Association for Information Systems
AIS Electronic Library (AISeL)

PACIS 2017 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

Summer 7-19-2017

Impact of E-business Technology on Operational Competence and Firm Profitability over Time

Jose Benitez
Rennes School of Business, Rennes, France, jose.benitez@rennes-sb.com

Yang Chen
Southwestern University of Finance and Economics, chenyang@swufe.edu.cn

Thompson S.H Teo
bizteosh@nus.edu.sg

Aseel Ajamieh
Princess Nourah bint Abdulrahman University, Saudi Arabia, aseelkhalil1987@hotmail.com

Impact of E-business Technology on Operational Competence and Firm Profitability over Time

Completed Research Paper

Jose Benitez
Rennes School of Business, France
University of Granada, Spain
jose.benitez@rennes-sb.com
joseba@ugr.es

Yang Chen
Southwestern University of Finance and Economics, China
chenyang@swufe.edu.cn

Thompson Teo
National University of Singapore, Singapore
bizteosh@nus.edu.sg

Aseel Ajamieh
Princess Nourah bint Abdulrahman University, Saudi Arabia
aseelkhalil1987@hotmail.com

Abstract

This study examines the evolution of the impact of e-business technology on operational competence and profitability using a panel dataset of 154 Spanish firms. We find that: (1) E-business technology has a positive effect on operational competence that decreases over time; and (2) the firm's proficiency in exploiting a portfolio of operational capabilities has a positive impact on profitability that becomes more significant over time. The findings provide some insights on how the initial and subsequent IT investments affect operational competence and profitability over time. This study illustrates methodologically how to perform a partial least squares estimation using panel data.

Keywords

E-business technology capability, operational capabilities, business value of IT.

Introduction

Firms invest millions of Euros in information technology (IT) to build process capabilities and increase their competitiveness (Chen et al. 2015, Cui et al. 2015, Wang et al. 2015, Ajamieh et al. 2016). However, not all IT investments generate the expected results (Carr 2003). This situation demands managers to carefully (re)assess all their IT investments (Shao and Lin 2002, Mithas et al. 2012).

Much of past research focused on IT impact on the supply chain and manufacturing activities through a cross-sectional design (Rai et al. 2006, Devaraj et al. 2007, Sanders 2007, Ayabakan et al. 2012, Setia and Patel 2013). What remains unclear is whether and how IT investments impact on a broader set of operational capabilities and performance over time. Considering that IT and operational capabilities, their relationship and effect on firm performance can be dynamic, this seems to be a significant gap that needs to be filled in our field.

This research focuses on e-business technology (one type of IT capability investment/resource allocation) and on whether, how, and under what conditions this capability creates business value. E-business technology can improve the firm's operations management system by enabling the real-time interchange of information across the supply chain (Devaraj et al. 2007, Setia and Patel 2013). However, e-business technology has become commoditized and can be affordable for most large firms, which can reduce its potential to create operational advantages over time (Carr 2003). This leads to our first research question: How does the time of investment in e-business technology affect the firm's operations management system (specifically, operational competence comprising a portfolio of capabilities) over time? We believe that our field needs to provide an answer to this critical research question. This is what we try to achieve in this research.

Related to the firm's operations management system, we focus on the firm's operational competence, which refers to the firm's proficiency in exploiting its portfolio of operational capabilities (Wu et al.

2010, Setia and Patel 2013). This competence is related to the heart of the business model of a firm, which supposes a natural starting point in this research (Benitez et al. 2015). Based on the work of Tatikonda et al. (2013), we focus on a portfolio of operational capabilities that determines operational competence: gross margin, employee productivity, operational talent management, and operational excellence. These operational capabilities are related to product margin control, productivity management, talent management, and manufacturing and service excellence; they are a good representation of the potential portfolio of operational capabilities that a contemporary firm may possess to be successful and survive in the long run (Tatikonda et al. 2013).

The operational capabilities of the firm can be refined through time and experience. In this sense, early developers of operational capabilities through early investment in e-business technology can achieve greater competitiveness based on longer duration and experience to develop their operational capabilities. This leads to our second research question: Do initial and subsequent e-business technology investments result in differences in the operations management impact on the firm's competitiveness over time? We address the above two questions in this study. Specifically, by drawing on the IT-enabled organizational capabilities perspective (Benitez and Walczuch 2012, Braojos et al. 2015a, Chen et al. 2015, Benitez et al. 2016a), the operational capabilities-based theory (Peng et al. 2008, Benitez et al. 2015), and the literature on the hierarchy of capabilities of the firm (Rai et al. 2006), the main goal of this study is to examine the evolution of the impact of e-business technology on operational competence and firm profitability over time. To achieve this goal, we use the structural equation modeling (SEM) technique with a panel dataset for the period 2008-2010 on a sample of 154 large firms in Spain. The empirical analysis suggests that the positive effect of e-business technology on operational competence decreases over time, while the positive effect of operational competence on firm profitability increases over time. The findings provide some insights on how the initial and subsequent IT investments affect operational competence and firm profitability over time. Early development of IT-enabled operational capabilities maximizes firm profitability based on the greater time and experience the firm possess to develop its operational capabilities. This study also illustrates methodologically how to perform a partial least squares (PLS) estimation using panel data.

