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ABSTRACT

This research addresses the important theoretical and empirical issue surrounding business value of information technology (IT). Several IT productivity studies have failed to find a significant relationship between contemporaneous IT spending and firm productivity. One reason is the delay or lag between spending on IT, and its resulting impact on production processes in the firm. This paper determines two important aspects about the lagged impact of IT. First, do contemporaneous and previous years' IT capital spending show positive correlation with firm output? Second, after what period does the relationship between IT capital spending and firm output become insignificant? We use a data spanning 23 years from the healthcare industry. We use a specialized econometric technique to determine lag lengths. We find that, on average, IT capital shows a positive impact at the sixth year after the spending, and only for two years following that. By the 8th year, the impact of IT is not significantly different from zero.

Keywords

IT productivity, econometrics, lagged impact.

INTRODUCTION

This research addresses the important theoretical and empirical issue surrounding business value of information technology (IT). It reports on an investigation of the relationship of current productivity to past information technology (IT) spending in firms – hence, delayed or lagged impact of IT on productivity. Lagged impact of IT refers to the positive impact of IT for several years after the acquisition of IT. In other words, the impact of IT is negligible in the initial few years after its acquisition. Research and practice in IT provide ample reasons for studying lagged impacts of IT (Kohli and Devaraj, 2003). First, lagged impacts have been cited as a reason for not finding significant IT productivity impact using contemporaneous data (Brynjolfsson, 1993). Second, lagged impact on production is not directly visible in financial impact studies that have used forward-looking measures such as Tobin's q (Bharadwaj, Bharadwaj, and Konsynski, 1999). Improving operations through accumulation of IT stock has not been validated yet. Third, ignoring accumulation of assets such as IT can overstate the strategic impact of return from other activities such as product market activities (Dierickx and Cool, 1989). Fourth, the financial theory of capital investments suggests adjustment costs from capital acquisition are convex (Jorgenson, 2001). That is, not only is the positive impact from a technology delayed, but adjustments costs can drive the impact to negative values in the initial period. Fifth, the lag length – when and for how long IT spending from one year sustains a significant positive correlation to future output – provides an estimate of the economic life of IT. This is useful for the accounting of intangible assets, particularly hardware and software capitalization and amortization (Lev, 2003). Though the current paper does not address software capitalization due to the lack of data, it provides the technique to do this in future research. Finally, the behavior of the lag impact can be applied to cost-benefit analysis of IT projects, so that IT managers can better estimate the date and size of benefits that accrue from IT spending.

One reason that lag lengths have not been determined in the past is the unavailability of data with several years of observations. Because the Bureau of Labor Statistics estimates the economic life of IT capital at 7 years (prior to 1980 and at 5 years after 1980; BLS 2003), the data must span at least seven years. We use a data set spanning 23 years (1979-2001) for all general hospitals in Washington. This data set is an updated version of the 1979 to 1996 data set (by including 1997-2000 data) used by Menon, Lee, and Eldenburg (Menon et al 2000).

The results show that IT spending impact on productivity is much delayed – about five years. The impact sustains for the next two years, and then vanishes. The cumulative impact, however, of all IT spending on current productivity is significantly positive. The paper is organized as follows. We first motivate the hypotheses of the research. We then describe an empirical model for lagged impact of capital using the distributed polynomial lags technique to address econometric issues. The results are described in the following section. Conclusions are presented in the final section.

CONCEPTUALIZATION OF LAG IMPACT

The main premise of the paper is that positive impact from IT is observed some time after its acquisition. The positive impact, however, is sustained for a few years in the future. Studies on IT productivity have not conclusively shown a significant correlation between contemporaneous output and IT spending. Typically in any organization, significant time elapses between IT implementation, its adoption by users, and the subsequent institutionalization.

The impact of IT spending on the productivity of organizations has been seen in IT productivity studies. However, this link is not a direct link, but is rather dependent on several intermediate organizational variables such as IT usage, IT capability and organizational change (Figure 1). Organizations need to go through substantial organizational changes and adoptions during and after IT acquisition and implementation (Breshnahan, Brynjolfsson, and Hitt, 2002). The conversion of IT technology spending/acquisitions to productivity and profitability (Figure 1) is explained in terms of the transforming role of IT, a role that involves fundamentally redefining business and industry processes and relationships (Dehning, Richardson, and Zmud, 2003). The main thesis of this paper is that it takes a long period of time for an IT implementation and the organization to go through the above stages of metamorphosis.

