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UNDERSTANDING INFORMATION TECHNOLOGY COMPLEMENTARITIES USING AN AUGMENTED ENDOGENOUS GROWTH FRAMEWORK

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Abstract

The complex relationships between information technology investments and organizational practices have been the focus of intensive research in recent years. The research focus appears to have shifted to investigating the effects of various organizational practices and their interactions with information technology capital. There also is emerging evidence of recent emphasis on organizational factors and a greater shift toward IT complementarities in which value addition is linked to combining complementary organizational practices with IT investments.

In this paper we focus on the contributions of IT use and organizational practices and their interactions. We use firm-level data to extend previous studies in three ways: (1) by using a large sample covering 3,299 firms spanning 11 industries, (2) by focusing on a large number of organizational practices, and (3) by augmenting the endogenous growth accounting framework with a data mining technique. Our findings indicate that the set of interrelated organizational practices that complement positively to IT use is different from the set of practices hindering IT use. We conclude that IT complementary factors that positively affect productivity growth do not necessarily have a reverse effect when they are reduced or removed. It appears that some organizational factors have asymmetrical effects on growth.

Keywords: Productivity paradox, business value of IT investment, complementarity

Introduction and Motivation

Since the original formulation of the information technology productivity paradox,[1] a range of useful findings, models, and methods have emerged. They serve to provide new insights into the multi-faceted relationships between IT investments and productivity and business value. One of the critical issues that remains unresolved is the dual role played by IT in organizations. Apart from being a type of input capital directly used in the production process, IT can also act as an enabler to enhance productivity by supporting many value-adding activities in organizations. Many studies have argued that information technology investment is not the major factor in achieving productivity and business performance. Rather, it is the way IT is being used, such as the *complementary organizational practices* effectively linking IT with business processes, that can make the difference. Although a consensus has been reached as to the need for methodological advancement in analyzing the complementary relations between IT investments and organizational practices performance, our understanding of such complex relationships remains sketchy.

[1]Solow (1987) argued that, "You can see the computer age everywhere but in the productivity statistics."

The concept of *complementarities*[2] offers a useful perspective to study the complex relationships between organizational practices and the use of IT. Milgrom and Roberts (1990, 1995) proposed the "web of complementarities" theory, marking a paradigmatic shift. They argued that organizational activities and practices are mutually complementary and so tend to be adopted together, with each enhancing the contribution of the other. In other words, the whole is more than the sum of the parts. Based on this view, the rapid fall in IT cost could potentially lead to increases in many IT intensive activities, which through their complementary relationships, lead to increases in a related set of organizational practices as well.

In this paper, we report on one of the first attempts to explore the impacts of complementary relationships between a large set of organizational practices and IT use on productivity growth at the firm level. In the next section, related literature is presented. We proceed to describe our research design and provide a description of the data. We discuss the results using our model. In conclusion, we evaluate our findings and suggest directions for further research.

Literature Review

Using the resource-based perspective, Penrose (1995) conceptualized the firm as a collection of resources within an administrative framework, where the speed of accumulation and assimilation of resources is the key to firm growth as firms continually search for innovative ways to enhance productivity and business performance. Many research studies have investigated complementary factors that influence IT payoff through organizational practices; for example, practices such as business process reengineering (Barua et al. 1996), job rotation, and team work (Arvanitis 2004). These factors are believed to have different ways of affecting the production process, where the arrangement and utilization of all inputs (including IT) may be affected, in turn influencing the output performance. The key assumption here is that these complementary factors are also associated with the intensity of IT use. These complementary factors have been found to explain some of the variations in estimates of return to IT investments (Black and Lynch 2001). This can also help us explain why some firms achieve higher returns than others.

Barua et al. (1996) presented a theory called *business value complementarity* and argued that IT investments and reengineering cannot succeed if implemented in isolation. They also postulated that technology and business processes are complimentary. Black and Lynch (2001) argued that, until recently, there has been very little direct analysis of the impact of workplace practices on productivity. They found some synergies among various workplace practices but concluded that the important issue is not whether an organization adopts a particular work practice but rather how that work practice is implemented in conjunction with other complementary practices.

Bresnahan et al. (2002) and Brynjolfsson et al. (2002) examined the influences of a number of important organizational factors and management practices in conjunction with the effects of IT investments on organizational performance. Bresnahan et al. surveyed approximately 400 large firms to obtain information on aspects of organizational structure such as allocation of decision rights, workforce composition, and investments in human capital. They found that these work practices are correlated with each other (and particularly with IT use). They argued that these practices are part of a complementary system. They defined *organizational capital* as the built-up knowledge in a firm's routines, procedures, reporting structures, staff training, work flows, company positioning, decentralized organizational structure, and IT investment, which in combination contribute to productivity growth.

At the empirical level, these factors are generally measured and tested for interaction effects (e.g., Zhu 2004). Athey and Stern (1998) pointed out two empirical challenges in analyzing the interactions between elements of organizational practices. First, in contrast to analyses of traditional factor inputs such as capital or labor, the relevant input prices for adopting organizational practices are not easily observed and, therefore, not often available. Second, organizational practices are often adopted in clusters (i.e., when organizational practices are complements), and some of the important organizational variables are sometimes omitted in the production analyses. Even if they are considered, they are often investigated independently. Following this argument, we posit that hypothesizing the economic impact from a specific organizational factor independent of its complements is not sufficient to capture the true influence of the joint impact of a set of complementary factors.

