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INFORMATION TECHNOLOGY AND ORGANIZATIONAL LEARNING: AN EMPIRICAL ANALYSIS

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Abstract

Organizational learning theory suggests that organizations "learn from experience" and are thus able to adapt their range of potential behaviors through the processing of information. Our research integrates this perspective with information systems economics theory and empirically tests whether new information technology investments contribute to an organization's ability to learn from experience. Based on a cross-sectional time series analysis of data spanning 48 months and six independently operated payment processing facilities owned by a major international financial institution, our results indicate that IT has a significant positive impact on the rate at which organizations can translate learning from cumulative experience into incremental productivity gains.

Keywords: Organizational learning, information technology, business value of information technology, process-level analysis, productivity

Introduction

Information technology investments, even in periods of relative economic downturn, are substantial. While actual amounts vary by industry, firms invest an average of 37 percent of capital budgets annually in new information technologies in efforts to improve business productivity and profitability (Kirkpatrick 2002). Even so, IT business value research has been unable to establish precise links between a firm's IT investment and the business value it receives, particularly at work group and business process levels (Kohli and Devaraj 2003). Likewise, research in the field of organizational behavior and learning has successfully applied learning curve analysis to investigate the nature of increases in organizational performance, yet establishing linkages between learning curves and potential causes of performance changes revealed by those curves has proven to be just as elusive (Kluge and Schilling 2000). This study integrates the relevant IT economics and organizational behavior literatures, offers theory describing IT's relationship to organizational learning, and tests this theory empirically using archival data obtained from a major international financial institution.

Not surprisingly, the fields of IT business value research and organizational behavior focus on understanding many of the same phenomena but from different perspectives. One example of this commonality is research on how the domains of the respective fields contribute to work group performance. Perhaps more surprising, however, is that so little research has attempted to integrate the two fields empirically. This is unfortunate because each discipline has a great deal to offer in informing the other. For example, IT business value theory suggests that IT is positively related to firm performance and can contribute to such performance by improving a firm's ability to solve problems, coordinate work, communicate, administer and manage work, or share knowledge. Yet, while research on IT business value in recent years seems to have affirmed this theory, little work has been done to establish how IT actually makes such contributions, particularly at levels below the aggregate firm level where group processes are operative. Similarly, in the field of organizational behavior, organizational learning theory has suggested that learning is evidenced when organizations change their performance over time based on experience gained through knowledge acquisition, information distribution, and information interpretation (Huber 1991), but very little empirical research has been conducted to investigate how information technology in particular may be responsible for variation in such learning. Thus, while both learning curve theory and IT business value research seek common explanations of how their respective processes affect organizational performance, neither has fully explored those impacts in an integrated context.

The current study extends the literature on both business value of IT and organizational learning by examining the central question of whether IT has positive effects on changes in process-level organizational learning over time. A further contribution is the integration of the IT value and organizational learning literatures, providing a more unified perspective on a key means through which IT operates to improve business value while adding to the empirical work in organizational theory seeking to identify factors that account for differences in organizational learning.

The remainder of this paper is organized as follows. First, a brief discussion of prior research from the learning curve and IT business value literatures is provided as a general context for the proposed integrated research model and as motivation for our primary conjecture that IT positively affects organizational learning rates. The paper proceeds with a description of the data and method, including descriptions of the mathematical models, and concludes with a discussion of results, theoretical and practical implications, and opportunities for additional research.

Grounding in Prior Research

This research builds on two significant bodies of research—one related to organizational learning and the other related to the business value of information technology. In the organizational learning literature, the phenomenon of the *learning curve*—or the idea that an organization's labor required for production decreases at a decreasing rate as the organization produces more of the product—is widely accepted as a fundamental pattern in organizational behavior (Argote 1999; Epple et al. 1991). While research has shown that there is considerable variation in the rate at which organizations learn (Adler and Clark 1991; Argote and Epple 1990; Darr et al. 1995; Dutton and Thomas 1984; Hayes and Clark 1986; Joskow and Rose 1985; Yelle 1979; Zimmerman 1982), there remains a paucity of research examining factors underlying such differences (Kluge and Schilling 2000; Miner and Mezias 1996).

