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ABSTRACT
This research studies the impact of complementarities at the application level of IT systems. Relative impact on supplier performance is assessed for two configurations of reverse auction systems – full-informate and rank-informate. The impact is proposed to be contingent on the task and behavioral environment in which the systems are used. The multilevel data analysis using hierarchical linear modeling suggests significant findings for task complementarities and interesting insights for behavioral interactions.

KEYWORDS
Business Value of IT, Complementarities, Reverse Auction, HLM

INTRODUCTION

Business value research has studied the impact on firm performance of the IT investments and recent research has applied the theory of complementarities to explain the impact of IT on firm performance (Brynjolfsson & Hitt, 1996; Rai et al., 2006; Banker et al., 2006). According to the complementarities perspective, the IT applications interact with other organizational and process characteristics to create the desired impact (Barua and Mukhopadhayay, 2000). While the business value research has studied the impact of IT at the firm and industry level, very little research has studied the impact at the application level. The application-level analysis is recommended as it captures the value at the actual process of its creation and involves actual use as against IT investments (Barua et al., 1995; Devaraj and Kohli, 2003). At the application level, Mukhopadhayay et al., (1997) earlier found the impact of mail sorting application on quality. While their research established the process impact of value creation through IT, in this research we further extend the application-level research by studying the complementarities effect associated with value creation.

Studies at the application level have vastly explored the impact of supply chain technologies (as EDI and mail sorting applications) on the operational and firm performance (Banker et al., 2006; Rai et al., 2006).In this research, we explore the value creation for suppliers through the use of reverse auction systems that are often used for procurement in supply chains. We studied two different configurations of reverse auction systems - full-informate and rank-informate – to induce the variance at the IT application level. A similar categorizations of IT systems was previously used by Dehning et al. (2003), to assess the differences in value created by different IT strategic roles (automate; informate-up; informate-down and transform).

While the reverse auction applications provide the suppliers with real time information during the bidding process and may make the process more transparent, the behavioral and task complexities might jeopardize the proposed benefits due to the lower transaction and coordination costs (Gurbaxani and Whang, 1991). Thus, in this research our findings address the dynamics in the use of reverse auction systems faced by procurement organizations. Specifically, the research question we explore is: “Are there significant behavioral and task complementarities that interact with reverse auction configurations to impact the supplier performance?”

As we wanted to study the characteristics of the systems and their interaction with task and behavioral variables, we used an experimental design to explore our research questions. This gave us the ability to manipulate the variables in a controlled way and randomly assign them to the subjects. Hierarchical linear modeling (HLM) is used for the analysis of multilevel data (Raudenbush and Bryk, 2002). HLM helps us tease out the effects at supplier and auction level and, hence, is apt for the analysis of the multilevel design used for the study.

LITERATURE REVIEW

Theory of Complementarities

Complementarities are said to exist between two things when "doing *more* of one thing *increases* the returns to doing *more* of another". (Milgrom and Roberts, 1995). This notion of Edgeworth complementarities is widely accepted and was initially applied by Milgrom and Roberts (1990, 1995) to study the shift from mass production to flexible or lean manufacturing systems. The lack of fit between the firm's strategy, structure, and managerial processes in these environments was proposed as being detrimental to the performance of these new production technologies in the organization. To formulate this problem, which involves a pay off function that is not smooth and does not meet the concavity assumption, Milgrom and Roberts (1995) used the supermodularity[1] property of functions. The mathematics of supermodular functions is based on the lattice theory, and these functions help study the relative impact of one variable in the presence of other, which in the case of well-behaved functions is done using the mixed double partial derivatives.

Complementarities perspective has been widely applied to study the organizational phenomenon (Parthasarthy and Sethi, 1993; Ichinowski et al., 1997). The business value research studying the impact of IT on performance of firms has also studied the complementarities in the use of IT systems (Melville et al., 2004; Ray et al., 2006; Zhu and Kraemer, 2002; Banker et al., 2006; Zhu and Kraemer, 2002). Contingency perspective has also been used to evaluate the fit of the implemented technology with the organizations strategy and structure (Whittington et al., 1999; Parthasarthy and Sethi, 1992, Milgrom and Roberts, 1995). Parthasarthy and Sethi (1993), for example, tested the fit of flexible automation systems [2] with different strategy types, structure, shop floor personnel skills, etc. The differing configurations of these variables were found to have differing fit with the flexible automation systems. While large research studying the complementary interaction has addressed the fit at the firm and the national level, the IS research has emphasized the interactions at the more micro process levels (Barua et al., 1995; Laursen and Foss, 1993; p.247). Thus, in this research we study the complimentary interaction of reverse auction applications, contingent upon the task and behavioral assumptions that are specific to the context of use.

