PARAMETER HETEROGENEITY IN A MODEL WHICH ESTIMATES THE BUSINESS VALUE OF INFORMATION TECHNOLOGY

by

Robert J. Kauffman

Avijit Ghosh

and

Arun Bansal

Leonard N. Stern School of Business
Information Systems Department
New York University
90 Trinity Place
New York, NY 10006

Revised August 1989

Center for Research on Information Systems
Information Systems Department
Leonard N. Stern School of Business
New York University

Working Paper Series

CRIS #197
STERN #89-9

Note: An earlier version of this paper was presented at the ICIS Doctorial Consortium, Pittsburgh, December 1987.

PARAMETER HETEROGENEITY IN A MODEL WHICH ESTIMATES

THE BUSINESS VALUE OF INFORMATION TECHNOLOGY

Robert J. Kauffman, Avijit Ghosh and Arun Bansal

Abstract

Developing *robust* and *refined* measures to quantify strategic impacts is a major challenge facing researchers who seek to improve methods for information technology (**IT**) investment evaluation. This paper presents a means to test for parameter heterogeneity in a model which *quantifies* the strategic contribution of IT. An iterative "jackknife" procedure is used to diagnose if different local competitive and demographic conditions present in branch banking *enhance* or *suppress* leverage on deposit market share associated with membership in an automated teller machine (**ATM**) network. The results are validated using correlation analysis and re-estimating partitioned data sets for a market share model developed by Banker and Kauffman (1988). Overall, the results suggest this new approach will be useful for managers who need to evaluate similar ITs which operate in different environments.

1. Introduction

1.1. Robust and Refined Measures for IT Business Value

Quantifying the strategic contributions of information technology (**IT**) is a major challenge facing researchers who seek to improve the methods managers use to evaluate IT investments. An acid test which effective measures must pass is whether they can win the confidence of senior managers, who make decisions based on information the measures convey. Just as a "hands-on" manager knows why a strategy works well in one market and poorly elsewhere, business value measures for IT must similarly be *refined*, to capture the rich information a decisionmaker normally has at hand. Otherwise, IT business value measures will not exhibit *robustness* across the variety of competitive conditions under which IT investments are made.

In this paper, we extend results presented by Banker and Kauffman [2], who investigated a model to measure the business value of an IT which has transformed retail banking: automated teller machines (**ATMs**). The authors quantified the value of ATM network membership by estimating *multiplicative competitive interaction* models representing competition for market share in retail deposits. The authors' results suggested ATM network membership can play an important role in increasing a branch's market share of deposits. By partitioning large data sets for demand and savings deposit market share, the authors also suggested that different geographic areas in which retail banking competition occurs do not provide a constant set of conditions under which business value can be realized for all ATM deployments. Instead, territories which had one-third or fewer of the total machines belonging to the regionally larger network were attractive areas to locate new machines connected to that "regionally dominant" network, because they differentiated the services of their owners.

A review of the results by bank managers led them to speculate that other aspects of the competitive and demographic environment may enhance or suppress the deposit market share-generating ability of ATM networks. Thus the business value estimates for network membership should vary across the different territories, since competitive and demographic environments do not remain constant. In this paper, we employ the "jackknife" technique, which enables us to detect conditions under which IT business value is enhanced or suppressed. This will allow us to test for heterogeneity in the parameters of the model estimated by Banker and Kauffman, to further refine the business value estimates produced.

1.2. Outline of the Paper

The next section briefly reviews recent developments in the IT value literature that have aided our current refinements. Section 3 presents the rationale for utilizing market share models to capture the business value of ATMs, and reviews the Banker and Kauffman [2] model for ATM business value estimation. It also makes the case for how jackknife statistics can be used to refine IT business value estimates from econometric models. Section 4 presents the jackknife results in order to support the argument that spatial differences affect the business value estimates for ATMs. This section also presents diagnostic regressions we carried out to determine which demographic aspects of the competitive territories played a role in moderating ATM value. The paper concludes by investigating the predictions of a refined market share model which incorporates information about how spatial differences in local competitive environments may affect business value.

2. Previous Research

2.1. Econometric Models for IT Value Analysis

Recent developments in methodologies to measure the economic value of IT have increasingly focused on the use of econometric tests to empirically validate the linkage between investment and benefits to the firm. In many cases, the major problem is to identify secondary, sometimes intangible effects, which nevertheless are important components in IT cost-benefit analysis. Econometric models which empirically test for IT impacts are useful adjuncts to conceptual approaches, such as Strassmann's "return on management" [23] or Parker and Benson's "information economics" [21], since they operationalize the analysis using a well-defined model.

Kauffman and Kriebel [14, 16] have advocated providing "hard" evidence for the existence of a "business value linkage" between the IT investment and economic outputs which lead to increases in the value of the firm. This can be accomplished with a variety of models that incorporate IT investment-related variables, and represent "intermediate production processes" in a firm. These models are then estimated to measure the marginal contribution of the IT investment to the economic goals of the firm. When the model captures the production process for a less tangible, but strategic impact on a firm, it becomes possible to *quantify* marginal impact, relative to other related factors.

