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Information technology capability and firm performance: A longitudinal study

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Abstract

Research Question: We investigate the relationship between information technology (IT) capability and firm performance of US firms during 1989-2012.
Motivation: We identify the model misspecification and estimation problems in Santhanam and Hartono (2003), Chae *et al.* (2014), Choi and George (2016), and Rahman and Zhao (2020) and provide new estimation results by using model specifications that better fit the characteristics of the sample data.
Idea: We compare the long-term trends of the IT capability-performance relationship between the IT leader and control groups.
Data: All data are from *InformationWeek* (IW) 500 and the Compustat database.
Tools: We use a dynamic panel model with the firm-specific effect which incorporates the main assumptions of the resource-based view (RBV) of the firm.
Findings: We find a positive association between IT capability and firm performance by using 1,308 IT leader firms chosen from the IW 500 from the period 1989 to 2012. We also find that the IT leader group's financial performance consistently outperformed that of the control group over the entire sample period. However, during the second half of the 1990s, a period marked by a significant increase in IT proliferation and investment, the financial performance of the IT leader group leveled off. It appears that, contrary to expectations, the returns to the IT leader group's superior IT capability did not translate into substantial improvements in operational efficiency during that period. We also observe that the financial performance of the control group experienced a much stronger recovery (with a threefold increase in magnitude) compared to the IT leader group during the 2000s.
Contribution: This study makes a significant contribution to the existing literature as it presents the first-ever longitudinal study on the IT capability-performance relationship spanning 24 years. Moreover, this study is the first to investigate the existence of any changes in patterns of the IT capability-performance relationship, both across different groups and over time.

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1. Introduction

Numerous studies have investigated the relationship between information technology (IT) capability and firm performance since the early 1990s. However, understanding the impact of IT capability on firm performance has remained a topic of debate, characterized by differing conceptualizations of key constructs and their interrelationship within this context (e.g., Brynjolfsson & Hitt, 1996; Kohli & Devaraj, 2003; Melville *et al*., 2004). Since the mid-2000s, a transformation in IT business landscapes has unfolded, ushering in new ecosystems that encompass mobile computing, cloud computing, social media, big data, and business analytics. This shift has redirected the focus of Information Systems (IS) studies towards understanding how IT capabilities can be leveraged to create higher-order organizational capabilities and sustained competitive advantage (e.g., Bardhan *et al.*, 2013; Mithas *et al.*, 2013; Wamba *et al*, 2017; Xue *et al.*, 2021). The IS community generally agrees that superior IT capability can confer competitive advantages upon a firm over its competitors. However, recent studies also reported mixed findings regarding the direct influence of IT capability on firm performance.

IS researchers draw upon the conceptual foundation of the relationship between IT capability and organizational performance, rooted in the resource-based view (RBV) of competitiveness within the realm of strategic management. The RBV of the firm posits that, to attain a sustainable competitiveness advantage, a firm must operate based on its resources that are deemed valuable, rare, difficult to imitate, and irreplaceable by other resources (Barney, 1991). Bharadwaj (2000) is among the earlier studies grounded in the RBV of the firm, which explores the link between IT capabilities and firm performance. According to Bharadwaj (2000), a firm's IT infrastructure, the expertise of its IT personnel, and its ability to leverage IT for intangible benefits collectively constitute firm-specific resources. When combined, these resources give rise to a firm-wide IT capability. While each of these individual IT resources is intricate to obtain and challenging to imitate, firms that gain a competitive edge through IT have also mastered the art of effectively integrating their IT resources to establish an overarching IT capability. She contends that a firm can achieve superior financial performance by outperforming its competitors when it attains a sustainable competitiveness advantage by adopting a value-generating strategy that optimally exploits its unique IT capabilities.

To empirically test her hypothesis, she gathered a group of 56 IT leader firms chosen from the IW 500 covering the years 1991 through 1994. This group was then compared to a control group of firms matched in terms of industry and size, utilizing the financial time series data from the Compustat database. Her findings revealed that the IT leader group consistently outperformed the control group in terms of profitability and cost efficiency. In a subsequent study, Santhanam and Hartono (2003) raised concerns regarding her study's treatment of the financial halo effect inherent in the sampled firms. They proposed the use of an autoregressive model to mitigate the financial halo effect on the financial data. However, when they replicated Bharadwaj's (2000) study, employing her IT leader group in conjunction with all other firms in the industry from which an IT leader firm was identified as the control group, their results corroborated with those of Bharadwaj (2000).

Chae *et al.* (2014) posited that while the 1990s marked an era dominated by proprietary information systems, the 2000s witnessed a shift towards standardization and the widespread integration of enterprise resource planning (ERP) systems and web technologies, as documented by Wang (2010). These transformations facilitated easier emulation of IT capabilities by firms, ultimately diminishing the competitive edge of the leaders. They revisited the prior findings, using 296 pairs of IT leaders and control firms from 2001 to 2004. Interestingly, Chae *et al.* (2014) did not observe a significant association between IT capabilities and performance, which challenged prior beliefs. Choi and George (2016) then replicated the Chae *et al.* (2014) study but expanded their control group to encompass all other firms in the same industry as an IT leader firm. Contrary to Chae *et al.* (2014), they reported a positive influence of IT capabilities on firm performance. In their more recent study, Rahman and Zhao (2020) reexamined this relationship, analyzing 55 IT leader-control pairs from the period 2010 to 2013. Their investigation, however, did not uncover a significant relationship between IT capability and firm performance.

In this study, we endeavor to address issues related to model misspecification and estimation problems as observed in the works of Santhanam and Hartono (2003), Chae *et al*. (2014), Choi and George (2016), and Rahman and Zhao (2020). Our goal is to present new estimation results achieved through model specification that more accurately align with the characteristics of the sample data. Instead of introducing an entirely novel model, our focus is on refining the discussion within the domain of dynamic models employed in previous research.

For our empirical investigation on the IT capability-performance relationship, we employ a dynamic panel model that incorporates firm-specific effects. In contrast to the cross-sectional dynamic models used in prior research, this model incorporates the fundamental tenets of RBV of the firm, which posits that firm's strategic resources are distributed heterogeneously across firms, and these disparities remain stable over time. Controlling for the financial halo effect originating from prior financial performance, we apply the dynamic panel model

with firm-specific effects to compare the financial performance of IT leader firms with that of a control group over the period of 1989-2012.
Furthermore, we investigate the assertion put forth by Chae *et al*. (2014) and Rahman and Zhao (2020) that the influence of IT capability on firm performance diminished from the early 2000s through the early 2010s. Our aim is to explore any existing trends and their evolution in the relationship between IT capability and financial performance over the 1989-2012 period. We also address the impact of omitted variable bias on the estimation of the financial halo effect in previous studies. For our investigation, we utilize 1,308 IT leader firms selected from the IW 500 between 1989 and 2012 to construct a short panel of annual time series data sampled from the Compustat database. We present a summary of the previous studies in Table 1.

The remainder of our study is structured as follows: In Section 2, we review the relevant literature, while also addressing model misspecification and estimation issues observed in previous studies. Section 3 outlines the formulation of our research hypotheses, introduces a novel dynamic panel model, and expounds on the corresponding estimation method. This section also covers the selection process for our sample data. In Section 4, we present our test results concerning the relationship between IT capability and firm performance. Section 5 delves into the issue of omitted variable bias, associated with model misspecification as identified in prior research. This section also discusses the issues in selecting the control group observed in the previous studies and provides our new empirical findings. Our conclusions are provided in Section 6.

2 Related works and problems

2.1 Related works

In her study, Bharadwaj (2000) built upon prior research that integrated the RBV framework with information systems (IS) research. She conducted empirical research to examine how IT capability influences a firm's performance. Her premise posits that a firm can achieve superior financial performance by capitalizing on firm-specific resources, including IT infrastructure, IT human resources, and IT-enabled intangible assets, to fully leverage its organization-wide IT capabilities to attain a sustainable competitive advantage. Her criterion for selecting IT leaders entailed identifying firms that had been consistently recognized as IT leaders by *InformationWeek* for at least two of the four years under investigation. Utilizing a matched-comparison group design, her findings revealed that the IT leader group consistently outperformed the control group in terms of average financial performance measures. She conducted a logistic regression analysis to investigate the presence of a financial halo effect in her dataset, in which no evidence of such an effect was uncovered. Thus, it should be noted that her test results were not influenced by the financial halo effect stemming from past financial performance.

