Fraudulent Financial Reporting and Technological Capability in the Information Technology Sector: A Resource-based Perspective

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Abstract

Motivated by the disproportionately high incidence of fraudulent financial reporting in the IT sector where technological capability is a major source of competitive advantage, this study investigates the possible relationship between technological capability and fraud probability in the IT sector. Technological capability is measured by a firm's technical efficiency relative to peers in transforming cumulative R&D resources into innovative output, which is a source of competitive advantage, according to the resource-based view (RBV) of the firm. Technical efficiency is estimated via data envelopment analysis. A sample of fraud firms taken from Accounting and Auditing Enforcement Releases is matched with control samples of non-fraud firms. Consistent with the RBV, technological capability is found to have a negative and economically significant effect on fraud probability. Moreover, fraud probability is insignificantly associated with the scale efficiency of innovative activities, as investment in R&D resources *per se* is not a source of sustainable competitive advantage.

Keywords: Fraudulent financial reporting; Technological capability; Resource-based view; Information technology sector.

1. Introduction

Motivated by the disproportionately high incidence of fraudulent financial reporting in the IT sector, where technological capability is a major source of competitive advantage, this study investigates the possible relationship between technological capability and fraud probability in the IT sector. Studies such as Fung (2015), Deloitte Forensic Center (2007), Martin *et al.* (2002), and Wu (2001) have documented that the IT sector is far beyond every other sector in terms of the incidence of fraudulent financial reporting. As in other sectors, revenue manipulation is the most common type of fraud investigated in the IT sector, with fictitious sales being the primary form of such manipulation. Such fictitious sales include the fabrication of purchase orders and shipping records as well as the misclassification of "round-tripping" barter and three-party transactions as revenue sources.[1]

The IT sector is notably different from other sectors in terms of product market turbulence. Studies such as Pavlou and El Sawy (2006) and Bauer *et al.* (2012) have observed that the IT sector is substantially more competitive and turbulent than are traditional sectors. The high incidence of fraudulent financial reporting by IT companies may be in part due to the large number of high-growth companies striving

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[1] For instance, Cyberkey Solution Inc. announced a fictitious USD24.5 million purchase order from the Department of Homeland Security in 2005 (SEC litigation release no. 20171). In another case, during 2000–2002, AOL Time Warner funded its own online advertising revenues by round tripping (SEC litigation release No. 19147).

to keep afloat in the highly competitive market. The IT sector also far exceeds other sectors in terms of R&D intensity. For instance, OECD (2010) reported that the IT sector's R&D spending was approximately one third of the total in OECD countries. In this sector where R&D and market competition are distinctively highly intense, technological capability is arguably a major source of sustainable competitive advantage, according to the resource-based view (RBV) of the firm (Dierickx and Cool, 1989; Nelson, 1991).

According to the RBV, a firm's competitiveness is determined by its possession of organizational resources and capabilities (Wernerfelt, 1984; Barney, 1991; Peteraf, 1993). This study argues that less technologically capable IT firms are less competitive and hence more likely to commit fraud under the enormous pressure to outperform rivals. Controlling for other factors such as executive compensation structure, growth expectation, liquidity, leverage, and flexibility for within-GAAP earnings management, this study finds that IT firms with lower technological capability are more likely to deceive or mislead investors with falsified financial statements. Conceptualizing technological capability as a firm's technical efficiency relative to peers in transforming R&D resources into innovative output, this study hypothesizes that the probability of an IT firm committing fraudulent financial reporting is inversely related to the firm's technological capability.

Studies of the RBV have examined the manner in which technological capability contributes to performance and survival (e.g., Bharadwaj, 2000; Li *et al*., 2010), but the relationship between such capability and fraudulent financial reporting has never been examined. Drawing on the current fraudulent financial reporting literature, this study adds insights into the RBV by investigating the possible relationship between technological capability and accounting fraud. Such a relationship implies an empirical regularity in accounting fraud and R&D productivity in the IT sector that researchers, investors, and regulators should not overlook.

This study also extends the fraudulent financial reporting literature by formulating fraud probability as a function of technological capability, which provides a new perspective to understand managerial incentives of committing fraud in the IT sector. In doing so, this study identifies a fraud risk factor stemming from the distinctive market and technological characteristics of the IT sector where the incidence of fraudulent financial reporting is substantially higher than in every other sector. Research has shown that firms underperforming the market are more likely to commit fraud (e.g., Fung, 2015). However, a fraud firm's true financial performance (e.g., earnings) is not revealed to investors until the fraud is discovered and the misstated performance is subsequently restated. Unlike financial performance, a firm's true ability to innovate cannot be easily misstated by managerial discretion. The findings of this study are therefore practically significant.

The remainder of this paper is organized as follows. Based on the RBV, Section 2 hypothesizes the relationship between technological capability and fraudulent financial reporting. Section 3 formulates an empirical framework to investigate the hypothesized relationship between technological capability and fraud incidence. Sections 4 and 5 describe the data and discuss the major findings, respectively. Finally, Section 6 concludes the paper.

2. Hypothesis

The hypothesis of this study is stated as follows:

> *The probability of an IT firm committing fraudulent financial reporting is inversely related to the firm's technological capability.*

According to the RBV of the firm proposed by Wernerfelt (1984) and Barney (1991), each firm is a bundle of resources and capabilities, where resources are factor inputs used to achieve the firm's business objectives and capabilities are the firm's abilities to deploy the resources (Amit and Schoemaker, 1993). As Grant (1991) and Makadok (1991) argued, while resources are basic units of analysis, firms actually obtain competitive advantage by assembling resources to create organizational capabilities. The RBV of the firm identifies a condition for a capability to provide *sustainable* competitive advantage – the capability cannot be transferred across firms (non-transferable) nor imitated by rival firms (non-imitable).

Among the various organizational capabilities, technological capability is regarded as the most important source of sustainable competitive advantage in the high-tech sector (see, for example, Dierickx and Cool, 1989; Nelson, 1991; Duysters and Hagedoorn, 2000). RBV research focused on the high-tech sector has conceptualized a firm's technological capability as its technical efficiency relative to peers in transforming R&D resources into innovative output (e.g., Dutta *et al*., 1999; Dutta *et al*., 2005; Li *et al*., 2010). Researchers interested in the IT sector have commonly adopted this capability notion of the RBV. They recognize that without sufficient technological capability, investment in R&D resources *per se* cannot provide sustainable competitive advantage because such investment can be replicated by competitors (see, for example, Bharadwaj, 2000; Santhanam and Hartono, 2003; Li *et al*., 2010).

