption of the model. In order to reach the fixed threshold value (the level that once exceeded, a reward will be given), any upward adjustment with a fixed magnitude, will cover more probability under the new distribution (which has smaller standard deviation). That is, compared to the original distribution of \( \sigma \), under the new distribution, a manipulation with same magnitude will have larger probability to exceed the threshold value. Since more manipulation, on the other hand, also means higher detection probability and hence imposes negative effect, the conclusion that the manipulation magnitude will be smaller under new distribution follows naturally.
Therefore \( \text{sgn} \, d(m^*_\mu) = \text{sgn} \, [\mu \cdot d\sigma - \sigma \cdot d\mu] \) and the sign of the total differential will depend on the direction of the expected benefits. An investment in a BI that mines the firm’s databases and allows the firm to identify the needs of customers and respond to changes in their preferences or needs in a timely manner is likely to not only increase sales forecasting accuracy \((d\sigma < 0)\) but also increase the volume of sales \((d\mu > 0)\). On the other hand, an investment that is geared to support the firm’s competency to integrate with its suppliers (i.e., an investment in a collaborative forecasting and replenishment initiative) is likely to lead to an increased inventory forecast \((d\sigma < 0)\) but also decrease the inventory cost \((d\mu < 0)\).

Table 1 summarizes all possible scenarios. The scenarios presented in the lower cells of Table 1 are presented for mathematical rigor, but are not intended to represent situations typically encountered in practice. Thus, our discussion will be focused to the upper two cells of Table 1 and we have the following propositions regarding the relative magnitude of manipulation:

<table>
<thead>
<tr>
<th>(d\sigma)</th>
<th>(d\mu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(d\sigma &lt; 0)</td>
<td>(d\mu &gt; 0)</td>
</tr>
<tr>
<td></td>
<td>((m^*<em>\mu)</em>\uparrow) &lt; 0</td>
</tr>
<tr>
<td></td>
<td>(\Rightarrow)</td>
</tr>
<tr>
<td></td>
<td>(m^*_\mu \downarrow)</td>
</tr>
<tr>
<td>(d\sigma &gt; 0)</td>
<td>(B(m^*) \downarrow)</td>
</tr>
<tr>
<td></td>
<td>(\frac{d\sigma}{\sigma} \cdot \frac{d\mu}{\mu} &gt; 0)</td>
</tr>
<tr>
<td></td>
<td>(\Rightarrow)</td>
</tr>
<tr>
<td></td>
<td>((m^*<em>\mu)</em>\uparrow)</td>
</tr>
</tbody>
</table>

**Table 1**

**Proposition 2a.** If \(d\sigma < 0\) and \(d\mu > 0\), then the total differential is negative, i.e., \(d(m^*_\mu) < 0\), which means the relative magnitude of the optimum fraud \((m^*_\mu)\) will decrease.

The adoption of a BI system that delivers both in terms of a performance improvement (e.g., the goal is to increase sales, so \(d\mu > 0\) is desirable) and more accurate forecasts will be associated with a greater temptation to commit fraud \((B(m^*) \uparrow)\) and the magnitude of fraud will decrease both in absolute \((m^* \downarrow)\) and relative terms \((m^*_\mu \downarrow)\).

**Proposition 2b.** If \(d\sigma < 0\) the result will depend on the comparison between \(\frac{|d\sigma|}{\sigma}\) and \(\frac{|d\mu|}{\mu}\).

If \(\frac{|d\sigma|}{\sigma} > \frac{|d\mu|}{\mu}\), then the total differential is negative, i.e., \(d(m^*_\mu) < 0\), which means that the relative magnitude of the optimum fraud \((m^*_\mu)\) will decrease.

On the other hand if \(\frac{|d\sigma|}{\sigma} < \frac{|d\mu|}{\mu}\), then the total differential is positive, i.e., \(d(m^*_\mu) > 0\), which means
that the relative magnitude of the optimum fraud \((m^*_\mu)\) will increase.