In a subsequent investigation, Santhanam and Hartono (2003) addressed methodological concerns raised in the earlier work by Bharadwaj (2000). While employing the same IT leader firms as Bharadwaj did during the 1991-1994 period, Santhanam and Hartono broadened their control group by including all other firms in the two- and four-digit SIC industry from which an IT leader firm was identified. Their supporting argument was that since the criterion for selecting an IT leader firm is the firm's IT capability in relation to all other firms in the industry, it is logical to have a control group consisting of all other firms in the industry. Moreover, they specifically critiqued that Bharadwaj did not consider the financial halo effect in her study. In response, they applied a first-order autoregressive (AR(1)) model to account for the financial halo effect of prior financial performance on current financial results. Nonetheless, their findings corroborated with those of Bharadwaj (2000). Furthermore, they extended their analysis to encompass the period from 1995 through 1997, revealing continued positive and sustainable effects of IT capability on firm performance.

Table 1. Comparisons between the Previous Studies and This Study

Study	Sample	Performance Measure	Main Result for IT Capability-Performance Relationship	Remarks
Bharadwaj (2000)	IW 500 from 1991 to 1994; 56 IT leader firms	ROA, ROS, OI/A, OI/S, OI/E, COG/S, SGA/S, OPEXP/S	Positive association	Matched-comparison group design analyses on an annual basis
Santhanam and Hartono (2003)	IW 500 from 1991 to 1994; 56 IT leader firms	ROA, ROS, OI/A, OI/S, OI/E, COG/S, SGA/S, OPEXP/S	Positive association	Cross-sectional analyses on an annual basis using AR(1) model
Chae *et al.* (2014)	IW 500 from 2001 to 2004; 296 IT leader firms	ROA, ROS, OI/A, OI/S, OI/E, COG/S, SGA/S, OPEXP/S	No significant association	Cross-sectional analyses on an annual basis using AR(1) model
Choi and George (2016)	IW 500 from 2001 to 2004; 296 IT leader firms	ROA, ROS, OI/A, OI/S, OI/E, COG/S, SGA/S, OPEXP/S	Positive association	Cross-sectional analyses on an annual basis using AR(1) model
Rahman and	IW 500 from	ROA, ROS,	No significant	Cross-sectional

Study	Sample	Performance Measure	Main Result for IT Capability-Performance Relationship	Remarks
Zhao (2020)	2010 to 2013; 276 IT leader firms	OI/A, OI/S, OI/E, COG/S, SGA/S, OPEXP/S	association	analyses on an annual basis using AR(1) model
This Study	IW 500 from 1989 to 2012; 1,308 IT leader firms	ROA, ROS, OI/A, OI/S	Positive association; see Table 5 for more results	Longitudinal analyses using firm-specific effects dynamic panel model

Notes: Return on assets (ROA), return on sales (ROS), operating income to assets (OI/A), operating income to sales
(OI/S), operating income to employees (OI/E), cost of goods sold to sales (COG/S), selling and general administration expenses to sales (SGA/S), and operating expenses to sales (OPEXP/S). AR(1) stands for first-order autoregressive.

Chae *et al*. (2014) suggested that, in the 1990s, proprietary information systems were prevalent, while the 2000s marked an era characterized by a transition to more standardized and homogeneous information systems, with the rapid adoption of ERP systems and web technologies (Wang 2010). These changes made it easier for firms to emulate IT capabilities, ultimately eroding the competitive advantage of IT leaders. They also employed the AR(1) model with a difference in selecting their control group by using the matched-comparison group design. Investigating 296 pairs of IT leader-control firms from 2001 to 2004, their findings contradicted those of Bharadwaj (2000) and Santhanam and Hartono (2003), as they reported that the IT leader group did not exhibit superior financial performance compared to the control group. In a following investigation, Choi and George (2016) replicated Chae *et al*. (2014) by considering all other firms in the two- and four-digit SIC industry in which an IT leader firm was situated as the control group. In contrast to Chae *et al*. (2014), however, they discovered a positive impact of IT capability on financial performance.

In a recent study, Rahman and Zhao (2020) undertook a replication of the research conducted by Chae *et al*. (2014), using 55 IT leader-control pairs sourced from the IW 500, along with financial data extracted from the Compustat database spanning the years 2010 to 2013. Their findings, much like those of Chae *et al*. (2014) in the early 2000s, revealed no statistically significant association between IT capability and firm performance during the early 2010s. Consequently, they posited that the superior financial performance of the IT leader group to that of the control group dissipated from the 2000s through the 2010s, after accounting for the financial halo effect. However, it is imperative to scrutinize this assertion when comparing the outcomes of the Wilcoxon signed-rank test (refer to Tables 5 & 6 on pages 609-610) with those from the AR(1) model analysis (see Table 7 on pages 611-613). The results of the Wilcoxon signed-rank test, as presented in Tables 5 and 6, indicate that IT leaders consistently achieved and sustained higher profit ratios than the control group, specifically before adjusting for the financial halo effect throughout the period from 2010 to 2017 (excluding 2010). In contrast, a closer examination of the results shown for the AR(1) model in Table 7 reveals that, in all cases, prior year's performance has no significant effect on current year's performance at conventional levels. Considering the significant findings of the Wilcoxon signed-rank test, as evidenced in Tables 5 and 6, and the insignificant coefficient estimates of the financial halo effect variable presented in Table 7 , it would be paradoxical to observe the lack of statistical significance in the coefficient estimates for dummy variable denoting IT leaders' superior financial performance (except for ROA in 2011, which is statistically significant at the 5% level), as presented in Table 7 across the years under consideration. Hence, their claim made across the two tables would appear inconsistent.

It is evident that the samples employed in the prior studies are notably limited in size, ranging from 55 to 296 IT leader firms. As these firms are distributed across the four-year sample periods in question, the annual count of firms available for comparison diminishes. The prior studies employed Bharadwaj's method to select IT leader firms, where a firm was included in the IT leader group if it was rated as a leader in at least two of the four years studied, following Bharadwaj (2000). It is important to note that the small sample sizes gathered over the four-year periods limit the generalizability of findings from the previous studies. Additionally, Chae *et al.* (2014) and Rahman and Zhao (2020) asserted that the influence of IT capability on firm performance dwindled from the early 2000s through the early 2010s. However, generalizing their results based on the initial four years of each decade for the entire decade duration would be challenging. Besides the issue of small sample sizes used, we have identified other problems in previous studies. For instance, Santhanam and Hartono (2003) reported in Table 4 (page 137) that, in the case of the return on sales (ROS) dependent variable, their AR(1) model produced a coefficient estimate for the financial halo variable of 0.999 (in 1993 and 1994), signifying statistically significance at the 1% level, with R-squared values of 0.999 and 0.994. Similarly, Chae *et al*. (2014) reported in Table 7 (page 314) that, when ROS was the dependent variable in their AR(1) model, they observed estimated coefficients for the financial halo effect variable ranging from 0.556 (in 2001) to 0.030 (in 2003), both statistically significant at the 1% and 5% levels, respectively. The R-squared values for both years were 0.227 and 0.010, respectively. These estimates raise concerns as they suggest potential issues related to model misspecification and the choice of an incorrect estimation method, topics we will discuss in more detail in the next section.

2.2 Model misspecification

In 2000, Bharadwaj conducted a logistic regression analysis aimed at investigating the financial halo effect of prior financial performance within her sample data. Her findings failed to yield any supporting evidence for such an effect. In contrast, Santhanam and Hartono (2003) provided a critique of her methodology. They argued that her choice of using the average financial performance from the previous five years, rather than the immediate prior financial performance, likely compromised the integrity of her final test results. They contended that her study may have been marred by the omission of the financial halo effect. To account for the financial halo effect of prior financial performance, Santhanam and Hartono (2003) proposed the following AR(1) models as an adjustment measure:

$$FP_{i,t}=\beta_0+\beta_1 FP_{i,t-1} \quad (1)$$

$$FP_{i,t}=\alpha_0+\alpha_1 FP_{i,t-1}+\alpha_2 D \quad (2)$$

where $FP_{i,t}$ is financial performance of firm i in year t, $FP_{i,t-1}$ is lagged $FP_{i,t}$, and D is a binary variable indicating that a firm belongs to the IT leader group. To be precise, Equations (1) and (2) are not complete because there are no error terms. The usefulness of Equation (1) is also questioned. Unlike Bharadwaj (2000), Santhanam and Hartono (2003) structured their control group differently, comprising all other firms within two- and four-digit SIC industries where IT leader firms operated. Chae *et al*. (2014) followed suit but adopted a matched-comparison group methodology, using more recent data spanning from 2001 to 2004. Choi and George (2016) used the same dataset as Chae *et al*. (2014) but replicated Santhanam and Hartono's (2003) control group selection approach. In a similar vein, Rahman and Zhao (2020) emulated Chae *et al*. (2014), selecting 55 IT leader-control pairs from 2010 to 2013.