Technological capability in terms of technical efficiency relative to rivals fulfills the RBV condition of being a source of sustainable competitive advantage because such capability embedded in a firm's intra-organizational processes is usually developed from internal path-dependent learning by doing, which cannot be transferred across firms nor imitated by rivals (Coombs and Bierly, 2006). Through learning by doing, a firm's unique understanding of its own successful development processes by which prior knowledge emerges gives it advantages in creating new knowledge along the same research stream (Helfat and Raubitschek, 2000). For instance, Irwin and Klenow (1994) found that inter-generational learning within a firm provided a competitive advantage in the semiconductor industry. Similarly, Boh *et al*. (2007a) highlighted the non-imitability of firm-specific knowledge created from learning by doing in computer software development. Such firm-specific experiences of knowledge creation give the innovating firm an understanding of new knowledge that competitors cannot obtain from patent disclosures or reverse engineering (Bogner and Bansal, 2007; Nahapiet and Ghoshal, 1998). Therefore, a firm's technological capability is unlikely to be understood and replicated by competitors without similar experiences. This probably explains the finding of persistent inter-firm heterogeneity in technological capability in the semiconductor industry in Dutta *et al*. (2005).

Given the distinctive market and technological characteristics of the IT sector (i.e., high intensities of R&D and market competition), an IT firm's non-imitable and non-transferable technological capability is arguably a major source of its sustainable competitive advantage. Sustainable competitive advantage influences a manager's decision to commit fraudulent financial reporting because a firm with such an advantage relative to competitors is less likely to consistently underperform the market (see, for example, Barney, 2001). Finance and auditing research has found evidence showing that firms underperforming the market are *ceteris paribus* more likely to manipulate their financial statements in an attempt to improve their short-term financial appearance. For instance, Fung (2015) found that the probability of a firm committing fraudulent financial reporting increases with the likelihood of the firm's financial performance (e.g., earnings) falling below the mean performance of its competitors. In practice, however, a fraud firm's true financial performance is not revealed to investors until the fraud is discovered. Unlike statements of financial performance, a firm's reporting of innovative output cannot be easily misstated by managerial discretion because each innovation is impartially examined by the US Patent and Trademark Office before a patent is granted. As this study's hypothesis states, the probability of fraudulent financial reporting is expected to be inversely related to technological capability. The key idea is that non-imitable and non-transferable technological capability provides and sustains competitive advantage.

3. Empirical framework

3.1. Measuring technological capability

A major criticism of the RBV is the difficulty involved in measuring capabilities. Makadok (1991) suggested that firm-specific capabilities, which are embedded in intra-organizational processes, provided economic returns by allowing a firm to be more *efficient* than its rivals at deploying resources. Similarly, Amit and Schoemaker (1993) emphasized that capabilities represented a firm's abilities in *efficiently* combining resources for productive activities. Capabilities in terms of a firm's technical efficiency in transforming organizational resources into outputs are sources of sustainable competitive advantage because such capabilities embedded in intra-organizational processes cannot be transferred or imitated. Following this argument, Dutta *et al*. (1999) measured capabilities as a firm's technical efficiency relative to its peers in transforming inputs into outputs.

Like prior RBV research (e.g., Dutta *et al*., 1999; Dutta *et al*., 2005; Li *et al*., 2010), this study measures technological capability as the relative technical efficiency with which a firm transforms R&D resources into innovative output. Following Griliches (1979, 1984), the cumulative R&D resources of firm *i* in year *t*, denoted by $RND_{i,t}$, is defined as

$$RND_{i,t} = RDE_{i,t} + \sum_{1}^{\tau}(1-\gamma)^{\tau}\, RDE_{i,t-\tau}, \qquad (1)$$

where $RDE_{i,t}$ is firm *i*'s R&D expenses in year *t*, and γ is the depreciation rate of R&D resources. Note that $RDE_{i,t}$ is an aggregated measure of research input including wages paid to employees performing research activities, supplies used in the conduct of research, and payments to outside contractors for the performance of research.[2] Without *a priori* knowledge of the values of γ and τ, this study follows Griliches's (1984) assumptions to set $\gamma = 0.4$ and $\tau = 3$.

Let $PAT_{i,t}$ be the innovative output measured by the number of patented innovations created by firm *i* in year *t*. Patented innovations are commonly considered as innovative output because every patented innovation must meet the patentable criteria set by the US Patent and Trademark Office (USPTO) – the invention must be novel and non-trivial and have commercial applications.[3] Each patent has application and grant dates, where the difference between the two dates is the "grant lag". As a common practice in prior research, $PAT_{i,t}$ is defined as the number of patents with applications filed in year *t* to capture the exact time at which the patented innovations were created (see, for example, Griliches, 1990; Popp *et al*., 2003).[4]

This study uses data envelopment analysis (DEA) to estimate each firm's technological capability in terms of its technical efficiency relative to peers in transforming cumulative R&D resources into patented innovations. The underlying idea of DEA involves constructing a non-parametric envelopment (production) frontier with the entire sample of input–output observations such that each observation lies on or below the frontier. Relative efficiency measures for each firm are derived from the

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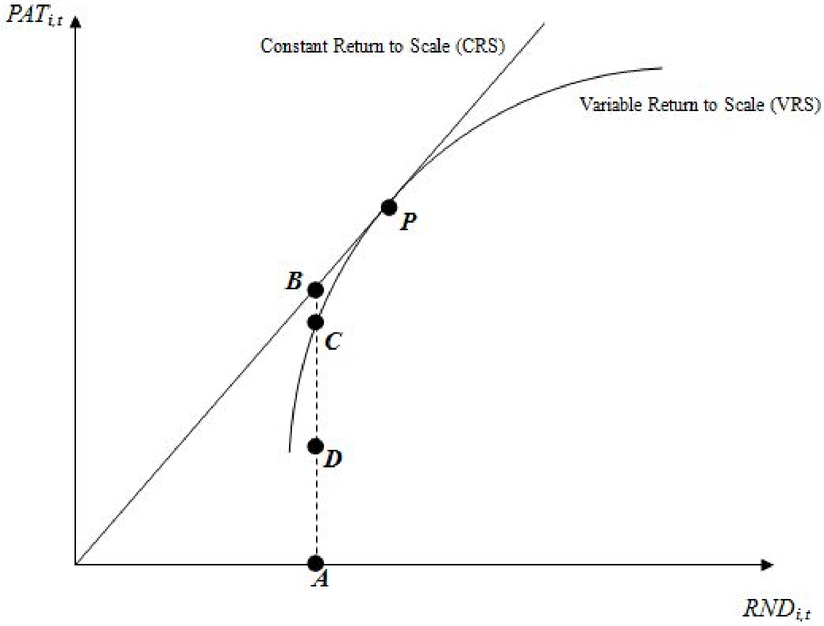
[2] See, for example, US Code § 41 Credit for increasing research activities.
[3] Refer to Griliches (1990) for a comprehensive review of the use of patent statistics in past research.
[4] The sample excludes unsuccessful patent applications.