Adoption of a BI system that delivers both in terms of performance improvement (e.g., goal is to reduce cost, so an \(\Delta u < 0\) is desirable) and more accurate forecasts \(\Delta \sigma < 0\), and produces a change in forecasting accuracy, which in absolute relative terms is larger than the change in performance, \(|\Delta \sigma/\sigma| > |\Delta u/\mu|\) will be associated with a greater temptation to commit fraud \((B(m^*) \uparrow)\) and the magnitude of fraud will decrease both in absolute \((m^* \downarrow)\) and relative terms \((m^*_\mu \downarrow)\). On the other hand, if the absolute relative change in forecasting accuracy is smaller than the absolute relative change in performance \(|\Delta \sigma/\sigma| < |\Delta u/\mu|\), it will be associated with a greater temptation to commit fraud \((B(m^*) \downarrow)\). However, while the absolute magnitude of the committed fraud will decline \((m^* \downarrow)\), the relative magnitude will increase \((m^*_\mu \uparrow)\).

The principal is most concerned with those scenarios where \((m^*_\mu \downarrow)\) is decreasing in relative and/or absolute magnitude. In these scenarios, the ability of the principal to detect manipulation and fraud is reduced, thereby increasing the agent’s temptation to commit fraud without detection and punishment. Of special concern is the optimal scenario for the principal, which occurs in the upper left quadrant of Table 1, as this scenario represents the ‘optimal’ temptation for the agent to commit fraud without detection. Under this particular scenario, additional investments in internal controls are critical.

**Forecasting Accuracy and Appropriation of Rents**

Finally, we examine the implications of knowledge workers’ opportunistic behaviour on the appropriation of benefits from investment in BI systems that can deliver, among other benefits, more accurate forecasts. Over the last twenty years numerous studies have focused on the theoretical underpinnings and empirical validation of payoffs from IT investments and productivity. The resource based view and micro-economic production functions have been used to theorize and validate the payoffs from IT investment using firm, industry, or country level data. The common denominator in all of these studies is the assumption that technology related characteristics, such as heterogeneity or inimitability and complementarity of IT investments with other resources, accounts for variations among payoffs from IT investments (Brynjolfsson and Hitt 1996; Mata et al. 1995; Melville et al. 2004; Piccoli and Ives 2005; Powell and Dent-Micallef 1997). Only recently, attention is shifting towards studies exploring the role of users. For example, Devaraj and Kohli (2003) postulate and show that actual usage of technology is strongly and positively associated with measures of hospital revenue and quality. Similarly, Aral et al. (2006) examine the role of IT use and skills, structure, and size of users’ communication networks on the productivity of knowledge workers.

Our study contributes to this line of research by introducing another factor that can account for a firm’s inability to appropriate all the benefits from IT investment. A firm’s ability to appropriate benefits associated with an investment to a specific IT resource is related to the rent generating potential of this resource (Amit and Schoemaker 1993; Collis and Montgomery 1995). Prior research has recognized that it is possible that an IT resource which is valuable and rare not to produce the desired benefits if the firm is unable to appropriate the expected benefits from this IT investment. While this inability to appropriate benefits has been considered in IT business value literature, this has mostly been done in terms of users exploiting labour market conditions in order to earn higher wages. For example, a firm may expect to gain a competitive advantage (economic rent) by hiring employees with rare and valuable skills. However, if the market demand for employees with such skills is very high, as it was the case with ERP-knowledge-able personnel during the 1999-2000 period, the benefit accruable to the firm may be appropriated away by the employee through higher than normal wages or compensation (Wade and Hulland 2004). Our study expands this line of research by examining the implications of knowledge workers’ opportunistic behaviour on owner’s ability to appropriate all the benefits from the BI system investment.