A variety of econometric tools will be required to effectively carry out tests to identify the economic impacts of IT investments. For example, in order to ascertain that an IT investment has delivered operating cost reductions we might require a model specialized to labor cost estimation. Experience gained from other empirical work in this area [8, 5, 25] suggests that measuring the *cross-sectional* industry effects of IT at *one point in time* requires methods different than those needed to assess the dynamic impact of IT *over time*. Thus, there is a large potential payoff from research on new methodologies which further expand the circumstances under which ITs which can be assessed well.

2.2. Bimodality, Conversion Effectiveness and IT Valuation

Barua, Kriebel and Mukhopadhayay [4] have argued that the methodological problem of measuring IT impacts at the strategic business unit level is further compounded by what they call "bimodality".

> [F]or the same IT expenditure (possibly high), some firms will be performing much better than others. Unless a partition based on performance between the "superior" and "inferior" firms is provided, analysis of pooled data when bimodality is present may negate [an analyst's] ability to detect IT impacts due to cancellation effects (i.e., the two populations may average out to zero or slightly negative contribution).[1]

Weill [25] emphasized that intra-organizational factors, e.g., levels of management and power relationships, also can lead to differential "conversion effectiveness" for technology investments. He defined conversion effectiveness in terms of variables which describe the organization in which the technology has been implemented. He argued that overly simple econometric analysis is doomed to failure, and that *process models*, representing the richness of the managerial environment in which IT investments are translated into benefits, may be needed for useful results to be achieved.

[1] Barua, Kriebel and Mukhopadhayay [4], p.1.

An earlier study by Cron and Sobol [8] of 138 surgical instrument manufacturers found that there was a bimodal distribution of performance for firms which invested heavily in IT. The methodology proposed by Barua, Kriebel and Mukhopadhayay [4] has merit because it provides an explanation for why previous studies may have failed to show that IT has much impact on firm and industry performance (for example, see [6, 18, 22]). It also provides constructive advice about the econometric tactics required to make sense of the data, irrespective of the specific impact analysis model used.

2.3. Market Share Models for IT Value Analysis

By adopting information technologies such as ATMs a bank can strengthen its market position relative to competitors. Thus one way to quantify the contribution of IT is to measure its impact on the firm's market share. A firm's market share is a function of its product delivery configuration, level of customer service offerings, level of marketing effort and any unique strategic advantage that it has over its competitors. The contribution of each of these factors can be isolated through econometric analysis that models each firm's market share as a function of these variables.

Market share models can take various forms depending on their functional specification (see Naert and Weverberg [19]; and Ghosh, Neslin and Shoemaker [11] for a review of different market share models). In this study the Multiplicative Competitive Interaction (**MCI**) model proposed by Nakanishi and Cooper [20] is used. The MCI model, which belongs to the general class of attraction models discussed in Naert and Weverbergh, has the following form:

$$MS_j = \frac{f(\mathbf{X}_j,\beta)}{\sum_{j\varepsilon J} f(\mathbf{X}_j,\beta)}$$

MS_j is the market share of firm j, and **X** is a vector of competitive design features distinguishing each firm from its competitors. β is the set of parameters which estimate the relative impact of a design feature on the market share of a firm, via the function, $f(\bullet)$, which maps design features into market shares for firms. This formulation represents the attractive power of firm j's competitive characteristics (the numerator), relative to the combined attractiveness of the set J of competing firms (the denominator).

One useful feature of the MCI model is that it yields "logically consistent" estimates of market share. That is, the predicted shares of all firms competing in a market add up to 100 percent. The MCI model is an "equilibrium model" in the sense that the estimated parameters of the independent variables provide a reading of the competitive equilibrium in the market. The signs and magnitudes of these variables reflect their relative impact on the firm's market share. This model is of use for IT value analysis because it is possible to incorporate variables which represent the deployment of IT; it provides a means to estimate how they leverage market share.

Prior studies in the marketing science literature have investigated the validity of this model using market share and consumer choice data from various industries and settings [13, 9, 10, 12]. In addition, a number of studies in the IS literature have recently begun to explore the use of those models for IT business value measurement. Kauffman, Kriebel and Zajonc [15] developed market share models to identify the impact of point-of-sale debit systems deployed at gasoline service stations on gasoline brand market shares. Banker and Johnston [3] modeled airline competition in an MCI framework in order to investigate how computerized reservation systems leverage a firm's national market share. Banker and Kauffman [2], whose results we will be extending below, also utilized an MCI model to measure the competitive value of ATM network membership on the deposit market shares of branch banks. Their work is described in more detail in the next section.