firm's distance from the frontier, as the frontier is interpreted as the "best practice" among peer firms.

Figure 1. DEA efficiency measures for innovative activities



The Appendix provides the technical details of an output-oriented DEA model controlling for exogenous technological progress. Figure 1 illustrates the input–output relationship between $RND_{i,t}$ and $PAT_{i,t}$ under the alternative assumptions of constant returns to scale (CRS) and variable returns to scale (VRS). Considering firm *i* operating at point *D*, its technical *inefficiency* in innovative activities is indicated by the distance between points *B* and *D* (hereafter denoted by *BD*) under CRS and the distance between points *C* and *D* (i.e., *CD*) under VRS. The difference between *BD* and *CD*, that is, *BC*, indicates the firm's scale *inefficiency* relative to the optimal production scale at point *P*.

It is important to note that scale inefficiency (*BC*) can be eliminated only by adjusting the input level toward point *P*, while technical inefficiency (*CD*) can be eliminated only by improving the efficiency of using the existing input.

Based on Figure 1, the DEA *efficiency* measures are defined as follows:

$$TEV_{i,t} = AD/AC, \tag{2.1}$$

$$SE_{i,t} = AC/AB, \tag{2.2}$$

where $TEV_{i,t}$ is the *technical efficiency* and $SE_{i,t}$ is the *scale efficiency* of firm *i*'s innovative activities. These efficiency measures have the following features:

- they take values between 0 and 1;
- they measure efficiencies relative to the "best practice" among peer firms;
- $\frac{1}{TEV_{i,t}} - 1$ is the proportional increase in the innovative output ($PAT_{i,t}$) without increasing the input ($RND_{i,t}$) if the firm maximizes its technical efficiency from point *D* to *C* in Figure 1; and
- $\frac{1}{SE_{i,t}} - 1$ is the proportional increase in the innovative output if there is no scale inefficiency at the existing input level (i.e., *BC*=0), which indicates how far the current production scale is away from the optimal scale at point *P*.

Although $SE_{i,t}$ is solely determined by the firm's investment in R&D resources to attain the optimal production scale, $TEV_{i,t}$ is associated with the firm's non-transferable and non-imitable technological capability in transforming R&D resources into innovative output. The capability notion of the RBV implies that $SE_{i,t}$ is unlikely to be a source of sustainable competitive advantage because investment in R&D resources is potentially replicable by rivals. Unlike $SE_{i,t}$, technological capability in terms of $TEV_{i,t}$ cannot be transferred across firms nor imitated by rivals because it involves intermediate steps between input and output embedded in the firm's intra-organizational processes (Dutta *et al.*, 1999, 2005). According to the RBV, such non-transferable and non-imitable capability is a source of sustainable competitive advantage.

3.2 Logit model of fraud probability

Let $R_{i,t}$ = 1 (= 0) if firm *i* has (has not) fraudulently reported its financial results in year *t*. The following logit model is designated to examine the effect of technological capability on fraud probability:

$$R_{i,t} = \alpha + \beta TEV_{i,t} + \rho_1 SE1_{i,t} + \rho_2 SE2_{i,t} + \delta CTL_{i,t} + \varepsilon_{i,t}, \qquad (3)$$

where $CTL_{i,t}$ is a vector of control variables and $\varepsilon_{i,t}$ is a logistically distributed error term. Equation (3) uses a binary dependent variable because, as O'Connor *et al*. (2006) argued, fraudulent financial reporting is an "either-or" phenomenon occurring irrespective of the size of the fraud.

β is expected to be negative if IT firms with stronger technological capability relative to competitors are less likely to commit fraud. Let $RND^*_{i,t}$ be the optimal scale (i.e., point P in Figure 1). Equation (3) decomposes $SE_{i,t}$ into $SE1_{i,t}$ and $SE2_{i,t}$ such that:

$$SE1_{i,t} = SE_{i,t} \text{ if } RND_{i,t} < RND^*_{i,t} \text{ and } = 0 \text{ otherwise;}$$

$$SE2_{i,t} = SE_{i,t} \text{ if } RND_{i,t} \geq RND^*_{i,t} \text{ and } = 0 \text{ otherwise.}$$

ρ_1 and ρ_2 are expected to be zero if the scale efficiency is potentially replicable across firms, and thus it cannot distinguish non-fraud firms from their fraud counterparts. $\rho_1 \neq \rho_2$ is also possible because the scale efficiency can be easier to improve when the firm is operating above rather than below the optimal scale. As the production scale is associated with firm size, $SE1_{i,t}$ and $SE2_{i,t}$ also capture the possible effect of firm size on fraud probability.

Based on findings from the auditing literature, the following control variables are included in $CTL_{i,t}$.

- Growth expectation ($GROW_{i,t}$), measured by the market-to-book ratio, which indicates investors' expectation about the firm's future performance.[5] An IT firm may commit fraud because investors' expectation of the firm is too high to meet, rather than because the firm is unable to innovate. Therefore, fraud probability is expected to increase with $GROW_{i,t}$ because firms with high investor expectation are under greater performance pressure (Bolton *et al*., 2006).

[5] A firm's book value increases with retained earnings and asset appreciation. The market-to-book ratio thus indicates whether investors are paying more/less than what is left if the firm is liquidated.