Similarly, research on the business value of IT, while making strides in linking IT investment to general increases in productivity, has shown limited evidence of *how* such investments actually translate into impact on organizational performance. IT research in the 1980s and early 1990s showed mixed results for the value of IT (Bailey and Chakrabarti 1988; Brynjolfsson 1993; Loveman 1994; Roach 1987; Salerno 1985), but most studies since the mid-1990s have shown significant positive impacts of IT investments (Barua et al. 1995; Brynjolfsson and Hitt 1996; Kudyba and Diwan 2002; Lehr and Lichtenberg 1999; Lichtenberg 1995; Mukhopadhyay et al. 1995; Srinivasan et al. 1994; Thatcher and Oliver 2001; Weill 1992).

While many of the studies indicate IT's positive impact on productivity, there has been little empirical exploration of *why* such impacts may occur. Firm-level studies have been unable to resolve important questions regarding the origins of payoffs from investments in IT, particularly with respect to understanding the time lags, duration, and process-level variations of those payoffs (Dedrick et al. 2001). One reason why IT impacts may not be clear and consistent is that a primary focus of IT business value research has been on measuring only the final effects of IT rather than attempting to understand how IT creates value. To address this, there has been a growing recognition that IT impact can be identified through process level contribution. For example, Mukhopadhyay et al. (1997) examined the impact of IT on the mail sorting process at the U.S. Postal Service. Tallon et al. (2000) adopted executives' perceptions of performance at the process-level to measure IT impacts. Davamanirajan et al. (2002) used a production function to model the relationship between the inputs and outputs of the trade services process. Mukhopadhyay and Kekre (2002) studied the impact of EDI technology adoption on the order-processing cycle for both suppliers and customers. Finally, Ray et al. (2004) found that measuring the effectiveness of business processes enhanced by IT resources may be more appropriate than adopting overall firm performance measures. On the basis of this literature, we argue that our focus on IT's impact on organizational learning dictates that we focus on a process rather than the organization as our unit of analysis.

With respect to research on the impacts of IT on organizational learning, although IT has been shown to be associated with increased productivity (Bharadwaj et al. 1999; Brynjolfsson and Hitt 1996; Devaraj and Kohli 2000), research on whether IT affects the ability of an organization to learn from experience is in its infancy. Boone and Ganeshan (2001) found mixed results on the impact of IT on learning curves. Consistent with suggestions of earlier research (Brynjolfsson and Hitt 1996; Hirsch 1952; Hollander 1965), their study concluded that the one IT system that enhanced productivity did so only because it was applied to a core operations process rather than used merely for documenting or collecting information. Because their study focused on specific software systems applied to highly variable production units (measured in the form of completed engineering projects rather than manufactured goods), their results offer an application-level view of the effect of IT. However, the relationship between IT investment and learning in larger-scale work processes remains an open question. Recently, Tippins and Sohi (2003) suggested that IT's strategic differentiation is partially explained by resource-based theory. Their results indicated that managers associate IT competency with certain characteristics of organizational learning, but their conclusions show no evidence that learning actually occurred in the organizations surveyed. Other studies have suggested that IT capital is one of many potential factors responsible for productivity increases, but none has examined the specific relationship to process-level learning curves (Kluge and Schilling 2000).

Motivation and Research Hypotheses

In this study, we perform an empirical investigation into the organizational learning "payoff" of IT investment at the work process level. To establish a baseline, we hypothesize that, consistent with organizational learning theory, work processes will exhibit characteristics of classic learning curves, implying that labor hours per unit produced will decrease due to increases in organizational knowledge distinct from increases due to pure economies of scale or other factors (Rapping 1965; Yelle 1979). Hence, our first hypothesis is

> H1(a). Labor per unit of production required at the process level will decrease as the organization gains experience in production.

