# Doctoral Dissertation

# "Essays in Information Technology Management"

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*To my parents.*

# ABSTRACT

Information Technology (IT) has become an integral part of the way firms do business. Equally important is the need to evaluate how firms manage their IT assets. In the first two essays, I try to measure the business value of Information Technology, and develop models that help understand how to use IT most effectively. In the third essay, I try to understand how and when project managers' skills impact project outcomes.

## Essay 1: Ushering Buyers into Electronic Channels

The Internet has emerged as a viable sales channel that influences the behavior of individual and institutional buyers. Recognizing this, many firms are adopting electronic channels in addition to the traditional (physical) channels for sales. The use of electronic channels raises several questions for sellers. When should products be sold through the physical channel and when should they be sold through the electronic channel? What type of product can be best sold through the electronic channel? How does buyers' use of the electronic channel change over time? Does introducing the electronic channel increase firm revenue? We develop a structural econometric model to examine these research questions in a particular setting: the sales of product from a medium-sized return center. We use archival data for over 43 months to conduct two sets of analyses. First, we understand and categorize buyers' response model by estimating the firm's current model. Later, we demonstrate potential improvements from understanding buyer response by using our structural model to simulate outcomes from a proposed policy change. We contribute to the growing body of research on electronic markets in the following ways. First, we empirically identify buyer shifts between electronic and physical channels. We use archival data to model existing sales processes and analyze seller's channel inertia and buyers' channel loyalty. We assess the impact of buyer heterogeneity on firm profitability. Finally, we show that mere adoption of the electronic channel may not lead to higher profits: a firm needs to adapt its strategy based on buyers' response to channel selection.

## Essay 2: Assessing the Value and Impact of RFID in Return Center Logistics

RFID technology is being widely embraced in the supply chain, by manufacturers, retailers, and logistics firms. Although its advocates include retail giants like Wal-Mart, not everyone is enthusiastic about its benefits. Indeed, measuring the business value of IT investments, especially for newer technologies like RFID, is difficult yet at the same time essential.

With a view to establishing the real benefits of RFID, we conducted a field study with GENCO, a third party logistics company that deployed RFID at one of its outbound logistics operations with a goal to reducing customer claims. We find that the RFID implementation had a significant impact on the outbound process: The intensity of claims incidence fell substantially after RFID deployment. After controlling for other factors in our model, we confirm that RFID was a key factor that contributed to the positive outcomes at this return center. RFID not only provided operational efficiency, but also reduced transaction costs. We also provide a framework with which the further benefits of RFID technology can be assessed.

*Essay 3: How do Project Managers' Skills Affect Project Success in IT Outsourcing?*

What skills do project managers (PMs) need, and how do these skills impact project success in IT outsourcing? In this study, we seek to identify what factors impact IT project outcomes, such as costs and client satisfaction, given the project characteristics and PM's hard and soft skills. We examine data collected from a field study conducted at a major IT service provider in India. Our results suggest that while hard skills such as technical or domain expertise may be essential in a PM, soft skills such as tacit knowledge of organizational culture and clients are the most important contribution that PMs bring to a project. Soft skills not only improve project outcomes directly, but they also help when projects have more complexity, more uncertainty, or less familiarity. The results are robust to different specifications.

# Contents

# Ushering Buyers into Electronic Channels

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**ABSTRACT**

The Internet has emerged as a viable sales channel that influences the behavior of individual and institutional buyers. Recognizing this, many firms are adopting electronic channels in addition to the traditional (physical) channels for sales. The use of electronic channels raises several questions for sellers. When should products be sold through the physical channel and when should they be sold through the electronic channel? What type of product can be best sold through the electronic channel? How does buyers' use of the electronic channel change over time? Does introducing the electronic channel increase firm revenue? We develop a structural econometric model to examine these research questions in a particular setting: the sales of product from a medium-sized return center. We use archival data for over 43 months to conduct two sets of analyses. First, we understand and categorize buyers' response model by estimating the firm's current model. Later, we demonstrate potential improvements from understanding buyer response by using our structural model to simulate outcomes from a proposed policy change. We contribute to the growing body of research on electronic markets in the following ways. First, we empirically identify buyer shifts between electronic and physical channels. We use archival data to model existing sales processes and analyze seller's channel inertia and buyers' channel loyalty. We assess the impact of buyer heterogeneity on firm profitability. Finally, we show that mere adoption of the electronic channel may not lead to higher profits: a firm needs to adapt its strategy based on buyers' response to channel selection.

*Key words:* Electronic markets, electronic channels, buyer heterogeneity, structural modeling

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# Ushering Buyers into Electronic Channels

## 1. Introduction

The Internet has emerged as a viable sales channel that has had a significant impact on the behavior of individual and institutional buyers. Electronic channels enable a seller to reach out to those buyers who were not accessible via the physical channels. Numerous articles in popular and academic press, such as Malone et al. (1987), underline the role of the internet in opening up a world of possibilities for online sales. Sellers now have an option to sell their goods via traditional physical channels (p-channels); or sell via online electronic channels (e-channels). In addition, e-channels are touted to be more profitable than their traditional counterparts, because of lower transaction costs; many sellers also adopt an auction mechanism for selling merchandise, leading to higher profit margins on e-channels (Choudhary et al., 1998).

Recognizing this, many firms have created electronic channels (e-channels) in addition to the traditional (physical) channels for sales (Bureau of Census report, 2006). The sellers seek increased revenues, a wider reach, and lower transaction costs on the new channel. At the same time, buyers have an option of using multiple channels for purchasing goods – and hence their adoption of the e-channel has tremendous implications for the sellers' profitability. Industry reports (for example, Forrester Research, 2006) suggest that buyers' adoption of e-channels may not be consistent over time, and that the buyers switch between electronic and physical channels. This switching impacts the adoption of these e-channels amongst the buyers and hence lowers their profitability for sellers. Clearly, use of e-channels for sales is not without its challenges.

[Insert Figure 1A about here]

To explore the incentives and challenges of adopting e-channels, we worked with a reverse logistics firm that had adopted an electronic sales channel, using auctions as the pricing mechanism. While the initial buyer response to the new e-channel was enthusiastic, the actual buyer adoption pattern was different from what the firm expected. Figure 1A shows the average number of bidders per transaction for the electronic channel over a period of 43 months, during which the e-channel was introduced. Initially the buyers are excited about the e-channel and adopt it, as is evidenced by the increasing number of bidders per transaction. However, over time, they seem to shy away, because this number declines over time. In figure 1B, we show the average sale prices on the e-channel for the same period, these show a similar trend, that is, the average monthly prices per order for the e-channel first increase and then decrease over time. In addition, note that the firm was unable to make any sales through the e-channel for some months during the later part of this time period. This adoption pattern seems to echo the switching behavior documented in the aforementioned industry reports, and warrants both an explanation and a solution.

It has been suggested by popular press and extant literature that the introduction of new electronic sales channel in general improves revenue (for example, see Lee and Clark, 1996). The buyer and seller search costs are reduced; in addition, the transaction costs are lower in the e-channel. Table 1 shows the average prices per unit for both the e- and the p-channel in our data set. We find that in general, the prices on the e-channel are higher compared to the p-channel. However, despite getting increasing adoption from the e-channel initially, the seller was not able to sustain the desired buyer adoption pattern in the long run. Thus, the way the channel was introduced may be suboptimal because buyers' adoption rate and the average sales prices decline over time. Such buyer behavior illustrates that mere adoption of technology, such as the new e-channel, does not guarantee increased profits. How firms introduce the new channel is also important;[1] the sellers should recognize the dynamics of buyer adoption in order to more effectively

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[1] Prior research on the business value of information technology echoes this, that mere adoption of technology may not lead to profitability, firms need to redesign their business processes or to identify innovative uses for the technology to derive real value from it. For example, see Bresnahan and Greenstein (1996).

introduce a new sales channel. While e-channels may lead to higher revenues in the short run, for long term gains, seller should anticipate and learn from buyer behavior, because the buyers themselves are learning and adapting to the new technology. Such strategic response is mandatory when the seller uses both the e- and the p-channel for sales and the buyers can also switch between the channels, as is the case with many sellers in the electronic market domain.

Dual channel strategy, or use of multiple sales channels, has been explored in the literature (e.g., Purohit, 1997). Tsay and Agrawal (2004) use a theoretical model to find that adequate compensations need to be made to the reseller in the offline sales channel when the manufacturer adopts an online direct sales channel. Chen et al. (2005) find that switching channel structures may only be beneficial in certain circumstances. However, empirical research on the efficacy and use of dual sales channels (online versus offline) has been lacking, with the exception of Ansari et al. (2006). They explore customer channel migration (between online and catalog channels) for B2C electronic markets, and find that online purchasing is associated with lower future sales and leads to lower channel loyalty; again suggesting that sellers may be myopic in introducing  e-channels, and a better strategy is needed to usher buyers into adopting the e-channel.

The extant literature has demonstrated that e-channel investments can have considerable value for sellers, but does not suggest how firms can steer the buyers towards using this channel. The current study, with its emphasis on the strategic introduction of the e-channel, fits in with literature on channel substitution (e.g., Balasubramanian, 1998) as well as the design of electronic markets. While there is a fecund body of research on electronic markets, the focus has mostly been on the efficiency aspect of these markets, that is, reduction in search and transaction costs, near perfect price competition, etc. For example, Brynjolfsson and Smith (2000) and Clemons et al. (2002) find evidence of price dispersion in online markets. Interestingly, Overby and Jap (2006) find that for goods such as used cars, electronic mechanisms may increase information asymmetry. Choudhary et al. (1998) treat electronic markets as an inter-organizational information system, and find that these systems may help buyers in best price

discovery. Malone et al. (1987) prophecy that increased use of IT would lead to an increase in the use of electronic markets. More recently, Zhong and Wu (2006) use non-price attributes in an e-sourcing setting and find that it may favorably rather than adversely impact long term buyer-supplier relationships.

Our research's focus is on the design and adoption of the e-channels from the seller perspective, while recognizing at the same time buyer behavior. In the physical channels, scanner data availability has already revolutionized how researchers analyze buyer behavior. Guadagni and Little (1983) used such data to study consumers' brand and size loyalty and its impact on their decision making. Kamakura and Russell (1989) and more recently, Sun (2005) have delved into how consumer behavior changes and evolves over time, and how it impacts demand. As yet, however, this strand of research has been limited to data gathered from stores or from scrapping websites.

In this study, we pose the following questions that have been inadequately addressed in the literature: What types of products are more profitable in the e-channel? How do buyers adopt the new e-channel over time? How does a firm usher buyers into accepting and participating in the e-channel? We develop a structural econometric model to examine these research questions using sales data for both physical and electronic channels from a medium-sized return center. We empirically model what drives buyer adoption of the new technology and draw implications for the firm to better introduce a new technology. Our unique data enable us to identify how and why the buyers switch between the two sales channels, and how the seller can take cues from these migrations.

Most of the prior empirical research has examined either one or the other sales channel.[2] If there has been a comparison of the two channels, more often than not the sellers and/or buyers differ across the two channels. It has been difficult to adequately answer the research questions that we pose based on the data that have been available.

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[2] One exception that we find is Overby and Jap (2006), who examine the physical and electronic sales channels operated by the same seller.

We examine buyers' choice of electronic or physical channel in a particular setting: a business-to-business market for salvage goods returned from a large retail chain. When the e-channel is introduced, it may be attractive to the buyers because of lower transaction and search costs. We contend that over time, by continually using the e-channel for their purchases, buyers develop a loyalty towards the e-channel, increasing their likelihood of future e-channel use. In our setting the seller uses auctions as a pricing mechanism.[3] As the number of buyers/bidders per transaction increases over time, the expected prices that buyers pay will also increase. We term these two effects as ***state dependence*** (e-channel loyalty) and ***price effect*** (total expenditure). The first effect increases e-channel loyalty, driving up the second effect, leading to eventual erosion from the e-channel.

What do these two effects portend for sellers? Because buyers are strategic in their purchase decisions, sellers need to recognize the above tension when making their channel choice decisions. Using simulation, we explore what levers the sellers have to influence buyer adoption of the e-channel; in particular, we examine how sellers can utilize buyers' state dependence to make better channel choices and ameliorate the price effect over the long run. While the data set we have is from a single firm, the study addresses more general issues on the design of e-channels.

This study contributes to the existing literature in the following ways. First, it augments research on multiple sales channels (Purohit, 1999; Zettlemeyer, 1999; Tsay and Agrawal, 2004; Chen et al., 2006; Ansari et al., 2006; Overby and Jap, 2006). Second, it looks at electronic markets and their impact on the relationship between buyers and sellers (Zhong and Wu, 2006; Choudhary et al., 1998). Finally, we not only study the adoption of new technology, but also add to the research on electronic markets by simultaneously looking at the e-channel use on both the demand and supply sides.

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[3] Auctions are adopted by many sellers as pricing mechanisms for sales through e-channels (Choudhury et al., 1998), and hence our data is representative of many electronic sales channels.

In particular, we contribute to the literature on electronic markets as follows. First, we improve understanding of buyer response to e-channels by (i) empirically identifying buyer shifts between electronic and physical channels, (ii) Using archival data to model existing sales processes and analyzing seller's channel inertia and buyers' channel loyalty, and (iii) assessing the impact of buyer heterogeneity on firm profitability. Second, we show that mere adoption of the electronic channel may not lead to higher profits: a firm needs to adapt its strategy based on buyers' response to channel selection. Thus we advocate a policy change to usher buyers into the new channel by (i) using buyer response to ascertain what channel and what quantities to use for an order, and (ii) using simulation to show how buyers can be made to adopt the e-channel. Our empirical results shed light on the understanding of how buyers respond to the introduction of new technology and why it is important that the firm should adapt its strategy to recognize and accommodate such buyer response. It is shown that by doing so, the firm can train the buyers to speed up channel adoption and improve revenue.

This paper is organized as follows. In the next section, we describe the research set up and the data. We present our structural model in section 3. We explore both the seller's channel choice, and how buyers reactionary model with a hierarchical Bayesian specification. In section 4, we first present our empirical results, and a brief discussion on what the estimates imply for the policy change that we advocate. We then present the simulated model, and show how the proposed model boosts e-channel adoption and profitability. We conclude with managerial implications in section 5.