3. Methods

3.1. An MCI Model for Assessing ATM Business Value

Banker and Kauffman [2] utilized an MCI model to capture the ATM network membership leverage on deposit market shares in branch banking operations. The mathematical form of the MCI model they tested to estimate branch market shares in competitive territories is shown below:

$$MS_{jk} = \frac{\prod_{c \varepsilon C} X_{jck}^{\beta_c}}{\sum_{j \varepsilon J_k} \prod_{c \varepsilon C} X_{jck}^{\beta_c}} \qquad \forall j, \forall k$$

where

MS_{jk} = *branch j's deposit share in territory k;*

X_{jck} = *the cth design characteristic of branch j in territory k;*

β_c = *estimated 'intensity' exponent for characteristic c;*

J_k = *the set of branches in territory k;*

C = *the set of branch design characteristics.*

The branch design characteristics studied by Banker and Kauffman are divided into four classes: organization type (COMMBK, S&L, MUTSAVBK), physical design characteristics (WALKUP, DRIVEUP, PLATFORM), IT design characteristics (ATM, MAC) and other characteristics (HIRATE, AGE, NAME). For definitions of the variables and the way they were coded in the estimation model, refer to Table 1.

The research site was a large commercial bank located in southeastern Pennsylvania, which participated in the "MAC" ATM network, the larger of two statewide shared ATM networks. MAC's major competitor at the time was "CashStream". In order to test the MCI model, all competing branches were assigned to geographic areas termed "branch operating territories" (**BOTs**). BOTs typically consisted of a branch of the bank, and its competitors in the local deposit market.

Table 1: Definition of Variables in the Banker and Kauffman MCI Model

VARIABLES	DEFINITIONS
	Dependent Variables
MS	Market share of demand and savings deposits for a branch in a BOT
	Independent Variables
COMMBK	Branch is a unit of a commercial bank; base case in savings market share estimation
S&L	Branch is a unit of a savings and loan or credit union; not in demand deposit estimation
MUTSAVBK	Branch is a unit of a mutual savings bank; base case in demand deposit estimation
HIRATE	Categorical variable identifying whether branch had higher than average deposit interest rate than competitors in 1986
AGE	Continuous variable for branch age, with branches > 12 years coded as 12 years
NAME	Scale variable indicates relative name recognition of bank name
WALKUP	Categorical variable for the presence of a walkup window
DRIVEUP	Categorical variable for the presence of a driveup window
PLATFORM	Continuous variable for number of non-teller service locations
ATM	Categorical variable for presence of an ATM on branch premises
MAC	Categorical variable for bank membership in MAC network

Banker and Kauffman [2] found that bank type, name recognition, branch age, and ATM network membership were significant predictors of branch market share. Banker and Kauffman obtained coefficient estimates for the business value of membership in an ATM network and ATMs deployed at branches. In their estimation of bank branch demand deposit market shares, the ATM network membership variable (MAC) was found to be a positive (0.26) and significant (.05 level) predictor of deposit market share. They suggested that the effect of membership in the regionally larger MAC network on deposit market share increased when MAC was locally under-represented. A similar result was obtained from estimating savings deposit market shares; the MAC network variable was also positive (0.27) and significant (.01 level). The authors found little evidence, however, that deploying a branch ATM had a significant effect on deposit market shares. In both market share estimations, the branch ATM variables (ATM) were found to be near to zero and not significant.

For this research we extended the data set used in Banker and Kauffman's study to incorporate demographic and competitive descriptors of the electronic banking environment that management believed were likely to enhance or suppress the local business value of ATM network membership.

3.2. Heterogeneity in Model Parameters

Banker and Kauffman's results establish the significant impact of ATM network membership on a branch bank's market share. The question remains, however, as to whether the impact is homogeneous across the bank's territories. It is possible that the impact of IT is more pronounced in some of the bank's operating territories than in others. In other words, the true parameters of the model may be heterogeneous, exhibiting statistically significant differences across the set of regions in which the firm competes. Such heterogeneity mat arise because of differences in the competitive environment in each of the territories or because the demographic characteristics of the firm's customers may vary from place to place. Because of variations in competitive and consumer environments the impact of IT can potentially vary across the different operating territories. It is important, therefore, to develop a refined estimate of the business value for IT that is sensitive to spatial differences in the business environment.

3.3. Detecting Heterogeneity

To develop a more accurate measure of IT impact first requires a means to detect whether there is significant heterogeneity in the estimated parameters. A number of approaches can be used to test whether a model's parameters are homogeneous across different territories. One approach, for example, would be to develop an extended MCI model which incorporates a separate network membership parameter for each territory. This approach, however, has two drawbacks. First, it necessitates the estimation of a large number of additional parameters -- one for each territory -- resulting in a loss of statistical efficiency. Second, while the variation in IT impact can be judged directly by examining the separate network membership parameters, it does not pinpoint the underlying factors causing heterogeneity.