In order to ascertain in subsequent hypotheses that effects are associated with learning and not with simple increases in single-period efficiency, we control for economies of scale (Womer 1979).

> H1(b). Controlling for scale economies, increases in cumulative organizational experience will result in lower labor hours per unit produced.

To further extend this baseline proposition, we next hypothesize a main effect on productivity resulting from the implementation of IT. The effects of IT on efficiency and productivity are related to the extent to which IT enhances storage, distribution, or execution of knowledge embedded in work group structure and processes or in the skill and knowledge of individual workers (Argote et al. 1990; Devadas and Argote 1990; Simon 1991). In the context of technology usage, which represents a form of embedded knowledge, IT implementations may replace the accumulated experience of human capital with knowledge embedded in new technology (Levitt and March 1988). In addition, the new technology itself incorporates the knowledge of the IT provider and its own experience gained from previous implementations (Thomas et al. 2001). The combined technology effects would be expected to contribute to reductions in labor required per unit of output, resulting in a downward shift in the learning curve beginning at the time the IT intervention took place. Thus, consistent with implications of organizational learning theory and information economics theory, it is expected that the impact of IT on productivity as measured by learning curves is both significant and positive, leading to our hypothesis on the general impact of IT as follows:

> H2. The implementation of process-level information technology results in a significant main effect of reducing labor hours per unit processed.

With these hypotheses as baselines, we move to our central research question regarding the extent to which IT impacts organizational learning, where *organizational learning* is defined as an organization's translation of knowledge gained through experience into productivity improvements. By embedding the organization's accumulated knowledge in technology that can be changed rapidly in response to new requirements, organizations can increase the rate at which their cumulative knowledge affects current performance (Hayes and Wheelright 1984; Joskow and Rose 1985). Automating and standardizing complex processes using IT may enable existing employees to recognize opportunities to improve processes based on accumulated experience and instantiate such improvements into the technology (Cohen and Levinthal 1990). Thus, we hypothesize that

> H3. The introduction of new information technology is associated with an increase in the rate at which organizations learn from experience.

Research Design

Our research methodology has three components: (1) research model, (2) data collection, and (3) analysis plan. The research model has as its foundation the basic organizational learning curve, relating the current effort required to produce a unit of output to the cumulative effort associated with output of that unit over a period of time (Womer 1979; Yelle 1979). The dependent variable is current productivity as measured by labor hours per unit of output for a given location in the current period. The canonical independent variable is the cumulative level of production and is related to the dependent variable in the classic equation,

$$LH_t = a \cdot CP_{t-1}^{-b}, \tag{1}$$

where dependent variable LH_t is the number of labor hours required to produce a unit in time t, constant a represents the labor hours associated with producing the first unit, and independent variables CP_{t-1} and b are, respectively, the cumulative number of units produced through time period t-1 and the rate of organizational learning over the period [0, t-1]. Following Argote and Epple (1990), this equation can be expressed in log form as follows:

$$\ln LH_t = \ln a - b \ln CP_{t-1} \tag{2}$$

where CP_{t-1} represents a proxy for knowledge acquired through past production. All other factors held constant, a statistically significant coefficient of organizational knowledge, b, is indicative of organizational learning.

Data Collection

Data used in the study were collected on the retail remittance processing, or "lockbox," operations of Mellon Financial Corporation. Headquartered in Pittsburgh, Pennsylvania, Mellon is one of the world's largest financial services institutions. The research sample consisted of monthly operating data for processing centers located in six different regions of the United States over the period from January, 2000, to December, 2003. The facilities are wholly owned by Mellon but operate under local management independently of one another.