This study proposes a different type of appropriation that accrues to agents motivated to commit fraud as a result of the increased temptation provided by BI systems that increase forecasting accuracy. Consider the following scenario. The agent (knowledge worker) is rewarded based on his/her ability to achieve a level of performance, which is above the historical average. The probability of achieving the goal is 50% and the amount of the reward is \(R\), therefore the expected value of the reward is \(E(R^*) = \text{Prob}(\text{Achieving Goal})R = R/2\). The owner of the company (principal) invests in a new BI system.
that the knowledge worker, with the appropriate experience and expertise, could use to produce more accurate forecast and thus achieve the performance goal. The new system can produce more accurate forecasts ($\Delta < 0$) and a higher performance level ($\Delta > 0$). Both principal and agent understand that the new investment will lead to superior performance. The principal offers the same reward as before. In other words, the agent will receive a reward ($R$) if s/he delivers a level of performance, which is above the new expected average. This means that the expected value of the agent’s reward will remain the same. The justification for the principal’s choice is based on the fact that the agent needs to apply the same level of effort as before in order to achieve the bonus, hence the reward should be the same. Additionally, the principal has made the investment and thus should be the only one that appropriates the incremental benefits from this investment. Therefore, the investment will result in Pareto equilibrium. However, as we have seen from our first proposition, higher forecasting accuracy will increase the agent’s temptation to commit fraud. If the agent succumbs to the temptation to commit fraud; the agent could achieve a level of payoffs ($B(m')$) that is higher than $E(R')$, and thus appropriate a portion of the BI investment benefits, that should accrue to the principal. The $B(m') - E(R')$ represents the ‘knowledge workers’ quasi surplus.’ As we have seen the maximum expected payoff $B(m')$ that the agent can achieve by committing fraud is given by (5) and it is equal to $(CR - GP + xP)/(C + G - x)$. Therefore if

$$(CR - GP + xP)/(C + G - x) \geq R/2,$$

then we have evidence of appropriation of IT benefits by the agent.

$$\frac{(CR - GP + xP)}{(C + G - x)} \geq \frac{R}{2} \iff \frac{R}{P} \geq \frac{2(G - x)}{C + G - x} \tag{7}$$

If we assume that the goal is set at the expected level of the distribution, i.e., $G = (x + \bar{x})/2$, then (7) becomes:

$$\frac{R}{P} \geq \frac{2(G - a)}{C - G + a} = \frac{2(b - a)}{2C - (b - a)} \tag{8}$$

From the first order conditions we know that manipulation will lead an optimum payoff if (3) is met. Recall that (3) is stated as follows: $\frac{c - x + g}{x - \bar{x}} \geq \frac{b}{R}$. If we replace $G = (x + \bar{x})/2$, then (3) will become as follows:

$$\frac{P}{R} \geq \frac{2(x - \bar{x})}{2C - (x - \bar{x})} \tag{9}$$

But (8) is same as (9) which means that every time the optimization constraint is met (i.e., 9 holds) then (8) holds too. This leads to our third proposition:

**Proposition 3:** Ceteris paribus, BI investments that provide agents with an increased ability to forecast future performance will provide agents the temptation to appropriate a larger portion of the benefits of IT investment.

**Discussion, Implications and Future Research**

A recent survey conducted by Gartner (2008) showed that CIOs ranked BI as their number one investment priority. The popularity of BI systems was propelled in part by a Harvard Business Review article by Tom Davenport (2006) on “Competing on Analytics,” a bestselling book by Davenport and Harris (2007) on “Competing on Analytics: the New Science of Winning,” and a series of technological development and consolidations in the BI industry that made BI applications more accessible (Henschen 2009). Davenport, in his writings, provided numerous examples of firms that were able leverage BI in order to optimize their supply chain, reduce inventory and stock-outs (Wal-Mart, Dell, Amazon), identify customers with greater...
potential and retain their loyalty (Harrah’s, Capital One), or detect quality problems and minimize them (Honda, Intel).