An alternative to the fully extended model is to partition the data set into groups and estimate separate models for each data partition. For example, separate models can be calibrated for rural and urban territories, if there is reason to believe that IT impact in rural areas is likely to differ from that in urban areas. Similar data partitioning schemes can be used to test for differences due to other environmental factors. Although easy to implement, developing a meaningful partition requires *a priori* knowledge of how impacts vary across territories. In practice, such *a priori* knowledge may be lacking. Rather the researcher may have to test a number of alternative hypotheses requiring multiple partitioning schemes.

An efficient way to detect heterogeneity, one that is used here, is the jackknife technique. The jackknife procedure compares parameter estimates based on the entire data set with a set of new estimates obtained by iteratively calibrating the model with a subset of observations left out. For example, for the demand deposit data set the Banker and Kauffman model was recalibrated 48 times by systematically deleting observations belonging to each BOT. For each of these new data sets a jackknife pseudovalue can then be defined as follows [24]:

$$D(\beta)_i = Z\,\beta_{all} - (Z-1)\beta_{-i}$$

where

$D(\beta)_i$ = *the jackknife pseudovalue of the estimated parameter, β, for the variable of interest, when subsample i is omitted from the data set;*

Z = *the number of subsamples created from the original data set;*

β_{-i} = *the parameter estimate after excluding observation i from the data set.*

The jackknife pseudovalues provide a direct indication of the extent of heterogeneity in the parameters of the original model. The greater the variation in the pseudovalues the more it is likely that the estimated parameter has different true values in different operating territories and that the impact of that variable on market share is not homogeneous.

4. Results and Extensions

4.1. Jackknife Results for ATM Network Membership

The jackknife procedure was performed to test for heterogeneity of the MAC ATM network membership variable (β_{MAC}). A summary of the means and standard deviations of the jackknife pseudovalues we obtained is reported in Table 2 below.

Table 2: Results of Jackknife Analysis for MAC ATM Network Variable

DATA SET	# BOTS	# BRANCHES	E(D)	σ(D)
DEMAND DEPOSITS	48	393	.25	.60
SAVINGS DEPOSITS	50	508	.25	.76

In the original Banker and Kauffman analysis the parameter β_{MAC} corresponding to this variable was positive and statistically significant at the .05 level in both the demand and the savings deposit models. Looking first at the demand deposits data, the average jackknife value for this parameter is 0.25 but the standard deviation is 0.60. The maximum and minimum values are -0.94 and 2.02 respectively. The jackknife values from the savings deposit model also vary, with a mean value of 0.40 and a standard deviation is 0.76. The maximum and minimum values range from -2.74 to 2.76 respectively. Figures 1 and 2 graphically depict the extent of the variation of the jackknife pseudovalues.

Figure 1: Distribution of Jackknife Pseudovalues: Demand Market Share

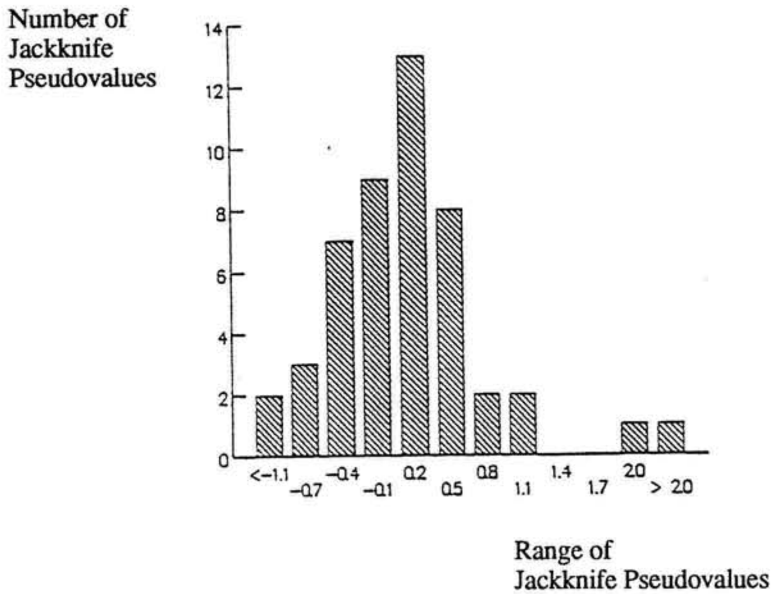
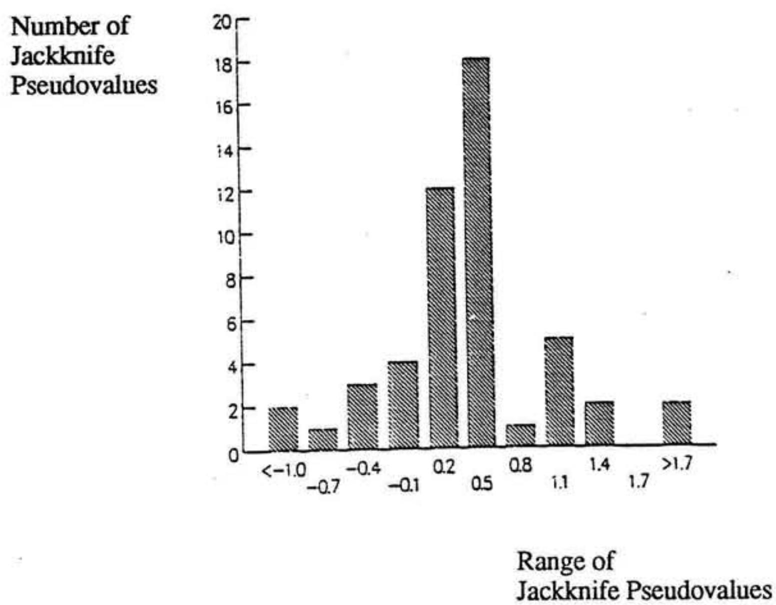