Reverse Auctions

Auctions are mechanisms to allocate resources using a bidding process that serves as the efficient market mechanism (Jap 2002). Variety of auction types[3] have been studied in the literature and internet-based reverse auctions are typically constructed as reverse English-type auctions, i.e. in these auctions suppliers/vendors bid down for a product/service being sold and the price of product/service decreases. Buyers host the reverse auctions as it increases the participation by the suppliers across the geographic limits. Multiple rounds of bid evaluations and coordination is saved as various suppliers compete in real time and the bid price is driven down until a rational market price is reached (Smeltzer and Carr, 2002). These savings in the coordination and documentation costs, however, might be nullified if the suppliers are negatively impacted by the real time bidding information. Differing levels of information of the competitor bidders' performance may lead to different supplier evaluations of the optimal bid. This differing level of information was coded through two configurations of reverse auction systems– full-informate and rank-informate, which are proposed to interact with the external task and behavioral environments and hence lead to complementarities. The basis of this interaction is in the foundation of IS theory, that proposes IT artifacts as being teleological and act as interface between internal and external i.e. they have fixed goal/objective (to facilitate optimal bidding performance by suppliers) and their internal environment (full-informate vs. rank-informate) interacts with the external environment (task and behavioral) for the fulfillment of these goals (Simon, 1996, Churchman, 1971).

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[1] Given a real-value function f on X, f is supermodular and its arguments are (Edgeworth) complements if and only if for any x and y in X, $f(x) - f(x \Lambda y) <= f(xVy) - f(y)$ where
$x \Lambda y$: is smallest element larger than x and y and
xVy: is largest element smaller than x and y. (Milgrom and Roberts, 1995)

[2] Flexible automation systems facilitate discrete production due to computerized programming capabilities and composed of four components

a. Computer Aided Design (CAD) Software b. Computer Aided Manufacturing (CAM) systems, c. Automatic storage and retrieval systems (AS/RS systems), and d. Supervisory computer systems.

[3] The ascending price English auction, descending price Dutch auction, and Vickery second price sealed bid auction are some of the most commonly studied auction types

RESEARCH MODEL

Full-informate versus Rank-informate

Digitally-enabled reverse auctions enable different levels of information sharing, ranging from complete sharing of information details to, more innovative, sharing of real time rank of the supplier during the bidding (Carter et al., 2003). These two reverse auction configurations are defined as full-informate and rank-informate respectively.

Effect of varying levels of information on the suppliers bidding and auction outcomes have been studied by various researchers studying the reverse auction systems (Jap, 2002; Lucking-Reiley, 1999). Also, prior research on aggregate and detailed data has found that while aggregated data may minimize information overload, detailed data results in more accurate decisions due to greater uncertainty reduction (Abdel-Khalik, 1973; Barefield, 1972). Greater information disclosure would lead to more precise supplier bidding as the complete information gives an exact estimate of the bid that needs to be made to be the winner supplier. In case of rank-informate systems, the uncertainty in the exact bid would lead suppliers to underbid, given the constraints and pressure in real time bidding (Carter et al., 2003). Thus,

H1: *Full-informate reverse auction systems will have more optimal bidding performance than rank-informate systems.*

Organizational Pricing Information

Milgrom (1989) found that even after winning the auction, a supplier might loose money due to reliance on the not-so-accurate market information for their own bid evaluation ('winner's curse'). Private value of information about product cost exists when a bidder has accurate information regarding his/her organizations' product/service cost without evaluating the product/service cost of other bidders (Ding et al., 2005; Milgrom and Weber, 1982). Alternatively, a bidder with common value organizational information does not know his/her costs with certainty and uses information available through market mechanism (i.e. bids of other auction participants) to better understand appropriate price levels (Milgrom, 1989; Klemperer, 2004).

