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EXTERNAL KNOWLEDGE AND INFORMATION TECHNOLOGY: IMPLICATIONS FOR PROCESS INNOVATION PERFORMANCE[1]

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Prior research highlights the vital role of information technology (IT) for innovation in firms. In this paper, we draw on the knowledge-based view of the firm to investigate how search in external knowledge sources and information technology for knowledge absorption jointly influence process innovation performance. Our model is tested on a nine-year panel (2003–2011) of Swiss firms from a wide range of manufacturing industries. Using instrumental variables, and disaggregating by type of IT, we find that data access systems and network connectivity hold very different potential for the effective absorption of external knowledge, and the subsequent realized economic gains from process innovation. Against the backdrop of today's digital transformation, our findings demonstrate how firms should coordinate strategies for sourcing external knowledge with specific IT investments in order to improve their innovation performance.

Keywords: Business value of IT, digitization, Industry 4.0, innovation strategy, knowledge-based view of the firm, absorptive capacity, open innovation, external search, process innovation, firm performance

Introduction

Firms commonly invest in information technology (IT) to innovate processes and achieve enterprise-wide cost reductions. A recent survey of more than 2,000 chief information officers (CIOs), representing a total IT budget of 230 billion USD, placed cost reduction, efficiency, operational results, and business processes improvement among the top 10 business goals for IT investments (Gartner Group 2013). Case reports add that firms frequently use IT to exploit their environment for ideas and technologies that will allow them to achieve these goals (European Commission 2012). Here we investigate this phenomenon by examining the *compound impact* of IT and search in external knowledge sources on firms' efforts to innovate production processes.

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Firms progressively embrace "open innovation" with the intent to exchange ideas, knowledge, and technologies with a multitude of external actors throughout the innovation process (Chesbrough 2006; Laursen and Salter 2006). Recently, innovation scholars found that in order to innovate production processes, modern-day manufacturing firms tend to rely on knowledge from a variety of external sources (e.g., suppliers, customers, universities, competitors, and consultants) (McCormack 2014; Robertson et al. 2012; Terjesen and Patel 2015; Un and Asakawa 2015). Information systems scholars, meanwhile, demonstrate that IT enhances innovation by increasing a firm's ability to search and absorb what knowledge external sources offer (Alavi and Leidner 2001; Joshi et al. 2010; Kane and Alavi 2007; Kleis et al. 2012; Roberts et al. 2012; Sambamurthy and Subramani 2005). Notably, the extant research on IT and innovation has tended to focus on *product* innovation (Joshi et al. 2010; Kleis et al. 2012; Majchrzak and Malhotra 2013; Nambisan and Sawhney 2007; Pavlou and El Sawy 2006), on IT as a *form of process innovation* (Carlo et al. 2012; Davenport 1993), or on how IT enables innovation by improving firms' utilization of *internal* knowledge (Bardhan et al. 2013; Joshi et al. 2010). Moreover, the extensive research on the linkages between IT and innovation (Roberts et al. 2012) has not explored the compound effect of IT and search in external knowledge sources on firms' *process* innovation.

The knowledge-based view of the firm (KBV) theorizes on the conditions under which firms effectively absorb external knowledge and the impact of knowledge absorption on economic performance (Cohen and Levinthal 1990; Grant 1996; Nonaka and von Krogh 2009). We build on this approach by offering a theoretical model explaining how a firm's IT and external search activity jointly influence process innovation performance. Our model uses a fine-grained conceptualization of IT that facilitates external knowledge absorption in the firm through (1) data access systems and (2) network connectivity. The model is tested using a nine-year panel (2003–2011) of firms from the Swiss manufacturing sector. We obtained our sample of 3,490 manufacturing firms from the Swiss Innovation Survey, which parallels the Eurostat Community Innovation Survey (CIS), a standard inventory for innovation studies in business and economics (e.g., Cassiman and Veugelers 2002; Garriga et al. 2013; Laursen and Salter 2006). The panel data allows us to identify suitable instrumental variables and provide rigorous econometric estimations that rule out concerns related to endogeneity. The results show that data access systems and network connectivity have different potentials to moderate the process innovation performance that firms achieve by searching external knowledge sources. These findings contribute to the literatures on IT and innovation (Joshi et al. 2010; Kleis et al. 2012; Roberts et al. 2012; Tambe et al. 2012).

Literature and Hypotheses

IT and Innovation

Scholars of information systems and innovation agree that IT positively affects many aspects of corporate innovation (see Hopkins and Brynjolfsson 2010; Nambisan and Sawhney 2007; Tambe et al. 2012; Xue et al. 2012; Yoo et al. 2012; Zammuto et al. 2007), specifically by supporting knowledge-intensive activities related to innovation (e.g., Bardhan et al. 2013; Hopkins and Brynjolfson 2010; Joshi et al. 2010; Kane and Alavi 2007; Kleis et al. 2012; Pavlou and El Sawy 2006). While many types of knowledge-intensive activities likely matter for innovation, recent innovation studies underscore how firms that deliberately search external knowledge sources achieve innovation performance above the average of their industry peers (e.g., Garriga et al. 2013; Katila and Ahuja 2002; Laursen and Salter 2006; Leiponen and Helfat 2010). Information systems scholars found complimentary evidence that IT is critical for enabling firms' search in external knowledge sources (for a review, see Roberts et al. 2012; see also Banker et al. 2006; Dodgson et al. 2006; Kleis et al. 2012; Majchrzak and Malhotra 2013; Malhotra et al. 2005; Nambisan and Sawhney 2007; Tambe et al. 2012).

While these works shed light on the separate impacts of external knowledge search and IT for *product* innovation, their compound effect on firms' *process* innovation performance remains unclear. This is despite the fact that the accumulated effect of process innovation on production cost, productivity, and sustained firm performance is substantial (e.g., Rosenberg 1982).[2] In line with previous work, we define process innovation as a new, efficiency-enhancing activity aimed at lowering the cost of producing a good or service (Davenport 1993, p. 4; see also Damanpour and Gopalakrishnan 2001; Ettlie and Reza 1992; Gopalakrishnan et al. 1999; Hatch and Mowery 1998; Un and Asakawa 2015; Utterback and Abernathy 1975).[3]

[2]Despite its prominence in the main theories of innovation, influential scholars have remarked that research on the determinants of process innovation is sparse compared with the abundant examination of product innovation (Adner and Levinthal 2001; Ettlie and Reza 1992; Hatch and Mowery 1998; Pisano 1997; Reichstein and Salter 2006).

[3]Arguably, process innovation may support various goals in the firm (e.g., accelerated time to market, improved product quality, improved production flexibility; see Pisano 1997), but scholars tend to agree that efficiency- driven innovation ultimately targets production cost reductions, thus making the pruning of such cost a key operationalization (e.g. Davenport 1993, p. 4; Flynn et al. 1999).