Building upon the foundation laid by Bharadwaj (2000), Santhanam and Hartono (2003), Chae *et al*. (2014), Choi and George (2016), and Rahman and Zhao (2020), all these studies underscored the significance of the RBV notion of IT capability as a rent-generating resource that is difficult to imitate or substitute. However, it's worth noting that none of these previous studies incorporated a control variable that accounts for this notion in Equations (1) and (2). This omission results in a model misspecification and introduces potential bias due to the omitted variable. We will examine this problem in Section 5.

2.3 Estimation errors

Prior studies used ordinary least squares (OLS) to estimate Equations (1) and (2). They considered the estimates of $\alpha_1$and β_1 as the financial halo effect for the sample on an annual basis across their four-year sample periods. However, it is important to note that these estimates of $\alpha_1$and β_1 do not represent the financial halo effect for the sample (or IT leader and control groups). It is because the financial halo effects of individual firms in the sample need to be estimated beforehand so that that for the sample (or IT leader and control groups) can be obtained. Speaking more specifically, we note that Equations (1) and (2) contain a lagged dependent variable, which allows for modelling a partial adjustment mechanism. Santhanam and Hartono (2003), Chae *et al.* (2014), Choi and George (2016), and Rahman and Zhao (2020) characterized this partial adjustment mechanism as the financial halo effect. It is worth emphasizing that this partial adjustment mechanism of the AR(1) model is designed to work over the entire history of time series observations, rather than relying on a single observation of the preceding period. As such, the coefficient of the lagged dependent variable of the AR(1) model cannot be estimated cross-sectionally by treating the lagged dependent variable as fixed. Consequently, the correct approach to estimate the financial halo effect for the sample entails utilizing panel data comprising annual item time series observations for all firms within the sample observed throughout the sample period.

While the presence of heteroskedasticity is highly probable in firm-level panel data, the previous studies did not employ heteroskedasticity-robust estimator of variance to address this issue. Additionally, none of the prior studies filtered the annual time series data to prevent unexpected estimation outcomes due to outlier observations. Data filtering is essential to avoid possible distorted valuation multiples such as return on assets and return on sales, among others. Furthermore, the Compustat database is known to contain missing codes and restated data for accounting changes, but none of the previous studies detailed their approach to handling these issues.

Table 2 provides a comprehensive summary of the test models, sample data, estimation methods, and results of the previous studies. It not only enumerates the number of IT leader firms selected from the IW 500 list, as employed in prior research, but also highlights instances where certain IT leader firms could not be matched with control firms when using the four-digit SIC code for pairing. It is worth noting that, for their control groups, Santhanam and Hartono (2003) and Choi and George (2016) adopted all other firms within the four-digit SIC industries where the IT leader firms were situated. However, Rahman and Zhao (2020) did not provide a list of the specific four-digit SIC codes used in pairing IT leader and control firms.

3. Hypotheses

Previous studies provided valuable insights into the relationship between IT capabilities and financial performance. Bharadwaj (2000) and Santhanam and Hartono (2003) found that the IT leader group consistently outperformed the control group during the early 1990s. However, Chae *et al*. (2014) observed a decline in the superiority of the IT leader group's financial performance during the early 2000s, while Choi and George (2016) reported contrasting results for the same period. Using more recent data from the early 2010s, Rahman and Zhao (2020) corroborated Chae *et al*.'s (2014) findings that the superior financial performance of the IT leader group also declined, much like it did in the early 2000s. Our study, encompassing 1,308 IT leader firms selected from the IW 500, spans 24 years from 1989 to 2012. This duration covers all three sample periods previously investigated: 1990-1994 (Bharadwaj, 2000; Santhanam & Hartono, 2003), 2000-2004 (Chae et al., 2014; Choi & George, 2016), and 2010-2013 (Rahman & Zhao, 2020). It is natural to explore any existing trends and their evolution in the relationship between IT capability and financial performance over the 1989-2012 period.

Table 2. Comparison of Methodologies used by the previous studies

Study	**Sample Period**	**IW 500 four-digit SIC industries used**	**No. of IW 500 leader firms used**	**No. of unmatched IW 500 leader firms with four-digit**	**Test Model**	**Estimator**	**Results**
Bharadwaj (2000)	1991-1994	35	56	19	Matched-comparison group design on an annual basis	Wilcoxon rank sum	Incorrect
Santhanam and Hartono (2003)	1991-1994	35	56	Not applicable	Cross-sectional AR(1) model on an annual basis	OLS	Incorrect
Chae *et al.* (2014)	2001-2004	163	296	102	Cross-sectional AR(1) model on an annual basis using matched-comparison group design	OLS	Incorrect
Choi and George (2016)	2001-2004	163	296	Not applicable	Cross-sectional AR(1) model on an annual basis	OLS	Incorrect

Study	Sample Period	IW 500 four-digit SIC industries used	No. of IW 500 leader firms used	No. of unmatched IW 500 leader firms with four-digit	Test Model	Estimator	Results
Rahman and Zhao (2020)	2010-2013	Not reported	55	Not reported	Cross-sectional AR(1) model on an annual basis using matched-comparison group design	OLS	Incorrect

Notes: Bharadwaj (2000) did not reflect the financial halo effect to her tests because she obtained insignificant test results on the effect. AR(1) stands for first-order autoregressive.

In order to resolve the conflicting claims made by previous studies, we will pursue several lines of inquiry. First, we will assess whether the IT leader group consistently outperformed the control group in terms of financial performance across the entire sample period from 1989 to 2012 (Hypothesis 1). Second, we will divide the panel data from 1989 to -2012 into two distinct twelve-year periods, specifically, 1989-2000 and 2001-2012. This division will allow us to scrutinize the findings presented in the previous studies concerning the 1990s and the 2000s, respectively. With the first set of panel data, we will explore whether there was an upward trend in the mean return for the IT leader group during the 1990s (Hypothesis 2), which may align with the conclusions of Bharadwaj (2000) and Santhanam and Hartono (2003). Third, we will examine the claims put forth by Chae *et al*. (2014) and Rahman and Zhao (2020). By employing the second set of panel data, we will assess whether the observed increasing trend in the mean return for the IT leader group during the 1990s diminished during the 2000s (Hypothesis 3).

Furthermore, if the conflicting findings regarding the shift in the trend of the mean return for the IT leader group, as reported by Chae *et al*. (2014) and Rahman and Zhao (2020), are accurate, this suggests changes in the levels of mean returns for both the IT leader and control groups over time. To investigate such temporal changes in the trend of the mean return for the IT leader group from the 1990s to the 2000s, a comparative analysis of the two trends of mean return for the IT leader and control groups is essential (Hypothesis 4). Additionally, we will compare whether the IT leader and control groups exhibited different trends in their mean returns during the 1990s and the 2000s, respectively (Hypotheses 5 & 6). Our hypotheses are summarized as follows:

H1: *Firms with superior IT capability have higher mean return than all control firms during the 1990s and the 2000s after adjusting for financial halo effect.*

H2: *The mean return of firms with superior IT capability has an upward trend over the 1990s, after adjusting for financial halo effect, because IT proliferation and IT investment were robust during the period.*

H3: *The mean return of firms with superior IT capability has no significant trend over the 2000s, after adjusting for financial halo effect, because information systems became standardized and homogeneous during the period.*

H4: *Firms with superior IT capability have different patterns of trend in the mean return from all control firms during the 1990s versus the 2000s after adjusting for financial halo effect.*

H5: Firms with superior IT capability have a different trend in the mean return from all control firms during the 1990s after adjusting for financial halo effect.

H6: Firms with superior IT capability have a different trend in the mean return from all control firms during the 2000s after adjusting for financial halo effect.

3.1 Data

As with the previous studies, we use the IW 500 to identify firms with superior IT capability in an industry. Since 1989, *InformationWeek* selected 500 firms as leaders in IT innovation each year and published their rankings in the IW 500. For our study, we collect 1,308 firms from the IW 500 over the 1989-2012 period. The number of IT leader firms collected each year varies between 274 and 426. We use all peer firms of IT leader firms in a four-digit SIC industry as the control group each year since 1989.