The private versus common value of product pricing often determines auction pricing and final auction outcome used by the supplier (Milgrom, 1989). The underlying uncertainty in determining the price of the product or service may either be a due to lack of organizational learning and knowledge systems for product pricing or due to inherent uncertainty in determining the cost of the product (across various industries). Due to product design and development complexities, for example, assessing software cost and pricing is more uncertain and has greater variation than understanding the costs and pricing of a more standard product like automobile parts (Ang and Beath, 1993).

As the suppliers with private information have an exact idea of the product costs, they are able to submit a more optimal bid through a proper evaluated response to the competitor's bid. Thus,

H2: *Suppliers using private value of cost information will have more optimal bidding performance than suppliers relying on common value.*

As the suppliers missing the private value information rely on competitors bids to assess the appropriate bids (Milgrom, 1989), the detail of the information revealed by auction system would apparently affect their evaluation. If the information is only related to rank of their own bid relative to others, the evaluation by the suppliers is likely to be coarser and off the mark. This relative evaluation across the detailed bid and rank information, however, is less likely to affect suppliers with private (and precise) value of their pricing information. The common value suppliers, thus, would vary more in their performance across the two auction configuration and these task complementarities are hypothesized as:

H3: *Suppliers with common value information of the organizational price will have more optimal bidding in the full-informate reverse auction systems compared with the rank-informate systems.*