External Knowledge and Process Innovation

KBV scholars agree that a mix of new knowledge, both codified and tacit, is required to realize economic gains from process innovation (Un and Asakawa 2015; see also Grant 1996; Gopalakrishnan et al. 1999; Nonaka 1994; Nonaka and von Krogh 2009). A study by Un and Asakawa (2015) confirms that external knowledge must be meticulously embedded in a firm's organization and technical systems to produce process innovation. This insight highlights a cardinal difference between product and process innovation: While a firm may use broad supplier search to identify a product or product component that can be licensed for production and sale (Garriga et al. 2013), innovating a manufacturing *process* for a product or component involves designing a plant floor, purchasing and installing equipment, integrating new and existing machinery, conducting pilot runs, learning through trial-and-error, and making numerical adjustments. Since much production-relevant knowledge is tacit, and thus costly to identify and transfer from an external source to the firm (Grant 1996), one may stipulate that successful process innovation occurs when a manufacturing firm is capable of searching *deeply* in a set of multiple external knowledge sources such as suppliers, research institutes, or competitors (see Azadegan and Dooley 2010; Duranton and Puga 2001; Terjesen and Patel 2015). Moreover, if economically valuable, the use of multiple external sources requires the efficient identification of external knowledge of technology that when introduced in the manufacturing firm is likely to solve production problems and reduce cost (Nickerson and Zenger 2004). Deep search allows the focal innovating firm to identify ancillary context and detailed knowledge surrounding a source's processes and production technology, which ensures that the transferred knowledge has a better fit on the organization's needs compared to the next best alternative (Nonaka 1994). The empirical question that remains is if and how a firm can enhance external knowledge absorption to improve process innovation performance.

IT and Knowledge Absorption

The KBV entails that firms must absorb external knowledge effectively to achieve process efficiency and realize economic value (see Grant 1996). The literature on absorptive capacity (Cohen and Levinthal 1990) suggests that firms need to *acquire* and *assimilate* internal and external knowledge, *recombine* existing and newly acquired knowledge, and *apply* the transformed knowledge to its operations (Jansen et al. 2005; Zahra and George 2002a). Correspondingly, KBV scholars expect IT to enhance a firm's external knowledge absorption (Zahra and George 2002b, p. 149; see also Joshi et al. 2010; Malhotra et al. 2005; Roberts et al. 2012) by supporting the storage and transfer of external knowledge, the creation of new knowledge by combining internal and external knowledge (Nonaka 1994; von Krogh 2012), and the application of new knowledge to firm operations (Alavi and Leidner 2001; Argote et al. 2003; Roberts et al. 2012; Sambamurthy and Subramani 2005).

Hypotheses

Based on a rich literature on the knowledge-related functions of IT (Alavi and Leidner 2001) and the conjectures from the KBV and innovation studies outlined above, we stipulate that two specific forms of IT—data access systems and network connectivity (Banker et al. 2006; Bloom et al. 2015; Hendricks et al. 2007)—will facilitate the deep search and absorption of external knowledge relevant for process innovation.

Data access systems support the *acquisition* of external knowledge, particularly when that knowledge is codified (Foray 2004; Teece 1998). Technological systems for enterprise resource planning (ERP), supply chain management (SCM), or customer relationship management (CRM) enhance transparency in process operations and performance by producing a seamless flow of production-related information, making manufacturing problems visible, and generating data to pinpoint potential production process improvements (Heim and Peng 2010; Hendricks et al. 2007; Masini and van Wassenhove 2009). Data access systems also diffuse production information throughout the firm, allowing organization members, teams, and departments to filter out low-quality external ideas and identify outside opportunities for future application to the production process (Heim and Peng 2010; Huber 1990; Robertson et al. 2012). A firm that utilizes data access systems will therefore have a better grasp of the problems to which new external knowledge could be applied, allowing it to conduct a more targeted and cost-efficient search in external sources such as customers, suppliers, or consultants (Dodgson et al. 2006; Kleis et al. 2012).

Data access systems can furthermore be expected to strengthen external knowledge *assimilation* in a firm by supporting the integration of new codified knowledge into organizational memory. For example, information systems scholars have shown that data access systems serve as digital knowledge repositories (Tseng 2008; see also Davenport and Prusak 1997), augmenting organizational memory by efficiently accessing, storing, and integrating knowledge from diverse external sources (Alavi and Leidner 2001; see also Huber 1990; Joshi et al. 2010; Kleis et al. 2012). Data access systems provide "templates" of knowledge (Jensen and Szulanski 2007) that ease the integration and *recombination* of new elements with a firm's existing internal knowledge. For instance, templates support the efficient recombination of manufacturing process specifications with standard operating procedures stored electronically. Therefore, a firm that utilizes data access systems can more efficiently assemble and transform new and existing codified knowledge into organizational knowledge (Nonaka et al. 1996; Nonaka et al. 2001).

Finally, data access systems are likely to permit the efficient *application* of new process knowledge to a firm's production. Such systems support knowledge integration in the firm by lessening dependence on a well-functioning transactive memory amongst individuals (Alavi and Leidner 2001; Alavi and Tiwana 2002; Masini and van Wassenhove 2009). Data access systems can similarly reduce the cost of applying externally acquired process knowledge in the firm (Jansen et al. 2005; Masini and van Wassenhove 2009), since they offer searchable repositories of codified (recombined internal and external) knowledge that can be accessed when needs arise in production (see Heim and Peng 2010; Hendricks et al. 2007; Joshi et al. 2010)—for example, standard operating procedures for handling problems with newly purchased equipment. To summarize, for manufacturing firms, we expect

> *H1: The interaction between data access systems and deep search in multiple external knowledge sources is positively associated with process innovation performance.*

A firm that utilizes network connectivity can be expected to have a greater capacity for knowledge absorption from external sources. Network connectivity includes local area networks (LANs) (Bloom et al. 2015), and has been found to facilitate interpersonal communication (e.g., Gold et al. 2001; Hansen et al. 1999; Jansen et al. 2005), broadening collaboration via electronic platforms (Bloodgood and Salisbury 2001; Scott 1998) and enabling efficient sharing of different views, experiences, and insights (Gold et al. 2001; Hansen et al. 1999; Huber 1990). For example, network connectivity may facilitate broader organizational involvement across time and place in benchmarking exercises undertaken as part of the firm's *acquisition* of external knowledge (Gold et al. 2001, p. 190; see also Huber 1990, p. 53). By reducing barriers to communication, network connectivity enables the *assimilation* of external knowledge by disseminating new process ideas, best practices, and solutions widely and rapidly among manufacturing personnel (Bloom et al. 2015; Gold et al. 2001).

Realizing process innovation performance in a manufacturing firm presupposes *recombination* and *application* of internal and external knowledge in a mix of codified and tacit elements. Although the firm may attempt to instantly act on ready-made, codified, and externally sourced production knowledge (e.g., high-speed machining, numerical control systems), prior studies have found that most firms expend considerable effort to transform that knowledge for use in internal operations (Lane et al. 2001; Robertson et al. 2012). Scholars have argued that network connectivity facilitates knowledge application by supporting the sharing of internal and external knowledge with both codified and tacit elements (Hildrum 2009; Mueller et al. 2011; Trusson et al. 2014; von Krogh 2012). A firm using network connectivity is likely to connect individuals and teams and support the integration of their knowledge and technical expertise (Alavi and Tiwana 2002; Vaccaro et al. 2009). When innovation involves the operation of novel machinery or other artifacts, transfering tacit knowledge between the relevant employees is critical (Robertson et al. 2012). Since process innovation involves complex problem solving (Lapré and van Wassenhove 2001; Pisano 1997; von Hippel 1994), successfully applying new ideas and technologies in production not only relies on codified, schematic, and rule-based elements but also on sharing tacit elements and learning and training physical skills among production engineers, managers, and floor operators (Hatch and Mowery 1998; Robertson et al. 2012; Szulanski 1996; von Hippel and Tyre 1995). Network connectivity has been found useful in supporting the required technical discussions, evolving common interpretations, and collaborative problem solving in the firm (Majchrzak and Wang 1996; Stadler 2011; Tippins and Sohi 2003, p. 751). Network connectivity further fosters communication between communities of practice in the firm, allowing the rapid identification of groups of experts who may hold important tacit knowledge for solving manufacturing-related problems (Brown and Duguid 2001; Huber 1990; Majchrzak et al. 2007). In effect, network connectivity is likely to facilitate the transformation and application of detailed knowledge acquired from searching deeply in multiple external sources, a process that relies on communication between various functions ranging from R&D to operations and full-scale production environments (Pisano 1997). To summarize, for manufacturing firms we expect