IT acquisitions add to the existing IT stock assets (IT portfolio) as they are deployed. IT stock assets created are both tangible and intangible. The tangible aspect of the assets includes the physical IT infrastructure components, and is the sum of all hardware and software assets. Intangible assets cover knowledge assets, customer orientation, and synergy –organizational sharing of resources and capabilities- as well as quasi-fixed human capital, which are technical and managerial IT skills (Bharadwaj, 2000). However, these intangible assets are not created in infinitesimal time as are tangible assets. Creation of intangible assets involves three major stages – IS implementation, IS usage (DeLone and McLean, 1992; Devaraj and Kohli, 2003), and creating IS capability (Bharadwaj, 2000). The main driver of IT impact is not the investment in the technology, but the usage of the technology. User acceptance is needed for a successful implementation of an IS (DeLone and McLean, 1992). Even before the acquisition of the tangible assets, the organization must prepare itself to absorb the new IT (Cooper and Zmud 1992).

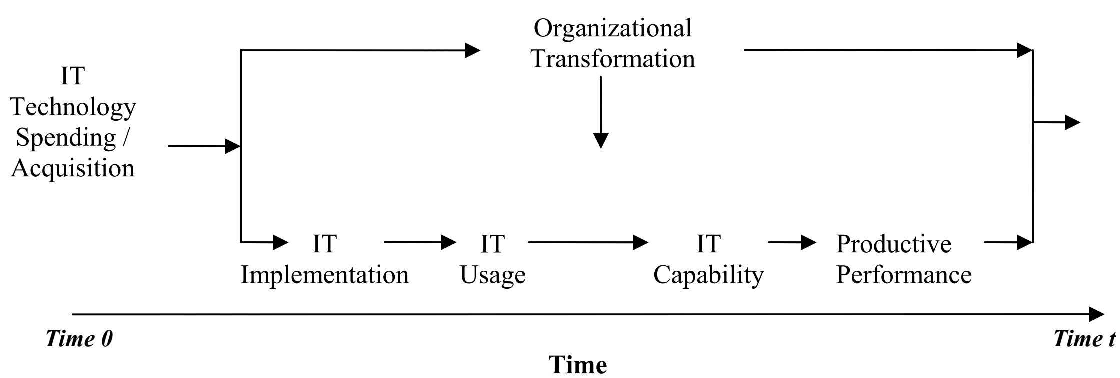

Figure 1. Process View of Lag Effects

Once IT is implemented and is used by users, the stage of assimilation of the IT moves from simple adoption to that of adaptation (Cooper and Zmud, 1992). This adaptation results in the creation of an IT capability (Bharadwaj, 2000). IT capability is an organizational resource that is more than the sum of its parts, namely, IT technology and IT staff. This resource cannot be easily imitated, and is highly contextual (Barney, 1986). Utilization from IT investments is possible only when IT is embedded in a way that produces valuable competitive advantage, and sustains resource complementarity. When integration is established, superior financial performance follows by increasing firm revenues and/or decreasing firm costs (Bharadwaj, 2000; Santhanam and Hartono, 2003). The IT capability has to be nurtured constantly for continuing importance to organizational performance. The organization must develop an absorptive capacity to continue to use the IT intangible asset to convert this capability to profitability (Dehning et al 20003; Zahra and George, 2002). The transformation of IT expenses into profitability is demonstrated on a time line in Figure 1.

The absorptive capacity in IS/IT is developed through changes and adoptions in organizational transformation elements, namely change of business process, change of decision making, and change of incentives (Ba, Stallaert, and Whinston, 2001). These must necessarily take place in a complementary fashion due to task interdependencies for the effective deployment of the new technologies. Organizational transformation can be the result of changing dependencies, and it can also be the cause of changing dependencies (Tillquist, King, and Woo, 2002). Generating the correct incentive structure, decision structure, and complementary business processes takes a significant amount of time, because this is mostly trial-and-error with new technologies. Organizational transformation is multifaceted process that requires considerable amount of adoption time. While IT is the cause of organizational transformation in some cases, and facilitates transformation in other cases, we propose that the steady-state is achieved in a period of over 3-4 years depending on the complexity and maturity and scope of the technology in question. The strategy literature promotes the slow and steady approach to asset accumulation (Dierickx and Cool, 1989). Time is a necessary ingredient along with IT stock portfolio to create an IT asset that sustains competitive advantage in the long run.