Remittance processing, or lockbox, services automate collection and reporting of bill payments for large-volume commercial customers of financial institutions. Wholesale lockbox services are provided to other financial institutions, who can then offer the service to their own retail customers. Retail lockbox services, on the other hand, are offered directly to industrial customers who have large volumes and wide geographic presence. For example, a cable television provider offering services in several states may contract directly with a lockbox service provider such as Mellon to provide a central facility for receiving and processing all payments from retail cable subscribers. Smaller companies, such as a local newspaper or mortgage company, may contract for such services directly with a lockbox provider or, alternatively, through their own commercial bank (who, in turn, may be a wholesale customer of Mellon's wholesale lockbox division providing the actual processing). Such services are appealing to large commercial and industrial customers because they reduce float and processing time, lower in-house processing costs, decrease handling and accounting errors, and improve control of funds. Other capabilities, such as image capture of payments, invoices, and remittance documents, eliminates the need for traditional paper delivery, helping industrial customers improve service to their ultimate retail consumers. Since Mellon's wholesale lockbox process employs different routines and technology, and since the information technology implementation we studied only applied to retail operations, we focus only on Mellon's *retail* lockbox process.

As part of a company-wide revenue enhancement initiative, Mellon had earlier identified the retail lockbox process as a target for cost reduction through increasing processing throughput and accuracy and lowering human capital required for manual processing steps. The strategic objective of the anticipated cost reduction would be to enable Mellon to be more aggressive in pricing their processing services, thereby both protecting and improving profitability of a stable revenue source as well as enabling continued growth even in the face of strong competition. Five of the sites operate three 8-hour shifts five days per week, while the sixth and largest location operates three daily shifts seven days per week. The process begins with one of several daily pick-ups of remittances at the local U.S. postal service mail processing center. Upon delivery to one of Mellon's lockbox facilities, the remittances are automatically sorted by company (i.e., by lockbox customer) and staged for processing. Ideally, processing encompasses automated opening of envelopes, removal and separation of payments (checks) from remittance documents, identification of payor accounts, comparison of courtesy amounts written on checks by payor with amounts printed on scan lines of remittance stubs, debiting of the payor's bank account, and transfer of the equivalent amount to the lockbox customer's account. Prior to implementation of the new IT system, each location's throughput was limited by the lower automation level of older technology and less efficient identification and handling of exceptions. Exceptions—such as envelopes containing multiple documents (e.g., two or more payments), customer correspondence, folded or stapled checks, or address changes—require manual intervention and fall into two categories. The *review* category contains items such as letters that may involve contact with the customer; the less involved *outsort* category involves manual removal of staples or unfolding remittance documents. The new IT technology enables higher processing speeds as well as increased automation of exception handling, resulting in a higher rate of items processed without manual intervention. Since the system also can identify exceptions by type, less time is consumed in routing exceptions to appropriate experts for resolution. Moreover, as new types of exceptions are discovered, the system enables human personnel to adapt procedures for addressing them specifically.

During the 48 month period for which detailed data were available, Mellon processed in excess of 1.3 billion homogeneous transactions on behalf of its lockbox customers over a well-defined pre-IT and post-IT period. Once the decision was made to implement the new technology, conversions at each location occurred rapidly, resulting in an impact profile that is essentially a step function. Over the study period, other process characteristics remained largely unchanged, enabling us to associate significant changes in organizational learning with the IT implementation itself, after controlling for seasonal variations, location-related factors, and scale economies. Our data are thus ideal for evaluating the impact of an IT implementation on organizational learning.

Analysis Plan

The symbols used throughout the paper and the variables they represent are listed below.

t = calendar time in months
q_{it} = thousands of remittance items processed by location i in month t
h_{it} = direct labor hours for location i in month t
Q_{it} = cumulative items processed, $\sum_{j=0}^{t} q_{ij}$, at location i in month t (in thousands)
IT_{it} = indicator variable for IT implementation at location i in month t (0 for pre-IT, 1 for post-IT)
loc_i = dummy variables for each location
m_k = dummy variables for each month k ∊ {1, 2, …, 12}
ε_{it} = error term

The variable Q is standard in organizational learning theory and acts as a proxy for location-specific knowledge, or knowledge gained through accumulated production experience, while the indicator variable IT acts as a transfer function representing implementation of the new information technology at each location. The location dummy variables control for variance associated with location-related differences such as local labor economy, management, and work group composition, while the dummy variables assigned to each month control for variance associated with seasonal demand fluctuations and equipment maintenance requirements. As we discuss later in more detail, we allow for serial correlation of the error term in each model.