## 2. Data Description

In order to draw conclusions about how buyers adopt and switch between physical and electronic channels, and how a seller can learn from these patterns, we need detailed sales data from both the physical and the electronic channels. Apart from this requirement, there are other data challenges. For instance, information asymmetry between the two channels, or unobserved firm level differences between

the sellers if the two channels are operated by different sellers, may contribute to buyers' channel migration. In the present study, none of these confounding factors impact our analysis.

Our data come from the return center of a third-party logistics provider (TPL) to many large US retailers, which processes returns on their behalf, and resells salvage through physical and electronic channels. The returns include returned-to-store merchandise, damaged merchandise, or unsold seasonal merchandise. Prior to June 2002, TPL would use the offline channel. It would call its set of buyers and let them know of the salvage returns available for purchase, and then ship it through the warehouse once the transaction was completed.[4] These buyers would typically be large salvage dealers. Note that even in the physical channel, the buyers would be unable to inspect the merchandise physically. In June 2002, TPL opened a B2B online market place, from where all buyers, large or small, could purchase salvage items. Meanwhile, TPL continued to sell through the physical channel. In either channel, a unique order is referred to as a Bill of Lading (BoL).

For the e-channel, TPL used first price auction as the pricing mechanism. The buyers would examine the details of the BoL being offered on the e-channel and bid on it. The bidders could also observe the number of bids and the number of distinct bidders for a particular auction, but not the identities of the other bidders. For either channel, the information content available to the buyers was similar and would include the product category, the number of pallets, and the number of units being offered in the BoL. Since these were salvage items, the buyers could also observe the retail cost of these goods so as to gauge how much they may be willing to pay for the BoL. The buyer (the winning bidder in case of the e-

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[4] It is apparent that even in the physical channel, the seller holds a pseudo auction; it calls up various buyers to tell them of the available merchandise, and sells to the highest bidder. The problem before the seller is thus not whether to auction the merchandise or not, but which channel to choose. Clearly, the p-channel makes it difficult for the seller to reach out to all the buyers without incurring significant search and transaction costs. Thus, it may not get the best price it could have for that particular order through the p-channel. We thank workshop participants at WISE 2007, for an opportunity of letting us clarify this point.

channel) would then pay for the transaction via an electronic funds transfer, and the BoL would be shipped to the buyer.

The unit of observation in our dataset is a BoL. We collected sales data for each BoL for both physical and electronic channel for two different product categories: toys and electronics, from June 2002 (when the e-channel was adopted) to December 2005, for each BoL. The data include details of the product mix (order size – #pallets and #units – and product category – toys or electronics), retail cost of the BoL, actual purchase price, buyer ids, sales channel used for the transaction, observed purchase price and the number of bidders and bids if the e-channel was used.

[Insert Table 2 about here]

Table 2 shows the sample statistics of all the variables we use in the model. We split the data into seller level and buyer level categories. The variable *Channel* represents the frequency of a BoL being offered through the e-channel. The e-channel was used 24.85% of the time since its adoption. The two product categories – toys and electronics – were offered 53.32% and 46.68% of the time respectively. We also have data on the total sale price of the BoL and the number of pallets in that BoL.

At the buyer level, we look at the retail price that the BoL may sell for. Since this is a salvage operation, the seller lists this price to indicate how much the buyer may regain from purchasing this BoL. Since the BoLs vary in the number of units and pallets, we use a normalized measure of this price. Thus *RPRICE* represents the unit retail price of the BoL. For toys, this is around $20, and for electronics, not surprisingly, this is around $80. *PRICE* is the sales price paid by the buyer, which we again normalize to a per unit measure. The mean *PRICE* for toys is $3, and that for electronics is $16. The margins on electronics as a category are thus slightly higher. The average number of units in a BoL for toys and electronics are respectively 1200 and 450. More interestingly, the number of bidders (*NBIDDER)* for a BoL on the e-channel for both toys and electronics are 2. However, the number of distinct bids on a BoL

is slightly higher for electronics (7.7 versus 5.5), indicating a dense but fierce competition for an electronics BoL.

We now explain why this data set is suitable for answering our research questions. First, in contrast to prior studies, we observe buyer and seller behavior on both p- and e-channels; the data cover a three and a half year period during which the new e-channel is introduced. Moreover, in our setting physical channel buyers do not have an advantage in their ability to observe product quality: this enables us to focus on the effects of state dependence and total expenditure. We observe the channel choice decisions of both buyers and sellers. Second, we have the time series information on buyer adoption of the e-channel and channel migration. This allows us to study how buyers respond to the introduction of new channel. Third, the new channel is an electronic channel, which is illustrative of the trend that more and more companies are adopting on-line channels to sell products. Fourth, interestingly, the e-channel adopts an auction mechanism to determine the price. Thus, instead of firm determining the price, the purchase price will be determined by buyers and their bidding behavior. As stated earlier, many firms are using auction as a pricing mechanism for the e-channel, hence our data set is again representative.

## 3. Model

We assume that the firm sells $j \in \{0,1\}$ (j=0 denoting toys and j=1 denoting electronics) types of products through $k \in \{0,1\}$ channels, with $k$=0 representing the p-channel and $k$=1 representing the e-channel. When the firm gets a product of size $Q_{jt}$ at $t$=1,...,T, it decides whether to allocate the product of type $j$ to the p- or the e-channel. Note that the order size $Q_{jt}$ in this setting is pre-determined; the firm only decides which channel to use for the order. We use a dummy variable $A_t(j, Q_t)$ to denote the seller's allocation decisions.

(1) $\quad A_t(j,Q_t) = \begin{cases} 1, & \text{if product of type j and quantity } Q_t \text{ is allocated to e-channel,} \\ 0, & \text{otherwise.} \end{cases}$

Assume there are $i=1,...,I$ buyers in the market who decide whether to buy the product of type $j$ and quantity $Q_{jt}$ offered by the firm in channel $k$ at time $t=1,...,T$. We use a dummy variable $D_{ikt}$ to denote the demand, that is, $D_{ikt}=1$ representing the case when buyer $i$ purchases the BoL as offered at time t and zero otherwise.

(2) $D_{ikt}(j,Q_t) = \begin{cases} 1, & \text{if customer } i \text{ purchases the product of type } j \text{ and quantity } Q_t \text{ from channel } k \text{ at time } t, \\ 0, & \text{otherwise.} \end{cases}$

Note the firm's allocation decision and buyer purchase decisions are product type and quantity specific. This takes into account the fact that product type and/or quantity affect where to allocate the product. For simplicity, we simply write them as $A_t$ and $D_{ikt}$ in the following discussion.

### 3.1. The Firm's Channel Choice

Our conversation with the firm indicates that the seller's current channel choice decisions for sales occasion $t$ are determined by the sale price that it got for that particular product category on the prior purchase occasion $t$ - 1. We let the expected revenue for TPL to be calculated as follows:

(3) $E[\Pi]_{kt} = PRICE_{jkt-1} * Q_t$

In addition to the expected revenue, the seller's utility for allocating a product to a particular channel would be driven by its comfort of using a particular channel. We follow marketing literature (Guadagni and Little, 1983) to define this 'comfort' or stickiness to a channel as the firm's loyalty to a particular channel, a weighted average of the past e-channel use and current e-channel experience. In addition, each order of size $Q_{jt}$ is packed into a standard size pallet. The number of pallets in a BoL is a proxy for the costs associated with processing a BoL, and hence affects TPL's utility (see for example, Tirole, 1988). We sum up this utility from each product category and channel as

(4) $V_{kt} = \gamma_{0ujk} + \gamma_{1i}.E[\Pi]_{kt} + \gamma_2.FLOYAL_{kt} + \gamma_3 PALLET_{jt} + e_{kt}$

Coefficient $\gamma_{0jk}$ is the intrinsic preference for the firm to choose channel $k$ for product type $j$. $\gamma_1$ measures the importance of the expected profit on firm's channel choice. $\gamma_2$ represents the importance of firm's channel inertia, or its habit of choosing channel $k$ to sell product type $j$. $\gamma_3$ is a proxy for the marginal cost for a particular BoL.

The above setup implies that when the firm decides on the channel on which to sell product of type $j$ and size $Q_t$, it compares the expected utilities obtained from using both channels. It chooses whichever channel offers it the highest utility.

We assume that $e_{kt}$ is the error term that summarizes all the unobservable factors affecting the firm's channel choice and it has standard Type I extreme value distribution. Then we have a binary logit model for firm's channel choice.

(5) $\operatorname{Pr}ob(A_t = 1) = \dfrac{e^{V_{kt}^*}}{1 + e^{V_{kt}^*}}$

### 3.2. Expected Purchase Price

We assume the buyer estimates a purchase price that affects her purchase decision. Thus, there is a sequential decision process for purchase price and then purchase decision. In the first stage, the buyer would predict the price to pay for the order, and in the second stage, decide whether to purchase this order.

We examine the price ( $PRICE_{jkt}$ ) as determined by resale value ( $RPRICE_{jkt}$ ), past prices paid on the same product type sold through the same channel ( $PRICE_{jk(t-1)}, PRICE_{jk(t-2)}$ ), and number of bidders in the previous period ( $NBIDDER_{jk(t-1)}$ , in the case of the e-channel). Thus, we have

$$
\begin{aligned}
PRICE_{jkt} &= \alpha_{jk0} + \alpha_1.RPRICE_{jkt} + \alpha_2.PRICE_{jk(t-1)} + \alpha_3.PRICE_{jk(t-2)} + \alpha_4.(D_{j(k=1)t}.NBIDDER_{jk(t-1)}) + \varepsilon_{jkt}, \\
&= \alpha_{jk0} + \alpha_{1-4}X_{jkt1-4} + \varepsilon_{jkt}
\end{aligned}
\tag{6}
$$

We use $X_{jkt1-4}$ to denote all the 4 right hand side variables, and $\alpha_{1-4}$ to denote the vector of corresponding coefficients. Thus, $X_{jkt1-4}$ are the price indicator variables. Here, $RPRICE_{kt}$ is the unit retail or resale price of product type $j$, which is known to the buyer. It determines buyers' resale revenue and should drive the winning price. Marketing literature has indicated that buyers value rely on price history as predictors of current prices. $PRICE_{jk(t-1)}$ and $PRICE_{jk(t-2)}$ are the winning margins paid for product type $j$ that was offered through channel $k$ at times $t$-1 and $t$-2, respectively. We include these two variables to capture the consistency of prices over time. $NBIDDER_{jk(t-1)}$ is the number of bidders that participated in the last auction for the same product $j$ through the same channel $k$. Both theoretical (e.g., Krishna, 2002) and empirical literature has established that number of bidders signals the common value of the auctioned item and increases bidders' willingness to pay and hence the winning price. We have bidders' data only for the e-channel, therefore we use $D_{j(k=1)t}.NBIDDER_{jk(t-1)}$, so that recall that $D_{jkt} = 1$ when e-channel is used, and zero otherwise.

Coefficient $\alpha_1$ captures how the resale price determines the winning margin resulting from a sale. Coefficients $\alpha_2$ and $\alpha_3$ measure the persistence of prices over time for the same product type through the same channel. Coefficient $\alpha_4$ indicates whether the number of bidders participating in historic bids will increase the expected price as predicted by the auction theory. In equation (6), $\alpha_{jk0} + \alpha_{1-4}X_{jkt1-4}$ is the

deterministic part of the expected price, $\varepsilon_{jkt}$ represents the unobserved factors that affect this expected

price. We assume $\varepsilon_{jkt} \sim N(0, \sigma_\varepsilon^2)$.

We use vector $\alpha' = [\alpha_{jk0} \ \alpha_1 \ \alpha_2 \ \alpha_3 \ \alpha_4]$ to represent all the coefficients in the purchase decision equation.

Note that the price equation is channel and category specific and estimated as such.

### 3.3. Expected Demand

The expected demand is as given by equation (2). Let $U_{ijkt}$ be the latent utility that determines buyers'

purchase decisions. We assume it is given by,

$$
\begin{aligned}
U_{ijkt} &= \beta_{ijk0} + \beta_{i1}.E[PRICE_{jkt}].Q_{ikt} + \beta_{i2}.LOYAL_{ikt} + \beta_{i3}.INV_{jt} + \zeta_{ijkt}, \\
&= \beta_i'.W_{ijkt} + \zeta_{ijkt} \\
&= U_{ijkt}^* + \zeta_{ijkt}
\end{aligned}
$$

(7)

Here, $U_{ijkt}^*$ is the deterministic part of latent utility that drives purchase decision, and the unobserved part

of this utility is $\zeta_{ijkt}$. $E[PRICE_{jkt}].Q_{ikt}$ is the total expected expenditure, or the ***price effect***, which impacts

the purchase decision. $LOYAL_{ikt}$ represents the channel loyalty developed by buyer $i$ up to time $t$ for

channel $k$. It is defined as the weighted average of the prior channel loyalty and the most recent adoption

of the same channel. This measurement has been first introduced by Guadagni and Little (1983) to the

marketing literature to capture consumer brand loyalty.

(8)     $$LOYAL_{ikt} = \phi_i.LOYAL_{ik(t-1)} + (1-\phi_i).D_{ik(t-1)} \ ,$$

where $\phi_i$ is a parameter to be estimated.[5] It is the weight buyers give to their past channel choice and thus measures inertia or stickiness to a channel. Note that the sum of loyalties for both channels will always be 1. Since only the physical channel was available to the buyers before the online channel was introduced, it is reasonable to assume that the buyers have zero channel loyalty to the on-line channel, or $LOYAL_{i10} = 0$ and $LOYAL_{i00} = 1$, for t = 0. Over time, as buyers start to purchase from on-line, they slowly build up their loyalty to the on-line channel. When, however, they purchase from the physical channel, the loyalty for the e-channel decreases consequently. Hence, the loyalty variable measures the shifting pattern of what channel the buyer chooses to make a purchase in each time period.