Figure 2: Distribution of Jackknife Pseudovalues: Savings Market Share



Both sets of results, therefore, indicate considerable heterogeneity in the impact of ATM network membership on branch market share. Thus, the true business value of the MAC ATM network membership parameter is not homogeneous across the different operating territories in which the bank competes.

4.2. Correlation Analysis: What Causes Heterogeneity?

Although the jackknife values exhibit considerable variation in the impact of ATM network membership across BOTs, they do not provide conclusive evidence that there is a systematic component in the model which is likely to lead to spatially heterogeneous parameter estimates. One cannot reject the hypothesis that the observed variations are simply due to chance. It is necessary to test, therefore, whether the observed heterogeneity is random or whether it results from systematic variations in IT impact across operation territories.

We investigated a number of variables describing the demographic and competitive environments of branch competition based on what was learned in Banker and Kauffman's field study of electronic banking operations. Management was interested in identifying one or two business value moderators from among a large set of population demographics tracked by its marketing department, and also wanted to know the extent to which the intensity of ATM deployment affected ATM value.

The analysis was performed first for the jackknife pseudovalues calculated when the demand deposit market share data set was iteratively estimated. A second correlation analysis was performed for the savings deposit market share data. The results are presented in Table 3 below.

Table 3: Correlation Analysis for Jackknife Pseudovalues

DATA SET	VARIABLES CORRELATED WITH JACKKNIFE PSEUDOVALUE	CORRELATION COEFFICIENT
DEMAND DEPOSIT MARKET SHARES	TOTAL DEMAND DEPOSITS	0.40
	# OF MAC ATMS DEPLOYED	0.33
SAVINGS DEPOSIT MARKET SHARES	AVERAGE HOUSEHOLD HEAD AGE	0.27
	# OF MAC ATMS DEPLOYED	-0.57

To interpret the correlation coefficients in Table 3 it should be first noted that according to the jackknife equation (shown in Section 3.3), territories in which the IT impact is less than average will have lower jackknife values, while territories with higher than average impact are associated with higher jackknife values. Thus, for demand deposits, the impact of network membership appears to be higher in BOTs with high total deposits and a larger number of MAC ATMs deployed. The correlation results for the savings deposit model jackknife pseudovalues tell a somewhat different story. The impact of membership in the MAC network appears to be less in territories that have a large number of ATMs linked to MAC and higher in territories with just a few MAC-linked ATMs. In addition, IT impacts on savings deposits are positively related to the average age of household heads in the territory. The higher the average age the greater the IT impact.

The correlation results for the savings deposit model have face validity. The negative correlation between the number of MAC-linked ATMs and IT impact in the savings deposit market shares demonstrates the strategic advantage gained by early adopters of IT. The first bank in a territory to link its ATMs to the regional network gains the greatest leverage from its IT investment. On the other hand, a bank which joins the network after most of its competitors already have joined will gain less strategic advantage. For demand deposits the impact of ATM membership is likely to be higher in territories with larger deposit bases. The positive relationship between household head age and IT impact in the savings model is quite similar to that between IT impact and deposit level in the demand deposit model. It is well known in the retail banking industry that average household head age is positively related to the volume of savings deposits: families in the early stages of the life cycle tend to have less savings deposits.

The one contradictory result we obtained is the positive correlation between the demand deposit share jackknife pseudovalues and number of MAC ATMs. This suggests that the dynamics of market share formation may be somewhat different for demand and savings deposits. Since territories with higher deposits and more MAC ATMs were the more competitive ones in our data set, it may be that what we are finding here is confirmation that all MAC member banks (at the expense of their CashStream-linked competitors) tend to be better off when local significant deployment of MAC ATMs has occurred locally. Of course, it will be harder to make the case that any MAC bank obtains competitive advantage at the expense of another MAC bank.