Production processes are disrupted during IT implementation. Operational and decision-making staffs adjust activities in line with the systems. In addition, existing systems must be adjusted in a way to incorporate the new technology. These costs are collectively called adjustment costs (Jorgenson, 1997). High adjustment costs would drive down the expected impact of IT at least in the first year of IT implementation. Thereafter, the impact of IT dominates, i.e., turns positive. These expectations precipitate the first hypothesis.

Hypothesis: The impact of IT capital spending on firm output will show lag effects.

Productivity gains from IT (or other capital) are not expected to endure forever. One reason could be that all other firms, in a competitive industry, also adopt the same technology leading to a dampening of the advantage provided by the technology. A similar thought is echoed by Davenport when he considers the consequences of all firms in an industry implementing an enterprise system package such as in SAP R/3 in the petro-chemicals industry (Davenport, 1998). The resource-based theory of the firm, however, does suggest that similar technological artifacts lead to different outcomes because of the unique combination and utilization of IT resources and skills (Bharadwaj, 2000). In either case, as technology evolves, the organization finds new and better ways to produce its output, and new IT replaces old IT to support the new processes. That is, technologies become obsolete, and are replaced.

THE DATA

The data used for this study spans 1979 to 2001, and was obtained from the Washington State Department of Health hospital database. The use of data from a single state removes the biases from accounting practices and regulation that vary between states in the US. The hospital financial data is available in three subgroups; inpatient accounts (surgery, Intensive Care Unit), ancillary accounts (laboratory, pharmacy, Magnetic Resonance Imaging), and cost accounts (data processing, laundry). Each account has annual data on salaries, capital depreciation, supplies and other expense fields. The salaries were deflated by the employment price index for health care services. The data was organized and aggregated in the following manner. First, to homogenize the hospital population, specialized hospitals were eliminated. Only general medical and surgical hospitals were used in order to justify the comparison across hospitals. Then, the accounts for each hospital were grouped into medical, and IT accounts to obtain a classification of spending, which is of an appropriate granularity for testing the hypotheses. Accounts with obvious data errors such as missing values were removed. A few accounts showed negative values for some fields. These are accounting adjustments, and, in none of the cases was the amount large enough to warrant concern about their impact on the results. Finally, for the years 1979 to 2001, we obtained data records for about 48 hospitals for each year with a total of 1088 observations for the 23-years span. The set of observations captures all the hospitals, large and small, in the state of Washington.

We classified capital spending data further as follows. As mentioned above, each account at a hospital was classified as one of medical, and IT (data processing, communications, and patient records accounts) classes. Within the medical accounts, a finer granularity of capital spending was achieved following Menon (Menon et al., 2000). Two types of medical capital were aggregated based on the accounts, namely medical IT capital spending (equipment used for diagnosis and therapeutic purposes, e.g., magnetic resonance imaging) and medical capital spending (equipment used in surgery, laboratory etc) for each hospital. Three types of capital spending were finally derived from the three account groups for each hospital – medical capital, medical IT capital, and IT capital. At final count, five input factors feed into the hospital production, namely, medical labor, IT labor, medical capital, medical IT capital, and IT capital.

Adjusted patient-days data is a good measure of the output of the hospital. Adjusted patient-days is the sum of inpatient days and outpatient "days" (visits converted into a "days" measure using revenue proportion of inpatient revenues and outpatient revenues) at the hospital level. An alternative for the output variable is total patient charges for the hospital. However, because the prices of hospital outputs are fixed in a state for several patient groups as a consequence of the Prospective Payment System, adjusted patient-days is sufficient, and appropriate for measuring the productive impact of IT in the healthcare context.