We also assume that the purchase decision may be driven by the inventory level that the buyer $i$ has in stock. We follow Sun (2005) to model the inventory constraint as follows:

(9) $$INV_{ijt} = INV_{ij(t-1)} + Q_{ij(t-1)} - S_{ij(t-1)}$$

Where $INV_{ijt}$ is the inventory that buyer $i$ has of product $j$ at purchase occasion $t$, $Q_{ij(t-1)}$ and $S_{ij(t-1)}$ are respectively the quantity purchased and the sales of product $j$ at the last purchase occasion ($t$-1) by the salvage dealer. The inventory levels for a buyer vary as per the last purchase, and consumption – in this case – of sales that the salvage dealer makes of her purchased goods. We assume that at $t$=0, the inventory is zero, and then built up or down as per the purchase pattern throughout the buyer's life cycle in the data sample.

Coefficient $\beta_{ijk0}$ represents the buyer's intrinsic preference for purchasing product type $j$ through channel $k$. Coefficient $\beta_{i1}$ measures the buyer's sensitivity to the total expected expenditure, which is similar to

---

[5] We started with a conservative value of $\phi_i$ (0.5), and increased it till we got consistent likelihood estimates. The final estimate of $\phi_i = 0.75$ is consistent with prior literature (e.g., Guadagni and Little, 1983).

price sensitivity. Coefficient $\beta_{i2}$ measures the importance of channel loyalty on the buyer's purchase decision. Finally, $\beta_{i3}$ measures the impact of inventory levels on the purchase decision. If the salvage dealer is running short on inventory, because of her own demand pattern, she may be willing to purchase a BoL despite price and other factors.

We use vector $\beta_i' = [\beta_{ijk0} \ \beta_{i1} \ \beta_{i2} \ \beta_{i3}]$ to represent all the coefficients in the purchase decision equation.

Equation (9) indicates that buyers' purchase decision is determined by the tradeoff between the channel loyalty and total expenditure. Intuitively, when the e-channel is introduced, buyer has almost zero loyalty to the e-channel, which decreases the probability of the buyer making a purchase if the product is offered through the e-channel. However, the same reason implies that number of participants in the auction for a BoL will be low, which means lower purchase price and total expenditure. This in turn increases the attractiveness (utility) from the e-channel and hence the probability for buyers to purchase the product offered at e-channel. Thus, whether to purchase from the e-channel depends on the relative strength of these two forces.

$\zeta_{ijkt}$ represents the unobservable factors that influence the purchase decision. We assume that the error term $\zeta_{ijkt} \sim N(0, \sigma_\zeta^2)$, for identification, we assume $\sigma_\zeta^2 = 1$. Thus, we have a binary probit model for buyer purchase decisions,

$$(10) \qquad \mathrm{Pr}\,ob(D_{it} = 1) = [1 - \Phi(\beta_i.W_{ijkt})]^{D_{it}} . [\Phi(\beta_i.W_{ijkt})]^{(1-D_{it})}$$

### 3.4. Heterogeneity

It is known that ignoring unobserved consumer heterogeneity leads to biased parameter estimates (Gonul and Srinivasan, 1996). Although TPL could investigate the buyer channel migration in a homogenous setting, it may not shed a light on how best to usher its buyers into adopting the e-channel over the long

run. We account for the buyer heterogeneity by estimating individual level parameters in the purchase decision equation,[6] which can be viewed as draws from a super population distribution often referred to as the mixing distribution. There are two common ways to represent consumer heterogeneity in choice models – continuous and discrete heterogeneity. We estimate a continuous heterogeneity model where the mixing distribution is continuous (e.g., normal) and individual specific parameters are drawn from this distribution. Monte Carlo Markov Chain (MCMC) methods are commonly used to estimate the exact posterior distribution of individual specific parameters (see Rossi et al., 1996 for more details on the hierarchical probit model).[7]

Following Rossi et al., (2005), we specify that the each individual specific parameter $\beta_{in}$ be drawn from a continuous normal distribution, that is, we specify the following multivariate regression:

$$(11)\ \beta_i = \Delta.Z_i + \upsilon_i, \quad \upsilon_i \sim iidN(0, V_\beta).$$

Here, the individual specific parameters $\beta_i$ themselves are regressed on observable buyer characteristics $Z_i$; $Z_i$ is the $m$ X 1 vector with an intercept term as well as $(m - 1)$ buyer characteristics. $\Delta$ is a $(l$ X $m)$ matrix; $l$ is the number of causal variables specified in the purchase equation. We specify $\upsilon_i$ as the unobservable component of the buyer heterogeneity, and assume that this is distributed normally with

---

[6] Note that we need not consider buyer heterogeneity for estimating equation 6. The expected price (and expenditure) is assessed using a common information pool. However the expected expenditure is perceived by each buyer differently and thus its impact on purchase decision would be different. Indeed, we need to consider buyer heterogeneity to identify the effect of total expenditure on purchase decision. As a robustness check, we estimated a mixtures model for equation 6, but found that the estimates were identical to what we report in table 3.

[7] In the case of discrete heterogeneity, the mixing distribution is discrete with mass points, which correspond to consumer segments or latent classes (e.g., Kamakura & Russell, 1989). In such a case, finite mixture model is used to estimate segment specific parameters. The number of segments existing is determined by parameters such AIC and BIC. See Greene (2002) for more details on latent class specification.

mean 0 and variance covariance matrix $V_\beta$. Recall that $\beta_i$ capture the impact of parameters such as total expenditure and loyalty on the purchase decision. In equation 11, we note that these parameters themselves are impacted by the buyer characteristics, which are both observed and unobserved. The variance covariance matrix $V_\beta$ determines the spread of the unobserved component.

A preliminary analysis of the data reveals that buyers differ in terms of the order size (*SIZE*) and diversification of the products that that they buy (*DIVERSITY*). Small buyers who purchase only toys, could be small specialty resellers catering to niche markets, and thus, may be very different in their perception of expenditure, loyalty, and inventory, compared to say large buyers who buy from both categories. First, note that buyers differ in their average order sizes. Order size is directly related to the total expenditure effect. Further, Brynjolfsson, et al. (2003) suggest that buyers may find the e-channels lucrative because of the product variety available on e-channel, and hence those buyers who purchase from both product categories may be different to those who do not.

We thus assume that *SIZE* and *DIVERSITY* are the two observable characteristics that vary across buyers and affect their purchase decision. Thus,

$$(12)\ \beta_i = \delta_0 + \delta_1.SIZE_i + \delta_2.DIVERSITY_i + \upsilon_i, \quad \upsilon_i \sim iidN(0, V_\beta)$$

In this specification, coefficient vectors $\delta_1$ and $\delta_2$ indicate how a buyer's size and diversity affect the covariates in equation 7 to influence her purchase decision. For example, the effect of $\delta_1$ on, say, $\beta_{i1}$ indicates the influence of buyer size on her price sensitivity towards making a purchase as specified.

## 4. Empirical Results

In this section, we first estimate the firm's allocation model and buyer response models to obtain the parameters that characterize how different factors drive the firm's channel choice and the buyers' response. Based on these estimates, we next run simulation using data from another region to demonstrate

whether the firm can speed up the adoption process and improve profit by recognizing the dynamics of buyers' adoption of e-channel. The estimation results are shown in tables 3-6 in the appendix.

### 4.1. Estimation and empirical results

**Firm's Channel Choice**

Given the practice that the firm makes channel choice decision independent of buyer response, we estimate the firm's channel choice model separately from the buyers' response models. The firm's model can be estimated using standard binary logit model. The results are reported in table 3.

[Insert table 3 about here]

The results at the firm level are as expected. Our estimates for the firm's channel choice indicate that the firm is less likely to sell electronics through the e-channel. Expected purchase price, which is higher for the e-channel, also plays a significant role. The firm would likely sell orders for which it expects a higher price on the e-channel. Larger order sizes, as proxied by the number of pallets in the order, make it less likely for the firm to sell through the e-channel. Indeed, our discussion with the revealed that those larger orders would likely be sold to large buyers, indicating that there may be costs and other constraints to selling large orders through the e-channel. Finally, we find that the firm develops channel inertia for the e-channel. This suggests that as TPL sells more and more orders through the e-channel, its loyalty towards this channel increases, leading to even more sales through this channel.

**Buyer response model**

We first estimate the price equation. We clarify that even though we have two stages in buyer purchase decision, they need not be estimated jointly. Because the purchase decision is conditional on price estimation, therefore, we can simply use the expected price effect in the purchase decision. We estimate the price equation for each channel and product category, the results are reported in table 4.

[Insert table 4 about here]

First, note that an increase in the number of bidders in the last period leads to higher expected price in the current period. This effect is especially strong for product category electronics, indicating that electronics is indeed a lucrative category that attracts more bidders, who in turn drive up expected prices more compared to the other product category. Next, note that past purchase prices for the same product category and the channel are persistent over time (this effect is significant in general for all channels and product categories, except for toys in electronic channel, p > 0.10 for prior purchase price in period (t-2)). The unit retail cost (*RPRICE*) is also a good indicator of what prices to expect.

For estimating the purchase probability at the buyer level, the likelihood function involves higher order multidimensional integrals, making classical inference based on maximum likelihood infeasible. Hence, we use hierarchical Bayesian model for inference, which involves getting the exact information about the posterior distribution of the model parameters. The advantages of using this approach are not merely computational ease. We have sparse observations for some of the buyers. Classical inference methods, which rely on asymptotic properties of large sample, may not provide us any meaningful estimates at the individual parameter level, if at all. In addition, we estimate a large number of parameters (300+ buyers, and 6 parameters each), Bayesian method allows partial pooling of data and offers more information that help estimate the individual specific parameters than would independent buyer models.

With our Bayesian hierarchical approach, the model specification is built through a series of conditional distributions (Rossi et al., 1996). That is,

(13a) $U_{ijkt} \mid W_{ijkt}, \beta_i, \zeta_{ijkt}$

(13b) $\beta_i \mid Z_i, \Delta, V_\beta$

As in standard Bayesian models, we set diffuse priors for the model parameters (see Appendix). We apply Markov Chain Monte Carlo (MCMC) methods (Gibbs sampler) and data augmentation coded in R for our estimation. This is especially suited for the hierarchical structure of the inference model, whence we build a Markov chain, which has a stationary distribution as the posterior. The approximations are done through a series of draws, and guidelines followed as to the convergence of this posterior distribution.

We run the MCMC simulation for 20000 draws, and discard the first 12000 as burn in. We also use a thinning parameter of 5, that is, every fifth of remaining draws was retained for the posterior distribution. This technique helps reduce storage space and computational burden of analyzing stored draws. The mean log likelihood is -16738.68, and the mean rejection rate for the Metropolis-Hasting (MH) algorithm is 0.74 (the desired rejection rate is 0.6-0.9). We conduct two diagnostic tests to check the convergence of the chains: Geweke convergence test (Geweke, 1992), and Heidelberger and Welch stationary test (Heidelberger and Welch, 1983). Both tests indicate adequate convergence, and we can conclude that our estimation is stable and convergent.

To demonstrate the effects of channel loyalty and buyer heterogeneity in the purchase decision, we estimate three models. We define our benchmark model that is similar to the proposed model; however it does not consider either channel loyalty or buyer level heterogeneity. This model assumes that the purchase decision is driven by inventory and budget constraints only, and that buyers are homogenous. The second benchmark model assumes that the buyers do develop channel loyalty, however, they are again assumed to be homogenous. The proposed model assumes both channel loyalty and buyer heterogeneity; the summary of the posterior distribution of individual specific means ($\beta_i$s) of the parameters are reported in table 5. These mean values are collected by averaging the mean value of parameter estimates for each buyer.

[Insert table 5 about here]

The results from benchmark model II and the proposed model suggest that buyers demonstrate channel loyalty. Channel loyalty has an important and significant impact on purchase decision, suggesting that buyers would prefer to buy from the new channel, ceteris paribus. This is in keeping with both the loyalty literature (Guadagni and Little, 1983), as well as the literature on electronic markets. The heterogeneous model estimates further suggest that the effect of e-channel loyalty differs across buyers, the effect of channel loyalty is quite startling in the proposed model.

We also find that the effect of net inventory is as expected only in the proposed model (Sun, 2005). When inventory levels are high, the buyer is less likely to make a purchase decision. The price effect in all three models is negative: higher total expected expenditure decreases the likelihood of purchase. The estimates also indicate that the buyers are more likely to buy electronics as compared to toys.

The effect of a BoL being offered on the e-channel, and the probability of purchase differs across the models. In the first benchmark model, marginal effect of the e-channel is higher as compared to the second benchmark model. However, the proposed model more strongly indicates that buyers are more likely to purchase when the BoL is allocated to the e-channel.

[Insert table 6 about here]

Next we estimate equation 11. In equation (11), we let the vector $\beta$ (estimated in table 5) itself be regressed on the observed buyer characteristics, that is, *SIZE* and *DIVERSITY*. Table 6 reports the estimation results of the posterior distribution of the hierarchical regression coefficient matrix $\Delta$.

The results show that buyers are heterogeneous. They perceive the effect of total expenditure and channel loyalty differently. There also seems to be a buyer self selection. The negative coefficients for *SIZE* on covariates e-channel and e-channel loyalty (–0.950, – 1.939 respectively) indicate that as their size increases, buyers tend to shy away from the e-channel. Thus, when a BoL is offered through the e-channel, large buyers are less likely to buy it and consequently less likely to develop e-channel loyalty.

The opposite is true of diversity – the coefficients for both the e-channel and e-channel loyalty are positive (0.428, 0.060). The more diverse buyers are more likely to buy from the e-channel. The effect of on inventory constraints is again as expected, note that a) the intercept is large, b) larger buyers are less sensitive to inventory constraints, they seem to stock pile. The effect of these observable characteristics on price is also interesting, large and undiversified buyers seem to be more sensitive to the price effect. To conclude, small and diversified buyers are more sensitive to channel loyalty and less sensitive to expenditure. Thus, they are more likely to try a new channel.

The results demonstrate that the popularity of the newly introduced e-channel is determined by the relative strength between price effect (as represented by total expenditure) and state dependence (as represented by e-channel loyalty).

First, the two effects are not static. They both vary over time. Since the channel loyalty is constructed as the weighted average of past loyalty and recent channel experience, the increasing or decreasing amount of experience with e-channel also increases or decreases over time. The purchase price depends significantly on the number of bidders in each auction (which happens in the case of e-channel); this effect also changes over time.