Theory and hypotheses

Conceptualization of E-business Technology, Operational Competence, and Firm Profitability

E-business technology capability is the firm's proficiency in leveraging its web-based technologies to interchange within and outside the firm for buying and selling activities with suppliers and customers (Teo and Ranganathan 2004, Devaraj et al. 2007, Sanders 2007). Operational competence refers to the firm's proficiency in exploiting its portfolio of operational capabilities (Wu et al. 2010, Setia and Patel 2013). Based on the work of Tatikonda et al. (2013), we focus on a portfolio of operational capabilities that determines operational competence: gross margin, employee productivity, operational talent management, and operational excellence. Gross margin is the firm's proficiency in managing/estimating proper product margins. Employee productivity refers to the firm's proficiency in stimulating the personnel to achieve higher individual performance (Pan et al. 2015). Operational talent management is the firm's proficiency in recruiting (sourcing, attracting, selecting), getting on board, developing, and retaining operational talent (Benitez et al. 2013, 2015). Operational excellence refers to the firm's proficiency in developing and executing operational routines to manufacture/supply products agilely (in an excellent way) to the market (Chen et al. forthcoming). This study focuses on firm profitability to assess the firm's business benefits.

E-business Technology and Operational Competence

E-business technology can enable the development of operational competence by facilitating the improvement of gross margin, employee productivity, operational talent management, and operational excellence. E-business technology can enable the firm's proficiency in managing successful product margins. Web-based technology enables the firm to have real-time interchange of accurate and timely information on product cost and demand with upstream suppliers and downstream customers, thereby enabling the firm to better manage its product margins (Devaraj et al. 2007, Sanders 2007, Benitez and Ray 2012). Similarly, e-business technology can also be leveraged to increase employee productivity (Banker et al. 2006). The firm's web-based communication networks (e.g., email, Intranet) enable the employees to access and share more heterogeneous/diverse knowledge (e.g., information about the manufacturing process/other employees) and learn to perform multiple tasks, which increase employee productivity (Bock et al. 2005, Aral et al. 2012).

E-business technology can also improve the management of operational talent. Through e-business technology, the firm acquires/provides accurate and timely information from/to the market to recruit and get on board outstanding operational talent to design and integrate its talent base. For example, Cortefiel (an apparel manufacturer in Spain) uses web-based social media tools such as LinkedIn, Facebook, and Twitter to recruit operational managerial talent that fits the profile needed in designing its talent base (Benitez et al. 2013). Web-based technology enables the firm to implement scheduling and workplace flexibility activities to retain operational talent, and to provide reliable information on goals completion, performance appraisal, and career planning to develop and retain operational talent (Benitez et al. 2015). Finally, leveraging web-based business applications (e.g., operational module of an enterprise resource planning) enables better execution of operational routines and agility in manufacturing/supplying products to the markets to pursue operational excellence (Law and Ngai 2007). We thus hypothesize that:

Hypothesis 1a (H1a): E-business technology has a positive effect on operational competence.

Firms may not need to invest substantially in IT every year/period. For example, Air Canada (the largest airline firm in Canada) invested in 2007 in its web-based technology to be the first airline in offering customer the online boarding pass and self-service IT applications to save costs (increase gross margin) and improve operational excellence. After its initial investments in e-business technology, Air Canada did not need substantial additional investments in e-business technology to keep its operational development in subsequent periods (Karimi and Rivard 2014).

We also predict that the positive effect of e-business technology on operational competence can decrease over time for two reasons. First, additional investments in e-business technologies (after investments in prior periods) can diminish the operational marginal returns (Aral et al. 2012). Second, e-business technology has been commoditized and can be affordable for most firms. Consequently, follower firms can learn to invest in e-business technology and develop e-business technology capability, which can convert e-business technology into a non-unique/imitable capability and its effect on operational competence can decrease over time (Carr 2003). We thus hypothesize that:

Hypothesis 1b (H1b): The effect of e-business technology on operational competence decreases over time.

Operational Competence and Firm Profitability

We also argue that operational competence has a positive impact on firm profitability. Since firms can develop different proficiencies in managing/estimating product margins, this operational capability can generate differences in firm's benefits and profitability (Tatikonda et al. 2013), thus indicating that it is rational to expect a positive impact of gross margin capability on firm profitability. Higher employee productivity and better firm's proficiency in recruiting, getting on board, developing, and retaining operational talent reduce costs and increase revenues, which in turn increase business benefits and profitability (Ahmad and Schroeder 2003, Stahl et al. 2012). For example, Mercadona (a leading retailer) is a top employer firm in Spain that offers excellent working conditions and an attractive career plan to develop and retain shop talent, which has enabled Mercadona to be the most profitable retailer of Spain (Ton and Harrow 2010, Benitez et al. 2015). Finally, by developing operational routines to achieve operational agility, operational excellence can increase profitability (Malhotra and Mackelprang 2012). Thus, we hypothesize that:

Hypothesis 2 (H2a): Operational competence has a positive impact on firm profitability.

Because the firm's proficiency in exploiting its portfolio of operational capabilities is the heart of the firm's business model (Peng et al. 2008, Wu et al. 2010) and this proficiency can be refined through time and experience, we expect that positive impact of operational competence on firm profitability to increase over time. Therefore, we propose the following hypothesis:

Hypothesis 2b (H2b): The effect of operational competence on firm profitability increases over time.

Although not stated as formal hypotheses, we expect that e-business technology, operational competence, and firm profitability in one period should affect the same construct in the subsequent period (Johnson et al. 2006). For example, since current business benefits are influenced by prior business benefits, we can also expect that firm profitability obtained in the prior period affects the firm profitability in the subsequent period (Bharadwaj 2000, Benitez and Ray 2012). Firm size in t_1, t_2, and t_3 were considered as exogenous variables, and they were not subsequently linked among themselves.

Firm profitability can be affected by the type of industry. We thus control for industry effect on firm profitability (Teo and Bhattacherjee 2014, Braojos et al. 2015a, 2015b).

Research methodology

Sample and Data

The proposed model is tested with a secondary dataset collected from a sample of 154 large manufacturing and service firms in Spain for the period 2008-2010. A panel of three repeated years is sufficient to investigate the evolution effects that we pursue in this research (Serva et al. 2011). Our sample is obtained from the Monitor Empresarial de Reputacion Corporativa (MERCO) database (http://www.merco.info/es/), which includes ranking and evaluation of corporate reputation and employer brand of firms in Spain and Latin America. Our sample is representative of the large manufacturing and service firms located in Spain because large firms in Spain participate in the annual MERCO evaluation and are included in the MERCO database.