EMPRICAL MODEL

The proposed model tests the relationship between adjusted patient-days and the five input factors (medical labor, IT labor, medical capital, medical IT capital, IT capital) mentioned above. In addition to the contemporaneous spending for the five input factors, lagged spending – previous periods' spending – is included for the three capital input factors, medical IT, medical, and IT capital (equation 1 below). The formulation is similar to a Cobb-Douglas production function. The subscript t indicates current period values, and subscripts such as t-1 indicate previous periods (years).

$$\begin{aligned}\log\left(Adj.Pat.Days_t\right) = a + \alpha_0 \log\left(Medical\_salaries_t\right) + \beta_0 \log\left(IT\_Salaries_t\right) \\ +\sum_{i=t}^{1} \rho_{t+1-i} \log\left(Medical\_Capital_t\right) \\ +\sum_{i=t}^{1} \lambda_{t+1-i} \log\left(MedicatIT\_Capital_t\right) \\ +\sum_{i=t}^{1} \gamma_{t+1-i} \log\left(IT\_Capital_t\right) \\ +\varepsilon_t\end{aligned} \tag{1}$$

Salaries are included only as contemporaneous variables in the model because the salary paid to an employee (or the labor price) is determined by the marginal value of the set of skills that the employee brings to the organization for that time period. Capital on the other hand is expected to provide a long-term impact as hypothesized earlier.

Positive coefficients (that are significantly different from zero at 90% confidence interval) for the hypothesized previous capital spending will validate the hypothesis regarding the length of the impact of the lags. The use of lagged values for capital spending is of empirical concern because of the high multi-collinearity among the regressors. To alleviate this, the distributed polynomial lags model is used. This provides a sufficient correction for the multi-collinearity in regression models that use lagged variables and time series data (Greene, 1997).

Note that the above model was described in terms of unspecified lag length. That is, the impact of capital spending in one period could last for several future periods, to the last period for the data. The estimation is then compromised by the loss of degrees of freedom by inclusion of several regressors from past periods. The solution is to use the Almon procedure of polynomial distributed lags that not only preserves the degrees of freedom, but also reduces the effect of multi-collinearity among lagged spending. The coefficients of the lagged values of the regressors are assumed to lie on a polynomial function of the length of the lag (Greene, 1997). The optimal lag length of the polynomial distributed model can be determined by using the Akaike Information Criteria (AIC) on a model estimated without polynomial restrictions, and with OLS. AIC is commonly used for time series model selection and is similar to the concept of an adjusted R2 that weights the fit of the model but penalizes the loss of degrees of freedom (Greene, 1997). Further, because the data is time-series, auto-correlated error terms can be modeled using the Yule-Walker technique to improve the estimation efficiency. The Polynomial Distributed Lagged (PDL) regression model for equation (1) now is shown below in equation 2.

$$\begin{aligned}\log\left(Adj.Pat.Days_t\right) = a + \alpha_0 \log\left(Medical\_Salaries_t\right) + \beta_0 \log\left(IT\_Salaries_t\right) \\ +\sum_{n=0}^{N}\left(\left(\sum_{p=0}^{P_1} \omega_n n^p\right) \log\left(Medical\_Capital_{t-n}\right)\right) \\ +\sum_{n=0}^{N}\left(\left(\sum_{p=0}^{P_2} \theta_n n^p\right) \log\left(MedicalIT\_Capital_{t-n}\right)\right) \\ +\sum_{n=0}^{N}\left(\left(\sum_{p=0}^{P_3} \xi_n n^p\right) \log\left(IT\_Capital_{t-n}\right)\right) \\ +\varepsilon_t\end{aligned} \tag{2}$$

The above equation shows that the relationship of all previous spending for each capital type in now replaced each by coefficients that form a polynomial curve. As mentioned above, each of the parameter $P_{1, 2, 3}$ is the maximum degree of the polynomial, and is determined from the data. The only constraint on this parameter is that its upper bound is the lag length. For each lag length for each capital spending, all degrees of the polynomial must be tested for the best model fit. The econometric details of the PDL model are beyond the scope of this research note. The model has been used in several applications such as in determining lagged impact of advertising (Ward, 1977), and in accounting (Lev and Sougiannis, 1996). The model is available as a standard procedure in statistical packages such as SAS.