4.3. Refined Business Value Estimates for ATM Network Membership

We next utilize the results of the jackknife and correlation tests to improve our understanding of the extent to which the moderating variables enhance or suppress the business value of ATM network membership. We partitioned the data sets based on two separate descriptive dimensions for each BOT. The first dimension identified whether the BOT had a two-thirds majority of ATMs that were connected to the MAC network (Banker and Kauffman [2] termed this a "MAC-dominated territory"). This partitioning was applied to both demand and savings deposit market share estimation data sets. The second dimension, in the case of the demand deposit market share data, was whether the BOT had a relatively large amount of total demand deposits. To determine this, we rank ordered all the BOTs in terms of total demand deposits, and then split the sample at the median, into a "HIGH DEPOSITS" and a "LOW DEPOSITS" group. For the savings market share data, we performed a similar procedure to determine BOTs which where characterized by older and younger average household head ages ("HIGH HHH_AGE" and "LOW HHH_AGE"). This yielded four partitions for the demand deposit data and four partitions for the savings deposit data as shown in the Table 4 below.

Utilizing the partitioned data sets we estimated four more MCI models, for demand and savings deposit market share. The results we obtained for these partitions are presented in Tables 5 and 6 below. In order to test for the stability of all coefficients in the partitions, we performed Chow tests [7] for the demand deposit partitions and for the savings deposit

Table 4: Data Set Partitions for Refined Business Value Estimates

	DEMAND DEPOSIT PARTITIONS		SAVINGS DEPOSIT PARTITIONS	
ATM NETWORK MEMBERSHIP	LOW DEPOSITS	HIGH DEPOSITS	LOW HHH_AGE	HIGH HHH_AGE
NOT-MAC-DOMINATED	PARTITION A 134 OBSERV.	PARTITION C 63 OBSERV.	PARTITION A 99 OBSERV.	PARTITION C 155 OBSERV.
MAC-DOMINATED	PARTITION B 57 OBSERV.	PARTITION D 139 OBSERV.	PARTITION B 158 OBSERV.	PARTITION D 96 OBSERV.

partitions separately. The Chow test for the demand deposit partitions showed that partitioning significantly improved model fit ($p = .05$) In addition, we obtained a gain in the R^2's for nearly all the partitions. This suggested a better overall fit for the models with refined parameter estimates. For the savings deposit partitions, the Chow test revealed that the partitioned estimates were not significantly different than the estimates that were obtained from pooled savings deposit market share data.

Since the Chow test showed partitioning the demand deposit market share data was worthwhile, the next step is to examine the parameter estimates obtained for β_{MAC}. The only partition in which the refined business value estimate for MAC network membership was significant (.10 level) was "PARTITION A: LOW DEPOSITS/NOT MAC-DOMINATED" ($\beta_{MAC} = 0.28$). Comparing this with the parameter estimate obtained by Banker and Kauffman ($\beta_{MAC} = 0.27$), we note that the difference is minimal. It is more interesting to note that our highest estimate of β_{MAC} was obtained in PARTITION C: HIGH DEPOSITS/NOT MAC-DOMINATED, where it rose to 0.44, yet was not highly significant. This matches the intuition obtained from the jackknife and correlation tests we performed, which showed that potential heterogeneity in the value of MAC network membership could arise in the presence of higher deposit levels.

The Chow test did not suggest the savings deposit partitions were characterized by significantly different coefficients overall, so we chose to investigate whether significant differences were apparent among the β_{MAC} coefficients in the four partitions. For three of the partitions (A, C and D) we obtained significant coefficient estimates. However, these three β_{MAC} coefficients were not significantly different from each other. Despite these results, the coefficient estimates we obtained for the savings deposit market share partitions largely matched our intuition. For example, the highest estimated β_{MAC} coefficient was found in PARTITION C: HIGH HHH_AGE/NOT MAC-DOMINATED.

As an extension of this work, a similar overall approach could be undertaken to examine the extent to which the variable for the presence of an ATM at a branch (β_{ATM}) varies spatially. However, this again would require obtaining separate jackknife

Table 5: Demand Deposit Results: Four Partitions Based on Jackknife Analysis

	PARTITION A		PARTITION B		PARTITION C		PARTITION D	
VARIABLES	COEF	2-TAIL SIGNIF	COEF	2-TAIL SIGNIF	COEF	2-TAIL SIGNIF	COEF	2-TAIL SIGNIF
COMMBK	1.86	***	1.05	***	2.71	***	2.09	***
MUTSAVBK	BASE	BASE	BASE	BASE	BASE	BASE	BASE	BASE
HIRATE	0.67		-0.65		2.27	*	0.57	
AGE	0.53	***	1.40	***	1.34	***	0.82	***
NAME	1.40	**	1.79	*	0.07		1.02	
WALKUP	1.01	**	1.34	**	1.60		0.11	
DRIVEUP	0.12		-0.48		-1.60	*	0.32	
PLATFORM	0.59	***	-0.04		0.26		1.05	***
ATM	-0.04		0.07		0.66	*	-0.44	
MAC	0.28	*	0.27		0.44		0.22	
R-SQUARED	.46		.54		.44		.36	
ADJ R-SQ	.43		.47		.35		.39	
# OBSERV.	134		63		57		139	