We used the name of firms selected from the MERCO database to collect additional information from the firm's websites, Sistema de Analisis de Balances Ibericos (SABI), Actualidad Economica and COMPUSTAT databases. SABI is a database produced by Bureau van Dijk that contains abundant financial information on firms in Spain and Portugal (https://sabi.bvdinfo.com/) (Benitez and Ray 2012). Actualidad Economica is a premier Spanish business magazine that develops annual rankings based on sales and innovation to compose a database with rich information on the most admired firms in Spain (http://www.actualidadeconomica.com/) (Benitez et al. 2015).

Measures

We measure all our constructs with secondary panel data for the period 2008-2010 that comes from five different sources. Table 1 provides the name, measure definitions, and data sources for all constructs. Consistent with prior Information Systems (IS) research (e.g., Zhu and Kraemer 2002, Braojos et al. 2015a), we measure e-business technology through the accumulated number of e-business technology services that each firm possesses to interact with its suppliers and customers with information collected from the firm's website.

Measurement models can be specified as factor or composite models (Rigdon 2012, Henseler et al. 2014). Factor models use reflective constructs and assume that the variance of a set of indicators can be perfectly explained by the existence of one unobserved variable and individual random error. It is the standard model of behavioral research (Henseler et al. 2014, Dijkstra and Henseler 2015). In contrast, composite models/constructs are formed as linear combinations of their respective indicators. A composite construct serves as proxy for the concept under investigation (i.e., the recipe) that is composed of a mix of indicators (i.e., the ingredients) (Henseler 2015). As an example, consider bread. Bread is constituted from wheat, water, salt, and yeast. If we were to examine the correlations between the amount of wheat, water, salt, and yeast in a sample of loaf of bread, the correlations are likely to be high. However, such correlations do not mean that bread is a reflective construct and that bread causes wheat, water, salt, and yeast. Rather, bread is a composite construct where wheat, water, salt, and yeast are the simple entities (i.e., the ingredients) which are combined to form the composite concept we call bread. Clearly, the temporal precedence of the ingredients also suggests that bread cannot be the common cause of the ingredients. The composite model does not impose any restrictions on the co-variances among indicators of the same construct, thereby relaxing the assumption that all the covariation among a block of indicators is explained by a common factor. Emergent and strong concepts should be modeled as composite constructs (Henseler et al. 2016). Composite constructs seem to be called the most promising type of constructs in research on business value of IT Consequently, the model of this study is composite.

Operational competence is defined as a composite first-order construct composed of gross margin, employee productivity, operational talent management, and operational excellence (Tatikonda et al. 2013). Gross margin and employee productivity are measured through gross margin and operating revenues per employee with information collected from SABI database. They are also the measures used by business executives to evaluate gross margin and employee productivity in the real world (Ton and Harrow 2010). We measure operational talent management through the score (from 0 to 10000) achieved by each firm in employer brand/reputation (Benitez et al. 2015) using information collected from MERCO database. Employer brand/reputation is a good proxy for operational talent management because top employers are also leading firms in recruiting, getting on board, developing, and retaining talent (Stahl et al. 2012, Benitez et al. 2013).

Operational excellence is measured through the rate of sectoral excellence (RSE) in sales with information collected from Actualidad Economica database (Benitez and Walczuch 2012). We assume that excellent firms in operations are also leader firms in sales (Benitez and Walczuch 2011). RSE in sales has a value between 0 and a value very close to 1 (termed the industry's maximum value). The closer the RSE is to the maximum value for the industry, the better the operational excellence of the firm (Benitez and Ray 2012). Firm profitability is measured through the return on assets (ROA) with information from SABI database. We control for firm size and industry. We measure firm size through the natural logarithm of number of employees (Zhu and Sarkis 2004) using information collected from SABI and Actualidad Economica databases. We classified firms in manufacturing (0) or services (1) to control for industry (Braojos et al. 2015a). All variables are measured for the years 2008 (t_1), 2009 (t_2), and 2010 (t_3).

Prior to data collection, we arranged two informal meetings with four executives (two came from IT and two from business area) and asked for their opinion about the congruence between the measures and constructs employed in the study (Benitez et al. 2015, Braojos et al. 2015b). They indicated that there was very good conceptual proximity between the measures and constructs. Overall, this shows satisfactory content validity for our constructs.

Empirical analysis

We use the variance-based SEM technique and the PLS method of estimation to test the hypotheses and examine the indirect effects involved in the proposed model. We use the statistical software package Advanced Analysis for Composites (ADANCO) (http://www.composite-modeling.com/) (Henseler and Dijkstra 2015). ADANCO is a modern statistical software package that enables the execution of a modern approach for variance-based SEM technique, including the method of estimation of PLS. ADANCO is particularly useful to estimate models that contain composite constructs, as in our study (Henseler et al. 2016).

It is appropriate to use PLS as the method of estimation for the following reasons. First, PLS is a full-fledged SEM method of estimation that can conduct exact test of model fit (Henseler et al. 2016). Second, the construct operational competence is identified as composite, and PLS is a suitable method for estimating models with this type of constructs (Rigdon 2012, Henseler et al. 2014). Third, the use of PLS SEM is advisable to estimate models that employ secondary data like our model (Gefen et al. 2011, Benitez and Walczuch 2012). Fourth, prior research in the Marketing domain has proven that PLS estimation is useful for testing models that use panel data (e.g., Johnson et al. 2006). Finally, PLS is a variance-based SEM technique that has been used and highlighted in prior IS research (Rai et al. 2006, Benitez et al. 2016b). To estimate the level of significance of weights, loadings, and path coefficients, we run the bootstrapping algorithm with 200 subsamples.