To test hypothesis 1, we estimate two models, one in which labor hours per thousand items processed depend on location-specific experience and another in which we add control variables for economies of scale. Thus, our basic model for testing hypothesis 1(a) is

$$\ln(h_{it}/q_{it}) = \beta_0 + \beta_1 \ln Q_{i,t-1} + \beta_{L_i} loc_i + \beta_{m_k} m_k + \varepsilon_{it} \tag{3}$$

In this and remaining equations, the variable Q represents cumulative items processed through the end of the previous month and is lagged on the right-hand side of each equation because it acts as a proxy for experience gained from past processing experience. For example, in Equation (3), if β_1 is significant, learning specific to each lockbox processing location has occurred. To test hypothesis 1(b), consistent with Womer (1979) and Epple et al. (1991), we add variables q_{it} and q_{it}^2 to the right-hand side of the equation representing first and second order economies of scale:

$$\ln(h_{it}/q_{it}) = \beta_0 + \beta_1 \ln Q_{i,t-1} + \beta_2 q_{it} + \beta_3 q_{it}^2$$

$$+ \beta_{L_i} loc_i + \beta_{m_k} m_k + \varepsilon_{it} \tag{4}$$

Hypothesis 2, which tests for the impact of IT on productivity as measured in a learning curve context, is evaluated with the indicator variable IT_{it} in the following model:

$$\ln(h_{it}/q_{it}) = \beta_0 + \beta_1 \ln Q_{i,t-1} + \beta_2 q_{it} + \beta_3 q_{it}^2 + \beta_4 IT_{it}$$

$$+\beta_{L_i} loc_i + \beta_{m_k} m_k + \varepsilon_{it} \tag{5}$$

If β_4 is significant and negative, then the IT implementation has main effects on reducing labor per item processed.

Finally, to test our central hypothesis (H3) for the effects of IT on organizational learning, we add a variable reflecting potential interaction between IT and cumulative location-specific experience:

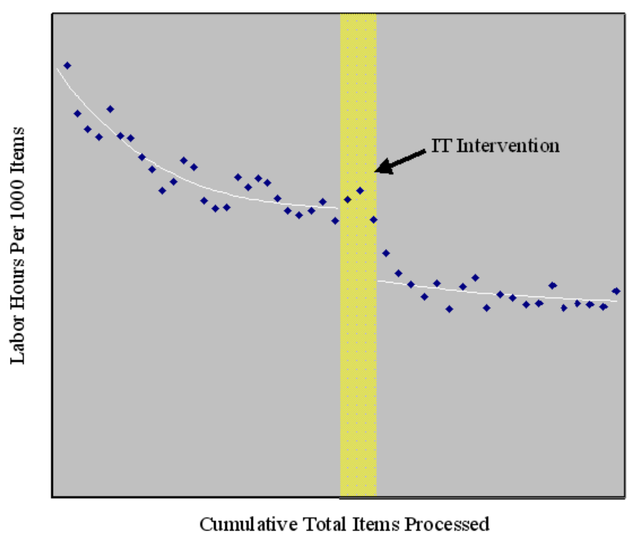
$$\ln(h_{it}/q_{it}) = \beta_0 + \beta_1 \ln Q_{i,t-1} + \beta_2 q_{it} + \beta_3 q_{it}^2 + \beta_4 IT_{it}$$

$$+\beta_5[\ln Q_{i,t-1} \times IT_{it}] + \beta_{L_i} loc_i + \beta_{m_k} m_k + \varepsilon_{it} \tag{6}$$