> *H2: The interaction between network connectivity and deep search in multiple external knowledge sources is positively associated with process innovation performance.*

Empirical Methods

Data

Our empirical analysis is based on representative data from the Swiss Innovation Survey (SIS) collected by KOF Swiss

Economic Institute. The SIS is similar in content and structure to the well-established EUROSTAT Community Innovation Survey (CIS) in other European countries, which is the primary data source for measuring firm-level innovation activity in Europe (Smith 2005).[4] CIS surveys have been applied internationally to confirm validity across contexts and constitute a reliable inventory for innovation studies (for examples, see Cassiman and Veugelers 2002; Garriga et al. 2013; Laursen and Salter 2006; Leiponen and Helfat 2010). Detailed data is captured on a wide range of aspects related to innovation in the respondent firms (e.g., innovation objectives, sources of innovation-relevant knowledge and cooperation, innovation constraints, R&D activities, etc.), as well as on general firm characteristics and economic performance. Unlike the CIS surveys in other European countries, the Swiss survey contains an extensive section on IT.

We make use of three waves of the survey (2005, 2008, and 2011) and thus test our hypotheses in a nine-year period from 2003 to 2011. Given the study's motivation, we look at the manufacturing sector only. Our final sample includes 1,262 (2005), 1,072 (2008), and 1,156 (2011) manufacturing firms. We categorize firms into industries according to two-digit NACE codes.[5] The composition of the (18) manufacturing industries in our sample is depicted in Table A1 in Appendix A.

Variables

Process Innovation Performance

In the survey, firms first indicate if they introduced any process innovation during the three years prior to the survey year. If they did, they are asked to estimate the share of production-related cost reduction achieved in the year prior to the survey year. The SIS states explicitly that

> process innovation refers to any first-time introduction of a new or improved technology for the production of goods or services. Pure organizational changes do not count as process innovations.[6]

Accordingly, we construct the proxy for *process innovation performance* as the cost reduction (in Swiss francs) the focal firm achieved due to process innovation, and then convert it to the natural logarithm (Cantner et al. 2011; Flynn et al. 1999).[7] Very few past studies have offered a quantitative measure of process innovation performance (see Cantner et al. 2011 for a rare exception), and instead adopt a binary variable to capture process innovation propensity (e.g., Reichstein and Salter 2006; Terjesen and Patel 2015; Un and Asakawa 2015).[8]

Information Technology

To build our *Data Access Systems* variable, we focus on responses in the survey (yes/no) about whether the focal firm employs systems for (1) enterprise resource planning (ERP), (2) supply chain management (SCM), and (3) customer relationship management (CRM). The focus on ERP, SCM, and CRM follows past work arguing that these three systems are key information technologies in the manufacturing sector (Banker et al. 2006; Heim and Peng 2010; Hendricks et al. 2007; Mulani and Lee 2001; see also Bloom et al. 2015). Our representation of each enterprise system as a binary variable follows several studies in the information systems literature (e.g., Banker et al. 2006; Heim and Peng 2010; Hitt et al. 2002). To operationalize *Data Access Systems,* we construct a variable that summarizes the three enterprise systems by adding the three binaries for ERP, SCM, and CRM (Banker et al. 2006; Joshi et al. 2010; Melville et al. 2004).[9]

To build our *Network Connectivity* variable, we focus on the response in the survey (yes/no) about whether the focal firm employs a local area network (LAN). Overall, our *Data Access Systems* and *Network Connectivity* measures are devoted to the firm-level presence of infrastructure related to information technology (for similar approaches, see Bloom et al. 2015; Banker et al. 2006; Hitt et al. 2002).

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[4]CIS surveys are based on the OECD's Oslo Manual (OECD 2005).

[5]The Swiss Innovation Survey classifies firms into industries according to NACE codes (Nomenclature of Economic Activities) and employs a four-digit code at the most detailed industry level (see Cassiman and Veugelers 2002). NACE codes are in line with the United Nations' International Standard Industrial Classification (ISIC) and with the North American Industry Classification System (NAICS).

[6]As in all CIS surveys, this definition is in line with the third edition of the Oslo Manual (OECD 2005), which focuses on technology-related process innovation and distinguishes it from purely organizational changes.

[7]The dependent variable (*Cost Reduction*) quantifies process innovation performance in economic terms and builds on past work that considers process innovation to be efficiency-driven and targeted to lowering production costs (Davenport 1993, p. 4; see also Cantner et al. 2011; Damanpour and Gopalakrishnan 2001; Un and Asakawa 2015). For the focal firm, production-related cost reduction represents the tangible realization of process innovation efforts in economic terms (i.e., successful innovation in the production process).

[8]Compared to studies that focus on product innovation, the *cost reduction* proxy is analogous to the *sales of innovative products*, a common proxy for product innovation performance (see Garriga et al. 2013; Laursen and Salter 2006; Leiponen and Helfat 2010).

[9]We also considered several alternative proxies for *Data Access Systems* by using individual binaries for ERP, SCM, and CRM (see Appendix D; for a similar approach, see Bloom et al. 2015).

External Search Depth

In line with previous research (e.g., Foss et al. 2013; Garriga et al. 2013; Laursen and Salter 2006; Terjesen and Patel 2015), we operationalize *External Search Depth* as the number of external knowledge sources (e.g., customers, suppliers, competitors, consultants, universities) utilized *intensively* by the focal firm in its innovation activities. Table B1 in Appendix B shows the complete list of sources. Firms respond on a five-point Likert scale (1 = no usage; 5 = high usage) regarding the use of each source for innovation activities. We coded each of the 14 sources as a binary with 1 corresponding to high degree of usage (firm response 4 or 5), and 0 otherwise.[10] Next, we computed the number of intensively used external sources by summing all the relevant binaries. Consequently, a firm scores 0 when no knowledge source is used intensively and 14 when all sources are used intensively. In effect, *External Search Depth* reflects the extent of external knowledge sources that the focal firm draws upon deeply for its innovation process.

Control Variables

IT Investments controls for IT investments as directly reported by firms in the survey (e.g., Bardhan et al. 2013; Kleis et al. 2012; Mithas et al. 2012).[11] Consistent with prior innovation studies, we control for external search breadth (e.g., Laursen and Salter 2006; for a similar approach, see Foss et al. 2013). Since we do not know *a priori* whether the search in external knowledge sources is tied to process or product innovation, we control for innovation objectives stated by the firm (for a similar operationalization, see Leiponen and Helfat 2010, p. 232). We include two further controls of a firm's innovation capability: R&D intensity, constructed as R&D expenditures to total sales (Chari et al. 2008), and the percentage of employees with academic degrees (Leiponen and Helfat 2010). Moreover, we control for several other factors related to key organizational characteristics and structural changes that may influence the performance of a firm's production process (Ettlie and Reza 1992), as well as for industry and time fixed effects. Table B2 in Appendix B summarizes the definitions and operationalizations for all variables. Table B3 in Appendix B presents descriptive statistics and correlations of the key variables.