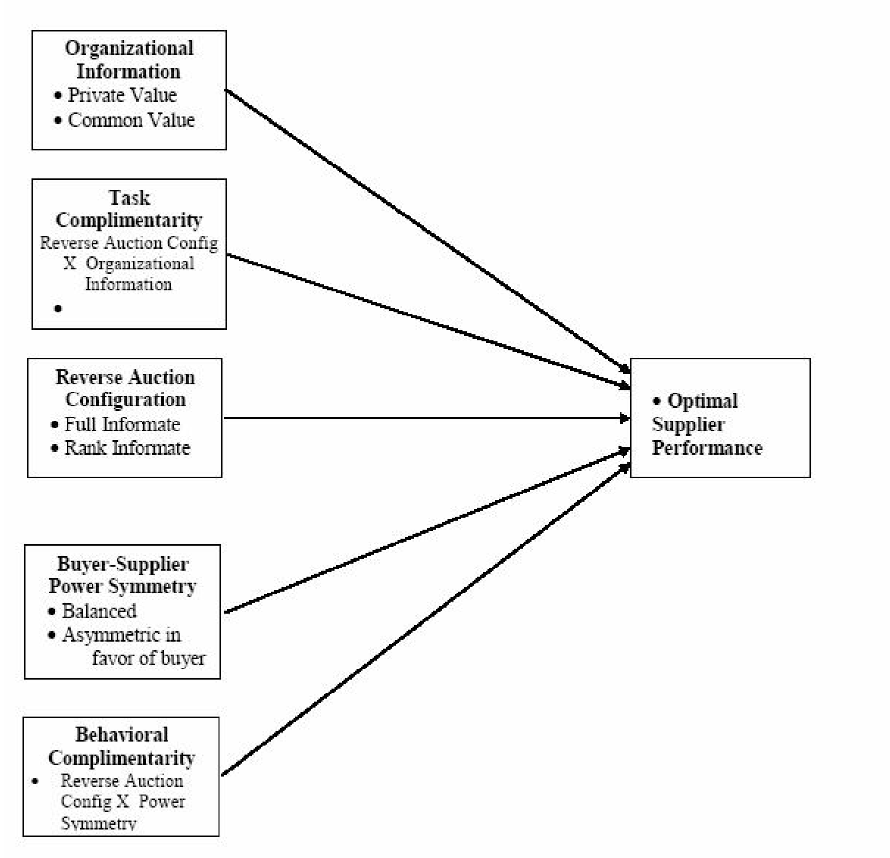

Figure 1: Research Model

Power Symmetry

Differential power distribution between the dyadic partners, due to relative demands and necessities for the resources, may create differences in the nature of business relationships (Choudhury, 1997; Hart and Saunders, 1997). Asymmetrical power relationship exists when one of the organizations is more dependent on the development or sustainability of a relationship (Resource Dependency Theory –RDT by Pfeffer and Salancik, 1978). Symmetric relationship of a (large) buyer with its supplier would imply that the supplier has significant resources (i.e., size or financial, etc.) and these resources might signal to buyer greater quality reputation and lesser dependency, and hence, have a positive relationship with price (Klemperer, 2004). On the other hand, suppliers with greater dependence in the bidding relationship might be forced to comply with demands of buyer (Morgan and Hunt, 1994; Pfeffer and Salancik, 1978). The weaker suppliers are even more vulnerable in the reverse auction context, known for buyer opportunism and strong dependence on the nature of buyer/supplier relationships (Emiliani and Stec, 2002; Jap, 2000). Thus we hypothesize

H4: *Suppliers having greater power symmetry with buyer will have more optimal bidding performance than suppliers having lesser power symmetry.*

While the early auction literature emphasized rational bidding by suppliers, recent literature has identified emotions as having integral influence on bidder's decision strategy. The stress levels are higher for suppliers for whom the bidding is critical due to their asymmetric relationship with the buyer, making them more vulnerable to auction outcomes. Strong emotions (i.e. excitement and frustration) develop based on the feedback from prior bids (Ding et al., 2005). Further, negative information (e.g. stress, anxiety etc.) can lead to less careful evaluation of information and less rational thought, resulting in increased risk taking (Bosman and Riedl, 2003). This outcome would get worse due to greater uncertainity, with the information itself being less precise The interaction is defined as behavioral complementarity:

H5: *Suppliers with lesser power symmetry will have more optimal bidding in the full-informate reverse auction systems compared with the rank-informate systems.*

Table 1.: Research Method Manipulation and Sample Size

Variable	**Treatment**	**Sample Size**
Organizational Pricing Information (PriComm)	Private	245
	Common	188
Power Symmetry (PowSym)	Symmetrical	222
	Asymmetrical (Buyer More Powerful)	211
Reverse Auction Configuration (RAConfig)	Full-informate	185
	Rank-informate	248

RESEARCH METHOD

A 2 x 2 x 2 unbalanced nested experimental design was implemented to test the hypotheses. In each auction, all the suppliers either had private or common value information of their pricing structures (private versus common, between auction). Further, power symmetry between buyer and supplier (symmetric versus asymmetric, between subjects/within auction) was manipulated within the auction, i.e. two suppliers had symmetric and two asymmetric power. The data collected is thus multilevel with power symmetry being measured at the supplier level and auction configuration and organizational pricing information measured at auction level.

Subjects

Five hundred and two business majors enrolled in a core information technology management program at a prominent Midwestern business school participated in this research study. All the subjects were told that they represented a vendor who is a potential supplier to a specific buyer. Subjects were then randomly assigned to treatments and each subject was given detailed information about its firm's capabilities based on this random assignment. Before participating in the reverse auction, all subjects were individually made to do a test bid auction that familiarized them with the interface and the contextual information about the firm and bidding process. Information on their product costs, prior selling prices, manufacturing processes, and profitability were provided based on the manipulations assigned to each student (see Variables below). Subjects participated in the reverse auction, where four subjects were assigned to a specific auction.

Variables

Independent Variables

Organizational Pricing Information (PriComm): Organizational pricing information was manipulated at two levels—private value and common value. Subjects with private value of organizational information were given specific information about product cost, profitability, and expected profit margins, while the subjects with common value were given the information about past pricing alone.

Reverse Auction Configuration (RAConfig): refers to the configuration of auction system used to provide real-time information of competitors' bid. Subjects in the full-informate manipulation were provided information regarding the specific bid amount made by each competitor throughout the duration of the reverse auction. Subjects in the rank-informate manipulation were provided information on the rank of the firm's bid as compared with others competing in the auction but were not given specific bid prices.

Power Symmetry (PowSym): Power symmetry refers to the degree to which the firm represented by the subject had equivalent or differential power as compared to the buyer. Subjects in the symmetric power manipulation were told that their firm had power equivalent with the buyer. Alternatively, subjects in the asymmetric power manipulation were told that the buyer had significantly more power then their firm.