Second, the relative strength of these two effects also changes over time. When the price effect dominates the state dependence effect, buyers are likely to purchase from e-channel because they think that the price is low. This is most likely to happen during the initial periods when the e-channel was newly introduced. As the e-channel gets more and more popular, loyalty for e-channel builds up. At the same time and for the same reason, purchase prices also become higher and higher. Buyers may thus now show a decreasing propensity of purchasing from the firm when the product is offered through the e-channel. This explains the first increasing and then decreasing pattern of adoption rate as we observed in Figure 1A. This may partially cause the average sales prices to decline as shown by Figure 1B.

Third, the price effect depends on quantity. When the order size is greater, the total expenditure will be higher given the same amount of unit purchase price. Thus, the popularity of e-channel depends on the relative strength of the price effect and channel loyalty, and this is amplified by the size of the order.

This discussion implies that when introducing the e-channel, the firm should make careful decisions on how to introduce this new channel because our empirical results indicate that buyers react to firm's channel decisions strategically. As is evident from our parameter estimates and the preceding discussion, the buyers are different in their perception of these three effects. The e-channel seems to be more attractive to the smaller and more diverse buyers, whereas the larger undiversified buyers are more likely to purchase through the p-channel. Thus, it is important for the firm to recognize the dynamics of buyer adoption in order to achieve the purpose of improving total profit. We next run a simulation to demonstrate how the firm can better introduce its new channel and improve channel adoption and revenue.

### 4.2. Simulation

We assume the firm now takes into account buyer dynamics when making channel choice decisions. To introduce buyer response model to the firm's decision making, we let the firm make channel choice decisions based on expected profit, which is given by total expected profit which is given by

$$(14) \qquad E[\Pi_{kt}] = \Pr ob(D_{ikt} = 1)[PRICE_{jkt} * Q_t],$$

where $PRICE_{jkt}$ is the expected purchase price as given by equation (6) and $\Pr ob(D_{ikt} = 1)$ is the expected demand as given by equation (2). We assume that the firm's channel choice decision is determined by the same utility function as described in equation (4), with the profit replaced by expected profit. Thus, the firm's channel allocation problem becomes an optimization problem as described below,

(15)
$$MAX_{A_j} V_{kt} = \gamma_{0ujk} + \gamma_{1i}.E[\Pi]_{kt} + \gamma_2.FLOYAL_{kt} + \gamma_3COST_{jt} + \gamma_4PALLET_{jt} + e_{kt}$$

Thus, the firm will choose the channel that offers it the higher utility. Note that by including purchase probabilities, i.e., $\Pr ob(D_{ikt} = 1)$, we also include the price effect and state dependence within the firm's decision. The order size ($Q_t$) is also contributing to the total expected expenditure. $\Pr ob(D_{ikt} = 1)$ denotes the popularity of e-channel versus p-channel and plays an important role in determining the expected revenue when the product of type $j$ is sold through e- versus p-channel.

For the simulation, we use data from another region to demonstrate whether by recognizing buyer dynamics, the firm can be better off. The simulation is performed as follows. We first use the coefficients estimated from the firm's channel choice and buyer response models. This takes into cognizance the impact of observable buyer characteristics, that is, order size and product diversity, into their price evaluation and subsequent purchase decision. For each order, we calculate the expected price if the BoL is offered through the e-channel or the p-channel, using coefficient estimates for equation 7. Next, we calculate the purchase probabilities for each buyer, using buyer level coefficient estimates, for both the e- and the p-channel. When the prior channel was p-channel, and thus the number of bidders unavailable, we draw the number of bidders from the standard uniform distribution. We assume that the BoL is purchased by the buyer with the highest purchase probability in either channel. Then we compute the total expected profit as given by equation 12 for each channel, and use these values for evaluating the allocation decision as per equation 13. Once this decision has been made, we adjust the firm and the buyer level channel loyalty. This process is repeated for each of the BoL in this data set. The proposed simulation demonstrates better channel allocation strategy because it takes into account the expected profit and the purchase probability, instead of relying on naïve price expectations from the past.

[Insert figure 2A about here]

Figures 2A, 2B, 2C, and 2D are comparable to figures 1A, 1B, 1C, and 1D, which are observed from our data. It is shown that by recognizing buyer dynamics, the proposed channel choice strategy differs from that observed in the data in the following ways: (i) the allocation of product type is changed; more diverse products are offered more often through the e-channel (ii) The average size of the order placed on the e-channel is smaller than that observed in the data, leading to better adoption of the e-channel. This is because our model estimates suggest that larger size amplifies the negative effect of total expenditure, which may be a result of the increasing popularity of the e-channel on buyers' purchase decision. By lowering the size of the order, the firm can mitigate the effect of price and enhance the effect of state dependence that has been built up to date. In addition, the estimates indicated that smaller sized buyers are more likely to buy if the product is offered through the e-channel, and hence, smaller order size would help the seller attract such buyers on the e-channel; in this way, the firm can increase the attractiveness of the e-channel. Also note that the firm is offering more electronics items through the e-channel, instead of only toys, thereby attracting more diverse buyers, that is, buyers who would like to purchase from both product categories (figure 2C). Figures 2A-2D indicate that such allocation strategy improves adoption of the e-channel as well as the unit sales prices, by lowering order size and by offering both product categories more often.

In general, our results indicate that the firm needs to revise its channel allocation strategies (e.g. adjust the allocation of product type and size) to train buyers to adopt the new channel. Our simulation results indicate that an adjustment of channel allocation strategy according to buyer dynamics helps the firm to increase the speed of adoption and improve profit.

The firm can improve its allocation decisions as follows. First, it can recognize the effect of not only the order size but also product diversity in the buyers. By offering more diverse products through the e-channel, it makes the channel more attractive to the diverse buyers. Second, it can allocate smaller quantities per order. As discussed earlier, quantity adjustment in the proposed manner lowers the total expenditure, thus mitigating the effect of increased per unit prices on the e-channel.

The firm can thus improve its profits from the e-channel by attracting smaller and more diverse buyers.

[Insert figure 3 about here]

In Figure 3, we plot the average purchase probability for small versus large and diverse versus non diverse buyers, for a given e-channel loyalty, to show the differential adoption rates. The figure shows that attracting the smaller and diversified buyers is a fruitful strategy. These buyers are less sensitive to the price effect, and develop a stronger affinity for the e-channel, and they are more likely to buy when the product is offered through the e-channel. In fact, the figure underlines the initial rationale for the firm's adoption of the e-channel. It is able to reach out to those buyers who were not willing to purchase from the p-channel, because of restrictively large order sizes or less diversification in product categories. Once the firm has trained the buyers to purchase from the new e-channel, it can keep on improving its profitability because the increased number of bidders per order would lead to further increases in the purchase price. At the same time the seller has to regulate the order size, so that the buyers would not drop out when the total expenditure increases.

## 5. Conclusion

Electronic sales channels offer sellers an opportunity to increase their installed base. More and more firms are adopting these channels to increase profitability in the long run. However, industry reports suggest that buyers are also becoming savvier, and may switch between the physical and electronic channels. Such buyer switching has profound impact in the profitability of these channels.

We explore the e-channel introduction strategy in this paper. Our research data come from a third party logistics provider who operates both physical and electronic sales channel. We find that although in the beginning the e-channel attracts a large number of buyers, over time, this installed base erodes. We estimate a structural model that takes into account (i) firm's initial channel selection strategy, and (ii) buyer response model. We first examine the effect of e-channel loyalty both on firm's allocation decisions

as well as buyers' purchase decision. We first find that the buyers' purchase decisions are largely driven by the price effect and the state dependence, and that these effects are opposite in nature. We introduce buyer heterogeneity into the model, using buyers' order size and diversity as the characteristics that influence their purchase decision. Our results indicate that e-channel is more attractive to small diversified buyers, who develop strong loyalty towards the e-channel and are more likely to buy when the product is offered through the e-channel. The e-channel offers buyers a chance to purchase a variety of product categories at lower transaction costs. In contrast, larger buyers seem to be more price-sensitive, and less attracted towards the e-channel. Firms should thus take advantage of such buyers' thought processes.

We next run a simulation in which the firm takes into account the strategic buyer responses when making channel allocation decisions. We show that this helps improve both e-channel adoption and firm profitability. We thus demonstrate that mere adoption of e-channel may not be enough to sustain long term profitability. Sellers need to react strategically to channel choice because buyers are learning and changing over time.

Ours is one of the first studies that uses detailed sales data for both physical and electronic channels. This allows us to examine how buyers shift between the channels. Our study has thus important consequences for those sellers who are considering using an electronic sales channel in addition to traditional channel. In line with studies on business value of information technology, we find that mere adoption of technology may not lead to the manna; a tactical response is needed to harness the technology, understand the impact of the technology on market structure and the installed as well as targeted buyer base.

Although the data we examine pertains to a B2B market in reverse logistics, the nature of our innovative model has wider implications. First, our study recommends an electronic market design that takes into account buyers' strategic response. Second, it indicates to sellers how best to allocate products between the electronic and physical channels. Our findings suggest that a more dynamic, responsive sales strategy

will help sellers. Recognizing buyer response and heterogeneity helps a firm fine tune its allocation strategy, thus successfully training and ushering the buyers into accepting the new channel. While the firm is increasing its profitability, the buyers also benefit from this strategy. Smaller and diversified buyers are able to find 'deals' in the e-channel, which were not available to them earlier.[8] This strategy effectively increases the market size for the seller.

Our research has certain limitations which should pave the way for future research. First, our data come from the same firm. While this allows us to focus on the research question at hand without worrying about other confounding firm level factors, at the same time, these results could be indicative of the idiosyncrasies at this particular firm. Thus, even though our results are intuitive and follow rational decision making, these need to be interpreted with care. Future research could look at sales strategies at multiple firms, and for more product categories.

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[8] As Brynjolfsson et al., (2003) find, increased product variety available through e-channel would increase consumer surplus.

# Assessing the Impact of RFID on Return Center Logistics

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**ABSTRACT**

As many manufacturers, retailers, distributors, and logistics firms adopt RFID, the technology is becoming pervasive in the supply chain. Although its advocates include retail giants such as Wal-Mart, not all companies are enthusiastic about its benefits. It is not clear whether RFID is a boon or a curse to the supply chain—its market growth may just be an issue of compliance. To establish the real benefits of RFID, we conducted a field study with GENCO, a third-party logistics company that deployed RFID in the outbound logistics operations at one of its return centers. Our analysis found that the RFID implementation had a significant impact on the GENCO outbound process. The number of customer claims fell substantially following the RFID deployment. After controlling for other factors in our model, we confirmed that RFID was a key factor that contributed to the positive results at this return center. The current study underscores the potential of RFID for today's businesses.

*Key words:* RFID; business value; process-level analysis; reverse logistics; supply chain.

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# Assessing the Impact of RFID on Return Center Logistics

## Introduction

"For Many Retailers, RFID Lacks ROI"

Business Week, October 2005

Since Wal-Mart adopted and mandated the use of RFID tags for its suppliers (RFID Journal 2003a, b), there has been a growing interest in the use of this technology in the supply chain. Widely adopted by manufacturers, distributors, retailers, and logistics companies, many have touted this technology as a way to improve supply chain efficiency and increase profitability (Clarke et al. 2006). Gartner predicts that the RFID market will grow from $504 million in 2005 to $3 billion in 2010 (RFID Update 2005). Retail giants, such as Wal-Mart and Gillette, have reported optimistic news detailing real and anticipated savings because of their pioneering RFID efforts (Faber 2005); these retailers are driving market growth. Similarly, a test IBM traffic system in Sweden that uses RFID has reduced rush-hour congestion by 25 percent (Termen 2006). These reports suggest that RFID is being adopted extensively and that it is beginning to deliver what it promised— at least to some.

However, not all is well in the RFID world. There have been conflicting statements about its value. Industry Week reported that manufacturers have been finding it difficult to financially justify its implementation because they have been unable to make a good business case (Katz 2005). Gozycki et al. (2004) describes a recent case study that examines a retailer's financial analysis of an RFID implementation decision, indicating the challenges of quantifying the benefits of RFID. Instead, manufacturers and suppliers may be adopting RFID solely to comply with demands from key customers (e.g., Wal-Mart or government/defense agencies such as the Department of Defense) (Katz 2005). Many appear to be limiting their RFID projects to meet the minimum requirements needed to comply with these customer demands. Such ambiguity about RFID's value is not limited to small manufacturers; it

also applies to larger manufacturers, logistics firms, and partners throughout the supply chain (Kharif 2005, Moad 2006). These facts have cast doubts on whether RFID will become a cost-reducing panacea for supply chains— or a cost-producing white elephant.

A key determinant of the success of a firm's RFID implementation is the degree to which that company can change its business processes to leverage the technology most effectively. To derive benefit from any technology, a firm needs to redesign its business processes or identify innovative uses for that technology (Bresnahan and Greenstein 1996). Clarke et al. (2006) have emphasized that RFID should be used less as a glorified barcode and more as a tool to leverage business intelligence for strategic planning. They suggest using RFID to plug information black holes in the supply chain and thus to help reduce stockouts and improve fill rates. As we describe in this paper, it is also useful in reverse logistics processes. These all suggest that the ROI of RFID—the effectiveness and value of such uses of RFID technology—has yet to be established unequivocally.

To investigate the benefits of RFID, we conducted a field study with GENCO, a third-party logistics company that recently deployed the technology in the outbound logistics operations of one of its return centers (RC) to reduce customer claims. The scale of operations at this RC is large—on average, it processes more than 3,400 pallets and 800,000 items each month. GENCO customers file a claim when the goods they receive are damaged or do not tally with shipping documents. While GENCO's process already had a high accuracy rate and met customer expectations, GENCO sought even higher accuracy. Its intent in implementing RFID was to improve warehouse operational accuracy and quality of material flow, enhance customer responsiveness, and reduce shipment errors. Senior management felt that RFID might also deter fraudulent claims from GENCO's buyers. In a sense, RFID would be a silent supervisor that would monitor and record the details of material movement and alert the dock staff of errors. Potentially, it could provide testimony on the accuracy of claim flows, resolve discrepancies between customer claims and GENCO-recorded details, and invalidate fraudulent claims.