Econometric Analysis

Estimator and Instruments

To circumvent concerns related to endogeneity (Wooldridge 2002), we apply instrumental-variables (IV) estimators based on the generalized method-of-moments (GMM) (Baum et al. 2007).[12] Using a panel of firms observed over nine years allows us to identify suitable instrumental variables and provide rigorous IV GMM estimations while treating the variables *Data Access Systems, Network Connectivity, External Search Depth*, and *IT Investments* as endogenous.[13]

The instrument set was chosen based on earlier studies that identified the lagged versions of endogenous variables, as well as competitors' IT investments (i.e., industry level of IT investments) as suitable instruments (Kleis et al. 2012; Mithas et al. 2012).[14] In sum, the instrument set consists of the three-year lagged variables of *Data Access Systems, Network Connectivity, External Search Depth*, and *IT Investments*, the three-year lagged competitors' IT investments, as well as the lagged interaction terms when interactions of the main regressors are included in the econometric models. All instruments pass the underidentification test (i.e., explain a substantial portion of the variance of the endogenous variables) and the test of overidentification restrictions (i.e., are not correlated with the error term (Baum 2006); see Appendix C).

[10]As a sensitivity test, we deployed an alternative operationalization of the *External Search Depth* variable where the value 1 for the binaries corresponded to firms responding 5. The results of the regressions were similar and are available by request.

[11]This variable allows for a more precise identification of the effects of our main IT variables. We insert the natural logarithm of IT investments in our model. Void of this control, the presumably positive effect of *IT Investments* would be caught by the *Data Access Systems* or the *Network Connectivity* variable depending on the respective amount of investments, and their effects are likely to be overestimated. Hence, given the focus of the current study, the *IT Investments* variable is an important control variable.

[12]Since we use a pooled sample, our dataset contains repeated observations for the same firms over time, that is, we cannot assume that the errors are independent and identically distributed. Hence, we cluster the standard errors on the firm level and, moreover, apply the Huber-White procedure to control for arbitrary heteroskedasticity and autocorrelation. We use the "ivreg2" command in STATA 13, extended by the "gmm2s" (two-stage efficient GMM estimator) option with standard errors clustered on the firm level. See Liu et al. (2012) for a similar approach.

[13]The instrumental variables regression as it is applied in our setting allows for time variant unobserved effects (i.e., omitted variables) and thus also covers the fixed-effects case, which only takes care of time-invariant unobserved effects (for an extensive description of the fixed-effects and instrumental-variables approach, see Wooldridge 2002).

[14]Competitors are defined as all firms that belong in the same industrial sector in our panel (NACE three-digit).

Results

Table 1 presents the results of the IV GMM estimations.[15] All four regressions have the same dependent variable (*Cost Reduction*) and include the full control vector as discussed above. Model 1 (Column 1) shows that the coefficient of *External Search Depth* is positive and significant (coefficient = .660, p < .10). In Model 2 (Column 2), we introduce an indicator for the presence of *Data Access Systems*, as well as its interaction with *External Search Depth.* We find a significant interaction effect of *Data Access Systems* and *External Search Depth* (coefficient = .504, p < .10), providing first evidence of support for H1. Model 3 (Column 3) has the same specification as Model 2, but instead of *Data Access Systems* we introduce an indicator for the presence of *Network Connectivity*, as well as its interaction with *External Search Depth*. We find a significant interaction effect of *Network Connectivity* and *External Search Depth* (coefficient = 3.092, p < .05), providing some first evidence of support for H2. In Model 4, we introduce simultaneously the variables for *Data Access Systems* and *Network Connectivity* (for a similar approach, see Bloom et al. 2015), as well as their respective interactions with *External Search Depth.* Interestingly, the inclusion of both interaction terms in the same specification (Model 4) drives the coefficient of *Data Access Systems * External Search Depth* into insignificance and a lower magnitude (coefficient = .168) (compare Columns 2 and 4), while *Network Connectivity * External Search Depth* remains of similar magnitude and statistical significance (coefficient = 2.810, p < .10 (compare columns (3) and (4)). In sum, the estimations show that, in terms of achieving process innovation performance, it is predominantly the firm's network connectivity infrastructure that leverages the effect of the deep search of multiple external knowledge sources.[16] The coefficient of *IT Investments* is positive and significant, confirming the importance of including this control in the model specification—removing *IT Investments* would significantly raise the observed effect of *Data Access Systems* and *Network Connectivity.*[17]

Discussion

Main Findings

This study examines the compound effect on firms' process innovation performance of (1) external knowledge search combined with (2) IT in the forms of data access systems and network connectivity. Our results from a large panel of Swiss manufacturing firms observed over nine years (2003–2011) show that the value of deep search in multiple external knowledge sources for process innovation performance in firms is moderated more extensively by network connectivity than by data access systems. We also find a positive direct effect of IT investments on economic gains due to process innovation.

Research Implications

Prior research in this area has focused on how IT facilitates product innovation or on IT as a form of process innovation (e.g., Carlo et al. 2012; Davenport 1993 Joshi et al. 2010; Pavlou and El Sawy 2006). This study instead provided detailed evidence on how IT *enables* process innovation by allowing manufacturing firms to more effectively absorb knowledge when searching deeply in multiple external sources.[18] These results support an important stream of research arguing that IT fundamentally changes firms' innovation processes (Joshi et al. 2010; Kane and Alavi 2007; Kleis et al. 2012; Roberts et al. 2012; Tambe et al. 2012; Yoo et al. 2012; Zammuto et al. 2007) by facilitating the exchange of knowledge within and among firms and other entities (Hopkins and Brynjolfsson 2010; Nambisan and Sawhney

[15]We also apply a Tobit estimator as a robustness test. The results are presented and discussed in Appendix D.

[16]In unreported regressions that exclude the interaction terms, we find that both coefficients of *Data Access Systems* and *Network Connectivity* are negative but insignificant, indicating that they do not significantly increase process innovation performance given that we already control for IT investments in the regression. This result lends further support to our main argument that the impact of IT infrastructure on innovation performance is unleashed through its enablement effect on the absorption of external knowledge.

[17]We conducted an additional analysis that includes the interaction effect between *External Search Depth* and *IT Investments*. Appendix E presents and discusses the results.

[18]Our results are bolstered by the use of a representative sample of census data. Importantly, and in contrast to other empirical studies, our dataset contains not only available information about innovation activities including quantitative information about process innovation success (notice, for example, that Compustat R&D data cannot be dissentangled into product or process innovation, see the discussion in Kleis et al. 2012, p. 56), but it also contains information about a series of variables referring to the use of IT. This has the advantage that we do not need to merge data (Bardhan et al. 2013), which usually comes with a loss of observations and selection issues (see the discussion in Bardhan et al. 2013, p. 13). Moreover, our data cover the industry structure of a whole economy and do not focus on specific segments of firms (e.g., only large, global, or publicly held companies).