- Non-cash net operating assets (*$NOA_{i,t}$*), defined as shareholders' equity plus total debt, minus cash and marketable securities, and then divided by total sales. This variable reflects the extent to which net assets are already overstated on the balance sheet, which reduces the flexibility for further within-GAAP earnings management. Fraud probability is therefore expected to be positively associated with $NOA_{i,t}$ (Barton and Simko, 2002; Dechow *et al*., 2011).
- Liquidity ($LQD_{i,t}$), defined as cash and cash equivalent divided by current liabilities. Fraud probability is expected to decrease with $LQD_{i,t}$ because a tight liquidity constraint (i.e., a small $LQD_{i,t}$) undermines a firm's competitiveness by reducing its ability to undertake innovative projects (Hall *et al*., 1998).
- External finance ($EXF_{i,t}$), measured by the sum of equity finance and long-term debt raised divided by total assets. $EXF_{i,t}$ indicates the firm's need to access external capital markets and is expected to be positively associated with fraud probability (Dechow *et al*., 1995, 2011).
- Managerial incentives, proxied by option-based compensation ($OPT_{i,t}$). Following Tufano (1996), $OPT_{i,t}$ is defined as the number of exercisable options held by the CEO.[6] Option-based compensation increases a risk-averse manager's appetite for risk because of the convex payoff structure of stock options (see, for example,

[6] Managerial incentives can be alternatively measured by *VEGA*, which is the sensitivity of a CEO's option-based wealth to the firm's stock return volatility (Core and Guay, 2002). However, data required for computing *VEGA* are no longer available from ExecuComp after 2005.

Tufano, 1996; Knopf *et al*., 2002; Coles *et al*., 2006). Burns and Kedia (2006) and O'Connor *et al.* (2006) found that firms granting more stock options to their managers were more likely to be involved in fraudulent financial reporting. Fraud probability is therefore expected to be positively associated with $OPT_{i,t}$.

- Firm performance ($\Delta ERN_{i,t}$), measured by the growth rate of earnings. Studies such as Barth *et al*. (1999) and Myers *et al*. (2007) have shown that the market rewards increasing earnings (i.e., $\Delta ERN_{i,t} > 0$). A positive $\Delta ERN_{i,t}$ indicates the firm's ability to meet the performance benchmark based on past performance (Graham *et al*., 2005). Fraud probability is therefore expected to decrease with $\Delta ERN_{i,t}$.

4. Data

4.1 Fraud sample

Mendelson and Kraemer (1998) broadly defined the IT sector to include the computer, telecommunication equipment, software, information services, and information content industries. These industries are coded in Compustat as 4510, 4520, and 4530. Following prior studies (e.g., Beasely, 1996; Bonner *et al*., 1998; Hennes *et al*., 2008; Dechow *et al*., 2010), this study took a sample of IT firms investigated by the US Securities and Exchange Commission (SEC) from the Accounting and Auditing Enforcement Releases (AAER) issued over the period of 2003–2013.

For the purpose of this study, the fraud sample includes only the IT firms accused of violating Rule 10(b)-5 concerning "*employment of manipulative and deceptive practices*."[7] A fraud firm-year is defined as the firm's fiscal year in which the violation was committed. The patent count in each fraud firm-year was taken from the USPTO database. A firm's patent count in year *t* is set to zero if the firm exists in the USPTO database but has no patent record in year *t*. Seventeen fraud firms were dropped from the sample because their names were not found in the entire USPTO database. The sample also excludes firm-years that have observations of other variables missing from Compustat and ExecuComp.[8] The resulting fraud sample taken from the AAER issued during 2003–2013 contains 141 fraud firm-years over 1998–2011. The fraud sample period is before the AAER publication period because there is a time lag between fraud commitment and prosecution. Table 1 reports the number of fraud firm-year observations by industry.

Table 1. Number of fraud firm-year observations by industry

Compustat industry code	Industry description	Number of fraud firm-year observations
4510	IT Consulting & Other Services; Systems Software; Data Processing & Outsourced Services; Data Processing & Outsourced Services; IT Consulting & Other Services; Home Entertainment Software; Systems Software; Application Software.	53

[7] In order for Rule 10(b)-5 to be invoked, an intentional fraud or deceit must be committed by the party charged with the violation.
[8] It turned out that the 17 fraud firms missing from the USPTO database also have observations missing from Compustat and ExecuComp.

4520	Communications Equipment; Electronic Equipment Manufacturers; Office Electronics; Computer Hardware; Technology Distributors.	48
4530	Semiconductor Equipment; Semiconductors.	40
		Total = 141

Notes: The sample period is 1998 to 2011. The source of data is the Accounting and Auditing Enforcement Releases issued by U.S. Securities and Exchange Commission in 2003–2013.

4.2 Control sample

This study constructed control samples of non-fraud firm-year observations (i.e., $R_{i,t}$ = 0) using Fung's (2015) method derived from Burns and Kedia (2008). As Fung (2015) pointed out, firm size and leverage are "confounding factors" because they affect not only fraud probability but also other firm characteristics (e.g., performance, growth, and liquidity). A typical way to avoid spurious regression caused by confounding factors is to construct a control sample with similar characteristics to the main sample in terms of those factors. With the entire 1998–2011 Compustat sample of IT firms as the basis, each control sample comprises non-fraud firm-year observations that are within $(1\text{-}q)\times100\%$ to $(1+q)\times100\%$ of the fraud firm-year observations' firm size and leverage. Parallel to the fraud sample, data on $PAT_{i,t}$ and other firm variables were collected from USPTO, Compustat, and ExecuComp.

Following the same procedures used to construct the fraud sample, each control sample excludes firms whose names were not found in the entire USPTO database. The patent count of a control firm in year *t* is set to zero if the firm exists in the USPTO database but has no patent record in year *t*. As seen in Table 2(a), the fraud and control samples have similar proportions of observations with $PAT_{i,t} = 0$. Like the fraud sample, the control samples exclude firm-years that have observations of other variables missing from Compustat and ExecuComp.[9] The resulting control samples with q = 0.10 and 0.15 have 110 and 258 non-fraud firm-year observations, respectively.