Prior to data collection, we performed a prior statistical power analysis. The maximum number of predictors in the proposed model was four (i.e., comprising the composite indicators of the constructs operational competence in t_1, t_2, and t_3). Assuming a medium effect size ($f^2 = 0.150$), the proposed model required a minimum sample size of 84 to achieve a power of 0.800 and an alpha level of 0.05 (Cohen 1988, Wang et al. 2015). Our sample size was 154, which is adequate to estimate the proposed model. This analysis suggested that our study had sufficient statistical power to detect the effects of interests. After estimating the proposed model, we also conduct a post-hoc statistical power analysis by using the software GPower 3.1.9.2[1] (Mayr et al. 2007, Aguirre and Ronkko 2015). The average effect size for the relationships included in the proposed model is 0.278, which with an alpha level of 0.05 and four predictors provides an achieved statistical power of 0.999, well above of the accepted threshold of 0.800. The results of the prior and post-hoc statistical power analyses confirm that the non-significant effects of the empirical analysis are not due to a problem with the sample size (Mayr et al. 2007).

Hypotheses Testing

We test the proposed model by performing a PLS estimation and analyzing the evolution of the effect size (f^2) for the hypothesized relationships. f^2 values of 0.020, 0.150, and 0.350 indicate a weak, medium, or large effect size of adding a link between an exogenous and endogenous variable (Henseler and Fassott 2010). Thus, we examine the evolution of beta coefficients, level of significance and f^2 values to test the hypotheses. Table 2 presents the results of the PLS estimation. The empirical analysis gives good support to the hypotheses. E-business technology has a positive effect on operational competence that decreases over time even becoming non-significant. The portfolio of operational

[1] GPower 3.1.9.2 is a free general power analysis program (Mayr et al. 2007).

capabilities has a positive impact on firm profitability that becomes more critical over time. The firm size effect on firm profitability is only significant in t_1. The effect of industry on firm profitability is significant at 0.05 level in t_1. All constructs are affected by the same construct in the prior period (significant at 0.05 level).

The values of the beta coefficients, their level of significance, the f^2 values and the R^2 values are individual measures of the explanatory power of the model. Beta coefficients around 0.200 are considered economically significant, and R^2 values higher than 0.200 indicate good explanatory power of the endogenous variables of the model (Chin 2010, Benitez and Ray 2012). The beta coefficients of the hypothesized relationships in our model range from 0.199^* to 0.473^{**}. The f^2 values for the six endogenous variables involved in the hypothesized relationships range from 0.043 to 0.333. The R^2 values for these relationships range from 0.091 to 0.732. Overall, this analysis suggests a good explanatory power for the proposed model.

Table 1: Construct name, measure definition, and data sources

Construct name	Measure definition	Source
E-business technology	Accumulated number of e-business technology services that each firm possesses on the following list of 26 e-business technology services: website, online catalogue, online ordering, banner, online order tracker, site map, search engine, bulletin subscription, email, discussion forum, online calendar/agenda, repository of documents, tools to provide recommendations to customers, invoice system, customer service management solution, shopping cart solution, payment system, website advertising, Intranet for employees, supplier management solution, shareholder solution, social media usage, frequently asked questions, online visitor counter, and customer loyalty solution. This measure ranges from 0 to 26	Proprietary content analysis of the firm's website
Profit margin	Profit margin (%) = (Earnings before taxes / Operating incomes) * 100	SABI
Employee productivity	Operating revenues per employee (in thousands of Euro) = Operating incomes / Number of employees	SABI
Operational talent management	Score from 0 to 10000 given by MERCO to the firm in employer brand/reputation	MERCO
Operational excellence	RSE in sales = 1 - (Ranking position of firm in sales / Total number of firms in the industry). RSE ranges from to 0 to 1	Actualidad Economica
Firm profitability	Return on assets (%) = (Earnings before taxes / Total assets) * 100	SABI
Firm size	Natural logarithm of the number of employees	SABI and Actualidad Economica
Industry	Dummy variable (0: Manufacturing, 1: Service firm)	SABI, Actualidad Economica and COMPUSTAT
Advertising spending	Advertising expenditure per employee (in thousands of Euro) = Advertising expenditure / Number of employees	SABI and COMPUSTAT (only for 2009 and 2010)

Overall Model Fit Evaluation

We evaluate the overall goodness of model fit for the proposed model by examining the standardized root mean squared residual (SRMR), unweighted least squares (ULS) discrepancy (d_{ULS}), and geodesic discrepancy (d_G) (Henseler et al. 2014). These measures of goodness of fit evaluate the discrepancy between the empirical correlation matrix and the model-implied correlation matrix (Henseler 2015). The lower the SRMR, d_{ULS}, and d_G the better the fit of the theoretical model (Henseler and Dijkstra 2015). All discrepancies are below the 95%-quantile of the bootstrap discrepancies (see Table 3), which means that the model should not be rejected based on an alpha level of 0.05 and that the model provides a good explanation of the business world.

Effect of Advertising Spending on the Proposed Model

The firm's advertising spending can increase firm profitability and can affect the impact of operational competence on firm profitability (Mithas et al. 2012). These effects may also happen over time. Because of missing data for a significant number of firms of the sample for t_1 in the SABI and COMPUSTAT databases, we do not control for advertising spending on firm profitability in the proposed model. As a robustness check, we estimate an alternative model in which we control for advertising spending on firm profitability in t_2 and t_3 for which we have available data. The beta coefficients of these two effects are not significant (-0.084 and -0.017) while all the other results are identical.