For this study, we first identify all active and inactive firms in 450 four-digit SIC 100–9997 with a greater than two-year history and annual data for fiscal years of 1989–2012 in the Compustat database. Then we narrow them down to 364 four-digit SIC industries from which firms listed in the IW 500 are selected one or more years over the period of 1989-2012. We replace SIC codes with historical SIC codes, when available. The Compustat database uses several missing value codes; we replace the ‘insignificant figure’ code with 0.001 and replace all other codes with missing values. The Compustat database provides restated data for some annual data items when they are amended by firms for accounting changes. When available, we use the restated data. We winsorize the top and bottom 1% of all annual item variables to control outlier observations. We also delete firms whose annual total assets or sales is less than $10 million. These steps are necessary to avoid possible distorted valuation multiples like return on assets and return on sales.

3.2 Dynamic panel model

For our re-examination of the relationship between IT capability and financial performance, we consider the following firm-specific effects dynamic panel model with linear splines characterizing change in the mean response over time:

$$Y_{i,j}=\beta_0+\beta_1 Y_{i,j-1}+\beta_2 Year_{i,j}+\beta_3 \left(Year_{i,j}-t^{\text{¿}}\right)_{+\text{¿}+\beta_4 Group_i+\beta_5 Year_{i,j}\times Group_i \text{¿}}$$
$$+\beta_6 \left(Year_{i,j}-t^{\text{¿}}\right)_{+\text{¿}\times Group_i+\beta_7 \text{¿}\text{¿} i,j-1+\beta_8 Munificence_{i,j}+\beta_9 Dynamism_{i,j} \text{¿}\text{¿}}$$
$$+\beta_{10} Complexity_{i,j}+\alpha_i+\varepsilon_{i,j}$$

(3)

where $Y_{i,j}$ is the financial measure for firm i in period j (e.g., return on assets $(ROA_{i,j})$ or return on sales $(ROS_{i,j})$). $Y_{i,j-1}$is lagged $Y_{i,j}$. $Group_i$ = 1 if the i^{th} firm is assigned to the IT leader group, and $Group_i$ = 0 otherwise. $Year_{i,j}$ indicates the measurement year for the j^{th} measurement on the i^{th} firm. α_i is the unobserved firm-specific time-invariant effect which allows for heterogeneity in the means of the $Y_{i,j}$series across firms and is permitted to be correlated with covariates. α_i can also be considered as a vector of unobserved firm-specific effects. It is important to note that α_i reflects the core tenets of the resource-based theory that firm strategic resources are heterogeneously distributed across firms and that these differences are stable over time (Barney, 1991). The disturbances $\varepsilon_{i,j}$ are independent across firms and serially uncorrelated. $(x)_{+¿¿}$ is a truncated line function that equals x when x is positive and is equal to zero otherwise (Fitzmaurice *et al.,* 2011). $t^{¿}$ is a common knot. Table 3 provides the variable definition, variable construction, and data sources.

3.2.1 Control variables

It is necessary to adjust performance measures for firm size at the firm level since firm size varies significantly among firms in the sample. For our analysis, we choose sales as the measure for firm size for reasons that follow. First our estimation results show that the marginal effect of total assets on performance measures is roughly half of that of sales despite the insignificant coefficient estimate at conventional levels. As a result, it is not considered further. Second, the number of employees may not be a true indicator of firm size based on the current reliance of outsourcing in manufacturing. Moreover, the Compustat database does not contain part-time employee data. Finally, market capitalization is a forward-looking measure, while the dependent variable $ROA_{i,j}$ or $ROS_{i,j}$ is a historical accounting measure. Thus, they are not suitable for our model. $¿¿i, j-1¿$ represents firm size and is the natural logarithm of lagged annual sales. Firm size is likely positively associated with firm performance.

Table 3. Variable Definitions and Data Sources

Variable Name	Variable Definition/construction	Source
Dependent variable	Firm performance such as ROA and ROS	Compustat
Dependent variable$_{-1}$	Lagged firm performance	Compustat
Group	1 if a firm belongs to the IT leader group; 0 otherwise	IW 500
Year	Measurement year	Compustat
Control Variable		
Size$_{-1}$	Logarithm of lagged annual sales (in millions of dollars)	Compustat
Munificence	Capacity, the availability of environmental resources to support sustained growth	Compustat
Dynamism	Stability-instability, the unpredictability of the change in external environment	Compustat
Complexity	Concentration-dispersion, the heterogeneity of the external circumstances	Compustat

Notes: Environmental dimensions (munificence, dynamism, and complexity) (Dess and Beard 1984).

Research in industrial economics, strategic management, and information systems argues that industry environments have significant impact on firm's strategic actions (Dess & Beard, 1984; Keats & Hitt, 1988; Palmer & Wiseman, 1999; Mithas *et al*., 2013). Industry-specific environmental variables have been the common form of multiple industry controls applied in strategic management research (Dess *et al.,* 1990). We use Dess and Beard's (1984) three environmental dimensions: munificence (abundance of resources or capacity to support growth) represented by $Munificence_{i,j}$,dynamism (stability-instability or turbulence) represented by $Dynamism_{i,j}$, and complexity (heterogeneity-homogeneity or concentration-dispersion) represented by $Complexity_{i,j}$.

Following Dess and Beard (1984) and Keats and Hitt (1988), we assess the five-year average growth and instability of sales and operating income within four-digit SIC industries to construct scales for munificence and dynamism. To construct the complexity scale, we rely on two key indicators: the four-firm concentration ratio and the Herfindahl index of concentration (Herfindahl, 1950). Using data sourced from the Compustat database, we compute these indicator variables for each of the 364 four-digit SIC industries within the IW 500 annually, spanning the years from 1989 to 2012. It is worth noting that the number of industries from which the IW 500 IT leaders are selected varies each year, ranging from 255 to 314 over the 24-year period.

3.3 Estimation methods

To estimate Equation (3), we employ the Arellano-Bover/Blundell-Bond system's GMM estimator, which is designed for estimating models with individual-specific time-invariant effects when independent variables incorporate one or more lags of the dependent variable. We assume that the independent variables are not strictly exogenous, and the errors are independent across individuals. This estimator is both consistent and efficient and exhibits robustness in the presence of heteroskedasticity and autocorrelation. To perform the estimation, we use Roodman's (2009a) xtabond2 Stata command. Additionally, we apply the Windmeijer (2005) correction using the robust option in our two-step GMM estimation to correct potential downward bias in the standard errors. We also adopt the collapse option of the gmmstyle(.) option, as recommended by Roodman (2009b), to reduce the instrument count.

4. Results

Before delving into the results of our dynamic panel model with firm-specific effects, we first analyze the descriptive statistics of the key variables under examination, as summarized in Table 4. As expected, the empirical distributions of total assets and sales for the control group exhibit positive skewness, while their empirical distributions of *ROA* and *ROS* display negative skewness. In contrast, the IT leader group's empirical distributions of total assets and sales are less skewed than those of the control group. Notably, the IT leader group has higher mean estimates for total assets and sales in comparison to the control group. The median estimate of total assets for the IT leader group is almost 13 times that of the control group, and its median sales estimate surpasses that of the control group by more than 17 times. Additionally, the interquartile ranges for total assets and sales of the IT leader group are much wider than those of the control group. Conversely, the control group exhibits wider interquartile ranges for *ROA* and *ROS* when compared to the IT leader group. Of particular interest is the fact that the IT leader group records higher mean and median estimates for *ROA* and *ROS* in comparison to the control group.

Table 4. Descriptive Statistics during 1989-2012

Variable	Mean	Std Dev	Min	Q_1	Med	Q_3	Max	N
IT Leader Group								
Total Assets	6,994	10,936	23	1,073	2,724	7,960	77,644	6,472
Sales	3,989	4,471	11	1,115	2,244	5,136	26,377	6,472
ROA	0.0414	0.0637	-0.9199	0.0145	0.0396	0.0699	0.4911	6,472
ROS	0.0552	0.0777	-0.8723	0.0190	0.0534	0.0885	1.0489	6,472
Control Group								
Total Assets	1,777	6,399	10	58	214	838	77,644	104,755
Sales	869	2,590	10	39	130	483	26,377	104,755
ROA	0.0052	0.1804	-6.9440	-0.0021	0.0265	0.0667	0.8238	104,755
ROS	0.0018	0.3560	-14.4053	-0.0026	0.0452	0.1037	1.6429	104,755

Notes: Total assets and sales are in 1980 million dollars. N is the number of observations. Q_1 is the first quartile and Q_3 is the third quartile.

Note that the maximum estimates for total assets and sales are identical for both groups. This uniformity arises from the process of winsorization, where we cap the top and bottom 1% of all annual item variables to mitigate the impact of outlier observations. The fact that both groups share the same maximum estimates suggests the presence of firms in both categories whose total assets and sales surpass the established maximum, representing the top 1% of all observations sorted in descending order. Conversely, we also observe that, for the control group, the minimum estimates for total assets and sales are set at $10 million. This measure is implemented to ensure the exclusion of firms with total assets or sales revenue falling below $10 million, as their inclusion could potentially distort the valuation multiples of performance measures.