RESULTS

We first ran an Ordinary Least Squares regression (OLS) model using equation 1. The results indicated a significant positive auto-correlation: the Durbin-Watson test statistics was much less than two. The test for autoregression found second-order auto-regression, AR(2), for the error terms. Hence the data was transformed using AR(2) characteristics for the error terms. There is no easy way to find the best combination of the degree of the polynomial and the lag length. One characteristic of the lag models is that once an estimate of the co-efficient in the polynomial function has become insignificant after having been significant for earlier periods, the estimate will not become significant again. Hence, the lag length of a capital spending is the point when the estimate for that capital becomes insignificant for two or more periods consecutively. The initial model is prescribed based on the hypotheses. The lag lengths were started as 7 for IT capital, and 12 for the medical capital. Slowly the lag lengths were perturbed in both directions to see if the model fit improved. The degree of the polynomial is less than or equal to the lag length, but typically never exceeds 4. We found it to be so in our case also. Constraints on the polynomial coefficients help with efficiency in estimation (Greene, 1997). Only one restriction was significant in the current data and that was for medical capital: the coefficients of the polynomial function should satisfy the condition that the -1st degree polynomial expression should be zero. We looked for the best model fit in terms of the highest Durbin-Watson statistic, the lowest AIC, and highest R-square values. Based on the above trials, we obtained the following lag lengths and polynomial degrees for the three capital spending that gave the best results.

Table 1. Best Fit Lag Length and Polynomial Degree for the Capital Spending

Capital Type	Lag Length	Polynomial Degree
Medical capital	4	2
Medical IT capital	4	3
IT capital	8	2

That is, the final model estimated and upon which the conclusions are based is given in equation 3.

$$\begin{aligned}\log\left(Adj.Pat.Days_t\right) = a + \alpha_0 \log\left(Medical\_Salaries_t\right) + \beta_0 \log\left(IT\_Salaries_t\right)\\ +\sum_{n=0}^{4}\left(\left(\sum_{p=0}^{2}\omega_n n^p\right)\log\left(Medical\_Capital_{t-n}\right)\right)\\ +\sum_{n=0}^{4}\left(\left(\sum_{p=0}^{3}\theta_n n^p\right)\log\left(MedicalIT\_Capital_{t-n}\right)\right)\\ +\sum_{n=0}^{8}\left(\left(\sum_{p=0}^{2}\xi_n n^p\right)\log\left(IT\_Capital_{t-n}\right)\right)\\ +\varepsilon_t\end{aligned} \tag{3}$$

Medical and IT salary expenses are found to have significant impact on output, respectively 0.48 and 0.13. As expected, medical labor at 0.48 captures most of the contribution to productivity. A summary of results of capital expenses is given in Table 2. Among the capital input variables, medical capital shows a significant impact in the second and third lags, 0.03 and 0.02 respectively. The contribution of the medical capital fades away at the fourth period. Medical IT capital utilization does not have positive impact on productivity. It shows a significant negative contribution in the third lag period, that of -0.018. Medical IT capital is used for the purchase and maintenance of equipments that are used for diagnostic and therapeutic purposes, such as magnetic resonance imaging. These equipments and their usage are quite costly that their usage is limited to only necessities, i.e. they are not used for every patient unless there is an immediate need for these equipments' assistance. Therefore, they are necessary to have in hospitals in order to increase the quality of service, but most of the time they do not contribute much to the hospital outputs and thus are not apparent in the productivity statistics. On the other hand, IT capital is used for equipment that is used for purposes such as billing and record keeping. In this sense, the investment on IT capital is utilized by every patient accepted to the hospital. Hence, utilization of IT capital is sounder compared to that of medical IT capital.

Table 2. Estimates of Capital Expense Coefficients of the Production Function

Input Factor	Impact Period	Estimate	Cumulative Effect
Medical Capital	Overall for four years		0.05
Medical IT Capital	Overall for four years		-0.018
IT Capital	Current	0.002	
	From a year ago	0.004	
	Two years ago	0.005	
	Three years ago	0.007	
	Four years ago	0.007	} 0.016
	Five years ago	0.008	
	Six years ago	**0.008***	
	Seven years ago	**0.008***	
	Eight years ago	0.008	
Durbin-Watson test statistic			1.8
Akaike's Information Criteria			229

^: Sum of all coefficients of lagged spending significant at p=0.1
*: p < 0.01; ** : p < 0.05; ***: p < 0.1; remaining estimates are not significant.