Table 2: Results of the PLS estimation

Relationship	**Beta coefficient**	**f^2 value**	**Effect size**
Hypothesized relationship	**Beta coefficient**	**f^2 value**	**Effect size**
E-business technology$_{t1}$ → Operational competence$_{t1}$ (H1a)	0.306^{*}	0.103	Medium
E-business technology$_{t2}$ → Operational competence$_{t2}$ (H1b)	0.023	0.002	Very weak
E-business technology$_{t3}$ → Operational competence$_{t3}$ (H1b)	0.005	0	Zero
Operational competence$_{t1}$ → Firm profitability$_{t1}$ (H2a)	0.199^{*}	0.043	Weak
Operational competence$_{t2}$ → Firm profitability$_{t2}$ (H2b)	0.209^{*}	0.067	Weak-medium
Operational competence$_{t3}$ → Firm profitability$_{t3}$ (H2b)	0.473^{**}	0.333	Large
Control variables	**Beta coefficient**	**f^2 value**	**Effect size**
Firm size$_{t1}$ → Firm profitability$_{t1}$	-0.170^{*}	0.031	Weak
Firm size$_{t2}$ → Firm profitability$_{t2}$	0.034	0.002	Very weak
Firm size$_{t3}$ → Firm profitability$_{t3}$	-0.042	0.003	Very weak
Industry → Firm profitability$_{t1}$	0.095^{*}	0.010	Very weak
Industry → Firm profitability$_{t2}$	0.026	0.001	Very weak
Industry → Firm profitability$_{t3}$	-0.091	0.012	Weak
Non-hypothesized relationships (between time periods)	**Beta coefficient**	**f^2 value**	**Effect size**
E-business technology$_{t1}$ → E-business technology$_{t2}$	0.477^{***}	0.294	Large
E-business technology$_{t2}$ → E-business technology$_{t3}$	0.620^{***}	0.625	Large
Operational competence$_{t1}$ → Operational competence$_{t2}$	0.850^{***}	2.530	Very large
Operational competence$_{t2}$ → Operational competence$_{t3}$	0.518^{*}	0.361	Large
Firm profitability$_{t1}$ → Firm profitability$_{t2}$	0.558^{***}	0.472	Large
Firm profitability$_{t2}$ → Firm profitability$_{t3}$	0.273^{*}	0.110	Medium

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, one-tailed test.

Table 3: Model fit evaluation

Discrepancy	Value	HI_{95}	Conclusion
SRMR	0.163	0.454	Supported
d_{ULS}	6.751	52.044	Supported
d_G	2.916	52.806	Supported

Discussion

Main Findings and Implications for Research

Although IT capability investments can develop and improve the firm's process capabilities and competitiveness (Benitez and Walczuch 2011, Chen et al. forthcoming), not all IT capability investments generate the expected results. This study focuses on e-business technology and examines the evolution of the impact of e-business technology on operational competence and firm profitability by performing a panel data investigation on a sample of 154 large firms in Spain. We uncover that: (1) e-business technology has a positive effect on operational competence that decreases over time even becoming non-significant, and (2) the firm's proficiency in exploiting a portfolio of operational capabilities has a positive impact on profitability that becomes more significant over time.

This study has several implications for research. First, the findings provide some insights on how the initial and subsequent IT investment affects operational competence and firm profitability over time. This study differentiates from past studies (e.g., Banker et al. 2006, Sanders 2007, Setia and Patel 2013) by performing a panel data investigation on the impact of e-business technology on operational competence and firm profitability. Our results suggest that early developers of operational capabilities through early investments in e-business technology maximize profitability based on a longer time and experience to develop their operational capabilities.

We find that the firm's proficiency in leveraging its web-based technologies has a positive effect on the firm's proficiency in exploiting a portfolio of operational capabilities (i.e., operational competence). We focused on a portfolio of operational capabilities that determines operational competence composed by gross margin, employee productivity, operational talent management, and operational excellence. We argued that this sample of operational capabilities are a good representation of the potential portfolio of operational capabilities that a contemporary firm may possess to be successful and survive in the long run (Tatikonda et al. 2013). The empirical analysis supports our theorizing. Web-based technology enables the firm to perform real-time interchange of accurate and timely information on product cost and demand with upstream suppliers and downstream customers to improve gross margin management. E-business technology also enables the firm to: (1) acquire/provide information from/to the market to recruit and get on board outstanding operational talent; (2) implement scheduling and workplace flexibility activities to retain operational talent; and (3) provide reliable information on goals completion, performance appraisal, and career planning to develop and retain operational talent. Finally, e-business technology also facilitates better execution of operational routines and greater agility in manufacturing/supplying products to markets. However, the positive effect of e-business technology on operational competence decreases over time even becoming non-significant. This result seems to suggest that firms can imitate IT investments from its competitors and learn to develop an e-business technology capability over time, which may convert e-business technology into a non-unique (i.e., lower-order in the hierarchy of capabilities) capability to enable operational competence. This implies that early investors/developers of e-business technology are the firms that mainly achieve e-business technology-based operational development.

We find that operational competence has positive impact on profitability that becomes more significant over time. Through a better management/estimation of product margins, greater employee productivity, an appropriate recruitment, the development and retention of operational talent, and a higher product manufacturing/supply chain agility, the firm can increase its profitability. Since the firm's operational competence is the heart of the business model and can be refined through time and experience, the operational competence impact on firm profitability increases over time. This result suggests that the timing of e-business technology investment for the operational development is critical to maximize firm profitability over time.