4.1 New estimation results

We now present the results of our estimation, followed by specification tests. Table 5 reports the results of the firm-specific effects dynamic panel estimation of the impact of IT on performance measures. The estimation results of the dynamic panel model version of Equation (2) are shown in the columns labeled models 1 and 2. The dependent variable of model 1 is *ROA*. We observe that the estimated coefficient of the lagged dependent variable is 0.3329 ($p < 0.001$) and it means that the financial halo effect is about 33%. The estimated coefficient of *Group* is 0.0158 ($p < 0.001$) which indicates that the average *ROA* of the IT leader group is higher than that of the control group. When the dependent variable is *ROS* (model 2), we observe that the effect of *Group* on *ROS* on 0.0199 ($p < 0.001$), and 25% larger in magnitude than that on *ROA*, while the financial halo effect of 0.3080 ($p < 0.001$) and is 8% small than that of model 1.

It is important to note that Table 4 shows that the average firm size (in terms of total assets or sales) of the IT leader group is more than fourfold that of the control groups. Moreover, given the fact that the firms are selected from 364 four-digit SIC IW 500 industries, we expect significant impacts of different industry environments on firm's strategic actions and performances. As such, it is necessary to control the effects of firm size and industry environments in addition to financial halo effect.

Next, we include the linear splines and the control variables in Equation (3) to investigate whether the IT leader and control groups deliver different impacts of IT on financial performance across the 1990s and the 2000s. The estimation results for Equation (3) are shown in the columns labeled models 3 and 4. When the dependent variable is *ROA* (model 3), we observe that the estimated coefficient of the lagged dependent variable is 0.2224 ($p < 0.001$), which indicates that the financial halo effect is about 22%. We also observe that the firm size variable ¿¿−1¿ is associated with a positive impact on *ROA*. The estimated coefficient of 0.0102 ($p < 0.001$) implies that a 1 unit increase in firm sales (in million dollars) would result in a 0.000102% increase in *ROA*. The positive estimated coefficient is consistent with the prior studies. We observe that the independent variables for industry environmental characteristics are all in line with the prior studies. The coefficient of *Munificence* is significant with a value of 0.0286 ($p < 0.001$).

Dynamism has a negative impact on *ROA* (with coefficient of -0.0548 (p < 0.001)), suggesting that *ROA* decreases by 0.0548 as *Dynamism* increases by 1 unit. *Complexity*, albeit insignificant, indicates the opposite direction posited by the theory on environmental dimensions. Thus, excluding *Complexity*, the coefficient estimates of the independent variables of model 3 are all significant at p < 0.001.

Table 5. System GMM Estimates from the Firm-Specific Effects Dynamic Panel Models with Linear Splines

	Model 1	Model 2	Model 3	Model 4
Dependent Variable	ROA	ROS	ROA	ROS
Dependent Variable$_{-1}$	0.3329***	0.3080***	0.2224***	0.3020***
	(0.0415)	(0.0258)	(0.0591)	(0.0259)
Year			-0.0039***	-0.0046***
			(0.0004)	(0.0004)
¿Year – t*)$_+$			0.0062***	0.0075***
			(0.0006)	(0.0007)
Group	0.0158***	0.0199***	-0.0274***	-0.0390***
	(0.0014)	(0.0017)	(0.0045)	(0.0048)
Group × Year			0.0033***	0.0043***
			(0.0005)	(0.0005)
Group × ¿Year – t*)$_+$			-0.0048***	-0.0062***
			(0.0008)	(0.0008)
Size$_{-1}$			0.0102***	0.0134***
			(0.0010)	(0.0010)
Munificence			0.0286***	0.0557***
			(0.0036)	(0.0049)
Dynamism			-0.0548***	-0.0895***
			(0.0095)	(0.0149)
Complexity			0.0003	-0.0031***
			(0.0009)	(0.0012)
Constant	0.0032	0.0078***	0.0106	0.0111
	(0.0008)	(0.0013)	(0.0099)	(0.0171)
Firm-Specific Effects	Included	Included	Included	Included
Wald Test (χ^2)	940.00***	1,086.03***	3,895.29***	4,441.74***
AR(1) Test (z)	-11.75***	-12.97***	-8.47***	-12.95***
AR(2) Test (z)	1.07 (*ns*)	0.52 (*ns*)	-0.33 (*ns*)	0.33 (*ns*)
Hansen *J* Test (χ^2)	1.26 (*ns*)	1.19 (*ns*)	0.25 (*ns*)	0.90 (*ns*)
No. of Instruments	4	5	12	13
No. of Observations	96,159	96,159	96,159	96,159
No. of Firms	11,703	11,703	11,703	11,703

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. Standard errors in parentheses. $(x)_{+¿¿}$ is a truncated line function that equals x when x is positive and is equal to zero otherwise. t* is a common knot at the year 2000.

When the dependent variable is ROS (model 4), we observe that the effects of all control variables on ROS are statistically significant and much larger in magnitude than those on ROA. Note that the financial halo effect of 0.3020 ($p < 0.001$) is 36% larger than that of model 3. The firm size variable has the estimated coefficient of 0.0134 ($p < 0.001$) which is 31% larger than that of model 3. The positive impact of $Munificence$ on ROS (with coefficient of 0.0557 ($p < 0.001$)) is almost twice of that of model 3. Similarly, $Dynamism$ has a negative association with ROS (coefficient = -0.0895 ($p < 0.001$)) and is more than 1.63 times of that of model 3 in absolute value. Moreover, unlike model 3, $Complexity$ has a significant, negative association with ROS with the coefficient estimate of -0.0031 ($p < 0.001$). As such, the estimated coefficients of all control variables of model 4 are in accordance with the previous studies on environmental dimensions.

4.1.1 Specification tests

We now present the results of specification tests with respect to the validity of the Arellano- Bover/Blundell-Bond system GMM estimation results. First, for consistent estimation of the dynamic panel models 1-4, the Arellano-Bover/Blundell-Bond system GMM estimator assumes that the disturbances are serially uncorrelated. If this assumption is not met, the estimation result becomes inconsistent estimation result. The Arellano-Bond test (1991) for zero serial correlation is applied to the residuals in differences. The test looks for second-order correlation in differences to check for first-order serial correlation in levels. The reason is that negative first-order serial correlation in differences is expected (i.e., the results of AR(1) tests ($p < 0.001$), as shown in Table 5). Table 5 presents the results of AR(2) tests of the null hypothesis of zero serial correlation in second differences of residuals. The AR(2) tests yield the insignificant z-statistic values ($p > 0.1$) for models 1-4, respectively. Accordingly, we conclude that there is no serial correlation in the original disturbances.

Next, we present the results of the Hansen (1982) J-test of overidentifying restrictions which is a standard specification check for two-step GMM estimation. The J-statistic has a χ^2distribution under the null hypothesis of joint validity of all instruments. Four and five instruments are employed for the estimation of models 1 and 2, respectively, while 12 and 13 instruments are used for models 3 and 4, respectively. The insignificant chi-squared values ($p > 0.1$) for models 1-4 shown in Table 5 indicate that the null hypothesis that the overidentifying restrictions are valid is not rejected. In other words, the J-test results imply that the instruments employed for the estimations of the dynamic panel models 1-4 are valid. We also check the variance inflation factors (VIFs) of all the independent variables of models 3 and 4. None of the VIFs exceeds 2, indicating that there is no severe multicollinearity problem.

4.2 Has the strategic importance of IT capabilities diminished?

In order to get a feel on how the ROA and ROS behaved over the sample period, we plot the estimated means of ROA and ROS for the IT leader and control groups to investigate any trends existing in the ROA and ROS panel data over the sample period of 1989-2012. This is shown in Figure 1. Our observations in Figure 1 are summarized as follows. First, the estimated means of ROA and ROS reveal that, contrary to Chae *et al.* (2014), the IT leader group's financial performance was superior to that of the control group throughout the sample period. Second, it is shown that during the second half of the 1990s, the estimated means of ROA and ROS for the IT leader group leveled off after the recovery from the Gulf War Recession and then decreased in 1998 before they leveled off again till 2000, while those for the control group experienced significant downward trends from 1990 to 2002 (except 1995). According to Doms (2004), the growth in real IT investment was especially strong between 1995 and 2000. It averaged 24 percent per year. He considered only spending in IT equipment and software as IT investment in his research. However, the IT leader group did not seem to benefit from such massive investment in IT. Third, the estimated returns of ROA and ROS for the control group had stronger recoveries than those for the IT leader group during the 2000s.