Our analysis confirmed that the RFID implementation had a significant impact on the accuracy of

GENCO's outbound logistics process. Following its deployment, the number of claims fell substantially. After controlling for several factors in our model, we established that RFID was a key factor that contributed to the positive results at this RC. GENCO management forecasts of RFID's positive impact on logistics operations were accurate.

For readers who are not familiar with RFID technology, we provide a brief overview in the next section. In subsequent sections, we provide GENCO's rationale for deploying RFID, a synopsis of its RC operations, and a description of its processes prior to the RFID deployment. We then discuss the details of the implementation and its effect on GENCO's processes, including some of the implementation challenges. Finally, we provide an analysis of the benefits GENCO derived from the implementation, interpreting our results from senior management's viewpoint, and summarize its benefits. Our field study thus provides supporting evidence of the potential contribution that RFID can make to the bottom lines of operations similar to GENCO's.

**RFID - The Technology**

The RFID technology has come a long way since Marconi first transmitted Morse code-based signals in 1896; however, at a rudimentary level, it is essentially composed of three components (Figure 1). The tags and readers are the hardware components; the third component, the middleware, is the software that acts as a bridge between the data that the readers read from tags and a database. For a more complete description of the RFID technology, its emerging standards, and its potential uses, we refer the reader to Bhuptani and Moradpour (2005).

Insert Figure 1 about here.

*Tags*: An RFID tag is a small transponder attached to the object to be tracked. The tag holds data that are transmitted to a reader when interrogated. Typically, it consists of an integrated circuit with memory. There are currently three types of tags deployed: passive, semi-passive (or semi-active), and active.

Passive tags are low-cost and do not require battery power. These tags, when interrogated by a reader, reflect the radio waves that the RFID readers emit. In contrast, active tags have their own power and can transmit data, and are consequently more expensive. The semi-passive or semi-active tags use the RFID reader's radio field to draw limited power for simple operations.

*Readers:* Readers, which are the interrogators, track the tags. They collect and process information that is embedded in the tags. For passive and semi-passive tags, readers also provide the power to activate tags. A reader's radio field depends on its power and the associated frequency. The frequency determines the range, suitability for different materials, and data-transfer rates. A low frequency—less than 135 KHz—typically entails a lower data-transfer rate. It is best for metal and liquid goods, which low-frequency radio waves can penetrate, but which higher-frequency waves cannot penetrate easily. The high-frequency range, approximately 13.56 MHz, is more common. The typical retail and supply chains rely on ultra-high frequencies—in the range of 433 MHz and 860-930 MHz. An antenna is often used as a channel between tags and readers for data transfers.

*Middleware*: Although the tags and the readers have some software hardwired, middleware translates signals into usable data and facilitates the actual data operations. These software applications help in monitoring and managing the data that RFID tags and readers transmit and read. The data are then aggregated and standardized according to the specific application functionality. They can then be fed into the existing IT databases for reporting or other purposes.

Companies are adopting RFID for a variety of reasons and in a variety of situations, e.g., industrial automation and tracking material movement through the supply chain. They are also using it in access control, hospitals, tollbooths, and for animal and human identification. However, interoperability is a major concern. Because there could be numerous applications of the same tag as it travels through the supply chain, it is necessary to standardize the information embedded in the tags and the methods used

to harness this information. To this end, EPCGlobal has created global RFID standards; the reader can find the details of these standards at http://www.epcglobalinc.org .

**GENCO's Return Center Operations Prior to RFID Implementation**

GENCO is a third-party logistics provider for many large US retailers, including Sears Holdings Corporation (SHC). It processes returns on behalf of SHC at its four RCs in McDonough (Georgia), Grove City (Ohio), Fogelsville (Pennsylvania), and Woodland (California). An RC receives returns of merchandise that customers have returned to the retailer's stores, damaged merchandise, or pristine products, e.g., unsold seasonal merchandise.

There are two subsystems for the material flow. The "inbound" side commences from the receipt of goods from SHC and continues until their placement in storage pallets. The "outbound" side begins when the merchandise that has been taken from storage is "dispositioned." This occurs in one of three ways: the merchandise is returned to the manufacturer; it is sold at auction in small quantities to individuals; or it is sold in larger quantities to one of GENCO's 3000+ salvage dealers. We now describe the inbound and outbound systems for the GENCO RC in McDonough.

**Inbound Process**

Insert Figure 2 about here.

Incoming pallets and shipments from SHC retail stores, which contain customer returns, damaged goods, or marketing returns, enter the facility at the inbound receiving dock. (Note that marketing returns are the unsold, out-of-season products, or special buys and deals.) The retailer provides guidelines that enable GENCO to determine which products to send back to the manufacturers, auction to individuals, or sell to salvage dealers. The main processing steps in the inbound side are as follows. First, an operator scans the barcoded label on the pallet and examines the goods visually. The pallet is delivered to a scan station where a worker opens every carton and scans each UPC code. As a result of

this scanning process, product information is entered into a database to ensure that the RC acknowledges SHC inventory in the system. This scanning, which currently uses UPC and SHC SKU barcodes, helps GENCO to record inventory updates. The GENCO application then generates an internal system license plate (SLP) that a "putaway" process uses to assign items to cartons and/or pallets. Multiple scan lines perform this sorting and scanning operation.

When GENCO employees scan a product, they also obtain information that enables them to decide the disposition mode (Figure 2). While the two main dispositions are vendor return and salvage, there are other possibilities, some items are dispositioned through a separate electronic auction while others are dispositioned to salvage. (The decision on how to disposition a product is based on criteria such as vendor preference, the value of the product, and the cost of disposition.) We focus on the salvage-dispositioned product.

GENCO sells salvage items to salvage dealers based on product categories such as electronics, soft goods, and hardware. Because there is substantial variation in the average dollar value across different product categories, category identification helps salvage dealers gauge the value of the pallet that they are buying. GENCO stores items targeted for sale to salvage dealers (salvage items) in the warehouse until its asset recovery department decides upon a suitable sales channel. Smaller bills of lading (BoLs), consisting of four to six pallets, are usually sold via a separate B2B auction site; larger BoLs are typically sold in bulk to GENCO's largest salvage dealers. (Note that the B2B salvage-item auctions differ from the auctions that GENCO conducts for larger salvage BoLs.)

**Outbound Process for Salvage Items Prior to RFID Implementation**

In this section, we focus on the outbound process for sales to salvage dealers because GENCO initially implemented RFID in this process. The company recently implemented RFID for its entire outbound operation.

Prior to the final loading process, items are aggregated according to their category and placed onto a pallet that has an associated BoL. Each pallet is stretch-wrapped and affixed with a preprinted pallet ID that has a barcode mapped to the BoL and other pallet information. Salvage orders may consist of one or more BoLs. The pallet-level barcodes are scanned to ensure correct loading and the pallets are then loaded onto trucks and shipped out of the outbound bays at the RC.

One of the central issues driving the RFID implementation was the inadequacy of the pallet-ID barcode for ensuring process accuracy. Because barcodes may become dirty, wrinkled, or torn, they were prone to damage even before shipment out of the warehouse. Furthermore, a barcode requires a line-of-sight in order to scan well. Because of problems in reading and the operational inefficiencies of finding and scanning barcodes, RC personnel were not consistent in scanning the pallet-ID barcodes on the outbound side. As a result, they did only a visual check of most of the shipments; they did not scan the barcodes. The result, an increase of inaccurate shipments and erroneous loading onto the trucks, caused customer complaints and claims.

The actual business process results in unnecessarily high costs to both GENCO and SHC and is more complicated than we describe above. The costs to GENCO include costs from both operational errors at the RC and fraudulent claims. For example, personnel must do a manual, visual search to locate any pallets misplaced within the warehouse. Also, during times of high activity, it is possible to place pallets on the wrong truck and ship them to the wrong client/location (Figure 3).

Insert Figure 3 about here.

Such cases led to increased costs or losses for GENCO. When GENCO is able to locate pallets, it arranges for freight to route these shipments to the correct destination. However, it must refund to the client the value of any shipment that is truly lost (i.e., GENCO has made every effort to locate the

missing product but has been unsuccessful). Tracking and correcting these errors entail significant labor resources as well as overhead costs.

Our field study focused on claims of salvage dealers who asserted that they did not receive merchandise as ordered because the merchandise was missing, damaged, or incorrectly labeled. GENCO's inability to ensure accuracy of its process created the opportunity for an even more pernicious problem: the possibility that some salvage dealers could made fraudulent claims about merchandise that GENCO sent correctly. Neither GENCO nor the RC had an effective way of verifying or disputing the accuracy of such claims because they rarely had any barcode records on which to rely. The number of salvage claims, combined with the time and effort required to research such claims, had a direct financial impact on GENCO. This was especially true of claims for high-value items. Management opted to use RFID technology to counteract the mounting claims and increase the efficiency of the outbound dock operations.

**RFID Implementation**

In July 2004, GENCO decided to run an RFID pilot test at its McDonough RC for the outbound logistics link with salvage dealers. SHC sponsored this program because of the potential cost savings it could accrue from an expected increase in efficiency and the potential for a reduction in the number of claims at the RC. In addition, SHC believed that deploying this nascent technology could boost its image as a company on the cutting edge of technology and build its reputation in the marketplace.

Insert Figure 4 about here.

GENCO modified its outbound process to incorporate RFID. In the new process, it places the RFID tags on the pallets at the stretch-wrap machine, these tags include information about the pallet, its contents, order details, BoL numbers, etc. The advantages of using RFID tags for such an operation are multifold. These tags can help employees to locate lost pallets within the facility much more easily. Locating

pallets, however, is secondary to ensuring their correct loading onto trucks (Figure 4). To accomplish this, GENCO has equipped each forklift with an RFID reader and a screen. These signal to the operator whether the accompanying BoL includes the loaded pallets; they alert the operator immediately if a pallet is about to be placed on a wrong truck or if the number of pallets in the shipment is incorrect. Warnings include a flashing alert message on the forklift screen and other visual and audio warnings.

 The implementation was not without challenges. This nascent technology was not "plug-and-play," and the lack of widespread industry expertise in implementing RFID forced GENCO to experiment and arrive at its own solutions to practical implementation challenges. GENCO commissioned all its equipment from Intermec; tags and readers were initially ISO compliant; more recently, they are EPCGlobal GEN2 compliant. One early challenge was a high proportion of "dead tags" that readers could not interrogate. GENCO and Intermec worked closely to find and solve problems. For example, they found that the tightly wrapped coils in which tags were packaged created cracks in the tags; this resulted in dead or unreadable tags and caused high failure rates. This problem has diminished substantially over time—tag failure rates are now less than 0.5 percent.

Positioning tags and readers such that they comply with operational needs as well as ensure accuracy was another challenge. GENCO's approach was to place the RFID equipment on the forklift instead of using dock door portals. This setup allowed GENCO to verify that the forklift driver was selecting the correct pallet. GENCO also placed RFID tags at dock doors to verify that the driver was using the correct door. The initial approach was to place the RFID tags waist high on cement columns near the entrance to the doors. However, the readers, which were installed on the forklifts, would sometimes interrogate tags moving into adjacent doors. GENCO then tested an alternative approach—placing tags on the bottom of the door. Although this improved the operational process, the forklifts sometimes hit or knocked off the tags. Finally, GENCO placed environmentally sealed RFID tags on the outside of the door frame; this solved both the problems of false reads and damage to the tags. Interestingly, although the RFID implementation had technical changes, the actual operations and processes changed very little.

Indeed, it would have been difficult to isolate and identify the impact of RFID if GENCO had made changes in its processes at the same time.

GENCO also upgraded its software applications to take advantage of the RFID-generated data. It has now moved to Gen2 RFID equipment, which promises better encryption, faster reads and writes, and transparent software compatibility. However, these changes to Gen2 equipment have required changes to the middleware, hardware, and software applications.

**Benefits of RFID Implementation**

The advantage of RFID—as opposed to barcodes—to the outbound process is immediately apparent. RFID ensures automatic confirmation of the delivery of each pallet to the right truck as per the BoL; it also ensures that the correct number of pallets have been shipped for each BoL/order. In principle, barcodes could accomplish this as well; however, this is not true in practice because barcodes are often difficult to read and require the human intervention of scanning. Because of the additional time needed for manual scanning, the proper use of barcodes is rare. RFID tags require no intervention; therefore, a company can use them to monitor material flow at each processing point and ensure that no errors occur. Any mistake causes the generation of a message to the appropriate employee; the tags thus act as "silent supervisors" ensuring that no errors slip by. RFID potentially reduces costs of handling claims significantly by:

1. Reducing warehouse-employee errors at the loading dock;
2. Reducing time to research claims—GENCO maintains a time-and-place stamp showing when and where it has sent the shipment; accordingly, it can verify the occurrence of an error and pinpoint whether GENCO or the shipper was responsible for that error;

3. Providing a disincentive for salvage dealers to place fraudulent claims. GENCO can now instantly access shipment-detail records from its database; this ensures that a dealer cannot argue about a "fictitious" claim.

A cursory look at the data collected revealed that the number of claims during the 12 months following the RFID implementation was far lower than the number of claims in the prior 12 months. Inspection of the notes attached to the claims made after the implementation shows that all these claims were for damaged items or items for which the stated and actual item description did not tally. (Note that not all claims, particularly those made prior to the RFID implementation, include notes. Thus, we could not always ascertain the reason for the claim. Because of this inconsistency in the claim description, we could not include the claim reason as an explanatory variable. This factor is likely to be captured in the error term in our regression. However, it is unlikely to be correlated with either RFID implementation or other explanatory variables and hence will not bias our results.) Specifically, the claims incidence decreased by 54.29 percent (note that we are masking exact return levels to protect confidentiality) and the dollar value of claims decreased by 29.7 percent. While these results are promising, there are some other issues to address before we can draw a definitive conclusion.

One potential concern with such an aggregate analysis was that it did not control for changes in the mix of products in a BoL before and after the RFID implementation. For example, the electronics and hardware product categories have high incidences of claims. Figure 5 shows the percentage change in the number of claims for different product categories.

Insert Figure 5 about here.

To control for changes in volume before and after the implementation, we normalized these claims data by sales volume. Figure 5 demonstrates that declines in the incidence of claims after the implementation were widespread across the electronics, hardware, and others categories. Only the hardgoods category

experienced an increase in claims; however, this increase was small and statistically insignificant. While the data in this figure suggest that our results are not due to changes in product mix, we required further analysis.