SIGNIFICANCE: **** (.01 level)* *** (.05 level)* ** (.10 level)*

Table 6: Savings Deposit Results: Four Partitions Based on Jackknife Analysis

	PARTITION A		PARTITION B		PARTITION C		PARTITION D	
VARIABLES	COEF	2-TAIL SIGNIF	COEF	2-TAIL SIGNIF	COEF	2-TAIL SIGNIF	COEF	2-TAIL SIGNIF
COMMBK	BASE	BASE	BASE	BASE	BASE	BASE	BASE	BASE
S&L	0.19		0.66	**	0.55	***	0.67	***
MUTSAVBK	0.46		0.79	***	0.92	***	1.32	***
HIRATE	0.51	*	0.17		-0.13		-0.04	
AGE	1.06	***	0.67	***	0.51	***	0.84	***
NAME	0.08		0.28		0.97	***	0.82	***
WALKU	0.51	*	-0.29	*	0.18		-0.14	
DRIVEUP	-0.16		-0.05		-0.16		0.21	
PLATFORM	0.58	**	0.86	***	0.62	***	0.81	***
ATM	0.42	*	-0.03		0.18		-0.17	
MAC	0.37	*	-0.07		0.50	***	0.37	*
R-SQUARED	.35		.40		.37		.39	
ADJ R-SQ	.29		.36		.33		.32	
# OBSERV.	99		155		158		96	

*SIGNIFICANCE: *** (.01 level) ** (.05 level) * (.10 level)* pseudovalues for the ATM parameter by recalibrating the Banker and Kauffman MCI model, iteratively dropping observations associated with individual BOTs, and then correlating the jackknife pseudovalues obtained with demographic and competitive variables which managers believe tend to enhance or suppress branch ATM business value. Since the demand deposit partitions were found to have significantly different coefficients, it is noteworthy that the business value coefficient for a branch ATM is maximized in PARTITION C: HIGH DEPOSITS/NOT MAC-DOMINATED (β_{ATM} = 0.66, .10 level). Although we cannot conclude conclusively that relatively high deposit levels in a BOT tend to make people value branch ATMs more highly, our results suggest the possibility that this is the case. Additional analysis is still needed.

5. Conclusions

By detecting systematic heterogeneity in IT valuation models and then determining what causes it, researchers will be better able to answer the key questions that managers pose about the business value of IT.

- In which markets will the potential of IT be maximized?
- What are the factors which enhance or suppress the business value of an investment in IT?
- How do the magnitudes of these effect differ, influencing the potential returns from IT?

In this paper, we have presented and illustrated a method which managers can use to answer questions concerning the circumstances under which the business value of IT is maximized. Given that competitive situations and consumer characteristics typically vary over space, homogeneity in the value of IT is likely to be the exception rather than the rule.

Alpar and Kim [1], in a recent paper which utilized translog cost function estimation to identify the business value of IT investments in commercial banking, have written that:

> the time for more rigorous approaches [to IT value measurement] has come. Their application may be still hindered by a lack of data. However, if the value of the rigorous approaches can be demonstrated to firms, they will be more willing to collect the necessary data ...

We believe that the methods we have illustrated are a step in the direction of greater rigor in IT business value measurement. They have especially broad applicability for refining econometric models which test for IT value. Although we have focused on a jackknife procedure to examine the strength of an IT-related variable on retail banking deposit market shares, this approach can be applied in many other IT evaluation contexts. In fact, the jackknife procedure we have discussed is just one of a family of jackknife and bootstrap methods from statistics which we believe deserve further scrutiny.

The results of this research can be usefully extended in several ways. First, it would be interesting to extend the data set to incorporate a time-series of market shares, descriptive branch characteristics and retail banking demographics. Kauffman and Weill [17] have recently recommended utilizing longitudinal data, whenever possible, to "power up" the evaluation of how IT business value changes over time. Applying jackknife pseudovalue analysis to the results of a panel data estimation of market share model would substantially improve our ability to capture the relative influence that key moderating variables have on the value of ATM membership as the market share equilibrium shifts. A second possible extension is to recast the framework to forecast the impacts on branch deposit market shares of planned or expected IT investments by competitors. This would enable an analyst to perform sensitivity analysis to determine the IT deployment tactics best suited to protecting market share. With investment analysis methods available for IT investments, managers are more likely to be able to carry out programs in which IT investments help to maximize the value of the firm.

References

[1] Alpar, P, and M. Kim.
A Comparison of Approaches to the Measurement of IT Impact.
1989.
Working Paper, Center for Research on Information Management, University of Illinois at Chicago.