IT capital input has a much prolonged time before positive impact accrues. This is due to the disruption caused by IT installation to the production process. The positive impact from IT spending is felt at the sixth year after the spending, and only for the next two years. The accrued IT impact on current productivity is derived by summing up all, positive and negative values of coefficients significant at 10%. The accrued IT impact is 0.016, and the 90% confidence interval computations indicate that zero is not in this interval. Similarly the accrued impact of medical capital types indicates an overall positive impact from medical capital, and a negative impact from medical IT capital.

The results of the lag model give the duration for which the impact of capital becomes positive, and the period until which it stays positive. This lag impact is in the line with the theory discussion in conceptualization section and Figure 1. The transformation of IT acquisitions and spending to profitability and productivity requires learning process and organizational transformation to take place. The completion of these processes requires some time and thus leads to lagged effects. In the case of health care industry, results of Almon lags indicate that IT spending needs six years to appear in productivity statistics. The slow accrual of positive impact indicates a disruption (adjustment costs) in the production due to IT. The gradual ascent corresponds to the learning period for the new investment. Then, the economic value drops after the seventh year. The overall IT impact result obtained by Menon (Menon et al., 2000) is 0.018, which is close. Rather than contemporaneous IT capital data, they used cumulative IT capital stock by assuming straight line accounting depreciation. Our paper differs from the previous result on the same dataset because rather than assume accounting depreciation values, we allow the data to provide us evidence of the economic depreciation.

IMPLICATIONS

As mentioned earlier, this line of research and its results have several important implications. First, we show that lagged IT variables emerge more important than contemporaneous IT variables. Second, the data shows positive impact of IT on the output production starting only from the sixth year. For a dataset that includes public or for-profit firms, it will be useful to test the translation of this operational benefit into financial benefit. Third, the results show the presence of adjustment costs through the negative impact of contemporaneous medical IT, and through delayed impact of IT capital. Fourth, the evidence of lag impacts can now be used in IT project planning research and practice. The significance of lags validates the general wisdom that IT managers should be conservative in estimating the time when rewards from IT will commence. A wellknown debacle in this is regard is the ERP implementation at Fox-Meyer. The managers at Fox-Meyer priced orders low in anticipation of cost-savings from ERP, even before the projected 18-month implementation was completed (Olson, 2003). Because the results indicate a sixth and seventh year impact for every dollar spending on IT, but a decreasing impact thereafter, the planning horizon for expecting IT payoffs should be at least seven years.

Even though, many other research studies mention that IT spending would have lagged impact on productivity, this argument is not supported empirically in any study. In this study, the lagged impact of IT spending and acquisitions in health care industry are presented empirically. Finally, this line of research also has policy implication such as on the estimate of the economic life of IT. The Bureau of Labor Statistics prescribes a 7-year life for IT. The 7-year life for IT is used as a benchmark in accounting depreciation, and assumes that the value accrues from IT immediately. Our results show that this benchmark differs from the actual economic depreciation. It is desirable that economic and accounting depreciation are close to avoid mis-stating revenues and costs (see accounting literature, for example Kim and Moore 1988). Sophisticated policies for amortizing hardware and software costs may be developed based on empirical estimates of the economic life of IT. For example, R&D spending is amortized over 20 years, recognizing the long-term benefit from R&D (Lev, 2003). Similarly, our results indicate that IT capital spending in healthcare should be amortized after a lag of five years, and over a period of two years thereafter. However, because the data is industry specific, the current estimates may not be generalized to all contexts.

CONCLUSION

In this study, we validated the lag impacts of IT and other capital expenditures in healthcare industry by using an appropriate model to analyze collinear and auto-correlated lagged data. Our results indicate that the capital expenditure of different types of capital have varying lagged effects on productivity of the healthcare industry. The insignificance of the impact of IT in the first five years may indicate that there is disruption of the production process by its introduction. Furthermore, the presence of new IT installation may set off learning effects that diminish productivity. Its impact is positive in 6th and 7th years since its acquisition. It then drops back to zero. The accrued impact of IT from all past spending on one year's output is average about 1.6%. Hence IT impact is late, not "never" as implied in contemporaneous studies of IT impact. The results have implications for IT project planning, and accounting policies, and for future IT productivity models.

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