Dependent Variable

The dependent variable implemented in the study was supplier profit. Given the nature of the study, suppliers might make a profit or could lose money relative to their costs. Thus, the dependent variable was measured as the deviation from minimal profit, required where this minimal profit was a value calculated based on information provided to the subjects. The information gave them the ability to calculate the optimal price, which was then substracted from the final bid made by them to reach at the deviation from the optimal price.

Control Variables

We believed that prior individual experiences might influence decision-making performance, either directly or indirectly, and thus prior experience at product costing, experience with reverse auctions, and participation in auctions (e.g., eBay) were measured using a pretest. None of these measures of prior experience had a significant impact on the dependent variable and hence these were excluded from subsequent analysis.

The Experiment

The auction environment implemented for the study was developed using Active Server Page 3.0 (ASP.NET) with VB Script, Microsoft Access 2003, and HTML 4. In both the full-informate and rank-informate configurations, subjects were given a request for quotation and could submit an initial bid and then make an unlimited number of changes to this bid in response to competitor activity. The auction system including the software environment and the task was pilot tested and enhanced (to remove any ambiguity) in the two semesters prior to the actual data collection. Further, the manipulation checks supported the manipulations.

HLM ANALYSIS

We used Hierarchical Linear Model to analyze the nested data.(Raudenbush and Bryk, 2002). Following Ang et al. (2002), we followed an incremental model building approach to analyze the data. Our first model (model 1) is a null model - a simple one-way ANOVA with random effects. Model 1 helps assess the variability in optimal profits at each level and hence is a prerequisite for the detailed multilevel analysis. Further, after testing for model 1, we include the power symmetry to test the impact at supplier level through model 2. In model 3, we include the auction level predictors for the intercept to test for the constant effect of auction type on the optimal bidding performance of suppliers. Finally, model 4 is the cross level model to test the complimentary effects at the supplier and the auction level. In this model, we study the interaction of suppliers with different power symmetries and pricing information with the different IT system (reverse auction) configurations.

Similar to the procedure followed by Ang et al. (2002), we centered our variables before analysis to decrease multicollinearity. Further, the robust standard errors were used to guard against any inflation in test statistics due to heteroskedasticity and non-normality.Full maximum likelihood with empirical Bayes procedure and EM algorithm is used to test our model in HLM (Raudenbush and Bryk 2002; Ang et al., 2002). Our model specification is with random coefficients. The random coefficient model is appropriate since the selected variables represent only a subset of the variables. For example, there could be other possible configuration of reverse auction systems. Similarly, organizational pricing information and power symmetry could have multiple (more than two) states across suppliers. Following is the description of models used in the analysis.

Model 1 (One way ANOVA with Random Effects)

$$Y_{ij} = \beta_{0j} + r$$
$$\beta_{0j} = \gamma_{00} + u_0$$

Supplier- Level Model (Model 2) (Predictors at the Supplier Level)

$$Y_{ij} = \beta_{0j} + \beta_{1j}*(\text{PowSym}) + r$$

Auction- Level Model (Model 3) (Including Auction Level Predictors of Supplier Level Intercept)

$Y_{ij} = \beta_{0j} + \beta_{1j}$*(PowSym) + r

$\beta_{0j} = \gamma_{00} + \gamma_{01}$*(PriComm) + γ_{02}*(RACongif) + u_0

Cross – Level Model (Model 4)4 (Auction Level Predictors of Supplier Level Intercept and Slope)

$Y_{ij} = \beta_{0j} + \beta_{1j}$*(PowSym) + r

$\beta_{0j} = \gamma_{00} + \gamma_{01}$*(PriComm*RAConfig) + u_0
$\beta_{1j} = \gamma_{10} + \gamma_{11}$*(RAConfig) + u_1

RESULTS AND CONLUSION

The results of model 1 suggest that there is significant variation in optimal profits due to the independent variables at both levels. The intraclass correlation coefficient (ICC) is 25.8%[5], suggesting that approximately one-fourth of the variance is explained at the auction level.