The aim of this research is to highlight a set of fundamental issues and questions that are critical to understanding the mechanisms by which IT investments result in higher productivity. In particular, it addresses the complementary effects. An earlier suggestion was that the enabling effects of IT consist of some aspects of intangible organizational capital. Given that organizational factors are the main focus of this study, the theoretical challenge here is to devise a way of dealing with the fractal-like, interlocking nature of IT and organizational practices, which can potentially produce higher returns.

[2]The original concept of complementarities was first developed by (1881), it defines activities that are complements if doing (more of) any one of them increases the returns to doing (more of) the others.

Methodology

Theoretical Background

In the economic literature, two possible explanations have emerged for analyzing "excess return" from IT investment. The first explanation is related to the technological advancements in developing the IT products. The economic benefits are passed from IT-producing sectors to IT-using firms as the quality of the IT product continues to improve without price increase. The second, and more interesting, explanation is related to additional productivity produced by using IT beyond the economic contribution from the improved IT product itself. Figure 1 is a conceptual framework to illustrate the potential sources of productivity gains from IT investments.

The concept of complementarities discussed here is represented by "supermodularity" of a function with respect to two or more complementary variables. Topkis (1978) showed that supermodularity dictates that the sum of the increases in the value of a function when the levels of the complements are changed one at a time would be less than the increase in the function's value when the levels are changed simultaneously. In other words, if complementarities between IT use and various organizational activities exist, the productivity and value gains from increasing these complementary activities in concert should be larger than the sum of the individual increases. Moreover, the test for complementarities must consider an appropriate performance measure in the context of a function that is hypothesized to be supermodular. The relevant hypothesis here is that the complementary factors exhibit a relationship characterized by excess returns.

Under the endogenous economic theory (Romer 1986), firms face constant returns to scale to all inputs, with the exception of the technical progress, multifactor productivity, arising from the accumulation of organizational capital. This connection can be considered as a consequence of "learning-by-doing" described by Arrow (1962). The production function equation can be modified as follows:

$$Q = A(g)\, f\,(K, L, g(IT \otimes ORG)) \tag{1}$$

This approach hypothesizes that the value-added (Q) is an exponential function of the factor inputs capital (K) including IT capital and labor (L), where g() is some function capturing the complementary relationships between a set of interrelated organizational practices (ORG) and some measure of IT use (IT). From equation (1), the concept of supermodularity is modeled. That is, considering organizational practices with IT use simultaneously may achieve a higher incremental effect on productivity growth over and above to the productivity impact attributable to capital and labor as part of the aggregate capital asset. Equation (2) can be expressed in Cobb-Douglas function form:

$$Q = Ae^{g(IT \otimes ORG)} K^{\alpha} L^{\beta} \tag{2}$$

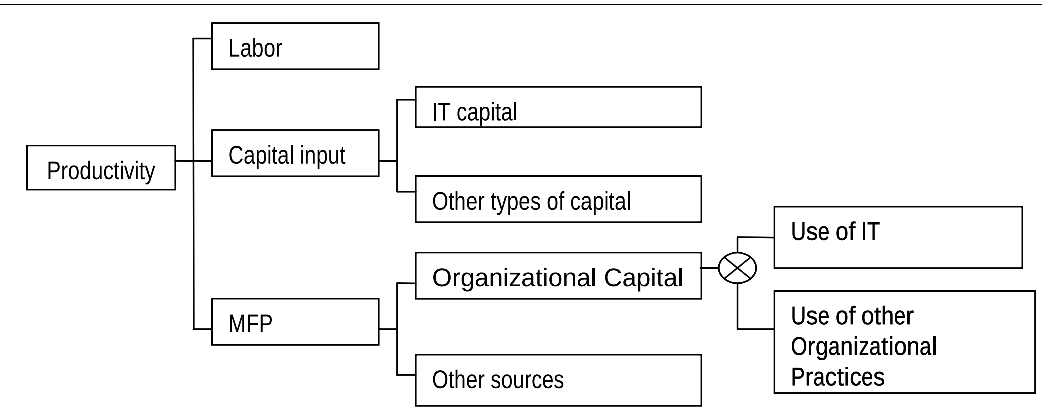

Figure 1. Components of Productivity Growth for IT-Assisted Production

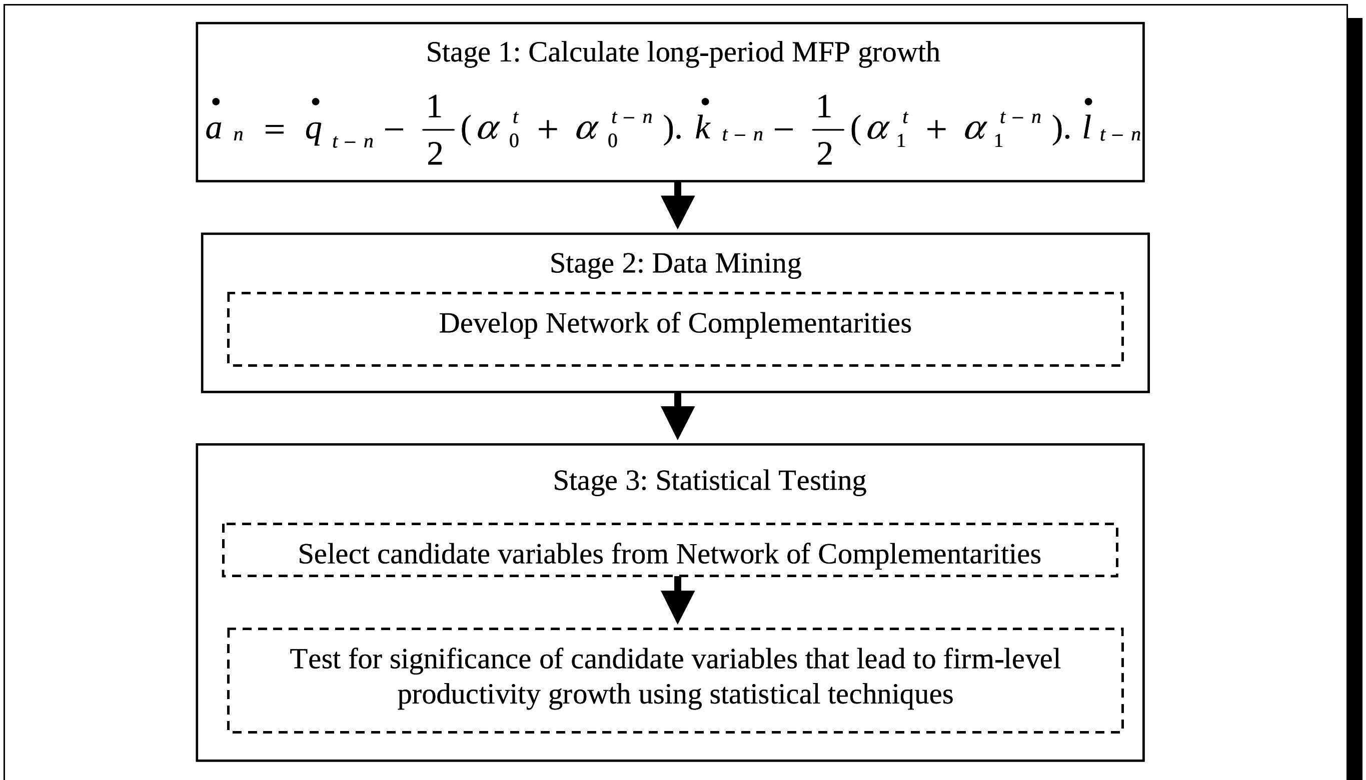

Figure 2. Three-Stage Research Model

where $\alpha + \beta = 1$ (i.e., assuming constant return to scale). Multifactor productivity (MFP) in this case is a proxy for technological progress which shifts the production function. The MFP can be broken down into two components: (1) the function representing the complementary relationships among organizational practices and the use of IT ($e^{g(IT \otimes ORG)}$) and (2) the residual (A). Hence,

$$MFP = A.e^{g(IT \otimes ORG)} \tag{3}$$

Equation (3) reveals that organizational practices complementary to IT use would be expected to increase multifactor productivity. The idea is that IT-using firms learn a specific form of "organizational doing" by coupling complementary organizational practices to produce more efficiently. This organizational capital generated by effective IT use can explain the technical progress endogenously and may not suffer from diminishing returns.

Model Development

This paper employs an augmented endogenous growth approach to explore the impacts of complementary relationships between organizational practices and IT on productivity growth at the firm level. This analysis consists of three stages. In the first stage, we calculate the long-term MFP growth based on the growth accounting framework. In the second stage, we discover the organizational practices that enhance or hinder MFP growth using a data mining technique. In the third stage, we validate the resulting model of organizational practices from the previous stage with appropriate regression analyses. These three stages are illustrated in Figure 2.

This growth accounting framework has the advantage that it enables a direct measure of output elasticity and thus the contribution of IT investments to output growth can be measured using a nonparametric method. The extent that IT investments associated with unmeasured complements or intangible assets that might legitimately be part of the productive assets of the firm (i.e., organizational capital) can also be analyzed.

Data Source and Description

The main dataset used in this study is obtained from the Australian Bureau of Statistics (ABS) Business Longitudinal Survey (BLS) from 1994–1995, 1995–1995, 1996–1997, and 1997–1998. The longitudinal survey was designed to provide information on the growth and performance of Australian-owned businesses and to identify various economic and structural characteristics of these businesses (ABS 2000). The BLS contains about 9,550 confidential respondent records; 3,864 records participated in all four surveys. For confidentiality reasons, all large businesses (those employing more than 200 people) have been removed from the dataset by ABS. Using Australian data has the advantage that it is a developed country like the United States and at the same time has a very small IT-producing industry. This dataset is particularly useful in studying the IT effects on a predominantly IT-using economy. Out of 3,864 records, only 3,299 records contain all of the necessary data items for this analysis.

The BLS survey contains a total of 787 variables with diverse coverage of organizational characteristics and measures including various business intentions, capital expenditures, organizational practices, and performance variables. One of the limitations of this data set is that IT capital investment is not separately collected from machine and equipment capital investment. Descriptions of the capital investments, labor, and output variables are provided in Table 1.