Given the observations from Figure 1, we conduct the Chow tests to test the null hypothesis that the IT leader and control groups share the same estimated coefficients of Equation (3). When the dependent variable is ROA, the Wald statistic of $\chi^2 = 33.85$ ($p < 0.001$) indicates the rejection of the null hypothesis at conventional levels. That is, the two groups had different estimated coefficients during the sample period.

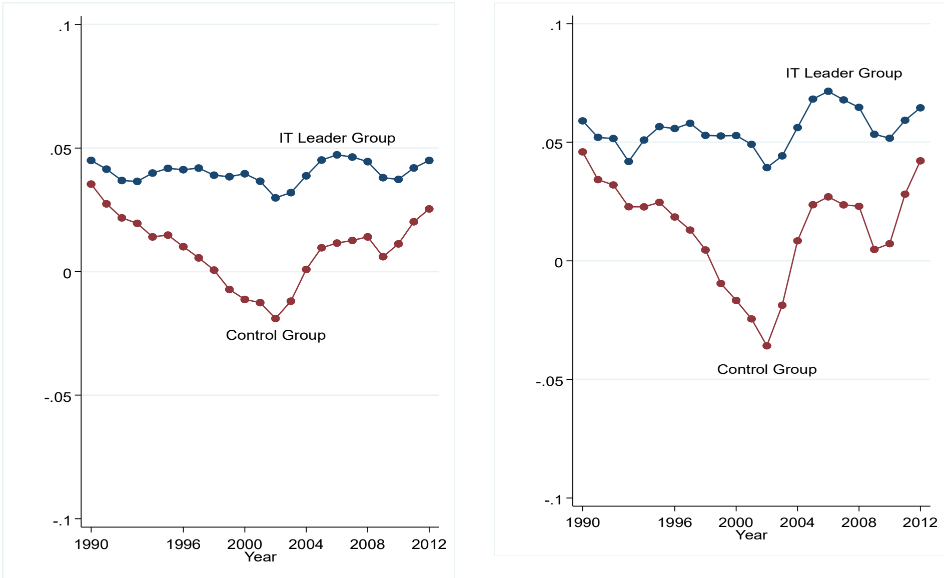

Figure 1. Estimated Mean Returns for the IT Leader and Control Groups from the Firm-Specific Effects Dynamic Panel Model during 1990-2012

When the dependent variable is *ROS*, we obtain the Wald statistic of $\chi^2 = 38.72$ ($p < 0.001$) which also rejects the null hypothesis. Thus, our test results support Hypothesis 1. In order to test the claim made by Chae *et al.* (2014), we split the sample period of 24 years into two twelve-year subsample periods by setting for knot at the year 2000. The first subsample period of 1989-2000 represents the period that proprietary information systems prevailed, in which the IT leader group is expected to show an upward trend of higher return than the control group. On the other hand, if the claim was correct, then we would expect to see a similar trend in the estimated means of *ROA* and *ROS* for the IT leader and control groups during the second subsample period of 2001-2012 (Hypotheses 2 and 3). To test Hypotheses 2 and 3, we summarize the estimated regression coefficients and standard errors on piecewise linear parts of Equation (3) for the periods before and after the year 2000 in Table 6. In doing so, the lagged dependent variable, the firm size variable, and the three environmental dimension variables are held fixed. When the dependent variable is *ROA* (model 3 of Table 5), we observe that all slope estimates for both groups are significant (p-value < 0.001 except coefficient = 0.0007 (p-value = 0.029)) except that that for the IT leader group is insignificant at p-value = 0.109 (coefficient = -0.0006) before 2000. Similarly, when the dependent variable is *ROS* (model 4 of Table 5), all slope estimates, except that for the IT leader group before 2000 (coefficient = -0.0003 (p-value = 0.379)), are significant (p-value < 0.001) and are larger in absolute value than those for *ROA*. Thus, we do not support Hypotheses 2 and 3 for both *ROA* and *ROS*. It is important to note that there is a contrary to expectations when it comes to the insignificant slopes of ROA and ROS for the IT leader group before 2000. It appears that superior IT capabilities of the IT leader group did not appear much in improved operational efficiency. On the other hand, as shown in Table 6, during the 2000s, the significant positive slopes for the control group are about three times the IT leader group's significant slopes.

Next, we investigate the truthfulness of the claim by testing the null hypothesis of no group differences in patterns of trend in the mean return during the 1990s versus the 2000s (Hypothesis 4). For comparison of the mean returns in model 3 between the IT leader and control groups, we express the null hypothesis as $H_o : \beta_5 = \beta_6 = 0$. The Wald statistic of $\chi^2 = 42.40$ ($p < 0.001$) indicates the rejection of the null hypothesis at conventional levels. That is, the two groups had different patterns of trend in the estimated mean return during the 1990s and the 2000s. Next, we separately compare the two groups before and after the year 2000. For comparison of the 1990s, we express the null hypothesis of no group differences in trend in the mean return (Hypothesis 5) as $H_o : \beta_5 = 0$. The Wald statistic of $\chi^2 = 42.25$ ($p < 0.001$) rejects the null hypothesis and indicates that the linear trends for the IT leader and control groups were different. Similarly, for the 2000s, we express the null hypothesis of no group differences in trend in the mean return (Hypothesis 6) as $H_o : \beta_5 + \beta_6 = 0$. As with the test result for the 1990s, the z-statistic of -4.33 ($p < 0.001$) rejects the null hypothesis, indicating that the linear trends for the two groups were also different during the 2000s. Using model 4 where the dependent variable is ROS, we obtain the Wald statistic of $\chi^2 = 73.13$ ($p < 0.001$) which also rejects Hypothesis 4. For testing differences in trend inf the mean return in each subsample period, we observe that the z-statistic of 8.55 ($p < 0.001$) rejects Hypothesis 5 for the 1990s. Similarly, the z-statistic value of -4.41 ($p < 0.001$) does not support Hypothesis 6 for the 2000s. Thus, we conclude that the patterns of trend in the mean return for the two groups changed across the 1990s and the 2000s. Additionally, the two groups had different trends in the mean return during each subsample period. These observations conflict with Chae *et al.* (2014) and Rahman and Zhao (2020) who argued that the superiority of the IT leader group faded during the 2000s and the 2010s, respectively.

Table 6. System GMM Estimates of Regression Coefficients and Standard Errors on Piecewise Linear Parts of the Firm-Specific Effects Dynamic Panel Model, with Common Knot at the Year 2000, Holding the Lagged Dependent Variable, the Firm Size Variable, and the Three Environmental Dimension Variables Fixed

Return on Assets				
	IT Leader Group		Control Group	
Year	Intercept	Slope	Intercept	Slope
Before 2000	-0.0168	-0.0006	0.0106	-0.0039***
	(0.0105)	(0.0004)	(0.0099)	(0.0004)

After 2000	-0.0329***	0.0007**	-0.0635***	0.0023***
	(0.0122)	(0.0003)	(0.0113)	(0.0002)

Return on Sales

Year	IT Leader Group		Control Group	
	Intercept	**Slope**	**Intercept**	**Slope**
Before 2000	-0.0028	-0.0003	0.0111	-0.0046***
	(0.0182)	(0.0004)	(0.0171)	(0.0004)
After 2000	-0.0435**	0.0010***	-0.0785***	0.0029***
	(0.0193)	(0.0004)	(0.0182)	(0.0003)

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors in parentheses.

Tables 7 and 8 summarize the main results of this study and the hypothesis test results, respectively.

Table 7. Summary of Main Results

Main results
1. The 1,308 IT leader firms listed in the IW 500 between 1989 and 2012 showed a positive association between IT capability and firm performance.
2. The financial performance of the IT leader group was superior to that of the control group throughout the sample period of 1989-2012. This observation conflicts with Chae *et al*. (2014) and Rahman and Zhao (2020) who argued that the superiority of the IT leader group faded during the 2000s and the early 2010s, respectively.
3. The financial performance of the IT leader group leveled off during the second half of the 1990s when IT proliferation and IT investment were strong. This structural shift in the mean return appears to indicate that, contrary to expectations, the benefits of the IT leader group's superior IT capability did not significantly translate into improved operational efficiency during the period.
4. The IT leader and control groups had different patterns of trend in the mean return during the 1990s and the 2000s. The financial performance of the control group showed continuously downward trend for the entire 1990s (except 1995). However, the financial performance of the control group experienced a much stronger recovery (with a threefold increase in magnitude) compared to the IT leader group during the 2000s.