4.3 Sample characteristics

Table 2 reports summary statistics from the fraud sample as well as the two non-fraud control samples with q = 0.10 and 0.15. As seen from Table 2(a), the fraud firms on average transformed a substantially larger amount of cumulative R&D resources ($RND_{i,t}$) into a larger innovative output ($PAT_{i,t}$) than their non-fraud counterparts. The mean differences are statistically significant at the 1% level. The statistics show that an average fraud firm transformed USD720 million worth of cumulative R&D resources into 65 patented innovations each year, whereas the same figures for an average non-fraud firm were only USD164–170 million and 27 patented innovations. This observation appears to be counterintuitive because IT firms with abundant R&D resources for producing a large innovative output are usually those perceived as technology leaders who are less likely to commit fraud (e.g., Lucent Technologies Inc.).[10]

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[9] Those control firms missing from the USPTO database also have observations of other variables missing from Compustat and/or ExecuComp.

[10] Lucent Technologies Inc., a leading IT company, filed a total of 891 patents in 2000 and fraudulently

The aforementioned seemingly counterintuitive observation can be explained by the non-fraud firms' substantially larger innovative output per unit of R&D resources (i.e., the *PAT*-to-*RND* ratio) compared with that of their fraud counterparts (at the 1–5% level of significance). The statistics in Table 2(a) show that an average non-fraud firm produced 0.16–0.19 patented innovations for every USD1 million of cumulated R&D resources, whereas the same figure for an average fraud firm was only 0.13.[11] In other words, the non-fraud firms were more effective than their fraud counterparts in deploying their existing R&D resources. Consistent with the "capability notion" of the RBV, the preliminary findings from Table 2(a) imply that a firm's probability of committing fraud is associated with its efficiency in undertaking innovative activities rather than its possession of R&D resources *per se*.

Table 2. Summary statistics

(a) Mean and standard deviation

Variable		Fraud sample	Control sample (q=0.10)	Control sample (q=0.15)
$RND_{i,t}$	Mean	719.88	170.37 (-3.64**)	164.29 (-3.68**)
	Std. dev.	1792.34	198.94	180.28
$PAT_{i,t}$	Mean	64.95	27.44 (-2.49**)	27.54 (-2.50**)
	Std. dev.	178.71	49.88	53.95
Proportion of observations with $PAT_{i,t}$ = 0		16.3%	14.5% (-0.39)	14.3% (-0.53)
PAT-to-*RND*	Mean	0.13	0.16 (1.98*)	0.19 (3.96**)
	Std. dev.	0.18	0.21	0.27

reported USD 1.148 billion in revenue in the same year (SEC litigation release no. 18715).

[11] For instance, Lucent Technologies Inc.'s *PAT*-to-*RND* ratio was only 0.11 in 2000 when the company fraudulently reported its revenues.

$GROW_{i,t}$	Mean	6.21	6.15 (-0.07)	6.16 (-0.06)
	Std. dev.	10.62	11.00	11.64
$NOA_{i,t}$	Mean	0.42	0.38 (-1.98*)	0.38 (-1.98*)
	Std. dev.	0.24	0.19	0.19
$LQD_{i,t}$	Mean	1.56	1.83 (2.63**)	1.81 (2.43*)
	Std. dev.	1.22	1.37	1.41
$EXF_{i,t}$	Mean	0.01	0.01 (0.00)	0.01 (0.00)
	Std. dev.	0.35	0.39	0.30
$OPT_{i,t}$	Mean	206.26	203.23 (-0.08)	202.87 (-0.09)
	Std. dev.	455.71	349.57	419.46
$\Delta ERN_{i,t}$	Mean	0.04	0.06 (0.72)	0.07 (1.08)
	Std. dev.	0.33	0.36	0.29

Notes: $RND_{i,t}$ is the cumulative R&D expenditures of firm i in year t; $PAT_{i,t}$ is the number of patents whose applications were filed in year t; $GROW_{i,t}$ is the market-to-book ratio; $NOA_{i,t}$ is shareholders' equity plus total debt, minus cash and marketable securities, and then divided by total sales; $LQD_{i,t}$ is cash and cash equivalent divided by current liabilities; $EXF_{i,t}$ is the sum of equity finance and long-term debt raised divided by total assets; $OPT_{i,t}$ is the number of exercisable options held by the CEO; and $\Delta ERN_{i,t}$ is the growth rate of earnings. Each control sample comprises non-fraud firm-year observations that are within (1-q)×100% to (1+q)×100% of the fraud firm-year observations' firm size and leverage. Values in parentheses are the t-statistics for testing the differences between the control sample and the fraud sample means. ** indicates significance at 1% level. * indicates significance at 5% level.

Table 2. Summary statistics (continued)

(b) Correlation coefficient

	$RND_{i,t}$	$PAT_{i,t}$	$GROW_{i,t}$	$NOA_{i,t}$	$LQD_{i,t}$	$EXF_{i,t}$	$OPT_{i,t}$	$\Delta ERN_{i,t}$
$RND_{i,t}$	1							
$PAT_{i,t}$	0.82	1						
$GROW_{i,t}$	0.01	0.01	1					
$NOA_{i,t}$	0.15	0.12	0.017	1				
$LQD_{i,t}$	-0.14	-0.12	-0.04	-0.46	1			
$EXF_{i,t}$	0.06	0.14	0.00	0.14	0.02	1		
$OPT_{i,t}$	-0.01	-0.04	0.02	0.07	-0.05	-0.03	1	
$\Delta ERN_{i,t}$	-0.18	-0.10	0.01	0.04	0.02	0.21	0.03	1

Table 2(a) also shows that apart from differing technological characteristics, the fraud firms tend to have a higher level of non-cash net operating assets and a lower level of liquidity than their non-fraud counterparts do (at the 1–5% level of significance). However, there is no statistically significant difference between the fraud and non-fraud firms in terms of other firm characteristics. The fraud and non-fraud firms are rather uniform in terms of their high growth expectation ($GROW_{i,t}$) and high intensity of option-based compensation ($OPT_{i,t}$). The control variables are not highly correlated, as shown in Table 2(b).

As a caveat, what is observed in Table 2(a) cannot be taken as conclusive evidence for the hypothesized relationship between technological capability and fraud incidence. First, the effectiveness of innovative activities as indicated by the *PAT*-to-*RND* ratio does not distinguish technological capability (i.e., technical efficiency) from scale efficiency. Hence, one cannot determine whether the pattern drawn from Table 2(a) is attributable to technological capability, scale efficiency, or both. Second, fraud incidence is likely to be associated with technological capability as well as other fraud-inducing factors such as managerial incentives and investors' expectation. Results from further empirical analyses to be presented in the next section should strengthen the evidence.