In addition to concerns about changes in product mix, the volume at the RC varied because of seasonal factors; the warehouse had to cope with high volumes of returns following the busy holiday shopping season. Reductions in volume may also contribute to reduced claims. Clearly, if we were to isolate the effect of RFID, we had to control for the product mix, seasonality, and other relevant factors. Otherwise, we ran the risk of claiming benefits that are at least partially due to factors not related to RFID, and misinterpreting the results. To do this, we pursued a regression analysis that controlled for differences in shipment composition, process complexity, and salvage-dealer characteristics. We describe this analysis in the next section.

## Disentangling the Impact of RFID – the Thought Process

In this section, we describe our process for analyzing how RFID influences the probability that a salvage dealer will issue a claim on a given shipment. The isolation requires controlling for shipment characteristics, salvage-dealer profile, and process complexity. This approach is consistent with previous empirical literature on measuring returns from technology deployment (Barua et al. 1995).

In the analyses that we report here, we focus on RFID's impact on the likelihood of claims. In subsequent analyses, the data revealed that once we accounted for RFID's impact on the likelihood of a claim, RFID had no effect on claim value. This suggests that its primary impact is on the claims incidence only. For brevity, we do not report the results of the claim-value analyses here; however, they are available from the authors upon request.

We now describe the thought process behind our analysis. First, we considered the factors—the explanatory variables—that could influence the probability of a claim occurrence. These could be

process, product, and dealer related. We elicited these factors during discussions with RC personnel. Certain types of products, such as electronics, were more prone to claims because of their very nature in terms of volume or value. Likewise, the workload at the center increased substantially during shopping seasons (e.g., Christmas, Thanksgiving, and bonus days) when the return levels surged. These high volumes required hiring temporary staff. Because such staff was sometimes less familiar with all the correct quality-assurance processes than the permanent staff, this could lead to errors. In addition, we saw that some dealers filed claims more often than others. Based on our interviews, we compiled all the potential claim drivers and placed them into four categories: transaction intensity, shipment characteristics, buyer characteristics, and RFID.

*Transaction intensity at the RC*: We hypothesized that the more intense the shipping activity at the center, the greater the chances of dockworker errors. In turn, more errors would lead to more claims by dealers. To measure transaction intensity, we collected data on the monthly shipment volume (i.e., load) at the facility. This captures the throughput from the outbound bays and directly measures the transaction intensity at the center.

*Shipment characteristics:* The shipment characteristics that we felt would most likely affect the chances of a claim were the total shipment value, the average item value, and the type of items in the shipment. A claim is more likely if the value of the shipment is large than if its value is small; the customer is more likely to disregard the latter. Similarly, a claim is more likely if the average value per item is higher; otherwise, the costs and hassles associated with the claims procedure could render a claim unprofitable. For the total shipment value, we use the offered shipment value by the salvage dealer for our analysis because it captures the actual payment made for the BoL.

Value density is the average value of the individual items in a shipment. The accounting staff at GENCO indicated that value density also drove claim rates. We computed this from the ratio of (offered) shipment value to the number of items in the shipment.

The number of claims was highest in the electronics category, which seemed more prone to claim filing. Interviews at the site confirmed this. This meant that the BoLs associated with the electronics category, because they have a higher value and because salvage dealers are more likely to inspect them more thoroughly, resulted in a higher number of claims. We created a dummy variable to control for the presence of electronics in a shipment. This variable is equal to 1 if the shipment category is electronics and 0 otherwise.

*Incentive issues with the salvage dealer*: GENCO does not closely monitor the transaction completion with a salvage dealer; consequently, agency issues arise. Salvage dealers may falsely claim nondelivery of pallets and/or items. We expected that a salvage dealer who has had a long-term relationship with GENCO would be less likely to make a fraudulent claim than one who has had a relatively short relationship. In addition, we felt that the salvage dealers who have made claims in the past would be more likely to make claims in the future, ceteris paribus. Habitual claimants will capitalize more often and seek fraudulent claims; they may also be the dealers who inspect more closely. Hence, we used prior claims and prior shipments as variables to capture the history of the business relationship with GENCO and to determine the impact of the dealer profile on claim rates.

*RFID*: We included RFID as one of the variables that affect claims. We believe that we can attribute the reduction in claims rate from RFID to two sources. The first is the process efficiency arising from alerts triggered when workers commit errors; this allows instantaneous problem resolution. Tags serve as an electronic "pokayoke"—the Japanese term for foolproof processing. Fewer errors then lead to lower claims. Secondly, RFID reduces claims because of its "deterrent" effect. Agency issues decrease because the tags provide monitoring by the principal; any fraudulent claim is more likely to be dismissed because tags record every movement of the goods. The combined effect—process efficiency and deterrence—imply that the claim rate should fall. Note that it is difficult for us to isolate the two sources of improvement because this would require detailed data and history. In addition, because of confidentiality and legal issues, the elaboration is sensitive.

To capture the effect of RFID, we deployed a dummy variable to indicate whether the order date was before or after the RFID implementation (July 2004). We hypothesized that error rates would be significantly lower after the implementation. Thus, we expected RFID to have a negative impact on the probability of claim, once we controlled for all the other factors.

Insert Figure 6 about here.

**Data Description and Research Approach**

We collected archival data from the shipment logs and the claim-settlement databases that GENCO maintains for this RC. The data included shipment and claims records from July 2003 to December 2005. The final data sample included 5,607 records for 475 salvage dealers with a wide range in the number of transactions—the highest number was 785 for one salvage dealer.

While the shipment data was readily available in a digital format, records of claims were available only in paper format. In general, these data did not include information on the type of claim filed (e.g., missing or damaged goods). As a result, we were unable to distinguish the effects of RFID on operational efficiency from its deterrent effect on fraudulent claims.

Claims in our sample were made shortly after the shipment date. When we checked the time lag between the shipment date and claim date in our data, we found the maximum time lag to be two weeks. GENCO confirmed that the lag in claims reporting is typically brief because salvage dealers make payments in advance of salvage pick up.

The shipment data include the BoL and order number, the dollar value of each BoL, order-transaction date, category of items in the BoL, the total number of pallets and items in the BoL, and buyer-specific data such as the buyer's ID, name, etc. The claim data include the BoL against which the claim was made. We first merged the claims and the shipment data together based on the BoL. Based on our claims

data, we then created a dummy variable to flag if a claim was filed against that particular BoL. Therefore, the unit of observation in our analysis is a BoL (i.e., we examine the likelihood of a claim against a particular BoL). As noted above, we generated other variables, such as GENCO business history and relationship, to control for the outbound process complexity and the salvage-dealer profile.

Insert Figure 7 about here.

Figure 7 shows the distribution of these variables before and after the RFID implementation using box plots. The middle line of the box indicates the median, while the top and bottom edges indicate the first and third quartile. The edges of the whiskers indicate the highest and lowest values that are not outliers. For the purpose of confidentiality, we mask sensitive information such as the actual number of claims, and the shipment and claim value. Before we performed our regression analyses, we examined whether the distribution of any of our explanatory variables changed concurrently with the RFID implementation. We found that this was not the case. The mean of total prior claims increases over time because this is a cumulative variable. Similarly, for the dummy variable electronics, we compared the means before (0.2506) and after (0.2483) the RFID implementation. In total, our sample included 5,607 observations—62.1 percent of them are after the RFID implementation.

Since our dependent variable was binary, there were a number of concerns with using a linear regression model for this analysis (Maddala 1983). Instead, we used the traditionally prescribed probit model. We tested the model with logit as well as complementary log log regression. As expected, the coefficients and their signs, as well as the significance, were unchanged with respect to the probit regression. We also found the marginal effects for both logit and complementary log log models to be similar to the marginal effects of the probit model. The probit model estimates the probability of a claim occurrence for any BoL profile. See Maddala (1983) for additional discussion of the probit model. (Note that the standard deviation in some of the explanatory variables is quite large. Hence we use log(Offer),

log(Value Density), log(Total Monthly Shipments), log(Buyer's Total Prior Shipments), and log(Buyer's Total Prior Claims) in our regressions.)

## Results and Analysis

In this section, we present the results of our estimated probit model. We first present the marginal effects of each of the variables in the structural model (Figure 6). Table 1 shows the results of the probit model and parameter estimates.

Insert Table 1 about here.

Marginal Effects: Since the coefficient estimates of the probit model are difficult to interpret, we examined how changes in each of our variables individually influence the likelihood of a claim. In our analysis, we examined the marginal effect of RFID, which we define as the percentage change in the likelihood of a claim from a change in each of the variables. For example, the marginal effect of RFID use quantifies the change in the likelihood of a claim filed for a typical BoL before and after RFID installation. In the computation, we use the average value for all the control variables so that we have an 'average' BoL profile.

$$\text{Marginal Effect of RFID} = \frac{\Pr(Claim|RFID,\ Other\ \ factors) - \Pr(Claim|No\ \ RFID,\ Other\ \ factors)}{\Pr(Claim|No\ \ RFID,\ Other\ \ factors)}.$$

Likewise, the marginal effect of the "electronics" dummy variable provides the percentage change of the likelihood of a claim filing for a BoL of electronic products compared to a BoL of non-electronic products. We similarly calculated the impact of changes for each of the other variables on the likelihood of claims. For instance, we assessed the marginal impact of the total shipment value on likelihood of claims by computing the percentage change in magnitude of the probability of a claim filing when the shipment value increased (by one-half standard deviation).

We found that, other than RFID, only two variables (Value Density and Total Monthly Shipments) had a significant effect on claims. Using the procedure described in the prior two paragraphs, figure 8 shows how changes in RFID and other variables influence the likelihood of claims. We summarize the results below.

- The use of RFID reduces the likelihood of a claim by 83 percent.

- A one-half standard deviation increase in the value density, equivalent to an increase of 49.59 percent, increases the likelihood of a claim by 35.1 percent.

- A one-half standard deviation increase in the total volume of monthly shipments at the warehouse, equivalent to a 1.92 percent increase, increases the likelihood of a claim by 19.3 percent.

Insert Figure 8 about here.

Clearly, RFID significantly reduces the probability that a claim will be filed when compared to other variables. However, note that once we account for RFID's impact, the impact of changes from other variables—other than value density and total monthly shipments—is not statistically different from zero.

Slicing the data: We also examined how the impact of RFID on how claims incidence varies with changes in other factors. Our intent was to assess the interaction of RFID with other variables, e.g., how RFID affected electronic items as compared to nonelectronic items at varying workloads at the RC. We present some of these results below. For confidentiality, we mask the actual probabilities; instead, we show the normalized probability, which we define as

$$Norm.\Pr = \frac{\Pr(Claim \mid RFID, Other\ factors)}{\Pr(Claim \mid No\ RFID, Other\ factors)}.$$

In other words, these results show the likelihood of a claim with RFID relative to that without RFID, controlling for other factors. The insights are largely as we expected. For a shipment of low-value, non-

electronic items during a period of low monthly traffic, this ratio is quite low: the probability of a claim with RFID is only 13.7 percent relative to one without RFID, i.e., the normalized probability is 13.7 percent. For a shipment of non-electronics items of average value during a period of average monthly traffic, this ratio rises to 18.02 percent. For a shipment of high-value electronic items during a period of high volumes, this ratio is 21.89 percent. Therefore, we prove that RFID is effective in reducing claims both at lower end of the shipment spectrum and in the worst-case scenario. We hypothesize about some of the drivers of these results below.

Insert Figure 9 about here.

**Figure 9: RFID implementation reduces the probability of a claim; however, it may have less impact as the total BoL value increases.**

Figure 9 plots the ratio of the probability of a claim with and without RFID against the log of total BoL value at high monthly volume. First, we see that at high volumes and at high total BoL value, RFID's impact was less pronounced. For example, the probability of a claim decreases by 81.9 percent when the BoL value is 22,026 (log(BoL Value)=10) and by 84.4 percent when the BoL value is 148.4 (log(BoL Value)=5). One possible reason for this could be that at higher loads, GENCO employs more temporary workers who are not as experienced as the permanent staff in the RC processes and operations. This could lead to errors that RFID cannot control, or improper use or interpretation of RFID technology. Second, because of time constraints in high-volume situations, the forklift operators may not wait for the confirmation that the reader has read the RFID tag correctly.

We also plotted the normalized probability of claims against the log of average value per item (value density) in a BoL for different volumes and found a similar trend. Figure 10 shows these results.

Insert Figure 10 about here.

For below-average, average, and above-average monthly shipment volume at the RC, the probability ratio with and without RFID increases marginally as the average item value increases. The higher intercepts indicate that an increase in process complexity or transaction intensity, as measured through the increase in monthly volume, increases the ratio of the likelihood of claims with and without RFID. In short, RFID reduces the likelihood of claims for all shipments; however, this is more evident for lower-valued items at low volumes than for higher-valued items at higher volumes.

RFID was most effective for low-value BoLs shipped at low volumes. One possible reason for this could be that errors, as opposed to breakage, fraud, or inaccuracies in the BoL, could cause a larger proportion of claims for such low-density shipments; therefore, RFID could cause a larger decrease in claims. In addition, at lower volumes, because of shorter time constraints, the forklift operators are likely to be more patient in waiting for correct RFID reads. Thus, RFID was more successful.

As our probit estimates indicate, the average value of an item in a BoL is more significant in predicting the claims incidence than the total value of the BoL. To understand why, consider this example. Suppose that the BoL consists of 10 televisions with a total value of $20,000 and an average price of $2,000. Contrast this with a hardware order that consists of 10,000 spare parts with a total value of $20,000 and an average price of $2. Clearly, if a single unit is missing or damaged from each order, there is a higher likelihood of a claim in the first instance.

Similarly, the total number of shipments in a month affects the likelihood of claims. A higher total indicates that the process was more complex in the given month; therefore, we can expect a higher error rate and a higher claims incidence.

When we performed sensitivity analysis for all the significant variables in our estimated model, we developed the following key insights:

1. The likelihood of claims falls significantly, to a low normalized probability of 13.7 percent, after RFID implementation.

2. Changes in other control variables, such as monthly shipment volume, value density, shipment category, or total value, do not affect the impact of RFID deployment. The normalized probability in the most extreme scenario, electronic goods BoL of above-average value shipped at above-average volumes, is still lower than 20 percent.