While several academic studies have examined benefits from the coupling of BI and the underlying data warehouse infrastructure (Cooper et al. 2000; Counihan et al. 2002; March and Hevner 2007; Wixom and Watson 2001; Wixom et al. 2008), exploitation of the BI benefits remains challenging both technically and organizationally (Shankaranarayanan and Even 2006; Wixom and Watson 2001). Using a micro-economic model we show that one of the main benefits of BI (i.e., higher forecasting accuracy) is likely to tempt knowledge workers to behave opportunistically and in a morally hazardous fashion. More specifically, in our first proposition we show that as a knowledge worker’s ability to produce more accurate forecasts increases they can increase their expected payoff through manipulation; thus their temptation to engage in manipulation increases. This has serious implications for firm stakeholders since it is unknown how the manipulation may affect the firm. For example, if manipulation manifests in the form of creation of slack, operating cost will rise. On the other hand, if manipulation entails a behavior that increases the company’s risk exposure in a way that alienates customers or entails some form of accounting fraud, the results may be detrimental to the long-term goals of the firm and its stakeholders.

The corollary stemming out of our first proposition and the assumption of our model is that the magnitude of manipulation will decrease with increases in information accuracy attributable to BI systems. At first glance, this seems desirable; however there is an underlying threat that the firm’s control systems will be less likely to detect manipulations of smaller magnitude. Hence, the firm may be exposed to a risk of “death by a thousand cuts.” The second finding of this study is that the relative magnitude of the manipulation will depend on the type of goal (maximization or minimization) and the relative change in forecasting accuracy versus the relative improvement in the targeted performance metric itself.

Our third finding has significant implications for managers and researchers alike. Assuming a fixed contract, the knowledge worker can appropriate a higher portion of payoffs from IT investments by behaving opportunistically. This means that BI investments that produce more accurate forecasts are likely to enable knowledge workers to appropriate a relatively larger portion of the firm’s rents from such investments. In other words there is a quasi knowledge worker surplus that is not likely to be captured in the total benefits from such investments. Thus, managers and researchers evaluating the payoffs from IT investments are likely to underestimate the total benefits.

By its very nature, the neo classical micro-economic model presented in this study has some limitations. First, we assume that knowledge workers will make decisions purely in terms of monetized expected risks and expected rewards. However, we know that such decisions are much more complicated in nature and they will be affected by a host of other psychological and sociological factors. A follow up to our study would be to design an experiment in which we could control for as many of these factors as possible in order to see if our propositions would hold.

Another limitation stemming from the nature of our study is the inability of our model to incorporate or capture the exact type of manipulation that the knowledge worker will adopt. Earlier in our discussion we have alluded to the fact that creation of slack may not be as detrimental a form of manipulation as creating intentional stock outs. However, the actual effects of the manipulation may be context specific. Perhaps case studies such as those performed by Sia et al. (2002) or Elmes et al. (2005) or even fine grained studies on IT actual usage such as those performed by Aral et al. (2006) or Devaraj and Kohli (2003) will be needed to shed more light on the way knowledge workers behave.

Finally, our propositions are based on option-like contracts (i.e., the knowledge worker receives a fixed amount for achieving a certain goal). Option-like contracts have been shown to impact earnings management and induce dysfunctional behavior in the budgeting process (Healy 1985; Lambert 2006). Jensen (2010) argues that linear contracts could solve many of these problems such as an agent’s incentive tomisreport performance in the area where the discrete jump occurs. Anecdotal evidence suggests that some firms use a linear form of incentive system (i.e., the agent will receive a fixed price for achieving a minimalist goal and then be paid extra for each incremental unit of increase or decrease beyond the minimum level). However, while linear contracts could eliminate the agent’s motivation to misreport performance, they would not eliminate the incentive to manipulate performance (Lambert 2006). An extension of our work would be to contrast agent behavior under a fixed versus a linear contract to determine if linear contracts will mitigate the opportunistic behavior induced by higher forecasting accuracy.
References


Gartner Newsroom 2008. “Gartner EXP Worldwide Survey of 1,500 CIOs Shows 85 Percent of CIOs Expect ‘Significant Change’ Over Next Three Years.”

Henschen, D. 2009. “Next-Gen BI Is Here; Predictive analytics, real-time monitoring, and the speed of in-memory analysis are changing what companies should expect from BI,” in *InformationWeek*, p. 21.