Prior IS research (Aral et al. 2006) has proposed the virtuous cycle argument to explain the firm IT investments over time. This argument suggests that firms that invest in IT in t_1 reap benefits and then invest more in IT in subsequent periods. Over time, these effects become magnified, leading some firms to continue investing more in IT compared with their historical investment and that of their competitors (Mithas et al. 2012). Is this IT behavior economically rational? Our results are consistent with the virtuous cycle argument [beta (e-business tecnology$_{t1}$ → E-business technology$_{t2}$) = 0.477***] but also suggests two new interesting insights that extend the virtuous cycle argument: (1) firms continue investing in IT in subsequent periods although they do not see immediate benefits [beta (e-business technology$_{t2}$ → Operational compertence$_{t2}$) = 0.023]; and (2) firms may be investing in IT in subsequent periods although they do not really need it, which is not economically rational. This trend may also be due to capturing "low hanging fruits" (i.e., easy benefits compared to cost) through initial IT investment, with subsequent IT investment being more difficult to have similar impact. Future research should explore whether this IT behavior also occurs in large firms of other countries.

Second, the findings also provide theoretical implications on the impact of IT on the development of operational capabilities. Past research has explored the effects of IT on the following manufacturing capabilities: just-in time manufacturing, and supplier and customer participation program (Banker et al. 2006), supply chain information integration (Devaraj et al. 2007), organizational collaboration

(Sanders 2007), and operational absorptive capability (Setia and Patel 2013). In a different way, we focus on the impact of e-business technology on a different set of operational capabilities: gross margin, employee productivity, operational talent management, and operational excellence. The results suggest that e-business technology has a positive effect on the development of operational capabilities, which is consistent with past studies (e.g., Banker et al. 2006, Setia and Patel 2013). However, a key insight from our results is that the effect of e-business technology on operational development decreases over time at least in subsequent periods.

Third, this study has also methodological implications because it illustrates how to perform a panel data investigation focusing on the evolution effects by using SEM and the PLS method of estimation. Few studies have performed this type of analysis (Roemer 2016). In this sense, we develop and extend Johnson et al.'s (2006) study (in the Marketing domain) that uses the method of estimation of PLS to examine the evolution of loyalty intentions. While Johnson et al. use three-year survey dataset, we use a three-year secondary dataset. We also show that this method can be applied to IS research examining the evolutionary impact of e-business technology on operational competence and firm profitability. In addition, we show that the analyses of effect size and the confidence intervals are a useful tool to examine the evolution effects on this type of dynamic models. Drawing from the Roemer's (2016) methodological work, this paper provides an illustration of how to test whether the trends over time are significant in a business value of IT domain.

Finally, this study has also theoretical implications for the literature on the hierarchy of firm's capabilities (e.g., Grant 1996, Rai et al. 2006). In the hierarchy of capabilities, lower-order capabilities require other higher-order capabilities to affect firm performance. This research extends our understanding on the hierarchy of capabilities by finding and explaining the role of timing in the effect of e-business technology (a lower-order capability) on firm profitability (the business outcome variable) through operational competence (a higher-order capability). In this sense, timing performs a critical role in the relationship between lower-order and higher-order capabilities, and business gains.

Limitations and Future Research Opportunities

This research has two key limitations. First, the results of this study may be only generalized to large firms in Spain. Future research can explore whether these results remain under other environmental conditions, in other countries and/or specific industries. Second, IT investments may take some time to fruition. The findings of this study should be viewed within a context of a three-year panel data. We were unable to extend our analysis to a longer duration panel data due to the unavailability of data for some variables (e.g., e-business technology). Nevertheless, even with a three-year panel data, our results suggest that the effect of e-business technology on operational competence decreases over a three-year period even becoming non-significant. Future research can explore whether this result remains valid over a longer duration panel data (e.g., 10 years) period.

Implications for Practice

Our findings also provide important managerial implications. First, this study shows how managers can develop e-business technology and operational competence to maximize firm profitability. Second, our findings suggest to IT managers to control IT investments over time. Early e-business technology investments provide more time and experience to refine the firm's portfolio of operational capabilities, thus improving the operations management system and increasing their firm profitability in the long run. In other words, early investment in IT can enhance operational competence and result in an increase in profitability over time. Thus, deciding well when the firm should allocate IT resources is critical for operational development and maximizing firm profitability. This lesson learned seems to have been institutionalized in the past by firms like Air Canada that invested in 2007 in its web-based technology to be the first airline in offering customer the online boarding pass and self-service IT applications to save costs and improve operational excellence. After its initial investments in e-business technology, Air Canada did not seem to need substantial additional investments in e-business technology to keep its operational development in subsequent periods (Karimi and Rivard 2014).

Financial analysts should pay attention to the firm's IT allocation decisions over time because these decisions can provide early signals about subsequent operational development and firm profitability over time (Mithas et al. 2012). Finally, our results also provide some empirical evidence to managers that investment in e-business technology do enhance operational competence and firm profitability. Such evidence can help managers to better justify investments in e-business technology.

Concluding remarks

This study examines the evolution of the impact of e-business technology on operational competence and firm profitability by performing a panel data investigation on a sample of 154 large firms in Spain. We find that e-business technology has a positive effect on operational competence that decreases over time even becoming non-significant, and that the firm's proficiency in exploiting a portfolio of operational capabilities has a positive impact on profitability that becomes more significant over time. One key implication of the findings is that early IT investment is critical for the operational development and effect on firm profitability over time. Early development of IT-enabled operational capabilities maximizes firm profitability based on a longer time and experience to develop their operational capabilities.

Acknowledgments

This research was sponsored by the European Regional Development Fund (European Union) and the Government of Spain (ECO2013-47027-P), the Regional Government of Andalusia (Research Project P11-SEJ-7294), and the COVIRAN-Prodware Chair of Digital Human Resource Strategy at the School of Human Resource Management of the University of Granada. This research was partially performed while the first author was affiliated with the University of Granada. This manuscript has benefited from the comments of Andres Navarro and the overall support of Ana Castillo and Jessica Braojos.

References

Ahmad, S., and Schroeder, R. 2003. "The impact of human resource management practices on operational performance: Recognizing country and industry differences," *Journal of Operations Management* (21:1), pp. 19-43.