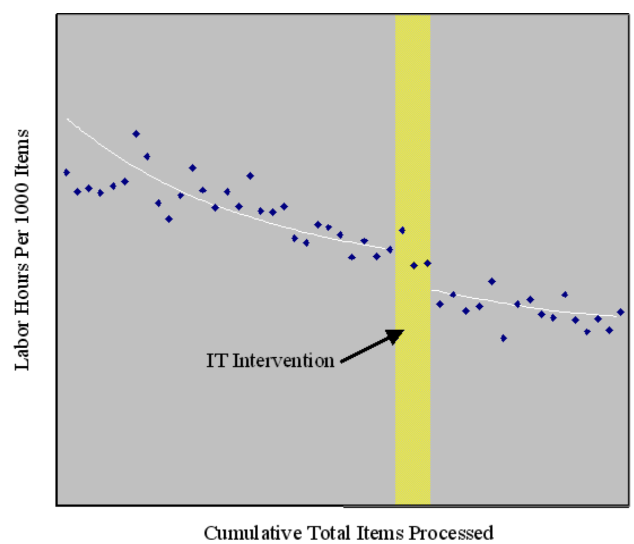
In Equation (6), if β_5 is significant and negative, the implementation of new information technology, other factors held constant, has positive impacts on organizational learning by increasing the rate at which the organization learns from experience.

Results

Figures 1a and 1b depict learning curves for two of the six lockbox processing locations. We found these curves to be representative of the learning curves for all locations. The archetypal organizational learning behavior of the curves is revealed in the decrease in labor hours per unit as cumulative experience increases. Characteristically at each site there appears to be a visual discontinuity between pre- and post-IT periods, with the post-IT period displaying a discernible shift downward.



(a)



(b)

Scales for x and y axes have been removed to protect confidentiality of data. To further protect the confidentiality of data, we do not present details on each location's processing and labor hours.

Figure 1. Learning Curves for Two Typical Regional Retail Lockbox Processing Facilities Showing Period of IT Intervention

Statistical Model

In testing the hypotheses, we found that our data most appropriately fit a linear exponential smoothing model (Brown 1963). Linear exponential smoothing models represent a class of autoregressive integrated moving average (ARIMA) models incorporating two non-seasonal differences in conjunction with moving average terms. Based on an extensive analysis of models fit using the Akaike Information Criterion (AIC) and Schwarz's Bayesian Criterion (SBC), we determined that an ARIMA (0, 2, 2) model improved substantially on the second-differenced series and yielded the lowest AIC and SBC values among autoregression, moving average, and mixed (integrated) approaches (Akaike 1973; Schwarz 1978). Based on an ARIMA (0, 2, 2) model, each of the error terms in equations (3) through (6) then becomes

$$\varepsilon_{it} = \theta_1 \varepsilon_{i,t-1} + \theta_2 \varepsilon_{i,t-2} \tag{7}$$

where θ_1 and θ_2 are the MA(1) and MA(2) ARIMA moving average coefficients. Details of the time series analysis are available from the authors.

Effect on Organizational Learning

Results of our model estimations are shown in Table 1. Since the models include the exponential smoothing coefficients θ_1 and θ_2, the model is nonlinear in the parameters; moreover, we cannot assume that past unobserved errors are equal to zero. Thus, our algorithm develops maximum likelihood estimates in which the likelihood function is maximized via nonlinear least squares using Marquardt's (1963) method. Although we found that location dummy variables explain a significant portion of the variance (approximately 20 percent), probably reflecting regional differences in customer mix and labor profiles, results were similar across models and are thus not included in Table 1. Similarly, we also found the coefficient for the month 1 (January) dummy variable to be similarly significant across models, owing to seasonal spikes in equipment installation and maintenance requirements, but we do not report this parameter in the table. Other seasonality did not exhibit significance.

Based on the ARIMA model's maximization of the likelihood function for our pooled time series cross section data (n =288), coefficient estimates for equation (3) are found in column 1 of Table 1. In this model, the coefficient for location-specific learning, β_1, is significant and negative, indicating that lagged cumulative output is a strong predictor of decreasing labor hours per unit as cumulative output increases. Thus, we find support for hypothesis 1(a) indicating the presence of organizational learning.