5. Results

5.1 Estimating technological capability

Each sample firm's technical efficiency ($TEV_{i,t}$) and scale efficiency ($SE_{i,t}$) in innovative activities were estimated by DEA with cumulative R&D resources ($RND_{i,t}$) as input and patented innovations ($PAT_{i,t}$) as output (see the Appendix for technical details). The estimation was conducted separately for each industry in recognition of inter-industry technological differences. To provide summary statistics describing the sample firms' technological capability, the mean estimates of $TEV_{i,t}$ and $SE_{i,t}$ in each of the fraud and control samples are reported in Table 3.

Although $SE_{i,t}$ indicates the closeness of the firm to the optimal scale, $TEV_{i,t}$ measures the firm's non-transferable and non-imitable technological capability relative to peers. The efficiency estimates vary with the value of q because the DEA production frontier is the "best practice" within a peer group whose composition changes with q. Considering q = 0.10 in Table 3(a), for instance, the mean $SE_{i,t}$ of the control sample implies that an average non-fraud firm can produce $\frac{1}{SE_{i,t}} - 1$ = 47% more in innovative output if there is no scale efficiency at the current input level. Considering the same value of q in Table 3(b), the mean $TEV_{i,t}$ of the control sample implies that an average non-fraud firm can increase its innovative output by $\frac{1}{TEV_{i,t}} - 1$ = 308% without increasing R&D resources if the firm is able to replicate the "best practice" in terms of technological capability. The efficiency estimates for the fraud sample as reported in Tables 3(a) and (b) have the same interpretation as those for the control samples.

Tables 3(a) and (b) also compare the fraud and non-fraud firms in terms of their mean differences in $SE_{i,t}$ and $TEV_{i,t}$, as denoted by *Se_Diff* and *Tev_Diff*. As shown in Table 3(a), *Se_Diff* is not significantly different from zero for both values of q and hence suggests no significant difference between the fraud and non-fraud firms in terms of scale efficiency. Consistent with this study's hypothesis, *Tev_Diff* is significantly different from zero for both values of q as reported in Table 3(b), implying that the non-fraud firms are technically more efficient than their fraud counterparts. Taken together, the evidence thus far seems to suggest that the fraud and non-fraud firms are distinguishable from each other on the basis of technological capability rather than production scale.

Table 3. DEA efficiency

(a) Scale efficiency ($SE_{i,t}$) in innovative activities

q	Sample	Mean $SE_{i,t}$	$(1/SE_{i,t})$-1	*Se_Diff*
0.10	Control sample	0.679 (0.079)	47%	*Se_Diff* = 0 (0.101)
	Fraud sample	0.592 (0.064)	69%	
0.15	Control sample	0.521 (0.044)	92%	*Se_Diff* = 0 (0.072)
	Fraud sample	0.485 (0.055)	106%	

(b) Technical efficiency ($TEV_{i,t}$) in innovative activities

q	Sample	Mean $TEV_{i,t}$	$(1/TEV_{i,t})$-1	*Tev_Diff*
0.10	Control sample	0.245 (0.007)	308%	*Tev_Diff* > 0 (0.011)
	Fraud sample	0.220 (0.008)	355%	
0.15	Control sample	0.260 (0.004)	285%	*Tev_Diff* > 0 (0.008)
	Fraud sample	0.220 (0.008)	355%	

Notes: Each control sample comprises non-fraud firm-year observations that are within $(1-q)\times100\%$ to $(1+q)\times100\%$ of the fraud firm-year observations' firm size and leverage. With the combined fraud and control samples for each value of q, $TEV_{i,t}$ and $SE_{i,t}$ were estimated by DEA with the cumulative R&D expenditures ($RND_{i,t}$) as input and the number of patents ($PAT_{i,t}$) as output. *Se_Diff* and *Tev_Diff* are the mean differences in *SE* and *TEV*, respectively, between the control and fraud samples. Values in parentheses are standard errors.

5.2 Logit regression

Table 4 reports the results from estimating Equation (3) by logit regression. To check for robustness, the estimation matched the fraud sample with two alternative control samples with q = 0.10 and 0.15. In line with the preliminary evidence from Tables 2 and 3, the significantly negative coefficient on $TEV_{i,t}$ for both values of q suggests that IT firms with stronger technological capability relative to competitors are less likely to commit fraudulent financial reporting.

Table 4. Fraudulent financial reporting and technological capability

Independent variable	Expected sign	Control sample with q=0.10	Control sample with q=0.15
$TEV_{i,t}$	–	–3.876* (1.897)	–6.642** (1.652)
$SE1_{i,t}$	insig.	–0.153 (0.255)	–0.041 (0.248)
$SE2_{i,t}$	insig.	–0.188 (0.209)	–0.113 (0.203)
$GROW_{i,t}$	+	0.022	–0.0005

		(0.014)	(0.001)
$NOA_{i,t}$	+	3.018* (1.306)	3.123** (1.119)
$LQD_{i,t}$	–	–0.573** (0.213)	–0.451** (0.168)
$EXF_{i,t}$	+	0.806 (1.044)	0.846 (1.049)
$OPT_{i,t}$	+	–0.018 (0.032)	–0.016 (0.031)
$\Delta ERN_{i,t}$	–	–0.616 (0.498)	–0.681 (0.559)
Industry dummy 1	n.a.	0.104 (0.405)	0.106 (0.411)
Industry dummy 2	n.a.	–0.092 (0.447)	–0.094 (0.403)
Constant	n.a.	0.722 (0.635)	0.713 (0.622)
Pseudo R^2		0.458	0.433
Sample size		251	399

Notes: $R_{i,t} = \alpha + \beta TEV_{i,t} + \rho_1 SE1_{i,t} + \rho_2 SE2_{i,t} + \delta CTL_{i,t} + \varepsilon_{i,t}$ was estimated by logistic regression, where $R_{i,t}$=1 (=0) if firm i has (has not) committed fraud in year t; $TEV_{i,t}$ is technical efficiency; $SE1_{i,t}$ ($SE2_{i,t}$) is scale efficiency given the firm is below (at or above) the optimal scale; $CTL_{i,t}$ is a vector of control variables containing $GROW_{i,t}$, $NOA_{i,t}$, $LQD_{i,t}$ $EXF_{i,t}$, $OPT_{i,t}$, and $\Delta ERN_{i,t}$. Each control sample comprises non-fraud firm-year observations within (1-q)×100% to (1+q)×100% of the fraud firm-year observations' firm size and leverage. Values in parentheses are standard errors. ** stands for significance at the 1% level. * stands for significance at the 5% level.