Table 1. Descriptions of the Capital Investments, Labor, and Output

	Description	Annual Average per Firm
Capital investment (K)	Sum of all capital expenditure† constant at 1998 dollars	$694K
Labor (L)	Total number employees	27.67 persons
Value-added (Q)	Total income minus purchases constant at 1998 dollars	$3,491K

†They are plant, machinery, and equipment; land, dwellings, other building and structures; and intangible assets.

Table 2. Collection of Organizational Practices

1994–1995	1995–1996	1996–1997	1997–1998
Comparing prices	Significantly increase production levels	Production technology	Structured training courses
Comparing costs	Introduction of new products or services	Use computer	On-the-job training
Comparing quality of products or service	Total quality management		Seminars, workshops, conferences, etc.
Comparing marketing or advertising strategies	Quality assurance		Job rotation and exchanges
Comparing client services	Just-in-time management		Management training
Comparing range of products and service	Implementation of strategic plan		Professional training
Business process improvement	Implementation of business plan		Training for computer specialist
	Implementation of budget plan		Trade and apprenticeship training and traineeships
	Income and expenditure report		
	Implementation of business network		
	Business comparison		
	Export marketing		
	Implementation of business link		
Perform research and development in any of the four years			
Changes in stock level between 1998–1997 and 1996–1995			

Apart from the capital and labor input variables, the BLS also collected a set of variables each year based on a particular theme for that year. As shown in Table 2, the focus of the BLS data collected in 1994–1995 was on benchmarking, in 1995–1996 it was on various organizational processes, in 1996–1997 it was on computer and production technologies, and in 1997–1998 was on training. The dataset revealed that most of the variables capturing the organizational practices are discrete. All the variables listed in Table 2 are either binary coded (Yes/No) or categorical with three values ([Increase/No Increase/NA] or [>25%/<=25% or NA]).

Note that the measure of IT in the dataset is a binary variable to indicate if the business unit used IT (or not) for their business. Banker and his colleagues modeled input variables in the form of use versus nonuse instead of actual levels of usage or intensity (such is expenditure). They argued that the benefit of using the binary measure is to broaden the performance impact not only on input price but also on the intangible potential. (See Banker and Johnson 1995; Banker and Kauffman 1990; Banker et al. 1988.) In our case, IT use is considered to be a type of organizational practice.

Analysis and Results

Stage 1: Measuring Firm-Level MFP Growth

We use a standard growth accounting approach to calculate the MFP growth extending from a 1-year difference to a multi-period difference (3 years in this case) MFP growth, allowing us to observe the effects of slow-changing organizational factors. Based on Bartelsman et al. (1994), Brynjolfsson and Hitt (2003) suggested that the longer period differences can be interpreted as long-run effects of input changes and, further, these changes include not only the direct effect of factor inputs, but also the effects of adjustment of complementary factors. The long-period MFP growth term is calculated as follows:

$$\dot{a}_n = \dot{q}_{t-n} - \frac{1}{2}(\alpha_0^t + \alpha_0^{t-n}).\dot{k}_{t-n} - \frac{1}{2}(\alpha_1^t + \alpha_1^{t-n}).\dot{l}_{t-n} \tag{4}$$

where the term a_n is MFP growth,[3] $\dot{q}$, $\dot{k}$ and $\dot{l}$ are log-change form of value-added, capital and labor inputs growth, respectively, and α_0 and α_1 are their corresponding factor income shares. The underlying principle is with reference to a Cobb-Douglas production function. This type of productivity framework is usually implemented in time series or panel data settings by taking the time differences of variables in logarithms to yield growth rates. Based on the growth accounting framework, we calculate the theoretical values of factor income shares (α_0 and α_1) for two different years[4] for each industry. The average industry-level factor income shares between the two periods are 0.56 for α_0 and 0.44 for α_1.[5]

We then calculate the multifactor productivity (MFP) growth based on equation (4) for each firm. Different factor income shares are applied to firms in different industries. We find that the average MFP growth of all 3299 business units is –6.9 percent and that 1,579 (48 percent) of the business units obtained positive MFP growth, with 1,720 (52 percent) of the business units obtaining zero or negative growth. The detail of the MFP results is provided in Table 3.

Stage 2: Development of Network of Complementary Factors

Association analysis is applied to the organizational variables in order to generate association rules with specific consequent (i.e., positive and negative) MFP growth generated in stage 1. Association rule mining is one of the more popular techniques in data mining and is perhaps the most common form of knowledge discovery applied when there is very little knowledge about the underlying pattern of the data (Agrawal and Srikant 1994). The objective of this technique is to find dependencies between different variables (called items) in a large dataset. Unlike a standard statistical approach to *test* for correlation between variables, association rule mining casts the problem as a search for dependencies (called frequent itemsets). In order to scale-up the method for very large datasets and variables, a weaker measure (called support) is used to guide the search process.

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[3]The term MFP is often used in preference to total productivity factor (TFP), as not all changes in all inputs are taken into account.

[4]See Aspden (1990) for a detailed method to estimate MFP growth.

[5]The detailed calculation of factor income shares is not reported in this paper.