TABLE 2 : Results of HLM estimation of Optimal Supplier Profits

	Optimal Profit			
Variable (Coefficient)	**Model 1**	**Model 2**	**Model 3**	**Model 4**
INTERCPT (γ00)	3870.313***	3870.358***	3874.815***	3867.50202***
	(242.142)	242.143	(114.798)	132.468
PowSym(γ10)		341.962*	341.962*	343.487*
		(160.636)	(160.636)	(160.869)
PriComm(γ01)			-4600.612***	
			(219.760)	
RAConfig(γ02)			-695.759**	
			(235.586)	
PriComm*RAConfig (γ01)				-1998.179***
				(105.824)
PowSymm*RAConfig (γ11)				122.502
				(328.558)

Notes: N = 433 at the supplier level and N = 120* at the auction level. Unstandardized coefficient estimates and robust standard errors (in parentheses) are reported.
Coefficients significant at * p < .05 , ** p< .01, *** < .001
*Auctions with two or more missing suppliers or outliers were dropped to reach at this number.

[4] The inclusion of dichotomous variables PriComm and RAConfig along with PriComm*RAConfig, due to high level of multicollinearity will lead to failure of HLM analysis. The multicollinearity in the current model was not a problem and the VIFs for all the variables were under the 2.0 limit (1, 1.2 and 1.2 respectively for PowSym, RAConfig and PriComm).

[5] ICC is the proportion of variance in Y between auctions and is the ratio of of maximum likelihood estimate of variance of auction means to the total variance at the level of supplier (2737533.06) and at auction level (950686.87) (Raudenbush and Bryk 2002)

Further, models 2 and 3 are used to test the main effects at the supplier and auction level respectively. The data finds support for hypothesis H1, with rank-informate auction configuration leading to less optimal supplier performance than full-informate configurations (γ_{02} = -695.759; p<.001). The support for the hypothesis H1 indicates the presence of main effects of IT on supplier performance. At the application level, IT is found to lead to desired objectives, and the different reverse auction configurations, due to the difference in information disclosure, are found to lead to differential supplier performance. At the firm level, similar impact of IT systems (automate, informate up, informate down, and transform) has been found on different firm valuations (Dehning et al., 2003). Our results study the IT impact at the more micro application level. This low level analysis of the IT impact is in line with the current consensus in the business value research of opening the black box of IT to assess the organizational impact of IT systems.

Further, the coefficient for impact of organizational pricing information is negative, suggesting that suppliers' environments relying on the common value of price information are worse off. The hypothesis H2 is thus supported and the common value suppliers have a significant greater negative deviation from the optimal bid compared with the suppliers bidding in private value environments (γ_{01} = -4600.612; p<.001). Similarly, hypothesis H4 for the impact of differential power symmetry with buyers is supported. The suppliers with symmetric power with the buyer are found to perform more optimal priced bidding as compared with suppliers with lesser power compared with the buyer (γ_{00} = 341.962; p<.05). The results for H2 and H4 represent empirical support for the presence of these effects in the reverse auction environments.

The complementarities theory argues that these organizational effects will interact with the IT application, and hence, the interaction effects were analyzed (hypothesis H3 and H5) through model 4. While H3 is supported (γ_{01} = -1998.179; p<.001), the coefficient for interaction of power symmetry and reverse auction configuration (H5) is not significant (γ_{11} = 122.502). These results support the presence of task complementarities. However, the behavioral complementarities are not found. Thus our analysis indicates that IT systems do not interact with the behavioral bias in the buyer supplier relationships. However, they do have a significant nullifying impact in the adverse task environments. While the missing impact of behavioral complementarities is surprising, it suggests that the implementation of IT application with superior information disclosure is not able to nullify the presence of power imbalance between the buyer and supplier, which seem to be a strongly entrenched effect.

The research has following contribution. Firstly, it evaluates the application level impact of IT on the performance of suppliers in reverse auction, and hence, through the micro level analysis, opens the black-box of IT impact. Secondly, the research empirically studies the impact of traditional pricing assumptions (private vs. common value), different system configurations, and the role of power differences amongst trading partners in the context of reverse auctions. This adds to the nascent but growing literature on the use of reverse auction systems. Finally, the research differentiates the complementarities effects in IT use at the application level as behavioral and task related. The findings further enhance our understanding of the process through which IT impacts the organizational performance. While the behavioral complementarities were found to be non-existent, we found support for the task-related complementarities. This multiple complementarities perspective at the application level will further stimulate debate on the role of complementarities in realizing business value of IT.