[2] Banker, R. D., and R. J. Kauffman.
Strategic Contributions of Information Technology: An Empirical Study of ATM Networks.
In *Proceedings of the Ninth International Conference on Information Systems*. Minneapolis, Minnesota, December, 1988.

[3] Banker, R. D., and H. Johnston.
Complementarity and Substitution in the Strategic Use of Information Technology and Labor: Evidence from the Airlines' Computerized Reservation Systems.
1989.
Working Paper, School of Urban and Public Affairs, Carnegie Mellon University.

[4] Barua, A., C. H. Kriebel, and T. Mukhophadhayay.
A New Approach to Measuring the Business Value of Information Technologies.
1989.
Working Paper, Graduate School of Industrial Administration, Carnegie Mellon University.

[5] Chismar, W. C., and C. H. Kriebel.
A Method for Assessing the Economic Impact of Information Systems Technology on Organizations.
In *Proceedings of the Sixth International Conference on Information Systems*. Indianapolis, Indiana, December, 1985.

[6] Chismar, W. C.
Assessing the Economic Impact of Information Systems Technology on Organizations.
PhD thesis, Graduate School of Industrial Administration, Carnegie Mellon University, 1986.

[7] Chow, G. C.
Tests of Equality Between Subsets of Coefficients in Two Linear Regressions.
Econometrica :519-605, 1960.

[8] Cron, W., and M. Sobol.
The Relationship between Computerization and Performance: A Strategy for Maximizing Economic Benefits of Computerization.
Information And Management 6:171-181, 1983.

[9] Ghosh, A., and S. McLafferty.
Locating Stores in Uncertain Environments: A Scenario Planning Approach.
Journal of Retailing 58:5-22, Winter, 1982.

[10] Ghosh, A., and C. S. Craig.
Formulating Retail Location Strategy in a Changing Environment.
Journal of Marketing 47:56-68, Summer, 1983.

[11] Ghosh, A., S. Neslin and R. Shoemaker.
A Comparison of Market Share Models and Estimation Procedures.
Journal of Marketing Research 21:202-210, May, 1984.

[12] Hansen, M. H., and C. B. Weinberg.
Retail Market Sharing in a Competitive Environment.
Journal of Retailing 55:37-46, Spring, 1979.

[13] Jain, A., and V. Mahajan.
Evaluating the Competitive Environment in Retailing Using Multiplicative Competitive Interactive Model.
Research in Marketing 2:217-235, 1979.

[14] Kauffman, R. J., and C. H. Kriebel.
Modeling and Measuring the Business Value of Information Technology.
Measuring the Business Value of Information Technologies.
ICIT Press, Washington, D.C., 1988.
Edited by ICIT Research Study Team #2.

[15] Kauffman, R. J., C. H. Kriebel and P. C. Zajonc.
Measuring Business Value for Investments in Point of Sale Technology.
December, 1988.
Working Paper #193, Center for Research on Information Systems, Stern School of Business, New York University.

[16] Kauffman, R. J., and C. H. Kriebel.
Identifying Business Value Linkages for Production Processes Involving Information Technology.
In Y. H. Kim and V. Srinavasan (editors), *Advances in Working Capital Management: Volume II.* JAI Press, New Haven, CT, 1989.
Forthcoming.

[17] Kauffman, R. J., and P. Weill.
An Evaluative Framework for Research on the Performance Effects of Information Technology Investment.
In *Proceedings of the Tenth International Conference on Information Systems, Boston, MA.* December, 1989.
Forthcoming.

[18] Loveman, G.
An Assessment of the Productivity Impact of Information Technologies.
1988.
Working paper, Management in the 1990s, Sloan School, MIT.

[19] Naert, P. A. and M. Weverbergh.
On the Predictive Power of Market Share Attraction Models.
Journal of Marketing Research :146-153, May, 1981.

[20] Nakanishi, M., and L. G. Cooper.
Parameter Estimation for Multiplicative Competitive Interaction Model: Least Squares Approach.
Journal of Marketing Research 11:303-311, August, 1974.

[21] Parker, M. J., and R. J. Benson.
Information Economics: Linking Business Performance to Information Technology.
Prentice Hall, Englewood Cliffs, NJ, 1988.

[22] Roach, S. S.
Technology and the Service Sector: America's Hidden Competitive Challenge.
Economic Perspectives -- Morgan Stanley , August, 1987.

[23] Strassmann, P. A.
Information Payoff: The Transformation of Work in the Electronic Age.
The Free Press, New York, 1985.

[24] Tukey, J. W.
Bias and Confidence in Not Quite Large Samples.
Annals of Mathematical Studies 29:614, 1958.

[25] Weill, P.
The Relationship Between Investment in Information Technology and Firm Performance in the Manufacturing Sector.
PhD thesis, Stern School of Business, New York University, 1988.