Table 3. MFP Growth Results		
	Number of Business Units	**Average MFP Growth**
Positive MFP Growth	1579 (48%)	38.85%
Negative MFP Growth	1720 (52%)	-48.95%
Average MFP Growth	3299 (100%)	-6.9%

An association rule captures a weak form of correlation between the items in a dataset. In particular, we say that $X \rightarrow Y$ provided

- The support of $X \cup Y$, $\sigma(X \cup Y)$ is greater than a minimum threshold *minsup*. Sets with support greater than *minsup* are called frequent itemsets.
- All the records that contain X also contain at least a *minconf* percent of Y, i.e., $\frac{\sigma(X \cup Y)}{\sigma(X)} > minconf$. This is called the confidence of the rule.

These association rules are then used to build a multilevel, hierarchical (tree-like) association rule network (ARN) of IT complementarities in the form-directed hypergraph developed by Chawla et al. (2003). To apply this technique to our dataset, we consider a relatively large set of organizational practices. Assume each practice has a Boolean variable representing the presence or absence of that practice and each sequence of practices can be represented by a boolean vector of values assigned to these variables. The Boolean vectors are analyzed for patterns that reflect practices that are frequently implemented together. We use rule support and confidence as measures of interest.

The network of complementarities is built by a recursive association rules generation method. In this method, we first fixed the item (for instance, positive MFP growth) and all of the rules whose consequent is *MFP_Growth=positive* are generated. Then the antecedents (as first order variables) of these rules are considered as consequents in the subsequent round of association rule generation and all of the rules of these antecedents as consequents are generated. A total of 32 organizational practices (listed in Table 2) were used in the dataset. Recall that all of these practices are discrete variables either binary or three-valued coded. Furthermore, 20 percent (660 out of 3,299 records) were randomly retained as holdouts for statistical testing in stage 3.

Two separate ARNs are produced: one ARN with *MFP_Growth=positive* and another for ARN with *MFP_Growth=negative*. As there is no standard method of identifying the more appropriate values, the minimum support and confidence values were chosen by trial. Using CBA (a data mining software package), association rules were generated for different values of support and confidence. Finally, it was decided that a set of minimum values were required to generate an adequate number of rules to construct the network. For ARN with positive MFP growth as the goal, we set the minimum support as 10 percent and minimum confidence as 55 percent for the first order rules, and increased the minimum confidence as 99 percent for the second order rules with minimum support maintained at 10 percent. For ARN with negative MFP growth as the goal, we set the minimum support as 15 percent and minimum confidence as 65 percent for the first order rules, and increased the minimum confidence as 90 percent for the second order rules with minimum support changed to 10 percent. Figure 3 illustrates ARN with negative MFP growth while Figure 4 illustrates positive MFP growth.

Several interesting patterns emerge when both the ARNs are analyzed in reference to each other. First, the two ARNs generated are quite different. This result suggests that the variables that contribute to positive MFP growth are not necessarily the same as those contributing to negative MFP growth. For example, the ARN in Figure 4 shows that the three variable instances (i.e., reduce stock-level, use of computer, and use of budget plan) have the first order effect on positive MFP growth, while the ARN in Figure 3 shows another set of variable instances (i.e., increase stock-level, without implementing TQM, and without introduction of new goods) have the first order effect on negative MFP growth. Second, the positions of computer use in the two ARNs are different. These results suggest that while the use of computers has a direct effect on MFP growth positively, its absence has an indirect effect (i.e., mediated by TQM) on MFP growth negatively. Third, the set of interrelated organizational practices that are complementary to computer use to generate excess productivity are not necessarily the same set of organizational practices that hinder productivity growth. After examining all variables in both ARNs, we classify them using the following criteria:

- Variables with full ellipse if they exist in both ARNs
- Variable with dotted ellipse if they only exist in either ARNs
- First order variables are labeled with double line
- Second order variables are labeled with single line