REFERENCES

1. Abdel-Khalik, A. R. (1973) The Effect of Aggregating Accounting Reports on the Quality of the Lending Decision: An Empirical Investigation, Journal of Accounting Research, *Supplement to Journal of Accounting Research*, 104-38.
2. Ang, S. and C. M. Beath (1993) Hierarchical Elements in Software Contracts, *Journal of Organizational Computing*, 3, 3, 329-61.
3. Ang, S., S. A. Slaughter and K. Y. Ng (2002) Human capital and institutional determinants of information technology compensation: Modeling multilevel and cross-level interactions, *Management Science*, 48, 11, 1427-6.
4. Banker, Rajiv D., Indranil R. Bardhan, Shu Lin and Hsihui Chang (2006) Plant Information Systems, Manufacturing Capabilities and Plant Performance, *MIS Quarterly*, forthcoming.
5. Barefield, R.M. (1972) The effect of aggregation on decision making success: A laboratory study, *Journal of Accounting Research*, Autumn, 229-42.
6. Barua, Anitesh, Prabhudev Konana, Andrew B. Whinston and Fang Yin (2004) An Empirical Investigation of Net-Enabled Business Value, *MIS Quarterly*, 28, 4.
7. Barua, Anitesh, Charles H. Kriebel and Tridas Mukhopadhyay (1995) Information technologies and business value: An analytic and empirical investigation, *Information Systems Research*, 6, 1, 3-23.

8. Barua, A. and A. B. Whinston (1998) Complementarity Based Decision Support for Managing Organizational Design Dynamics, *Decision Support Systems*, 22, 45-58.
9. Barua, K and T. Mukhopadhyay (2000) Ch 5. In Robert W Zmud (ed.), Framing the domains of IT Managment. OH: Pinnaflex press.
10. Bosman, R. and A. Riedl (2003) Emotions and economic shock in first price sealed bid auction: An experimental study, Tinsbergen Institute discussion paper no. 2003-056. University of Amsterdam, Amsterdam.
11. Brynjolfsson, Erik and Lorin Hitt (1996) Paradox lost? Firm-level evidence on the returns to information systems., *Management Science*, 42, 4, 541.
12. Carter, C. R., L. Kaufmann, S. Beall, P. L. Carter, T. E. Hendrick and K. J. Petersen (2004) Reverse auctions grounded theory from the buyer and supplier perspectives, *Transportation Research*, 40, 3, 229-54.
13. Choudhury, V. (1997) Strategic choices in the development of interorganizational information systems, *Information Systems Research*, 8, 1, 1-24.
14. Churchman, C. West (1971) The Design of Inquiring Systems: Basic Books In.
15. Dehning, Bruce, Vernon J. Richardson and Robert W. Zmud (2003) The Value Relevance of Announcements of Transformational Information Technology Investments, *MIS Quarterly*.
16. Devaraj, S., R. Kohli (2003) Performance impacts of information technology: Is actual usage the missing link? *Management Science*, 49, 273–289
17. Ding, M. , J. Eliashberg, J. Huber and R. Saini (2005) Emotional bidders an analytical and experimental examination of consumers' behavior in a Priceline-like reverse auction, *Management Science*, 51, 3, 352-64.
18. Emiliani, M. L. and Stec D. J. (2002) Squaring online reverse auctions with the caux round table Principles for business, *Supply Chain Management*, 7, 2, 92-100.
19. Gurbaxani, V. and S. Whang (1991) The impact of information systems on organizations and markets., *Communications of the ACM*, 54, 1, 59-73.
20. Hart, P. J. and C. S. Saunders (1997) Power and trust: Critical factors in the adoption and use of electronic data interchange, *Organization Science*, 8, 1, 23-42.
21. Hitt, Lorin M and Erik. Brynjolfsson (1996) Productivity, business profitability, and consumer surplus: Three different measures of Information Technology Value, *MIS Quarterly*, 20, 2, 121.
22. Ichniowski, C., K. Shaw and G. Prennushi (1997) The effects of human resource management practices on productivity: A study of steel finishing lines, *American Economic Review*, 87, 291-313.
23. Jap, S. D. (2000).Going, Going, Gone, *Harvard Business Review*, 78, 6, 30-1.
24. Jap, S. D. (2002) Online Reverse Auctions: Issues, Themes, and Prospects for the Future, *Academy of Marketing Science Journa*l, 30, 4, 506-25.
25. Klemperer, PD. (2004) Auctions: theory and practice. Princeton: Princeton University Press.
26. Laursen, K. and N. Foss (2003) New HRM Practices, Complementarities, and the Impact on Innovation Performance, *Cambridge Journal of Economics*, 27, 243-63.
27. Lichtenberg, Frank R. (1995) The Output Contributions of Computer Equipment and Personal: A Firm-Level Analysis, Economics *of Innovation and New Technology*, 13, 201-17.
28. Luckign-Reiley, David (1999) Using field experiments to test equivalence between auction formats: Magic On the Internet, *The American Economic Review*, 89, 5, 1063-80.
29. Melville, N., K. Kraemer and V. Gurbaxani (2004) Information Technology and Organizational Performance: An Integrative Model of IT Business Value, *MIS Quarterly*, 28, 2, 283-322.
30. Milgrom, P. (1989) Auctions and bidding: A primer, Journal of Economic Perspectives, 3, 3, 3-22.
31. Milgrom, Paul and John Roberts (1990.) The Economics of Modern Manufacturing: Technology, Strategy, and Organization, *American Economic Review*, 80, 3, 511-28.
32. Milgrom, Paul and John Roberts (1995) Complementarities and fit strategy, structure, and organizational change in manufacturing, *Journal of Accounting and Economics*, 2, 3, 179-208.
33. Milgrom, P. and R. J. Weber (1982) A theory of auctions and competitive bidding, *Econometric*, 50, 1089--122.
34. Morgan, R. M. and S. D. Hunt (1994) The commitment-trust theory of relationship marketing, *Journal of Marketing*, 58, 20-38.