Table 1. IV GMM Regressions, 2003–2011

Regressors	(1) Coefficient (Std. Err.)	(2) Coefficient (Std. Err.)	(3) Coefficient (Std. Err.)	(4) Coefficient (Std. Err.)
	Dependent Variable (*Cost Reduction*)			
External Search Depth	0.660* (0.335)	0.032* (0.522)	-1.964* (1.062)	-1.854* (1.051)
Data Access Systems		-2.851** (1.235)		-2.057 (1.599)
*Data Access Systems * External Search Depth*		0.504* (0.292)		0.168 (0.399)
Network Connectivity			-8.135** (2.844)	-5.720 (3.882)
*Network Connectivity * External Search Depth*			3.092** (1.211)	2.810* (1.571)
IT Investments	0.561** (0.281)	0.724** (0.323)	0.651** (0.328)	0.739** (0.351)
External Search Breadth	-0.161 (0.116)	-0.075 (0.124)	-0.154 (0.128)	-0.115 (0.137)
Product Innovation Objective	0.710 (0.639)	0.550 (0.666)	0.584 (0.689)	0.501 (0.710)
Process Innovation Objective	4.858*** (0.913)	4.765*** (0.942)	4.473*** (1.021)	4.371*** (1.044)
R&D Intensity	9.647 (10.88)	6.993 (10.909)	8.390 (11.42)	7.399 (11.66)
% Employees Academic Degrees	0.052 (0.032)	0.071** (0.033)	0.059* (0.034)	0.068* (0.035)
Outsourcing Production (intermediate)	0.507 (0.904)	0.481 (0.948)	0.052 (0.997)	0.084 (1.031)
Outsourcing Production (all)	0.089 (0.879)	0.179 (0.932)	0.200 (0.931)	0.390 (0.987)
Mergers	-1.057 (0.867)	-1.009 (0.882)	-0.515 (0.955)	-0.477 (0.967)
Acquisitions	0.530 (0.653)	0.759 (0.685)	0.326 (0.698)	0.504 (0.739)
Firm Concentration on Core Business	-0.111 (0.571)	-0.202 (0.589)	0.086 (0.608)	-0.080 (0.614)
% Employees Further Education	0.019** (0.009)	0.017* (0.010)	0.017* (0.010)	0.017* (0.010)
% Costs for Further Education	-0.219 (0.135)	-0.120 (0.143)	-0.100 (0.149)	-0.068 (0.154)
Employees' Change of Responsibilities	0.337 (0.388)	0.457 (0.392)	0.251 (0.421)	0.381 (0.421)
% Employees Switch Function and/or Department	0.005 (0.034)	0.022 (0.036)	0.007 (0.037)	0.018 (0.039)
Size	0.082 (0.439)	0.155 (0.473)	0.122 (0.501)	0.249 (0.514)
Constant	-7.190*** (1.792)	-7.496*** (1.967)	-2.593 (2.455)	-4.521 (2.923)
Industry Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
No. of observations	1,057	1,057	1,057	1,057
Kleinberger-Papp rk	20.10***	30.45***	9.989***	9.367***
Hansen J	1.610	1.585	0.375	0.535
Wald test of exogeneity χ^2	7.196**	12.58**	14.27**	17.83***

Notes: Values are unstandardized regression coefficients. Huber-White robust standard errors are clustered at the firm level (i.e., robust to arbitrary heteroskedasticity and autocorrelation). The number of observations in the instrumental estimations is lower than the total observations in the sample (N = 3,490) due to missing values and the use of lagged variables as instruments; therefore, some firms were dropped as they did not possess consecutive years of data.
*p<.10; **p<.05; ***p<.01.

2007; Yoo et al. 2012). A number of factors may prompt manufacturing firms to search for external knowledge, including the increasing complexity and speed of technological change; lack of in-house capabilities to design production technology, equipment, and process architecture; exposure to intense global competition; the mobility of knowledge workers; the reconfiguration of value chains; and a denser integration of firms into industry-wide networks (e.g., Chesbrough 2006; Hamel et al. 1989; Hamel and Prahalad 1994; Pisano 1997). While innovation scholars have previously observed that manufacturing firms increasingly search outside their boundaries when innovating internal production processes (e.g., Reichstein and Salter 2006; Terjesen and Patel 2015; Un and Asakawa 2015), they have thus far downplayed the role of IT in pursuing such open innovation (Chesbrough 2006; Garriga et al. 2013; Salter and Laursen 2006). Our study offers evidence that open innovation is a salient phenomenon among manufacturing firms. Of greater importance, however, the results underscore the critical role played by external knowledge sources in opening up process innovation, and explains how and why IT allows manufacturing firms to leverage external knowledge to innovate their processes.

By conceptualizing IT as data access systems and network connectivity, we have also investigated the potential of each technology as a moderator between external search and process innovation performance. Drawing on prior work in the KBV, absorptive capacity, and information systems, we argued that data access systems and network connectivity support the absorption of external knowledge in internal operations. Interestingly, network connectivity emerged as the dominant moderating technology, which could be interpreted as process innovation relying more extensively on new knowledge creation than on information processing per se (Alavi and Leidner 2001; Nonaka and von Krogh 2009). Where data access systems enhance the gathering, interpretation, and synthesis of codified information in particular (Daft and Lengel 1986; Galbraith 1977), network connectivity facilitates the communication and sharing of tacit knowledge, as well. Our paper underscores the importance of the firm's physical network infrastructure; it is these tangible network links that enable the transfer of knowledge between employees and repositories of codified knowledge (e.g., ERP, CRM and SCM systems) and facilite interactions between people in various locations and functions. By allowing a firm to quickly identify experts internally, integrate external experts into internal communication, mobilize employees around process-related tasks, and support the sharing of detailed, process-related knowledge (Alavi and Leidner 2001; Parent et al. 2000; Stadler 2011), network systems support the innovative recombination of existing firm knowledge with the knowledge obtained using deep search. This may be particularly important when knowledge is heterogeneous and fails to fit in predefined templates, but is nonetheless key to innovation (Davenport and Prusak 1997). A case in point is the need for effective communication between machinery operators, industrial engineers, and purchasing professionals who jointly create solutions to production-related problems. Our results are thus aligned with the task–technology fit thesis in information systems research (Goodhue and Thompson 1995): the claim that the characteristics of the technology should match the nature of the work. When work is collaborative and tasks are interdependent, as they are in process innovation (see Grant 1996), network connectivity offers a fit in terms of work support (Jarvenpaa and Staples 2000). Overall, our findings are in line with Kleis et al. (2012), suggesting that innovation is not only enhanced by investments in R&D-related IT, but also by general IT infrastructure. Moreover, our estimations show that, in addition to external knowledge, internal capabilities—proxied by the share of employees with a tertiary education—have a direct and positive effect on the process innovation performance of a firm.

Implications for Practice

Our study has relevance for managerial practice in manufacturing firms. Chief information officers and other top management functions can expect that investing in communication platforms that allow employees to connect and exchange ideas online and offline should enhance the productive use of externally sourced knowledge for process innovation. This implication can be understood against the backdrop of the KBV. We demonstrate that manufacturing firms aiming to enhance process innovation performance must search deeply in multiple external knowledge sources, which in turn puts high demands on the ability to absorb that knowledge (both tacit and explicit) within the organization. Effective absorption demands technical dialogue, close observation, frequent feedback, and experimentation with new solutions to production problems (see De Jong and von Hippel 2009; Dyer and Hatch 2006; Hansen 1999). Network connectivity supports these activities.

Our findings should also be viewed against the backdrop of current advances toward smart manufacturing (Sirkin et al. 2015), connected products that force firms to rethink their production process (Porter and Heppelmann 2014), and an increasingly closer integration with select customers and supply chain partners (Chick et al. 2014). These developments drive manufacturing in potentially attractive yet uncharted waters (Markillie 2012; Sirkin et al. 2015). Already today, networked machinery collecting performance data has allowed manufacturers to develop pay-per-use business models, effectively changing machinery from a capital expenditure to an operating expenditure (e.g., Björkdahl 2009). Such IT-enabled process improvements can have a profound impact on bottom- as well as top-line growth. In preparing for the future, however, firms must consider that IT is not only improving traditional manufacturing processes, but is fundamentally turning innovation digital (see Yoo et al. 2012). Forward-looking managers ask not only how investments in IT lead to efficient manufacturing, but how *IT enables the effective creation of knowledge that supports innovation* (Lusch and Nambisan 2015). For example, our study would suggest that data analytics (in its simplest form) is not the panacea for innovation—merely possessing and analyzing data is not enough. For enduring effects on organizational performance external (and internal) data need to be molded into actionalble insights that can be communicated throughout the firm.