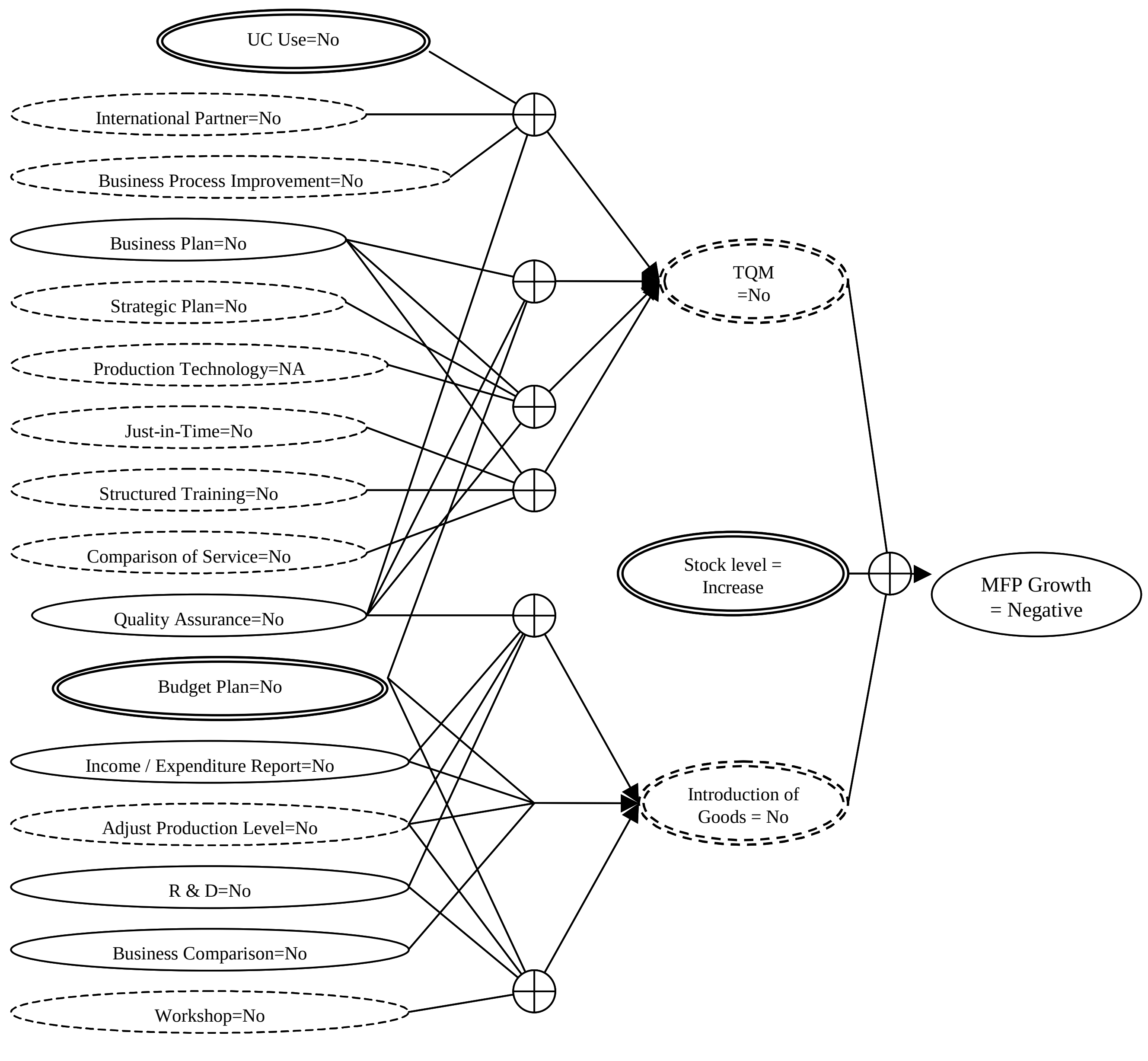

Figure 3. Association Rules Network with Negative MFP Growth

To reduce the complexity in the testing stage, we reduce the number of candidate variables to be tested by selecting only first order variable instances from either ARNs. We classify the 5 first order candidate variables into strong and weak candidate variables. To be considered as a strong candidate variable, two necessary conditions are required. First, variable instances must have to exist in both ARNs with opposite directions. Second, variable instances have direct impact to MFP growth. Table 4 shows the first order variable instances discovered in the ARNs.

Note that there are total of five different first order candidate variables. Out of the 5 first order variables, only 3 variables (i.e., adjustment in stock level, use of computer, and budget plan) appeared in both ARNs with opposite directions. In preparing the candidate variables, the 5 first order variables listed in Table 4 are selected as candidates for type level statistical testing in stage 3.