35. Mukhopadhyay, Tridas , Surendra Rajiv and Srinivasan . Kannan (1997) Information technology impact on process output and quality, *Management Science*, 43, 12, 1645.
36. Parthasarathy, R. and P. Sethi (1992) The Impact of Flexible Automation on Business Strategy and Organizational Structure, *Academy of Management Review*, 17, 86–111.
37. Parthasarthy, R. and S. P. Sethi (1993) Relating strategy and structure to flexible automation: A test of fit and performance implications, *Strategic Management Journal*, 14, 7, 529-49.
38. Pfeffer, J. and G. R. Salancik (1978) The external control of organizations: A resource dependence perspective: Harper and Row.
39. Rai, Arun, Ravi Patnayakuni and Nainika Patnayakuni (2006) Firm Performance Impacts of Digitally Enabled Supply Chain Integration Capabilities, *MIS Quarterly(forthcoming).*
40. Raudenbush, S. W. and A.S.. Bryk (2002) Hierarchical Linear Models. Thousand Oaks: Sage.
41. Ray, Gautam, A. Muhanna Waleed and Jay B. Barney (2005) Information Technology and the Performance of the Customer Service Process: A Resource-Based Analysis, *MIS Quarterly*, 29, 4, 625-52.
42. Simon, H. (1996) The Sciences of the Artificial. Cambridge, MA: MIT Press.
43. Smeltzer, L. R. and Carr A. (2002) Reverse auctions in industrial marketing and buying, *Business Horizons*, 47-52.
44. Whittington, R., A. Pettigrew, S. Peck, E. Fenton and M. Conyon (1999.) Change and complementarities in the new competitive landscape: A European panel study, 1992-1996, *Organization Science*, 10, 583-600.
45. Zhu, Kevin and Ken . Kraemer (2002) E-Commerce Metrics for Net-Enhanced Organizations: Assessing the Value of E-Commerce to Firm Performance in the Manufacturing Sector, Information Systems Research, 13, 3, 275-95.