Next, we controlled for the effects of scale economies as described in equation (4), results of which are shown in column 2 of Table 1. For this model, the negative and significant (at $p < 0.05$) coefficient β_2, although relatively small, indicates that labor hours per unit processed decreases as current volume rises. This is plausible since up to a point, the same fixed labor resources can deal with rises in processing volume. The coefficient for changes in the effects of scale economies, β_3, is not found to be significant, indicating that as processing volume reaches very high levels there appear to be negligible effects on labor required per unit processed. This is consistent with a highly standardized and automated process, since labor hours per unit processed can be added relatively easily in the lockbox operations via temporary employees. Even with the controls for economies of scale, however, β_1 remains negative and significant, indicating that economies of scale neither change nor appreciably explain the effect of learning on labor productivity. Thus, we cannot reject hypothesis 1(b) at $p < 0.0001$ and find that organizational learning persists even when economies of scale are controlled for.

With the addition of the "New IT" variable in model 3, we find strong support for hypothesis 2, based on the fact that IT's impact on labor productivity, as indicated by coefficient β_4 in column 3 of Table 1, is very significant ($p < 0.0001$) in the expected negative direction. Somewhat unexpectedly, however, β_2, which was only marginally statistically significant in model 2 (Table 1, column 2), is no longer significant; and β_3, which was not significant when IT was not incorporated, is now significant. This seems to indicate that variance associated with scale economies at low to moderate volumes of processing is no longer significant as we introduce the new IT variable in the analysis. However, the positive and significant coefficient β_3 implies that, *after* the implementation of the new IT system, the ability of existing human resources to address increased coordination costs associated with very high volumes may be impaired. This may be a temporary effect due to a combination of the newness of the technology to all employees and the use during peak periods of temporary employees who are less familiar with the new system in general. Finally, and most importantly, our last model adds the interaction of IT to accumulated experience. As shown in column 4 of Table 1, the coefficient for the variable representing interaction between the new IT implementation and lagged cumulative experience (β_5) is significant at $p < 0.0001$, indicating the positive effect of IT on the rate of organizational learning. The coefficient β_5 is appropriately negative, showing that IT and knowledge interact to reduce labor requirements per unit of processing in the lockbox facilities. Thus, we find strong support for our primary research hypothesis (H3) that IT improves the rate at which organizations learn.

Table 1. Coefficient Estimations for Learning Curve Models[a]

	1	2	3	4
Location-Specific Learning (β_1)	-0.32553‡ (0.05445)	-0.33689‡ (0.05281)	-0.22760‡ (0.05238)	-0.22403‡ (0.04494)
Current Items Processed (β_2)		-6.6955E-6* (3.33802E-6)	-0.00002120 (0.00001287)	-9.7967E-6 (0.00001042)
Square of Current Items Processed (β_3)		-1.84592E-9 (1.29276E-9)	3.7695E-9† (1.02318E-9)	3.16249E-9† (9.0722E-10)
New Information Technology (β_4)			-0.16957‡ (0.02498)	-0.17990‡ (0.02253)
New IT x Location-Specific Learning (β_5)				-0.01537‡ (0.001694)
MA 1, 1 (θ_1)	-0.58381‡ (0.04909)	-0.51924‡ (0.05853)	-0.19922‡ (0.06323)	-0.38926‡ (0.05538)
MA 1, 2 (θ_2)	0.35313‡ (0.05730)	0.43367‡ (0.05702)	0.50216‡ (0.05449)	0.48285‡ (0.05454)
Akaike Information Criterion (AIC)	-535.780	-544.099	-576.803	-641.475
Schwarz Bayesian Criterion (SBC)	-499.256	-500.269	-529.321	-590.390

[a]Standard Error is shown in parentheses.
$*p < 0.05$; $^{\dagger}p < 0.001$; $^{\ddagger}p < 0.001$