Limitations and Future Research

An econometric analysis of a single country's manufacturing sector will naturally be restricted in its level of detail about the variety of task–technology relationships. External knowledge sources may also differ across industries in the extent to which they offer technically relevant and advanced knowledge to firms' process innovations (Malerba 2002). Although our results should be seen against the Swiss background, this study opens doors to future scholarly work on the intersection between innovation and IT. In light of the rapid and ongoing digital transformation in industry, and as technology increasingly changes the nature of how employees communicate, access, and process data, future research could adopt an even more refined conceptualization of IT in order to investigate its role in a firm's value creation and performance.

Conclusion

We build on insights from the knowledge-based view of the firm to develop a theoretical model explaining how a firm's deep search in multiple external knowledge sources and its information technology, conceptualized as data access systems and network connectivity, jointly influence the firm's process innovation performance. Testing the model on panel data from Swiss manufacturing firms, we found evidence that it is predominantly the firm's network connectivity technologies that moderate the strong positive relationship between a firm's deep search in multiple external knowledge sources and its process innovation performance. The results underscore the role and importance of a firm's information technology for the successful absorption of external knowledge and the realization of economic gains from innovation.

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SPECIAL ISSUE: IT AND INNOVATION

EXTERNAL KNOWLEDGE AND INFORMATION TECHNOLOGY: IMPLICATIONS FOR PROCESS INNOVATION PERFORMANCE

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Appendix A

Sample Characteristics

Table A1. Industry Composition of the Sample

		2005		2008		2011	
	Manufacturing Industry	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**
1	Food/Beverages/Tobacco	107	8.48	83	7.74	95	8.22
2	Textile	31	2.46	21	1.96	23	1.99
3	Clothing	10	0.79	8	0.75	10	0.87
4	Wood	41	3.25	36	3.36	41	3.55
5	Paper & Paper Products	29	2.30	21	1.96	22	1.90
6	Printing	70	5.55	58	5.41	56	4.84
7	Chemicals & Chemical Products	95	7.53	87	8.12	102	8.82
8	Rubber/Plastics	48	3.80	38	3.54	54	4.67
9	Non-metallic Minerals	44	3.49	36	3.36	35	3.03
10	Manufacture of Basic Metals	30	2.38	26	2.43	28	2.42
11	Fabricated Metals	152	12.04	143	13.34	164	14.19
12	Machinery & Equipment	230	18.23	190	17.72	189	16.35
13	Electrical Equipment	70	5.55	60	5.60	54	4.67
14	Electronics	142	11.25	129	12.03	129	11.16
15	Watches	46	3.65	42	3.92	44	3.81
16	Vehicles	27	2.14	22	2.05	22	1.90
17	Other Manufacturing	39	3.09	28	2.61	32	2.77
18	Energy	51	4.04	44	4.10	56	4.84
Total		**1,262**	**100.00**	**1,072**	**100.00**	**1,156**	**100.00**

Note: Industry distribution for the Swiss manufacturing firms in the sample (two-digit NACE codes).

Appendix B

Variables and Descriptive Statistics

Table B1. Utilization of External Knowledge Sources

Sources		Mean Score
1	Customers	3.24
2	Suppliers (materials)	3.22
3	Suppliers (investment goods)	2.59
4	Suppliers (software)	2.36
5	Competitors	2.78
6	Own Enterprise Group	2.12
7	Universities	2.48
8	Public or Private Research Institutes	2.19
9	Consultants	2.02
10	Technology Transfer Offices	1.81
11	Patent Disclosures	2.01
12	Fairs/Exhibitions	3.12
13	Conferences/Scientific Literature	2.99
14	Databases (information networks)	2.48

Note: Mean values on survey responses (five-point Likert scale, 1 = no usage; 5 = high usage) over the nine-year sample period (N = 3,490).

Table B2. Variable Definitions

Variable Name	Variable Construction/Definition
COST REDUCTION (dependent variable)	Continuous variable: Cost reduction achieved by process innovation (log).
External Search Depth	Number of external knowledge sources utilized extensively: the questionnaire contains 14 external knowledge sources for innovation activities. The variable counts the knowledge sources which has been assessed as very important (value 4 or 5 on a 5-point Likert scale).
External Search Breadth	Number of external knowledge sources used: the variable counts the number of external knowledge sources (maximum 14) that are of some importance to the innovation activities of the focal firm (value 2, 3, 4, or 5 on the 5-point Likert scale).
Data Access Systems	Sum of three binary variables: Adoption of systems for enterprise resource planning (ERP) (0/1), supply chain management (SCM) (0/1), and customer relationship management (CRM) (0/1).
Network Connectivity	Binary variable: Adoption of local area network (LAN).
IT Investments	Continuous variable: Investments in IT (log).
R&D Intensity	Fractional variable: R&D expenditures to total sales.
% Employees Academic Degrees	Fractional variable: Percentage of employees with academic degrees.
Product Innovation Objective	Binary variable: value 1 if at least one out of five product innovation goals (improve product quality, replace outdated products, expand product portfolio, keep or increase market share) is assessed as very important by the focal firm (value 5 on a 5-point Likert scale); 0 otherwise.
Process Innovation Objective	Binary variable: value 1 if at least one out of four process innovation goals (increase flexibility of production, reduce labor costs, reduce material cost, reduce energy cost) is assessed as very important by the focal firm (value 5 on a 5-point Likert scale); 0 otherwise.
Outsourcing Production (intermediate)	Binary variable: value 1 if the focal firm outsourced the production of **intermediate products**; 0 otherwise.
Outsourcing Production (all)	Binary variable: value 1 if the focal firm outsourced **the whole** production process; 0 otherwise.
Mergers	Binary variable: value 1 if the focal firm merged with other firms; 0 otherwise.
Acquisitions	Binary variable: value 1 if the focal firm acquired other firms/parts of other firms; 0 otherwise.

Table B2. Variable Definitions (Continued)	
Variable Name	**Variable Construction/Definition**
Firm Concentration on Core Business	Binary variable: value 1 if the focal firm made steps towards a stronger concentration on its core business; 0 otherwise.
% Employees Further Education	Fractional variable: share of employees that received further education.
% Costs of Further Education	Fractional variable: share of costs for further education covered by the focal firm.
Employees' Change of Responsibilities	Binary variable: value 1 if there has been a change in the responsibilities of employees; 0 otherwise.
% Employees Switch Function and/or Department	Fractional variable: share of employees that switched function and/or department.
Size	Continuous variable: number of employees (log).
Industry	18 binary variables: industry dummies defined at the NACE two-digit level.
Time	3 binary variables: time dummies to capture the three waves of the survey.

Data source: KOF (Swiss Economic Institute), ETH Zurich.