Aguirre, M., and Ronkko, M. 2015. "Sample size determination and statistical power analysis in PLS using R: An annotated tutorial," *Communications of the Association for Information Systems* (36:3), pp. 33-51.

Ajamieh, A., Benitez, J., Braojos, J., and Gelhard, C. 2016. "IT infrastructure and competitive aggressiveness in explaining and predicting performance," *Journal of Business Research* (69:10), pp. 4667-4674.

Aral, S., Brynjolfsson, E., and Wu, D. 2006. "Which came first, IT or productivity? The virtuous cycle of investment and use in enterprise systems," in *Proceedings of the 27th International Conference on Information Systems*. Milwaukee, Wisconsin, USA, pp. 1819-1840.

Aral, S., Brynjolfsson, E., and Van Alstyne, M. 2012. "Information, technology, and information worker productivity," *Information Systems Research*, (23:3), pp. 849-867.

Ayabakan, S., Bardhan, I., and Zheng, Z. 2012. "The impact of IT-enabled manufacturing capabilities on plant profitability: New models and evidence," in *Proceedings of the 33rd International Conference on Information Systems*. Orlando, Florida, USA, pp. 1-19.

Banker, R., Bardhan, I., Chang, H., and Lin, S. 2006. "Plant information systems, manufacturing capabilities, and plant performance," *MIS Quarterly* (30:2), pp. 315-337.

Benitez, J., and Walczuch, R. 2011. "IT, proactive environmental strategy and firm performance: A resource-based analysis," in *Proceedings of the 17th Americas Conference on Information Systems*, Detroit, Michigan, USA, pp. 1-10.

Benitez, J., and Walczuch, R. 2012. "Information technology, the organizational capability of proactive corporate environmental strategy and firm performance: A resource-based analysis," *European Journal of Information Systems* (21:6), pp. 664-679.

Benitez, J., and Ray, G. 2012. "Introducing IT-enabled business flexibility and IT integration in the acquirer's M&A performance equation," in *Proceedings of the 33rd International Conference on Information Systems*. Orlando, Florida, USA, pp. 1-21.

Benitez, J., Llorens, J., and Fernandez, V. 2013. "The relationship between IT infrastructure leveraging, talent management and operational sustainability, and their effects on the business value of the operations strategy," in *Proceedings of the 19th Americas Conference on Information Systems*. Chicago, Illinois, USA, pp. 1-8.

Benitez, J., Llorens, J., and Fernandez, V. 2015. "IT impact on talent management and operational environmental sustainability," *Information Technology & Management* (16:3), pp. 207-220.

Benitez, J., Castillo, A., Llorens, J., and Braojos, J. 2016. "IT-enabled knowledge ambidexterity and innovation performance: The role of social media capability," in *Proceedings of the 22nd Americas Conference on Information Systems*. San Diego, California, USA, pp. 1-10.

Benitez, J., Henseler, J., and Roldan, J. 2016b. "How to address endogeneity in partial least squares path modeling," in *Proceedings of the 22nd Americas Conference on Information Systems*. San Diego, California, USA, pp. 1-10.
Bharadwaj, A. 2000. "A resource-based perspective on information technology capability and firm performance: An empirical investigation," *MIS Quarterly* (24:1), pp. 169-196.
Bock, G., Zmud, R., Kim, Y., and Lee, J. 2005. "Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate," *MIS Quarterly* (29:1), pp. 87-111.
Braojos, J., Benitez, J., and Llorens, J. 2015a. "Impact of IT infrastructure on customer service performance: The role of micro-IT capabilities and online customer engagement," in *Proceedings of the 19th Pacific Asia Conference on Information Systems*, Singapore, Singapore, pp. 1-17.
Braojos, J., Benitez, J., and Llorens, J. 2015b. "How do small firms learn to develop a social media competence?" *International Journal of Information Management* (35:4), pp. 443-458.
Carr, N. 2003. "IT doesn't matter," *Harvard Business Review* (81:5), pp. 1-8.
Chen, Y., Wang, Y., Nevo, S., Benitez, J., and Kou, G. 2015. "IT capabilities and product innovation performance: The roles of corporate entrepreneurship and competitive intensity," *Information & Management* (52:6), pp. 643-657.
Chen, Y., Wang, Y., Nevo, S., Benitez, J., and Kou, G. Forthcoming. "Improving strategic flexibility with information technologies: Insights for firm performance in an emerging economy," *Journal of Information Technology*, in press, pp. 1-16.
Chin, W. 2010. "How to write up and report PLS analyses," Esposito, V., Chin, W., Henseler, J., and Wang, H. (Eds.). *Handbook of partial least squares: Concepts, methods and applications*. Berlin, Germany: Springer, pp. 655-690.
Cohen, J. 1988. "*Statistical power analysis for Behavioral Sciences*" (2nd edition). Hillsdale, New Jersey, USA: Erlbaum.
Cui, T., Ye, H., Teo, H., and Li, J. 2015. "Information technology and open innovation: A strategic alignment perspective," *Information & Management* (52:3), pp. 348-358.
Devaraj, S., Krajewski, L., and Wei, J. 2007. "Impact of ebusiness technologies on operational performance: The role of production information integration in the supply chain," *Journal of Operations Management* (25:6), pp. 1199-1216.
Dijkstra, T., and Henseler, J. 2015. "Consistent partial least squares path modeling," *MIS Quarterly* (39:2), pp. 297-316.
Fosso, S., and Chatfield, A. 2009. "A contingency model for creating value from RFID supply chain network projects in logistics and manufacturing environments," *European Journal of Information Systems* (18:6), pp. 615-636.
Gefen, D., Straub, D., and Rigdon, E. 2011. "An update and extension to SEM guidelines for Administrative and Social Science research," *MIS Quarterly* (35:2), pp. iii-xiv.
Grant, R. 1996. "Prospering in dynamically-competitive environments: Organizational capability as knowledge integration," *Organization Science* (7:4), pp. 375-387.
Henseler, J., and Fassott, G. 2010. "Testing moderating effects in PLS path models: An illustration of available procedures. Esposito, V., Chin, W., Henseler, J., and Wang, H. (Eds.). *Handbook of partial least squares: Concepts, methods and applications*. Berlin, Germany: Springer, pp. 713-735.
Henseler, J., Dijkstra, T., Sarstedt, M., Ringle, C., Diamantopoulos, A., Straub, D., Ketchen, D., Hair, J., Hult, G., and Calantone, R. 2014. "Common beliefs and reality about PLS: Comments on Ronkko & Evermann 2013," *Organizational Research Methods* (17:2), pp. 182-209.
Henseler, J. 2015. "*Is the whole more than the sum of its parts? On the interplay of Marketing and Design research*," Enschede, The Netherlands: University of Twente, pp. 1-40.
Henseler, J., and Dijkstra, T. 2015. "*ADANCO*," Kleve, Germany: Composite Modeling, http://www.compositemodeling.com.
Henseler, J., Hubona, G., and Ray, P. 2016. "Using PLS path modeling in New Technology research: Updated guidelines," *Industrial Management & Data Systems* (116:1), pp. 1-23.
Johnson, M., Herrmann, A., and Huber, F. 2006. "The evolution of loyalty intentions," *Journal of Marketing* (70:2), pp. 122-132.
Karimi, F., and Rivard, S. 2014. "Air Canada: Flying high with information technology," *HEC Montreal Centre for Case Studies*, (HEC045), pp. 1-20.
Law, C., and Ngai, E. 2007. "ERP systems adoption: An exploratory study of the organizational factors and impacts of ERP success," *Information & Management* (44:4), pp. 418-432.
Malhotra, M., and Mackelprang, A. 2012. "Are internal manufacturing and external supply chain flexibilities complementary capabilities?" *Journal of Operations Management* (30:3), pp. 180-200.