Table 8. Summary of Hypothesis Tests

	Hypothesis	Results
H1	Firms with superior IT capability have higher mean return	Supported

	than all control firms during the 1990s and the 2000s after adjusting for financial halo effect.	
H2	The mean return of firms with superior IT capability has an upward trend over the 1990s, after adjusting for financial halo effect, because IT proliferation and IT investment were robust during the period.	Unsupported
H3	The mean return of firms with superior IT capability has no significant trend over the 2000s, after adjusting for financial halo effect, because information systems were standardized and homogeneous during the period.	Unsupported
H4	Firms with superior IT capability have different patterns of trend in the mean return from all control firms during the 1990s versus the 2000s after adjusting for financial halo effect.	Supported
H5	Firms with superior IT capability have a different trend in the mean return from all control firms during the 1990s after adjusting for financial halo effect.	Supported
H6	Firms with superior IT capability have a different trend in the mean return from all control firms during the 2000s after adjusting for financial halo effect.	Supported

5. Discussion

In this section, we delve into the influence of omitted variable bias on the previously observed financial halo effect. Additionally, we examine how the choice of selection method for the control group affects the investigation result. Lastly, we examine the two novel findings presented as main results 3 and 4, as summarized in Table 7.

5.1 Effect of omitted variable bias on financial halo effect

The omitted variable bias is due to model misspecification resulting from not incorporating the firm-specific effects. We also discuss the estimation results obtained by the system GMM estimator and the Within Groups estimator. In order to examine the magnitude of the omitted variable bias, we estimate Equation (3) by OLS. The second column of Table 9 presents the OLS estimation results of Equation (3). For comparison purposes, we also present the estimation results of model 3 of Table 5 in the system GMM column of Table 9. As shown, the OLS estimate of the coefficient of $Y_{i,j-1}$ ¿coefficient = 0.4694 (p < 0.001)) with the standard error estimate of 0.0034 is larger than twice the system GMM estimate of 0.2224 (p < 0.001) with the standard error estimate of 0.0591. Moreover, note that the OLS standard error estimate of 0.0034 is biased downward. When we relax the assumption of independence of the observations and use the cluster-robust standard error option, we obtain the standard error estimate of 0.0135 (not provided in Table 9) which is almost quadruple the size of the former with the same coefficient estimate of 0.4694.

It is important to note that the difference between two estimates of β_1 of Equation (3) meets the standard results for omitted variable bias in the case of dynamic panel models, which indicates that OLS levels estimator is biased upward at least in the large samples. The reason for this upward bias is that the firm-specific effect α_i, treated as being stochastic, is necessarily correlated with $Y_{i,j-1}$. With the assumption that the disturbances $\varepsilon_{i,j}$ are serially uncorrelated, the OLS estimator of β_1 of Equation (3) is inconsistent because $Y_{i,j-1}$ is positively correlated with the error $(\alpha_i+\varepsilon_{i,j})$ due to the presence of α_i. This positive correlation inflates the estimate of the coefficient of $Y_{i,j-1}$ by attributing the marginal effect of α_i to it as if α_i were included in Equation (3). It does not vanish as the number of firms in the sample gets larger, nor is it mitigated by increasing the number of time periods (Bond 2002).

Table 9. Comparison of Estimators

	OLS	**System GMM**	**Within Groups**
Dependent Variable	ROA	ROA	ROA
Dependent Variable$_{-1}$	0.4694***	0.2224***	0.1761***
	(0.0034)	(0.0591)	(0.0141)
Year	-0.0029***	-0.0039***	-0.0025***
	(0.0002)	(0.0004)	(0.0003)
(Year – t*)$_+$	0.0050***	0.0062***	0.0042***
	(0.0003)	(0.0006)	(0.0004)
Group	-0.0272***	-0.0274***	-0.0266***
	(0.0063)	(0.0045)	(0.0034)
Group × Year	0.0033***	0.0033***	0.0031***
	(0.0007)	(0.0005)	(0.0004)
Group × (Year – t*)$_+$	-0.0051***	-0.0048***	-0.0043***
	(0.0012)	(0.0008)	(0.0007)
Size$_{-1}$	0.0084***	0.0102***	-0.0116***
	(0.0003)	(0.0010)	(0.0015)
Munificence	0.0253***	0.0286***	0.0405***
	(0.0024)	(0.0036)	(0.0027)
Dynamism	-0.0464***	-0.0548***	-0.0537***
	(0.0067)	(0.0095)	(0.0094)
Complexity	0.0020*	0.0003	0.0013
	(0.0012)	(0.0009)	(0.0009)
Constant	0.0010	0.0106	0.1005***
	(0.0076)	(0.0099)	(0.0129)
Firm-Specific Effects	Included	Included	Included
Wald Test (χ^2)		3,895.29***	
F test (F)	2,363.80***		77.14***
AR(1) Test (z)		-8.47***	
AR(2) Test (z)		-0.33 (*ns*)	

	OLS	System GMM	Within Groups
Hansen *J* Test (χ^2)		0.25 (*ns*)	
No. of Instruments		12	
No. of Observations	96,159	96,159	96,159
No. of Firms		11,703	11,703
Adjusted R-squared	0.197		
$\sqrt{\alpha}$			0.194
$\sqrt{\varepsilon}$			0.131
ρ			0.687

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. Standard errors in parentheses. $\sqrt{\alpha}$ is the standard deviation of the firm-specific time-invariant effects α_i. $\sqrt{\varepsilon}$ is the standard deviation of the disturbance $\varepsilon_{i,j}$. ρ is the proportion of the total variance contributed by the panel-level variance component α_i. $(x)_{+¿¿}$ is a truncated line function that equals x when x is positive and is equal to zero otherwise. t* is a common knot at the year 2000.

We also present the estimation results obtained by the Within Groups estimator in the fourth column of Table 9. Note that the Within Groups estimator with the vce(robust) option of Stata produces larger standard errors even though the estimates of β_1 are the same with and without the option. The estimate of ρ which is 0.687 indicates that the panel-level variance component is important. The Within Groups estimator eliminates the above inconsistency by demeaning all variables of Equation (3) with their mean values across the $T-1$ observations for each firm i, and by estimating the transformed questions by OLS, where the original variables are expressed as deviations from these firm means. Note that this demeaning procedure also eliminates α_i because the mean of α_i is itself α_i. However, for short panel data, this transformation induces a non-negligible negative correlation between the first transformed lagged dependent variable $Y_{i,j-1}-\overline{Y_i}$ and the transformed disturbance $\varepsilon_{i,j}-\overline{\varepsilon_i}$ of the transformed equations. As with the OLS estimator, this negative correlation is not mitigated by increasing the number of firms in the sample, so that the Within Groups estimator is also inconsistent. That is, this negative correlation creates a bias in the estimate of the coefficient of $Y_{i,j-1}$ (Nickell, 1981). But unlike the OLS estimator, as the number of time periods gets large, the correlation induced by the demeaning transformation vanishes and the Within Groups estimator becomes consistent. Said differently, consistency for the Within Groups estimator implies that $\overline{\varepsilon_i}$ should be very small relative to $\varepsilon_{i,j}$, which expects that the number of time periods approaches infinity. However, a simulation study found that the least squares dummy variable estimates could be biased from 3% to 20 % of the true value of the coefficient even when T

= 30 (Judson & Owen, 1999). The estimated coefficient of $Y_{i,j-1}$ is 0.1761 ($p <$ 0.001) with the standard error estimate of 0.0141, which is smaller than 0.2224 ($p <$ 0.001) of the system GMM estimator. This estimate is in accordance with the standard results for omitted variable, which the Within Groups estimator is biased downward at least in the large samples (Bond 2002). Note that the first differencing approach which is the standard fixed-effects approach does not lead to the consistent estimate of the coefficient of $Y_{i,j-1}$, either. It is because the lagged difference of the dependent variable $Y_{i,j-1}-$¿ $Y_{i,j-2}$ becomes correlated with $\varepsilon_{i,j}-$¿ $\varepsilon_{i,j-1}$. Thus, estimating the first differenced model by OLS leads to the inconsistent estimate of the coefficient of the lagged difference of the dependent variable $Y_{i,j-1}-$¿ $Y_{i,j-2}$.

Taken together, as Bond (2002) points out, the OLS and Within Groups estimators are likely to be biased in opposite directions, and the estimate of a candidate consistent estimator is anticipated to lie between the estimates of these two estimators. The fact that the system GMM estimate of 0.2224 lies between the OLS estimate of 0.4694 and the Within Groups estimate of 0.1761 indicates that our estimation results are well supported.