Although we have depicted the significant impact of RFID on claims, these are only the immediate tangible benefits that GENCO saw. Other benefits were harder to quantify or measure. One such benefit is the operational efficiency that RFID introduces as both the technology and the learning curve improve at the facility. Because of lower errors, customer satisfaction also increases as salvage dealers receive their goods as per the BoL.

The benefits of RFID are also highly visible to the workforce. During a visit to the RC, we saw numerous instances in which an alert prevented the sending of an order without all its pallets correctly loaded or stopped a forklift driver from driving into the wrong truck bay. As of this date, we have not been able to record or capture such benefits; therefore, we do not see the absolute impact of RFID. Consequently, we have significantly undercounted the RFID benefits that we present in this paper.

**Conclusion and Discussion**

Like any new technology, RFID has received its share of bouquets and brickbats. Despite major advocates such as Wal-Mart, the attitude of organizations—including other manufacturers and retailers—has remained taciturn at best. We conducted this study to ascertain whether RFID does indeed provide benefits—specifically for a logistics company—and if so, to identify the business drivers of these benefits. At a GENCO RC, our field site, we examined the reverse logistics of its outbound operations. The rationale for this particular deployment was the direct impact of the technology to

improve operational efficiency for these operations, and in turn to enhance financial performance and customer satisfaction. Prior to the RFID implementation, operational inefficiencies resulted in many claims from GENCO's customers because of the erroneous processing of shipments. Moreover, GENCO was unable to identify whether these claims were a result of errors from its own warehouse staff or from shipper mistakes. A false claim could potentially slip through because auditing every claim was time consuming, costly, and not always feasible. Although GENCO barcoded all its outgoing shipments, technical and human limitations prevented the company from capturing the benefits accrued from time-stamping each step. GENCO then judiciously identified technology-based solutions and the need for RFID tags, as opposed to other measures. Management hoped that the deployment of these tags would unobtrusively record each shipment, alert operators of errors instantly, and help in resolving claims because it would be possible to retrieve data from a real-time tracking system.

Management thus challenged us to determine if the technology deployment had indeed paid off from a business process perspective. We conducted rigorous statistical analyses of the claims and shipment data. Using the claims incidence as our dependent variable, we estimated a probit model. Our explanatory variables included RFID, transaction-intensity-specific parameters such as total monthly shipment volume at the facility and shipment-characteristic variables such as the shipment value, average item value, and shipment category. We also included buyer-specific parameters such as prior transaction history and prior claims history to control for incentive issues.

Our analyses confirmed that the RFID deployment substantially reduced claims from salvage dealers. Not only did the process become more efficient, but RFID might have acted as a deterrent to fraudulent claims. Our numbers showed that after the RFID deployment, GENCO was able to eliminate the necessity of resolving disputes with dealers. The information intelligence that RFID provided raised efficiency, and potentially honesty, in the outbound logistics process.

Specifically, after the RFID implementation, the claims incidence fell by 83 percent. The deterrent effect of RFID on claims, as we discussed earlier, was robust enough to withstand other model specifications. We found RFID to be the solitary independent variable that explained 45.12 percent of the variation in the data in comparison to the full model. Compared to other control variables, RFID emerged as the strongest parameter, leaving no doubt that the technology is the key driver in the improvement of process performance.

Our study does have its limitations. We could not separate the impact of RFID on the overall improvement in operational quality and the agency issues with the salvage dealers. Furthermore, due to confidentiality reasons, we were unable to disclose the full financial impact. GENCO management expects the long-run ROI to be significant because of declining tag costs and substantial intangible benefits. Tag costs have fallen from $1.09 per tag at the start of the implementation in July 2004 to $0.18 in November 2006. GENCO's floor and claims operations were also streamlined. Because personnel spent less time tracking pallets or researching claims, there were both tangible cost benefits and an increase in employee morale. In addition, GENCO is using this implementation as a marketing tool to generate new business.

RFID's benefits, as measured through its impact on the claims incidence, were only part of the exciting findings. There were significant intangible RFID benefits as well; for example, the worker and supervisor satisfaction and comfort level with RFID was very high. This shows that if technology can assist human decision making by making the process pokayoke, the gains can be significant, ensuring smooth operations and making Crosby's goal of achieving zero defects attainable. (For details of Crosby's quality framework and the zero-defect model, we refer the reader to Crosby, 1979.)

These benefits will only increase as the cost of RFID hardware, including tags, decreases and will provide organizations with increasing incentive to deploy RFID at more micro levels. Encouraged by these results, GENCO has expanded its RFID deployment to all of its outbound operations at the

McDonough RC. We anticipate that its entire network will benefit from the greater visibility and monitoring of the value chain.

We also foresee that GENCO will leverage the data gathered by the RFID tags to provide business intelligence that will enable the company to be more proactive in managing its logistics process. The results that we documented in this study are the initial returns that GENCO was able to gain by rapid deployment. The implementation planted the seed for wider deployment; we will watch with keen interest to see the next round of benefits that GENCO will harvest. GENCO has shown it is a learning organization and that it can leverage business technology to transform its business processes to create more value for itself and its customers.

Our study underscored the potential of RFID for today's businesses. RFID not only provides tracking of goods through the supply chain, but also provides the potential for an organization to share this information with its partners along this chain. This takes information integration beyond ecommerce or traditional EDI. We need to develop an understanding of where and when we can apply RFID, and the information empowerment it provides, most profitably. We believe that this understanding will lead to reduced costs and enhanced value for all stakeholders.

# How do Project Managers' Skills Affect Project Success in IT Outsourcing?

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## ABSTRACT

What skills do project managers (PMs) need, and how do these skills impact project success in IT outsourcing? In this study, we seek to identify what factors impact IT project outcomes, such as costs and client satisfaction, given the project characteristics and PM's hard and soft skills. We examine data collected from a field study conducted at a major IT service provider in India. Our results suggest that while hard skills such as technical or domain expertise may be essential in a PM, soft skills such as tacit knowledge of organizational culture and clients are the most important contribution that PMs bring to a project. Soft skills not only improve project outcomes directly, but they also help when projects have more complexity, more uncertainty, or less familiarity. The results are robust to different specifications.

*Key words*: IT outsourcing, Project Management, Soft Skills, Hard Skills

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# How do Project Managers' Skills Affect Project Success in IT Outsourcing?

## 1. Introduction

Information Technology (IT) outsourcing is a growing industry. More and more firms are outsourcing their IT assets to external vendors. Typically, the IT outsourcing activities are formalized as different projects, which may involve building a new software application, or maintaining an existing software application. From both the vendors' and the clients' perspective, the allocation of the right person to lead a project is very important. For the client, having the right person in charge helps ensure better project outcomes in terms of higher software quality, lower risk of project failure, and more peace of mind. For the vendor, better project management reduces the risk of project failure and translates to favorable project outcomes like lower costs and higher client satisfaction.

Selecting the right person for leading a software project is a challenging task. For larger vendors – who have access to a myriad pool of talent and a vast divergence in projects – this is especially important and especially difficult to do well. This selection predicament is compounded in the case of IT outsourcing projects. An inadequate approach to project resource assignment can have severe consequences. For example, a common characteristic of failed projects is the lack of effective project management (for example, see Applegate et al. 1996). Poor project management can not only impact a firm strategically, economically, or culturally; but may also jeopardize client relationships, result in project cost overruns and tarnish the project team's spirit. Over the long term, the goal for an organization is to build capabilities that lead to an improved cost structure, and thus the resource allocation can be viewed as a strategic tool (Venkatraman and Prescott, 1990).

While the need for selecting a suitable project manager is well recognized, it has been fulfilled neither by existing literature nor by the industry. What skills should a PM bring to the project, and how do these

skills affect project success? What kinds of projects require more or less of these skills? We examine these questions in our study.

The goal of this research study is (i) to identify the kinds of skills needed for effective project management, and (ii) to develop a consistent approach to matching project characteristics with project managers' skills. Our study brings together two strands of research: literature related to software project management and IT personnel skills; and contingency theory and person-environment (PE) fit literature with a focus on software project management.

Lee et al. (1995) suggest that IT professionals need to have multi-dimensional skills; they should be well versed in not only technology and application domain but also in interpersonal and management skills. Kirsch (2000) has highlighted that successful project management requires both hard and soft skills. Hard skills comprise technological skills, domain expertise, experience – including overall IT experience as well as project management experience, and project management skills such as planning, monitoring, risk management and coordination. Soft skills are intangible, and are primarily concerned with managing and working with people and fostering inter- and intra- organizational "relationships." These include but are not limited to organizational knowledge, tacit knowledge in handling people within the organizational structure, leadership and management skills, and customer handling skills (Becker, 1975; Lee et al., 1995; Kirsch, 2000). Thite (1999) has emphasized that both technical and transformational leadership skills are required of IT managers. As prior research has found (e.g., Byrd and Turner, 2001), both hard and soft skills are necessary in IS professionals to achieve higher performance. However, to the best of our knowledge, there has been no study that measures the direct impact of the PM's skills, especially soft skills, on project success.

Prior literature has examined at the congruence between personnel's professional skills and project success (e.g., Pagell et al., 2000). This approach inherently assumes that there is a congruent relationship between the performance, organization, and context, and thus predicts a unidirectional effect between

skills and performance. But does allocating a higher skilled PM always ensure higher project success? While the direct impact of these skills is anticipated, we need to explore how the fit – between PM skills and the project characteristics – impacts project success. For example, Pagell et al. (2000) find that the impact of fit between skills and environment on performance is more significant compared to the direct impact of skills on performance.

Person-environment (PE) fit explores an individual's fit with the work environment: with the job or the organization (Kristof-Brown et al., 2005). Congruence between a person and her job is deemed desirable, but its conceptualization is a challenging task. In software engineering domain, PE fit takes into account various distinguishing characteristics of software, including project life cycle and uncertainties in various phases (Martin et al., 2004). Extant literature has often used difference scores in specifying this fit, where the scores consist of some deviation between the two constructs that measure the desired versus the actual characteristics (e.g., Vancouver and Schmitt, 1991; Venkatraman and Prescott, 1990). Resource allocation requires a matching of project characteristics with the skill sets of the PM. Such a matching can also be viewed as a strategic choice in response to the (project) environment. Venkatraman and Prescott (1990) suggest that any deviation from an optimal pattern of resource allocation should be significantly and negatively related to performance. Edwards and Parry (1993) advise the use of polynomial functions as an alternative to the difference scores. In contrast, contingency theory (Thompson, 1967), which implies fit through interaction effects (e.g., Drazin and van de Ven, 1985; Shenhar, 1999) suggests that while congruence between skills and performance is desirable, a fit, that is, an interaction between skills and organizational characteristics, should be even more beneficial. As Shenhar (1999) elucidates, projects vary in terms of technology uncertainty, scope, and complexity; hence it is naïve to assume that PM's skills will impact all projects equally. This motivates us to explore the contingency aspect of PM's soft skills with respect to project uncertainty, complexity, and familiarity in the current study.

While IS professionals' skills and their contextual fit have been explored with respect to project performance (e.g., Martin et al., 2004), we provide a unique perspective of these in the specific context of IT project management. We especially focus on the skills that a PM brings to the project. We first conceptualize hard skills as task familiarity. We then develop a model that links a PM's task familiarity and soft skills to the project characteristics. We explore the direct impact of these skills on project performance. We further explore the contingent impact of soft skills on project performance measures such as project costs and client satisfaction, given project characteristics.

While prior research has primarily used survey data to measure the fit and performance, we use detailed archival data and critical incident methodology to answer our research questions. Our data come from a leading software vendor, and include project and personnel (PM) level archival data from 530 projects. In addition, we have PM level survey data that consists of survey responses from 209 PMs. We use archival data to measure hard skills. We employ the critical incidents methodology (Wagner and Sternberg, 1985, Joseph et al., 1999) to assess soft skills. Our data and research setting allow us to calibrate not only the resource allocation issue but also to study (i) the differing impact of hard and soft skills on various project outcomes, and (ii) variable effect of soft skills on different project characteristics such as uncertainty, complexity and familiarity

We find that after controlling for project characteristics, PM's hard skills and experience, and team attributes, a PM's soft skills have significant favorable impact on project performance. This is an especially important finding in the case of IT outsourcing projects, where both project costs and client satisfaction can be important determinants of vendor profits and market share. We also find that hard skills can improve project performance, but the impact is less compared to that of the soft skills. With respect to the interaction effects, we find that PM's soft skills ameliorate costs for larger projects. Interestingly, we find that soft skills have a substitutive effect on project duration and team familiarity. Our results indicate that projects with longer duration or with higher team familiarity require lower levels of PM's soft skills, because they may need less coordination efforts (Kraut and Streeter, 1995;

Espinosa et al., 2007). Similarly, we find that hard skills and soft skills are substitutes of each other, thus a PM with higher soft skills may effectively manage a project even when she is not familiar with project's technological or domain requirements.

Although prior literature has examined measures of skills and how these fit with the job environment (Edwards and Parry, 1993; Kristof-Brown et al., 2005), there has been no research that examines how different kinds of PM skills impact software project outcomes. We contribute to the existing software project management literature in the following ways: (i) we incorporate both archival and survey measures of PM skills in our analysis and relate them to project performance, (ii) we provide unique empirical evidence of the importance of soft skills in a PM, and (iii) we extend the contingency theory by showing the contingent effects of soft skills for different kinds of IT projects.

This paper is organized as follows. In the next section, we present our theoretical framework. The methodological section describes both our qualitative and quantitative data sets and our empirical strategy. We next present our results and analysis. Finally, we discuss the results and conclude with managerial implications from this study and suggestions for further research.