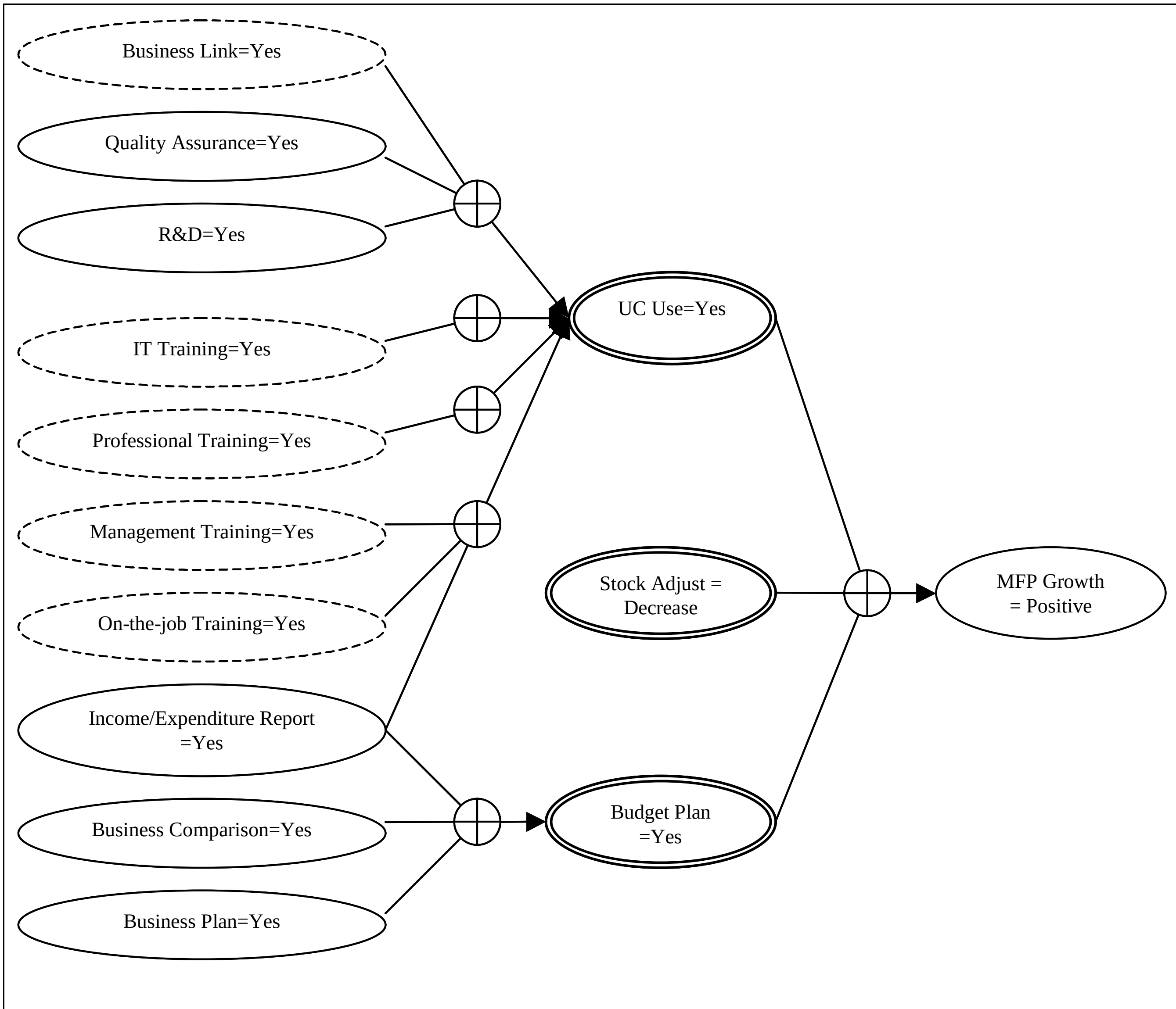

Figure 4. Association Rules Network with Positive MFP Growth

Table 4: Variable Instances Discovered in the Association Rules Networks

Positive MFP Growth	Negative MFP Growth	Strength of Candidate Variable	Label
Decrease stock-level (1st order)	Increase stock level (1st order)	Strong negative	Stock_Adjust
Use computer (1st order)	No use computer (2nd order)	Strong positive	UC
Use Budget Plan (1st order)	No use Budget Plan (2nd order)	Strong positive	BudgetPlan
	No Introduction of Goods (1st order)	Weak positive	IntroGood
	No Implementation of TQM (1st order)	Weak positive	TQM

Stage 3: Testing the Impacts of IT Complementary Factors

Based on the model suggested by the candidate variables selected in stage 2, we proceeded to carry out econometric analyses in two ways. The first is an analysis of the impact of individual organizational practice on MFP growth (note that computer use is one of the organizational practices). The second is the analysis of the impact of the interactions between computer use and each of the organizational practices.

Hypotheses Testing 1: MFP Growth and Individual Organizational Practices

The regression analysis performed in this stage tests for statistical significance of a set of candidate organizational variables that are potentially attributable to organizational capital. Based on the five organizational variables selected, a regression model can be derived as

$$\dot{a}_3 = \lambda + \beta_1 PC + \beta_2 Stock\_Adjust + \beta_3 BudgetPlan + \beta_4 TQM + \beta_5 IntroGood + industry + \varepsilon \tag{3}$$

where the dependent variable $\dot{a}_3$ is the longer-term multifactor productivity growth, and the independent variables *UC, Stock_Adjust*, *BudgetPlan*, *TQM*, and *IntroGood* are changes in stock level, use of computer, use of budget plan, implementation of total quality management (TQM), and introduction of new goods and services, respectively. Furthermore, *industry* variable is also modeled in the regression to adjust for the possible industry effect. The set of hypotheses for H1, no technical progress due to each organizational factor, is written as

H1a: Use of computer is positively correlated to MFP growth
H1b: Stock level adjustment is negatively correlated to MFP growth
H1c: Use of budget plan is positively correlated with MFP growth
H1d: Use of TQM is positively correlated with MFP growth
H1e: Introduction of goods is positively correlated with MFP growth

The estimation results in Table 5 show that four of the five organizational variables, namely, *UC, Stock_Adjust, BudgetPlan*, and *TQM* are significant at the 0.01 level. The remaining variable, *Introgood*, is found to be statistically insignificant. The sign of the coefficient for *Stock_Adjust* is negative, which is consistent to the findings in the ARNs. We conclude that the sub-hypotheses H1a through H1d are statistically supported. On the contrary, sub-hypothesis H1e is not supported. Therefore, only the four strong candidate variables are found significantly correlated with MFP growth.