5.2 Selection of the control group

Our choice for the control group is to include all other firms within the respective four-digit SIC industry where an IW 500 leader firm is situated, a practice in line with the methodology outlined by Santhanam and Hartono (2003, page 127). On the other hand, it is worth noting that utilizing a single control firm as a benchmark for a potential group of firms can render the test results sensitive to the selection of individual control firms. Moreover, practical challenges may arise when attempting to identify appropriate control firms over a four-year window.

To illustrate, Bharadwaj (2000) encountered difficulties in matching single control firms for 19 out of the 56 IT leader firms she selected, resulting in her recourse to two- or three-digit SIC industries. Similarly, Chae *et al*. (2014) faced a similar issue, as they were unable to match 102 out of the 296 sampled firms drawn from 163 four-digit SIC industries spanning 2001 to 2004. Consequently, both studies found themselves unable to match more than a third of their sampled IT leader firms effectively. Regarding Rahman and Zhao (2020), the lack of provided information about the firms used in their sample limits our ability to assess the quality of their matching process. As noted by Rahman and Zhao (2020, page 616), "the average sales and assets of the IT leaders' group were almost twice as much as those of the control group." As such, their matching process may not have been executed effectively either.

5.3 Two novel findings

As illustrated in Figure 1, a rather unexpected structural shift in the mean return for the IT leader group occurred during the second half of the 1990s. This period was marked by the adoption of proprietary information systems, a significant increase in IT proliferation and investment. One might have anticipated an upward trajectory in the mean return due to these advancements. Surprisingly, this shift in the mean return suggests that the benefits of the IT leader group's superior IT capability did not manifest significantly in improved operational efficiency during this period.

To explore this further, we examine the ratios of operating income to assets (OI/A) and operating income to sales (OI/S) for the IT leader group. These measures focus exclusively on operating income, which can be seen as a more direct indicator of IT-related business operations. To discern whether OI/A and OI/S exhibit distinct patterns compared to ROA and ROS in the second half of the 1990s, we plot the estimated mean values of OI/A and OI/S for both the IT leader and control groups from 1990 to 2012, as depicted in Figure 2. Figure 2 reveals a modest upward trend in the estimated mean of OI/A during the latter part of the 1990s, in contrast to ROA in Figure 1, which remains relatively constant during that period. On the other hand, we observe that the decline in the estimated mean of OI/S for the IT leader group is somewhat more pronounced than the decrease in ROS shown in Figure 1. Nevertheless, these differences do not offer conclusive explanations.

Figure 2 also highlights a remarkable trend – during the 2000s, the financial performance of the control group experienced a notably stronger recovery, with a magnitude three times greater than that of the IT leader group over the same period. This observation suggests that as the Internet technology revolution concluded in 2002 (as exemplified by Pastor & Veronesi, 2009), the control group, often considered as followers, began to bridge the gap and even surpass the IT leader group in terms of returns.

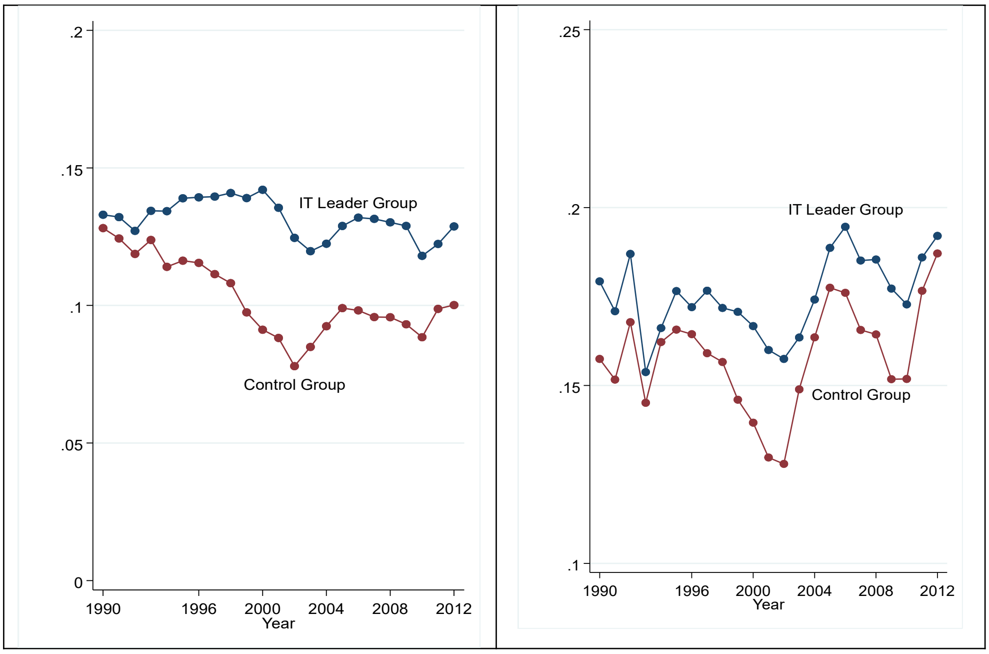

Figure 2. Estimated Means of Operating Income for the IT Leader and Control Groups from the Firm-Specific Effects Dynamic Panel Model during 1990-2012

6. Conclusions

In this study, we identify and address the model misspecifications and estimation issues prevalent in prior research employing cross-sectional AR(1) models. To address these issues, we introduce and empirically examine a dynamic panel model that incorporates firm-specific time-invariant effects, aligning with the core principles of the RBV of the firm, notably, resource heterogeneity across firms and resource immobility. Leveraging a sample comprising 1,308 IT leader firms listed in the IW 500 from 1989 to 2012 and a short panel of annual time series data drawn from the Compustat database, our longitudinal analysis reveals a positive correlation between IT capability and firm performance. Our findings also indicate that the financial performance of the IT leader group consistently outperformed that of the control group over the entire study period spanning from 1989 to 2012. These findings are at odds with the assertions made by Chae *et al*. (2014) and Rahman and Zhao (2020), both of whom contended that the superiority of the IT leader group waned during the early 2000s and early 2010s, respectively.

Furthermore, we note that the estimated means of *ROA* and *ROS* for the IT leader group plateaued during the latter half of the 1990s, a period marked by substantial IT proliferation and robust IT investments. Surprisingly, it seems that, contrary to expectations, the benefits of superior IT capability within the IT leader group did not significantly translate into improved operational efficiency during this timeframe. Additionally, we observe a stark contrast in the estimated means of ROA and ROS for the control group during the 2000s, exhibiting a threefold increase in magnitude compared to those of the IT leader group over the same period.

6.1 Contributions, limitations, and future research

This study makes a noteworthy contribution to the existing literature by conducting a comprehensive longitudinal analysis of the relationship between IT capability and performance, a perspective that hasn't been extensively explored before. While previous studies have primarily relied on cross-sectional analyses using four-year data, this research utilizes short panel data spanning over a 24-year period, providing a more in-depth perspective. Moreover, it pioneers an investigation into potential changes in patterns within the IT capability-performance relationship across different groups and over time.

For the selection of IT leader firms, this study adopts the IW 500 list published by *InformationWeek*, widely recognized as one of the most reputable and trusted sources of IT-related information. Nevertheless, it's essential to acknowledge certain limitations that might affect the results of our analyses. Firstly, *InformationWeek* frequently modified the criteria and procedures for designating IT leader firms to reflect the ever-evolving landscape of technology. This led to less consistency and reliability in the listings for research purposes. Secondly, the selection of firms in the IW 500 is grounded in subjective expert opinions rather than objective evaluations of their IT capability. Thirdly, the binary classification of firms as IT leaders hinders researchers from directly assessing the performance in relation to the incremental improvements in their IT capabilities, as noted in prior studies (Santhanam & Hartono, 2003; Chae *et al*., 2014).

Future research endeavors may address the following inquiry: We have observed that the estimated mean returns of ROA and ROS for the IT leader group exhibited a leveling off trend following the recovery from the Gulf War Recession. In 1998, these returns decreased briefly before stabilizing until the year 2000. This trend is somewhat unexpected given the substantial IT proliferation and investment during this period. Does this suggest that the IT leader group's superior IT capabilities failed to translate into sustained competitive advantages, preventing clear differentiation from other groups? Alternatively, can we attribute the plateaued mean returns of the IT leader group to the persistent competitive advantages stemming from its superior IT capabilities? In essence, did these sustained competitive advantages maintain the IT leader group's mean returns at a steady level, while the control group experienced significant declines?

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