Table B3. Descriptive Statistics and Pair-Wise Correlation Matrix of Major Variables

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1	*Cost Reduction*	1.92	7.36	1									
2	*External Search Depth*	3.29	2.65	0.21	1								
3	*Data Access Systems*	1.18	1.01	0.12	0.18	1							
4	*Network Connectivity*	0.85	0.36	0.18	0.23	0.37	1						
5	*IT Investments*	10.65	3.05	0.21	0.18	0.20	0.33	1					
6	*External Search Breadth*	10.36	3.28	0.17	0.45	0.18	0.32	0.24	1				
7	*R&D Intensity*	0.02	0.04	0.21	0.15	0.08	0.14	0.11	0.12	1			
8	*Product Innovation Objective*	0.31	0.46	0.28	0.27	0.11	0.17	0.17	0.16	0.24	1		
9	*Process Innovation Objective*	0.15	0.36	0.38	0.27	0.10	0.13	0.16	0.14	0.13	0.40	1	
10	*Size*	4.26	1.41	0.28	0.22	0.32	0.49	0.62	0.31	0.10	0.21	0.18	1

Note: Pair-wise Pearson correlations are reported based on the IV GMM estimations (N = 1,057). All correlations are significant at $p < .01$.

Appendix C

Endogeneity Tests

Test of Underidentification

A rejection of the null indicates that the selected set of excluded instruments is correlated with the endogenous variables. Since we present cluster-robust statistics, this test refers to the Kleibergen-Papp test, which is a generalization of the Anderson canonical correlation rank statistic in the non-i.i.d case (Kleibergen and Paap 2006). This test results in an LM statistic of 20.10 (significant at the 1% level) for Model 1, 30.45 (significant at the 1% level) for Model 2, 9.989 (significant at the 1% level) for Model 3, and 9.367 (significant at the 1% level) for Model 4 (see Table 1 in the main results). Therefore, all instruments pass the underidentification test (i.e., they are sufficiently correlated with the endogenous variables).

Test of Overidentifying Restrictions

Since the number of excluded instruments exceeds the number of our endogenous regressors (overidentification), we can test for the instrumental exclusion restriction, that is, test the joint null hypothesis that the group of instrumental variables is valid (i.e., uncorrelated with the error terms) (Baum et al. 2007). A rejection of the null would cast suspicion on the validity of the instruments. As we present heteroskedastic-robust covariance estimator, the Hansen's J statistic is reported. The Hansen J statistic reports values of 1.610 for Model 1, 1.585 for Model 2, 0.375 for Model 3, and 0.535 for Model 4 (see Table 1 in the main results). These values indicate that the null hypothesis is not rejected; thus, our instruments are valid.

Endogeneity Test

Finally, we test the null hypothesis that the specified endogenous regressors can actually be treated as exogenous (Baum et al. 2007). The Wald test of exogeneity reports the values 7.196 (significant at the 5% level) for Model 1, 12.58 (significant at the 5% level) for Model 2, 14.27 (significant at the 5% level) for Model 3, and 17.83 (significant at the 1% level) for Model 4 (see Table 1 in the main results). Thus, we confirm that the specified endogenous regressors cannot be treated as exogenous.[1]

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Appendix D

Robustness Tests

Alternative IT Proxies

Table D1 examines the introduction of a binary variable for the presence of *ERP* in the focal firm as an alternative proxy for *Data Access Systems* (for a similar approach, see Bloom et al. 2015). We keep the same model specification as in our main regressions. The interaction term *Data Access Systems (ERP) * External Search Depth* in the first column of Table D1 takes a positive and significant coefficient (coeffficient = 1.535, p < .05). This is in line with the finding of our main model depicted in column (2) of Table 1. Next, we introduce the *Network Connectivity* variable. The second column of Table D1 qualitatively reproduces the main results depicted in column (4) of Table 1. However, the focus on ERP as a measure of *Data Access Systems* causes the interaction term *Network Connectivity * External Search Depth* to lose its significance (p = .184). This ambiguity of the *Network Connectivity* interaction term may well be rooted in the fact that ERP—although a system that primarily affects access to information—may also to some modest degree be used for internal communication (for a similar disussion, see Bloom et al. 2015, p. 2878). Thus, ERP might cover some of the *Network Connectivity* (LAN) effect, causing the *Network Connectivity * External Search Depth* term to become insignificant. To examine this issue in more depth, we reran our regressions by substituting *ERP*, first, with a binary for *SCM* and second, with a binary for *CRM*. In contrast to ERP, SCM and CRM are enterprise systems with no internal communication capabilities, thus we should expect those systems to have less or no overlap with the *Network Connectivity* effect. Indeed, the results of these models reproduce our main findings in column (4) of Table 1.[2]

[1]We implemented the endogeneity tests using the "endogtest" option for the "ivreg2" command in Stata 13. Notice that the test on exogeneity is performed after the overidentification restrictions test, as the first is not valid if the latter rejects the validity of the instruments.

[2]In particular, the coefficients (standard errors) for *Network Connectivity * Intense Sources* become 3.506 (1.603) and 2.967 (1.331) for the models including *SCM* and *CRM*, respectively. Full results available upon request.

Table D1. Robustness Tests, IV GMM Regressions, 2003–2011		
	Dependent Variable (*Cost Reduction*)	
	Alternative *Data Access Systems* Measure (ERP)	**Alternative *Data Access Systems* Measure (ERP)**
Regressors	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
External Search Depth	-0.453 (0.657)	-1.838* (1.046)
Data Access Systems (ERP)	-7.379*** (2.606)	-5.753 (3.549)
*Data Access Systems (ERP) * External Search Depth*	1.535* (0.760)	0.846 (1.052)
Network Connectivity		-3.632 (4.253)
*Network Connectivity * External Search Depth*		2.251 (1.696)
IT Investments	0.732** (0.317)	0.787** (0.348)
External Search Breadth	-0.044(0.128)	-0.087 (0.139)
Product Innovation Objective	0.708 (0.661)	0.542 (0.706)
Process Innovation Objective	4.600*** (0.940)	4.298*** (1.022)

Notes: Values are unstandardized regression coefficients. Huber-White robust standard errors are clustered at the firm level (i.e., robust to arbitrary heteroskedasticity and autocorrelation). All columns include the full set of control variables as in the main regressions (see Table 1).
*p < .10; **p < .05; ***p < .01.

Tobit Estimator

The continuous dependent variable *Cost Reduction* includes a set of zero values since some firms did not introduce cost-reducing process innovations during the observed period. Consequently, the distribution of the dependent variable shows a pileup at the value zero (corner solution). Hence we conducted robustness tests by using an instrumental-variables Tobit (nonlinear) estimator (see Wooldridge 2002). Table D2 presents the results of the IV Tobit estimation and compares them with the ones obtained from our main regressions (IV GMM; see also Table 1).

While in linear models the interpretation of the coefficients of interaction terms is straightforward, this does not extend to nonlinear models like the Tobit. Unfortunately, inference and model testing of interaction effects cannot be conducted simply via the magnitude, statistical significance, or sign of the coefficients of the interaction terms. For example, the sign of the coefficient does not necessarily indicate the sign of the interaction effect (Ai and Norton 2003). Therefore, Tobit coefficient estimates for interaction terms should not be directly compared with the ones of linear regressions. As a consequence, we compare IV GMM with IV Tobit estimates, present Tobit estimates only for Model 1, and will not attempt to utilize Tobit estimates as robustness tests for the models with interaction effects (Models 2–4 in Table 1).

The comparison of the results between IV GMM and IV Tobit (Table D2) confirms the robustness of our main estimations shown in Table 1. In the IV Tobit estimation, all coefficients display the same sign and similar statistical significance as the corresponding GMM estimates. In particular, note that our main independent variable *Intense Sources* remains positive and even gains in significance (the magnitudes of the coefficients of the Tobit and GMM estimations are not directly comparable).