Unlike $TEV_{i,t}$, the coefficients on $SE1_{i,t}$ and $SE2_{i,t}$ are negative but statistically insignificant for both values of q, implying that fraud incidence is not associated with the scale efficiency of innovative activities. This finding is not surprising from the RBV if the investment in R&D resources required to attain the optimal production scale is potentially replicable by rivals. Indeed, the capability notion of the RBV implies that without sufficient technological capability, investment in R&D resources *per se* does not give a firm sustainable competitive advantage because such investment can be imitated by rivals (see, for example, Bharadwaj, 2000; Santhanam and Hartono, 2003; Li *et al.*, 2010).

The results concerning the control variables are mixed. As expected, the positive and significant coefficient on $NOA_{i,t}$ implies that managers have stronger incentives to commit fraud if there is insufficient flexibility for reporting higher earnings through non-fraudulent earnings management (Barton and Simko, 2002; Dechow *et al*., 2011). The significantly negative coefficient on $LQD_{i,t}$ is attributable to the argument of Hall *et al.* (1998) that firms with a tight liquidity constraint (i.e., a smaller $LQD_{i,t}$) are less competitive. However, fraud probability is insignificantly associated with other control variables including $GROW_{i,t}$, $OPT_{i,t}$, $EXF_{i,t}$, and $\Delta ERN_{i,t}$. Fraud and non-fraud firms cannot be distinguished from each other based on $OPT_{i,t}$ and $GROW_{i,t}$, probably because most IT firms rely on stock options to motivate key employees and are anticipated to be high-growth regardless of their potential to commit fraud.[12] A possible reason for the insignificance of $EXF_{i,t}$ and $\Delta ERN_{i,t}$ is the large variations of these two variables relative to their means, as shown in Table 2.

5.3 Economic significance

The empirical findings presented thus far strongly support the hypothesis that the

[12] Using option value to measure the CEO's option-based compensation yielded similar findings.

probability of an IT firm committing fraudulent financial reporting is inversely related to the firm's technological capability. A practical question to ask is, in what ways can the findings help investors identify IT firms with a high risk of fraud? Before answering this question, it is important to note that the purpose of this study is not to provide an absolute benchmark for distinguishing technology leaders from laggers. Instead, it is to formulate technological capability as a *relative* measure of innovative productivity in terms of a firm's technical efficiency in innovative activities relative to peers. Considering two otherwise identical firms with different levels of technological capability, it is possible to make a probability statement about the extent to which one of them is more or less likely to commit fraud than the other. To this end, the marginal effect of technological capability on fraud probability is calculated as the partial derivative of $\Pr(R_{i,t} = 1)$ with respect to $TEV_{i,t}$:

$$\frac{\partial \Pr\,(R_{i,t}=1)}{\partial TEV_{i,t}} = F(x'b)\{1 - F(x'b)\}\beta \;, \qquad (4)$$

where $F(.)$ is the c.d.f. of the logistic distribution, and $x'b = \alpha + \beta TEV_{i,t} + \rho SE_{i,t} + \delta CTL_{i,t}$. Equation (4) is non-linear and thus has to be evaluated by perturbing $TEV_{i,t}$ from one reference point to another. To illustrate this idea, the following alternative scenarios are considered:

(i) $TEV_{i,t}$ increases from 0 to 1,

(ii) $TEV_{i,t}$ increases from $\overline{TEV} - 0.5\sigma_{TEV}$ to $\overline{TEV} + 0.5\sigma_{TEV}$,

(iii) $TEV_{i,t}$ increases from $\widetilde{TEV} - 0.5\sigma_{TEV}$ to $\widetilde{TEV} + 0.5\sigma_{TEV}$,

where $\overline{TEV}$, $\widetilde{TEV}$, and σ_{TEV} are the sample mean, median, and standard deviation of $TEV_{i,t}$, respectively. The marginal effect of $TEV_{i,t}$ on fraud probability for q = 0.10 and 0.15 under each scenario is presented in Table 5, which suggests an economically significant relationship between the two variables.

Considering q = 0.10, for instance, a drastic increase of technological capability under scenario (i) lowers fraud probability by an average of 0.387. In other words, the most technologically capable ($TEV_{i,t}$ = 1) firm's probability of committing fraud is 38.7% lower than the least capable one ($TEV_{i,t}$ = 0) if the two firms are otherwise identical.[13] For the same value of q, a mild improvement of technological capability as considered under scenarios (ii) and (iii) lowers fraud probability by an average of 0.082–0.083. Thus, in the case of two otherwise identical firms that are respectively 0.5 standard deviations above and below the mean technological capability among peers, the one above is expected to be 8.3% less likely than the one below to commit fraud. The marginal effect of $TEV_{i,t}$ on fraud probability becomes even more economically significant if the fraud sample is matched with a larger control sample (i.e., q = 0.15).

Table 5. Marginal effect of technological capability on the probability of fraudulent financial reporting

Sample	$\partial TEV_{i,t}$	$\partial \Pr(R_{i,t}=1)$
	(i) from 0 to 1	−0.387

[13] $TEV_{i,t}$ = 0 if the firm has $RND_{i,t} > 0$ and $PAT_{i,t}$ = 0 in year t.

Fraud sample and control sample with q=0.10	(ii) from $\overline{TEV} - 0.5\sigma_{TEV}$ to $\overline{TEV} + 0.5\sigma_{TEV}$	−0.083
	(iii) from $\widetilde{TEV} - 0.5\sigma_{TEV}$ to $\widetilde{TEV} + 0.5\sigma_{TEV}$	−0.082
Fraud sample and control sample with q=0.15	(i) from 0 to 1	−0.416
	(ii) from $\overline{TEV} - 0.5\sigma_{TEV}$ to $\overline{TEV} + 0.5\sigma_{TEV}$	−0.116
	(iii) from $\widetilde{TEV} - 0.5\sigma_{TEV}$ to $\widetilde{TEV} + 0.5\sigma_{TEV}$	−0.109

Notes: $\partial \Pr(R_{i,t}=1)/\partial TEV_{i,t}$ is the partial derivative of fraud probability with respect to technical efficiency in innovative activities. $\overline{TEV}$, $\widetilde{TEV}$, and σ_{TEV} are the mean, median and standard deviation of $TEV_{i,t}$, respectively.