Discussion

The six lockbox facilities in our study exhibit characteristic learning curves that affirm, consistent with both organizational learning literature and recent research on IT business value, the decrease in labor hours per unit as cumulative experience increases. In addition to this important validation, the significant scientific contribution of our study is in revealing that IT positively affects the rate at which organizations learn. Our findings persist even when controlling for factors such as seasonality, technology changes over time, and regional differences, revealing that IT has much more than a one-time main effect on process productivity, efficiency, or quality (Thatcher and Oliver 2001). Evidence indicates that IT not only positively affects *current* period productivity but also magnifies an organization's ability to translate knowledge gained over *past* accumulated production experience into incremental productivity increases. In the lockbox operations in our study, although the IT was implemented in concert with a substantial reduction in human capital, the resultant learning curve impact enabled acceleration of internal innovation of remaining employees as knowledge accumulated with production experience, yielding continuing efficiency gains over and above the one-time gains associated with the faster processing speeds of the new IT.

In addition to value-related findings, our work joins a small but growing list of longitudinal studies revealing positive IT payoff, a result that is counter to Kohli and Devaraj's (2003) recent meta-analysis of firm-level IT payoff studies. Their study found that IT research conducted with primary data sources, larger sample sizes, productivity-based dependent variables, and specific industry sectors were more likely to show IT payoffs. On the other hand, their findings indicated that process-oriented approaches and longitudinal studies were not significantly associated with IT payoffs found. Our positive findings based on a longitudinal study at the process level are likely explained by our focus on the well-established theoretical framework of organizational learning.

Although our study confirms positive impacts of IT on organizational learning, we recognize there are potential limitations which may affect the study's validity, applicability, and extension. As a longitudinal study, we believe our results exhibit internal and construct validity, but outcomes would be more strongly supported with additional post-IT time series data. While we believe the trends exhibited by the post-IT periods are indicative of IT's impact, discriminant validity could also be improved with additional post-IT time series. For example, it is conceivable that employees who remained following the IT implementation were motivated to apply experience to productivity increases more out of fear of job loss than out of opportunities presented by the new IT system. Controlling for additional intra-locational differences would also boost discriminant validity. Although discussions with lockbox facility managers indicated that job size, job type, employee turnover rates, and use of contractors at peak processing volumes are similar across time and locations, future research should control for their potential effects along with other factors such as attitudinal and behavioral variables (Campion et al. 1996; Cohen and Bailey 1997; Devadas and Argote 1990; Goodman 1986). Employee tenure may also be an important control variable if additional hires were added over the study period; according to Mellon management, only employees with experience remained after work force contractions, but it is possible that an increase in average experience levels accounted for some of the learning revealed on our analysis. With respect to external validity, the analysis of one process in a single large organization presents some extension difficulties that should be replicated in other settings. However, we believe the homogeneity of the process investigated, multiplicity of independently operated facilities in different labor environments, and unique opportunity to capture effects of pre- and post-IT performance with minimal variation in other variables mitigates weaknesses in external validity to some extent. However, by replicating similar analyses with controls for industry, process, customer type, and job type by location, our conclusions may be more defensibly extended to process settings in other industries.

Future research on IT's impact on organizational learning should expand beyond evaluations of economic factors and into domains such as absorptive capacity, quality, learning transfer, and depreciation. For example, to what extent is IT's organizational learning impact attributable to or perhaps mediated by effects on the employee's absorptive capacity? Can IT's impact on organizational learning curves be reframed in terms of quality rather than labor hours? Does IT have positive interactive effects on learning transfer and depreciation similar to the positive effect we identified on organizational learning rates? It is possible that organizational learning is explained in part by knowledge transfer from other locations along with the location-specific learning we identified. In this case, IT may or may not be associated with this knowledge transfer. Future research should control for these factors and explore whether their effects provide greater insight into the impacts of the learning variable, Q_{it}, or alternative explanations of the effects of IT.

Conclusion

As important as information technology is to the success of today's organizations and the growth of the world economy, understanding how IT operates to improve organizational learning will have impacts on virtually every organization, whether public or private. By integrating IT business value research with organizational learning research, our empirical results demonstrate that IT enables organizations to more effectively translate the knowledge gained through cumulative experience into actionable, tangible productivity improvements continuously over time. IT induces not only direct main effects on labor productivity but also interactive effects on the rate of organizational learning.

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