Table D2. Comparison Between IV GMM and IV Tobit Regressions, 2003-2011

	Dependent Variable (*Cost Reduction*)	
	IV GMM	IV Tobit
Regressors	Coefficient (Std. Err.)	Coefficient (Std. Err.)
External Search Depth	0.660* (0.335)	3.383** (1.686)
IT Investments	0.561** (0.281)	5.285** (2.188)
External Search Breadth	-0.161 (0.116)	-0.995 (0.620)
Product Innovation Objective	0.710 (0.639)	2.507 (2.740)
Process Innovation Objective	4.858*** (0.913)	15.67*** (3.630)
% Employees Cont. Education	0.019** (0.009)	0.086* (0.046)

Notes: All columns include the full set of control variables as in the main regressions (see Table 1).
*p < .10; **p < .05; ***p < .01.

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Appendix E

Interaction Effect Between External Search Depth and IT Investments

The information systems literature makes wide use of IT investments in order to study how the IT artifact affects various types of performance (e.g. Bardhan et al. 2013; Kleis et al. 2012; Mithas et al. 2012; fir a review, see Melville et al. 2004). Thus, we also run a supplementary analysis with the interaction effect between *External Search Depth* and *IT Investments* in a model specification similar to the one in our main regressions. Analogous models including interaction effects have appeared in recent work on IT and innovation (Bardhan et al. 2013; Joshi et al. 2010; Kleis et al. 2012; Tambe et at. 2012).

Table E1 presents the results. Column 1 shows the baseline regression, which is also presented in column (1) of Table 1. The coefficients of *External Search Depth* and *IT Investments* are positive and significant. In column (2) we introduce the interaction between *External Search Depth* and *IT Investments*. The coefficient of *External Search Depth* * *IT Investments* is positive and significant (coefficient = 0.381, $p < .01$). Importantly, this result suggests that intense usage of multiple external sources interacts with IT investments to positively affect process innovation performance. However, while the coefficient estimates for the model with the interaction effect are informative, they have limited explanatory value with regard to the marginal effect of *External Search Depth* on process innovation performance. For example, the coefficient estimate of *External Search Depth* conveys little information about the marginal effect of *External Search Depth* on *Cost Reduction* conditional on the value of *IT Investments*. Notice that in this model, the marginal effect of *External Search Depth* is dependent on *IT Investments*, and therefore the coefficients of the constitutive term of *External Search Depth* should not be interpreted as the average effect of a change in the independent variable on the dependent variable. (This coefficient only captures this effect correctly when *IT Investments* is zero.) Moreover, the coefficient estimates fail to indicate whether *IT Investments* has a statistically significant impact on the aforementioned marginal effect of the *External Search Depth* variables within the sample range of observed *IT Investments* values.

Table E1. Interaction Effect (IT Investments)

Regressors	Dependent Variable (*Cost Reduction*) (1) Coefficient (Std. Err.)	(2) Coefficient (Std. Err.)
External Search Depth	0.660* (0.335)	-3.726** (1.520)
IT Investments	0.561** (0.281)	-0.032 (0.388)
*External Search Depth * IT Investments*		0.381*** (0.128)
External Search Breadth	-0.161 (0.116)	-0.034 (0.136)
Product Innovation Objective	0.710 (0.639)	0.915 (0.700)
Process Innovation Objective	4.858*** (0.913)	4.091*** (1.074)
% Employees Cont. Education	0.019** (0.009)	0.007 0.011)

Notes: All columns include the full set of control variables as in the main regressions (see Table 3).
*$p < .10$; **$p < .05$; ***$p < .01$.

In order to provide a substantively meaningful description of the marginal effect of *External Search Depth* while accounting for the interaction effect, we go beyond the traditional results table and graphically illustrate the marginal effect of the *External Search Depth* variable on process innovation performance conditional on IT investments, along with the corresponding standard errors (Brambor et al. 2006). The graphical results correspond to the instrumental-variables GMM estimator (column (2) of Table E1) with all other covariates being set to their mean values. Figure E1 illustrates the marginal effect of *External Search Depth* on *Cost Reduction*. The horizontal axis of the plot extends from the minimum observed value of *IT Investments* in the sample (0) to the maximum (19.1). The solid line in the figure indicates how the marginal effect of *External Search Depth* changes as IT investments increase. The significance of the marginal effect is depicted by the 95% confidence intervals around the sloping line: the marginal effect is significant when the upper and lower bounds of the confidence interval are either above or below the horizontal zero line (Brambor et al. 2006). We also overlay the frequency distribution of the *IT Investments* variable in the sample over the marginal effect plot. Figure E1 depicts that the marginal effect of *External Search Depth* is negative and significant when *IT Investments* is zero. This value of the marginal effect corresponds to the coefficient estimate of *External Search Depth* in column (2). As *IT Investments* increases, the marginal effect of *External Search Depth* increases (ascending line), a consequence of the positive coefficient of the interaction effect *External Search Depth* * *IT Investments*. The marginal effect becomes positive but still insignificant for *IT Investments* = 9.5, and converts to significant for *IT Investments* > 11.5.[3] This makes clear that *Intense Sources* has a positive impact on process innovation performance when the IT investments of the firm are moderate to high. Overall, the baseline model predicts a positive and significant relationship between *External Search Depth* and *Cost Reduction*, while the extended model predicts a positive and significant relationship for moderate to high IT investments.

To summarize, Figure E1 sheds light on the impact of the intensive usage of multiple external sources on process innovation performance, for different levels of IT investments. It also offers insights into the competitive significance of IT investments, while painting a nuanced and comprehensive picture of their strategic implications for process innovation performance. The graph illustrates the conditions under which the intense use of external knowledge sources is strategically beneficial to the firm, and shows that this use needs to be carefully orchestrated with a firm's IT investments for it to pay off in terms of production-related cost reductions.

[3] In our sample, 38.7% of the observations with *IT Investments* > 11; see histogram in Figure E1.

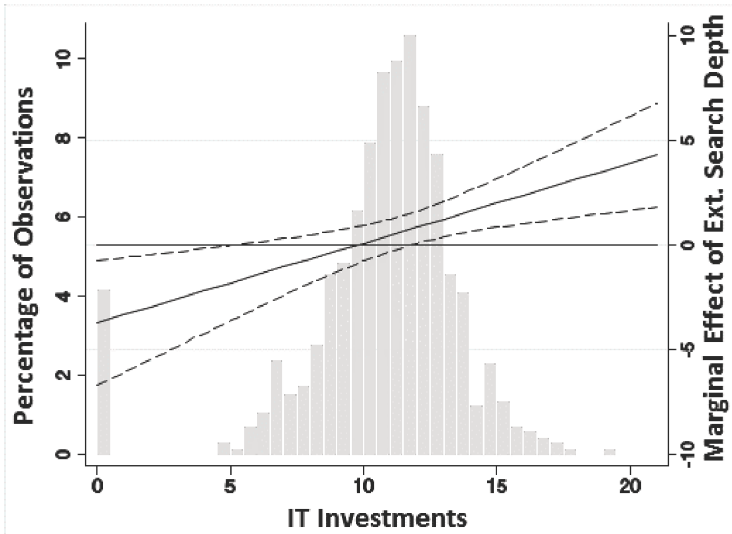

Figure E1. Marginal Effect of *External Search Depth* on *Cost Reduction*, Contingent on *IT Investments* (IV GMM, Column (2) of Table E1)

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