Mayr, S., Erdfelder, E., Buchner, A., and Faul, F. 2007. "A short tutorial of GPower," *Tutorials in Quantitative Methods for Psychology* (3:2), pp. 51-59.
Mithas, S., Tafti, A., Bardhan, I., and Goh, J. 2012. "Information technology and firm profitability: Mechanisms and empirical evidence," *MIS Quarterly* (36:1), pp. 205-224.
Pan, G., Pan, S., and Lim, C. 2015. "Examining how firms leverage IT to achieve firm productivity: RBV and dynamic capabilities perspectives," *Information & Management* (52:4), pp. 401-412.
Peng, D., Schroeder, R., and Shah, R. 2008. "Linking routines to operations capabilities: A new perspective," *Journal of Operations Management* (26:6), pp. 730-748.
Rai, A., Patnayakuni, R., and Seth, N. 2006. "Firm performance impacts of digitally enabled supply chain integration capabilities," *MIS Quarterly* (30:2), pp. 225-246.
Rigdon, E. 2012. "Rethinking partial least squares path modeling: In praise of simple methods," *Long Range Planning* (45:5-6), pp. 341-358.
Roemer, E. 2016. "A tutorial on the use of PLS path modeling in longitudinal studies," *Industrial Management & Data Systems* (116:9), pp. 1901-1921.
Sanders, N. 2007. "An empirical study of the impact of e-business technologies on organizational collaboration and performance," *Journal of Operations Management* (25:6), pp. 1332-1347.
Serva, M., Kher, H., and Laurenceau, J. 2011. "Using latent growth modeling to understand longitudinal effects in MIS theory: A Primer," *Communications of the Association for Information Systems* (28:1), pp. 213-232.
Setia, P., and Patel, P. 2013. "How information systems help create OM capabilities: Consequents and antecedents of operational absorptive capacity," *Journal of Operations Management* (31:6), pp. 409-431.
Shao, B., and Lin, W. 2002. "Technical efficiency analysis of information technology investments: A two-stage empirical investigation," *Information & Management* (39:5), pp. 391-401.
Stahl, G., Bjorkman, I., Farndale, E., Morris, S., Paauwe, J., Stiles, P., Trevor, J., and Wright, P. 2012. "Six principles of effective global talent management," *MIT Sloan Management Review* (53:2), pp. 24-32.
Tatikonda, M., Terjesen, S., Patel, P., and Parida, V. 2013. "The role of operational capabilities in enhancing new venture survival: A longitudinal study," *Production and Operations Management* (22:6), pp. 1401-1415.
Teo, T., and Ranganathan, C. 2004. "Adopters and non-adopters of business-to-business electronic commerce in Singapore," *Information & Management* (42:1), pp. 89-102.
Teo, T., and Bhattacherjee, A. 2014. "Knowledge transfer and utilization in IT outsourcing partnerships: A preliminary model of antecedents and outcomes," *Information & Management* (51:2), pp. 177-186.
Ton, Z., and Harrow, S. 2010. "Mercadona," *Harvard Business School Case*, (9-610-089), pp. 1-25.
Wang, Y., Chen, Y., and Benitez, J. 2015. "How information technology influences environmental performance: Empirical evidence from China," *International Journal of Information Management* (35:2), pp. 160-170.
Wu, S., Melnyk, S., and Flynn, B. 2010. "Operational capabilities: The secret ingredient," *Decision Sciences* (41:4), pp. 721-754.
Zhu, K., and Kraemer, K. 2002. "E-commerce metrics for net-enhanced organizations: Assessing the value of e-commerce to firm performance in the manufacturing sector," *Information Systems Research* (13:3), pp. 275-295.
Zhu, Q., and Sarkis, J. 2004. "Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises," *Journal of Operations Management* (22:3), pp. 265-289.