6. Conclusions

Motivated by the disproportionately high incidence of fraudulent financial reporting in the IT sector, this study empirically investigates the relationship between technological capability and fraud probability. The RBV of the firm implies that non-transferable and non-imitable technological capability is a major source of sustainable competitive advantage in the IT sector because such capability is developed from internal knowledge and experience that cannot be transferred across firms nor imitated by rivals. Under the enormous pressure to outperform competitors in the highly competitive IT sector, IT firms with lower technological capability relative to competitors are *ceteris paribus* more likely to commit fraudulent financial reporting in an attempt to improve their short-term financial appearance.

This study measures a firm's technological capability by its technical efficiency relative to peers in transforming cumulative R&D resources into innovative output. Comparing a sample of fraud firms taken from the SEC's AAER with control samples of non-fraud firms, fraud probability is found to be inversely related to technological capability. Consistent with the RBV, the findings also suggest that fraud probability is insignificantly associated with the scale efficiency of innovative activities.

This study brings the RBV of the firm from the strategic management literature into the growing literature on fraudulent financial reporting by formulating fraud probability as a function of technological capability. Specifically, it investigates how a dimension of non-financial performance – technological capability – influences fraud probability. By doing so, this study identifies an additional fraud risk factor stemming from the distinctive market and technological characteristics of the IT sector where the incidence of fraudulent financial reporting is substantially higher than in every other sector.

This study supplements past research evaluating fraud probability based on financial performance (e.g., earnings). In practice, a fraud firm's true financial performance is unobservable *ex ante* until the fraud is discovered and the misstated performance is subsequently restated.[14] As each innovation is impartially examined by

[14] The same logic applies to stock prices that reflect the firm's earnings power.

the USPTO before a patent is granted, managerial discretion plays a minor role in the reporting of a firm's patent-based innovative output. Therefore, knowing a firm's technological capability is useful to investors in evaluating the firm's probability of committing fraud.

A question remains: why do firms differ in technological capability? According to Wiseman and Gomez-Mejia (1998), innovating firms' managers bear high risks of job termination and negative reputation because the outcomes of innovative activities are highly uncertain, which reduces managerial incentives for conducting innovative activities. In line with this argument, Balkin *et al*. (2000) found that managers rewarded on the basis of innovative activities were more motivated to build their firms' technological capability than those rewarded purely on the basis of financial performance. As such, the observed inter-firm differences in technological capability may be due to variations in executive pay structure.

In addition to managerial incentives that influence technological capability, the shortage of and fierce competition for talents in the IT sector have been well documented. Research has shown that talents recruited from rivals enhance the hiring firms' productivity (e.g., Parrotta and Pozzoli, 2012; Singh and Agrawal, 2011). Strategies used by IT firms to compete for talents include offering employees various forms of financial incentives and forming “non-poaching” agreements with rivals.[15] How well an IT firm attracts and retains talents may determine its technological capability relative to competitors.

A limitation of this study is its use of archival data, which does not allow for in-depth understanding of the perception of managers as the main cause of fraudulent financial reporting in the IT sector under diverse technological settings and volatile market conditions. A survey-based approach to verify and supplement the present findings at the individual level is a potentially fruitful direction for future research.

Appendix

DEA compares the *relative* efficiencies of “decision-making units (DMUs)” (e.g., firms) in using similar resources to generate similar output. The efficiency score of each DMU ranges from 0 to 1. The most efficient DMUs have an efficiency score of 1 and is the benchmark of “best practice” (i.e., the frontier) among peers. The lower a DMU’s efficiency score is below 1 (i.e., below the frontier), the more inefficient the DMU relative to the best practice.

Based on the work of Banker *et al*. (1984), Fare *et al*. (1994), and Ruggiero (1996, 1998), this study specifies an output-oriented DEA model controlled for exogenous

[15] In 2014, Apple, Google, Intel, and Adobe Systems paid USD 415 million to settle a lawsuit accusing them of conspiring to prevent hiring each other’s employees during 2005–2009.

technological progress as the following linear programming problem:

$$\text{Max } \theta_h$$

$$\text{Subject to:} \quad Y\lambda \geq \theta_h PAT_h$$

$$X\lambda \leq RND_h$$

$$\lambda j = 0 \text{ if } t_j > t_h \text{ for all } j \neq h$$

$$I_N'\lambda = 1$$

$$\lambda \geq 0$$

where $1 \leq \theta_h \leq \infty$; $Y = (PAT_1, \ldots, PAT_N)$; $X = (RND_1, \ldots, RND_N)$; $t_1, \ldots, t_N$ is the time trend capturing exogenous technological progress; λ is a $N \times 1$ vector of weights; and I_N is a $N \times 1$ vector of ones. By imposing the constraint of $\lambda j = 0$ if $t_j > t_h$ for all $j \neq h$, this model excludes observations with more advanced technologies (i.e., a more favorable environment) from the reference set (Ruggiero, 1996, 1998). $I_N'\lambda = 1$ imposes variable returns to scale (VRS) on the solution (Banker *et al*., 1984).

The interpretation of $Y\lambda \geq \theta_h PAT_h$ and $X\lambda \leq RND_h$ is as follows. Choose a weighted combination of all input observations ($X\lambda$) that uses at most the input observation under evaluation (RND_h) to produce the largest possible multiple of the output observation under evaluation ($\theta_h PAT_h$). The input–output observation under evaluation is efficient if its output is best produced using its own input, i.e., one cannot find any λ that generates $\theta_h > 1$. This efficient observation with $\theta_h = 1$ defines a point on the frontier because its efficiency cannot be further improved relative to the other observations. If $\theta_h > 1$, $\theta_h - 1$ is the proportional increase in PAT_h without increasing RND_h. $1/\theta_h$ therefore defines an efficiency score varying between 0 and 1.

The value of θ for each input–output observation can be obtained by solving the preceding linear programming problem N times. To separate scale efficiency from technical efficiency, the former can be calculated as the difference between θ and θ', where θ' is the solution without the VRS constraint.

Compliance with ethical standards

The authors did not conduct studies with human participants or animals for this paper.

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