Table 5. Coefficients Estimates of Equation 5

	Estimates	Standard Errors	t-value
UC	.223***	.022	10.158
Stock_Adjust	-.084***	.010	-8.419
BudgetPlan	.062***	.012	5.104
TQM	.047***	.011	4.307
IntroGood	.019	.011	1.808
Control	*Industry*		
R^2	.351		
N	660		
F-value	23.217		

Key: ***p < .01 and *p < .05

Table 6. Mediating and Moderating Impact of Computer and Organizational Factors

Relationship	Candidate Interactions
Moderating	Computer use and stock level adjustment
Moderating	Computer use and budget plan
Mediating	Computer use is mediated by TQM
Unspecified	Computer use and introduction of goods

Hypotheses Testing 2: MFP Growth and Interactions among Organizational Practices

To analyze complementary organizational factors, one can classify interrelated variables into two forms: moderating and mediating. Based on the relative positions of the computer use variable and each of the other 4 first order candidate variables, two moderating relationships and one mediating relationship are revealed. The moderating relationships are computer use and stock level adjustment, and computer use and budget plan. The mediating relationship is computer use mediated by TQM. The candidate interactions are provided in Table 6.

Note that as the focus is to study the test for the complementary effects between computer use and organizational practices, mediation is not tested.[6] We represented both moderating and mediating relationships with the measure of interactions. The regression model, equation (6), can be written as

$$\dot{a}_3 = \lambda + \beta_1 PC + \beta_{12} PC * Stock\_Adjust + \beta_{13} PC * BudgetPlan + \beta_{14} PC * TQM + \beta_{15} PC * IntroGood + industry + \varepsilon \qquad (6)$$

where the dependent variable $\dot{a}_3$ is the longer-period multifactor productivity growth. βs, are the coefficients to be estimated for the interactions between *UC* and organizational variables. The *industry* variable is modeled in the regression to adjust for the possible industry effect. The set of hypotheses for H2, no technical progress due to complementary relationships between computer use and organizational factors, can be written as

H2a: Interactions between use of computer and adjustment of stock level is negatively correlated to MFP growth
H2b: Interactions between use of computer and use of budget plan is positively correlated to MFP growth
H2c: Interactions between use of computer and implementation of TQM is positively correlated to MFP growth
H2d: Interactions between use of computer and introduction of goods is positively correlated to MFP growth

The regression results show that three known interaction terms are statistically significant. The estimated coefficients are shown in Table 7. The coefficients for interactions between use of computer and stock level adjustment, the interactions between use of computer and use of budget plan, as well as the interactions between use of computer and implementation of TQM are statistically significant at the 0.01 level. We conclude that hypotheses H2a, H2b, and H2c are supported. However, hypothesis H2d is not supported.

[6] Baron and Kenny (1986) contended that moderators and mediators have conceptual and statistical distinctions: moderation indicates that the effect of the predictor on the outcome is dependent upon the moderator such that its influence can be represented as an interaction, and mediation accounts for the relation between the predictor and the outcome such that the mediator acts as an effect of the predictor and a cause of the outcome.

Table 7. Coefficients Estimates of Equation (4)

	Estimates	Standard Errors	t-value
UC	.249***	.023	10.762
UC*Stock_Adjust	-.093***	.010	-9.115
UC*BudgetPlan	.059***	.012	4.778
UC*TQM	.044***	.011	4.011
UC*IntroGood	.025	.015	1.337
Control		*Industry*	
R^2		.357	
N		660	
F-value		23.876	

Key: ***p < .01; *p < .05

When comparing the results between the two regressions, we find the R^2 has increased from 0.351 to 0.357, implying that the second regression has a marginally higher explanatory power than the first one. Furthermore, the coefficients estimated for *UC* and *UC*Stock_Adjust* have increased from 0.223 to 0.249 and -0.084 to -0.093. These changes in coefficients indicate that the impact of *UC* and the interactions between *UC* and *Stock_Adjust* are much stronger in the second case. Hence, complementary effect is found between *UC* and *Stock_Adjust*.

Discussion and Conclusions

This paper has addressed the impacts of IT complementarities on productivity growth based on endogenous growth assumptions. The innovative combination of the growth accounting framework and association analysis allowed us to search for interesting patterns and relationships among organizational practices for a large-sample firm-level dataset. The role of association analysis served to propose candidate hypotheses regarding to the impacts of variables and relationships among the variables, while statistical methods were used to validate the proposed hypotheses against data.

Although we have found evidence of productivity-enhancing complementarities between IT use and some organizational practices, our results have also shown that their relationships are more complex than been revealed by previous studies. The presence of clustering among organizational practices clearly implies that some combinations of practices make it difficult to precisely estimate the parameters and the interactions between these parameters using a regression of productivity on the practice combinations. Furthermore, our study has uncovered a new dimension to the complexity of the IT complementarities. Certain organizational practices that affect productivity positively do not necessarily have a reverse effect when they are reduced or removed. Furthermore, these practices complementary to IT use can be very different to the set of practices hindering IT use.

The contributions of this study are twofold. First, the study shows how the use of data mining techniques can provide further insights into what IT complementary practices are critical to improve and hinder productivity. Second, the study provides an illustration of situations in which traditional statistical estimation techniques are inefficient when the independent variables correlate with the dependent variable asymmetrically. We have highlighted some of the possible asymmetries in the way individual organizational practices can influence the return on IT investments through their complementary relationships with IT use. This paper provides a new approach to explaining the IT productivity paradox. The results of this paper provide the basis for further studies to investigate a broader model of IT complementarities. Our future research focus is to devise appropriate strategies in testing different types of complementary relationships and their effects on performance.

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