## 2. Theoretical Framework

The conceptual model that we employ in this study is shown in Figure 1. We utilize the contingency theory (Thompson, 1967; Nidumolu, 1996; Shenhar, 1999) and person-environment (PE) fit (Edwards and Parry, 1993; Kristof-Brown et al., 2005) literature to drive our theoretical model. Here, the fit is defined as the matching of PM characteristics, and the project environment. Structural contingency theory suggests that a fit between an organization and its environment is an important predictor of organizational effectiveness (Lawrence and Lorsch, 1967; Shenhar, 2001; Barki et al. 2001). Pagell et al. (2000) have demonstrated a strong link amid the fit between job requirements and employee skills on performance. A software project can be viewed as a "temporary organization within an organization,"

and hence we propose that the fit between a project and its PM would have a significant impact on project outcomes. The notion of fit is also consistent with practical intelligence (Sternberg and Hedlund, 2002), utilized by individuals to harness their skills to the work environment, and is essentially tacit in nature. For our analysis, we analyze the impact of the PMs' hard as well as soft skills on the projects. Because projects as well as PMs vary in their characteristics in our data set, we are able to identify the impact of these factors on project performance.
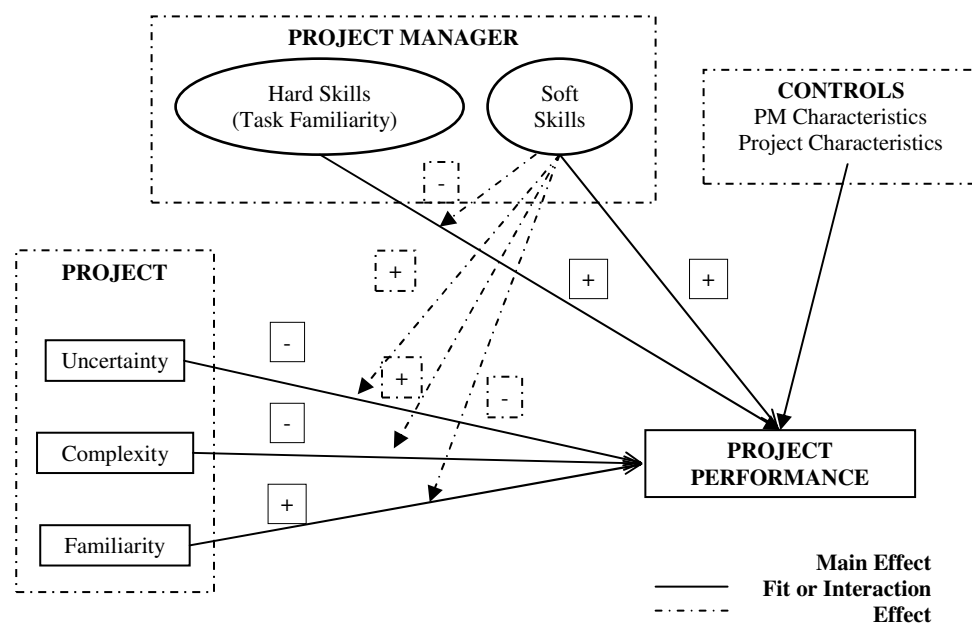


**Figure 1: Conceptual Model**

IT projects, especially in the outsourcing world, are complex (Kirsch, 1996; Weinberg, 1998) and require multifaceted management skills. A PM has to manifest not only project management related skills (Kirsch, 2000), but also technical and domain expertise as required by the project (Thite, 1999). Project management activities include but are not limited to defining project scope and requirements gathering, managing resources and relevant training issues within a project, advising about technical architecture, identifying specific and general project management practices and escalation procedures,

estimating project schedule and budget, ascertaining and managing risks within a project, preparing risk mitigation plans, ensuring adherence to organizational quality framework, effectively managing change control, and reporting project status to various stake holders (Duncan, 1996; Martin et al., 2004).

Software development or maintenance requires coordination within the project team (Kraut and Streeter, 1995). In case of IT outsourcing, PMs also interface with the client (Hirscheim et al., 2002; Lacity and Willcocks, 2001). More often than not, IT project teams are distributed geographically (onsite and offshore), making coordination issues a bigger challenge (e.g., Espinosa et al., 2007). PMs are thus expected to (i) provide technical and domain leadership, (ii) manage geographically and organizationally distributed teams, (iii) interact with the clients, and (iv) coordinate with all the stake holders across inter- and intra-organizational boundaries. Hence, we first posit that a PM needs a judicious mix of hard and soft skills for effective project management and improvement in project performance. Next, we explore the contingent aspect of IT projects. We conjecture that a PM's management or soft skills will moderate the impact of project complexity, uncertainty or familiarity on project performance.

**Direct impact of PM's hard and soft skills**

The matching or fit between a PM and project extends not only to the technical or domain skills as enumerated above, but also to other general project-PM profile attributes, such as prior exposure to the methodology experience (Swanson and Beath, 1990). A PM is likely the most senior person within a project. She is often perceived as a sounding board for technical and architectural decisions made for the project. In addition, as more strategic functions are IT enabled and outsourced, the PM is also expected to demonstrate a deep knowledge of the business objectives of the IT system being provided (Bloom, 1996). We conceptualize hard skills as task familiarity, that is, we incorporate the "fit" between the hard skills needed by the project and what the PM brings on board. As an example, a PM who is an expert in object oriented technology may not be able to successfully lead a project in say, mainframe technology. Similarly, domain experience may also be equally necessary in the PM. Prior literature has shown that

task familiarity helps in improving performance (e.g., Campbell, 1988; Goodman and Leyden, 1991). Prior exposure to the project characteristics such as technology, domain, or methodology would make the current task more familiar to the PM, and hence improve performance (for example, see Boehm, 1981; Brooks, 1995; Curtis et al., 1988; Banker and Slaughter 2000). Task familiarity is especially important in the case of software project management. As Kirsch (2000) and Thite (1999) suggest, PM should be able to take on the leadership role with respect to not only managing the project but also leading the technological initiatives. She should be able to advise team members as well as the clients on the various technology options available. She should understand the business needs of the application software being built or maintained, and realize its interdependence on other application software. Such familiarity would lead to lower coding and testing errors, improving efficiency and thus having positive impact on performance outcomes such as project costs, budget and schedule. A high task familiarity on part of the PM would make the client also feel more comfortable, knowing that the project is in good hands. Thus, the more hard skills a PM brings to the project, the greater would be the probability of project success. Thus, we expect that

**H1***: A higher level of PM hard skills is associated with an improvement in project performance outcomes, given project and team characteristics.*

While hard skills are essential in PMs, soft skills are especially important for PMs because of the nature of their role not only within the project team – requiring intangible management skills – but also in the organizational and client relationship structure. Lee et al. (1995) follow extant literature to argue that interpersonal and management skills are critical for the IS professionals, more so because of the boundary spanning role that these professionals must assume. In the outsourcing world, the PMs have to interact with many stakeholders. They have to not only manage internal project teams, their peers and superiors, but also interact with clients, using skills that are essentially non-technical in nature, and which may not be easily imitable. These include but are not limited to organizational knowledge, tacit knowledge in handling people within the organizational structure, leadership and management skills,

and customer handling skills (Becker, 1975; Lee et al., 1995; Kirsch, 2000). Within project teams, as individuals progress from technical roles to more managerial roles, these skills come into play, and help in effective project management. Wagner and Sternberg (1985) focus on skills that are tacit, and gained through experience rather than being taught in a classroom. They classify these skills as related to managing self, others, and career. They find that differences in these skills between a novice and an expert were consequential for career performance in professional and managerial career pursuits. Further, in the case of majority of the IT vendors, the PMs are rated on their performance on the project, hence we assume that the there exists an alignment between project outcomes and PMs' project performance. Because these goals are aligned, we argue that soft skills are correlated with PM's performance, and hence also with positive project outcomes. Thus, we hypothesize that,

**H2***: A higher level of PM soft skills is associated with an increase in project performance, given project and team characteristics.*

Do hard and soft skills impact project performance equally? Human capital theory distinguishes between general and specific human capital. General human capital comprises technological skills, domain expertise, experience – including overall IT experience as well as project management experience, and project management skills such as planning, monitoring, risk management and coordination. An individual can use general human capital to increase productivity in many firms. Specific human capital utilizes skills that are intangible, and may be specific to a particular firm or environment (Becker, 1975; Lee et al., 1995; Kirsch, 2000). We can thus broadly conceptualize general human capital as hard skills and specific human capital as soft skills. Slaughter, et al. (2007) show that IT managerial jobs require higher levels of firm-specific human capital compared to other IT jobs such as programming. Thus, as per the human capital theory, PMs with higher levels of firm-specific capital are expected to be more productive and hence more valuable compared to PMs with lower levels of firm-specific capital, given the nature of their job. As stated earlier, this notion is consistent with that of practical intelligence, where individuals need to tailor their skills to the environment (Sternberg and Hedlund, 2002). Hence,

we argue that PMs with higher levels of specific human capital, or soft skills, are more productive and should have better project outcomes. The core competency of a PM would not be general, but highly tailored to the environment, and hence specific. Researchers have also recognized that when it comes to poor performance of IS projects, technology is more often a secondary issue behind management, particularly of human resources (Sauer, 1993; Lowry et al., 1996). We expect the PM's soft skills to have a greater impact on project outcomes compared to hard skills. Thus, we posit that:

**H3***: PM's soft skills improve project performance more than her hard skills do.*

**Contingent impact of PM's soft skills**

IT projects vary in their characteristics, such as scope, complexity, uncertainty. They are ***dynamic, temporary and changing***, because of technological, functional or organizational constraints, and hence require active management. Shenhar (1999) suggests that projects should first be identified by their type, which should then affect the selection of project leaders and teams. For example, assembly line projects would require simple processes and tools, compared to more innovative projects. As IT projects grow bigger in size, scope, and complexity, coordination issues arise, and may hinder project progress. Because IT projects can theoretically be executed anywhere, they are especially prone to communication and coordination bottlenecks (Boehm, 1981; Curtis et. al., 1988; Brooks, 1995).

Kraut and Streeter (1995) further identify scale, uncertainty, and interdependence as the typical features of software development that inevitably lead to coordination problems, and which thus hinder project delivery and result in cost overruns. As IT projects grow in both size and scope, they require larger teams (Brooks, 1995). Moreover, software projects are non-routine activities that are inherently uncertain. Likewise, in a typical large project, there are several modules that need to be tightly integrated before the software can function. The scenario is even more complicated when project teams are dispersed across organizations or in different locations, as is the case with most IT outsourcing

projects. Although the extant literature has suggested ways and means to overcome coordination issues (for example, Crowston and Kammerer, 1998; Faraj and Sproull, 2000; Mookerjee and Chiang, 2002), coordinating software development remains a challenging task. Hard skills, that is, prior experience with project technology, domain, or methodology would not help a PM in such management tasks. Prior literature has also suggested the use of good software project management practices (e.g., Deck, 2001; MacCormack et al., 2003). Other factors, such as shared knowledge, understanding client needs, and practice implementation, along with coordination, ensure that project performance improves. However, these factors can only be fostered through better management and enhanced soft skills on part of the PM. It is the PM who fosters communication channels and common goal orientation within the team (Kraut and Streeter, 1995). Thus, the central role played by the PM in IT project management leads us to believe that PM's soft skills should moderate these project parameters in improving project performance. We elucidate these below.

**Project uncertainty**

IT projects typically are non-routine activities and may require new technology or methodology to execute well. Even a simple yet critical task such as requirements gathering is highly complex because the number of stake holders is large, and understanding of the system needs is imprecise. As Kraut and Streeter (1995) reason, more uncertain tasks are more difficult to coordinate. The information processing needs are higher; the participants must often reconcile conflicting information, and must synthesize and integrate such information to be productive. A PM's soft skills or management style will have an impact on how project uncertainty impacts project performance. We hypothesize that

**H4:** *Higher levels of PM soft skills will help more uncertain projects even more, given project, team, and PM characteristics.*

**Project complexity**

As IT moves closer to a firm's strategy and business core (e.g., Barua, et al., 1995), IT projects are increasing in both scope and size. In the case of IT outsourcing, as client firms do strategic sourcing, the number of stakeholders also increases (e.g., Aron and Singh, 2002; Craumer, 2002). For example, consider a client sourcing through multiple vendors for different modules that need to be integrated into single application software. Similarly, team sizes also increase with project scope and size (Brooks, 1995). Larger tasks are more difficult to coordinate because there are more people and elements to connect and manage. As software complexity increases, so does its interdependence with other software. Complex software development or maintenance requires an increased coordinative effort as developers and users need to interact more often and with more people (Wood, 1986). Prior literature has shown that an increase in complexity would lead to lower performance. At the same time, PM's soft skills should ensure smoother coordination leading to improved performance. We expect that

**H5:** *Higher levels of PM soft skills will help more complex projects even more; given project, team, and PM characteristics.*

**Project familiarity**

We have conceptualized and discussed PM's task familiarity and its impact on project performance earlier. While PM's hard skills play a role in determining project performance, team members also play a crucial role. In a complex cognitive activity such as software development, familiarity within the team should help in project performance. When team members are less familiar with each other, coordination effort required is greater, because familiarity can provide information about the task and task stakeholders (Espinosa et al., 2007). In contrast, when team members interact with each other over the course of a project, they develop a road map of expertise, that is, they know where and how to locate the expertise needed when in the next project (Boh et al., 2007). Because coordination is easier to accomplish in a more familiar team, we expect that PM's soft skills would help less familiar teams more. That is,

**H6** *Higher levels of soft skills will help less familiar project teams even more, given project and PM characteristics.*

## 3. Methodology

### <u>Research setting</u>

To empirically validate our hypotheses, we collected data from a leading IT outsourcing vendor in India. The vendor has expertise in software development and maintenance of complex IT business systems. The vendor provides IT services for multiple domains such as banking and finance, retail, telecommunications, etc. The vendor deploys stringent quality processes and has been assessed at CMM level 5. The organizational policies with respect to project management are thus perceived to be flexible yet measurable.

The data are from 530 IT outsourcing projects executed between 2002 and 2006 and involve 209 project managers. The data include both archival and survey data. We now describe how we measure key variables as well as the controls used in the model.

### <u>Archival data</u>

We collected project level financial, allocation, project characteristics, and personnel data. The financial data include project costs, profits and operating margins in USD.[1] The allocation data are detailed, and specify which employee was allocated to which project, in what capacity, and for what duration. The

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[1] 70% of the projects executed in our sample had the base currency as USD. When projects were delivered in countries other than USA, the currency was specified. The other currencies included were CAD (Canadian dollar), EURO, GBP (Great Britain pound), or AUD (Australian dollar). We converted these to USD using the historical exchange rates at the time of project transaction. These historical rates are available from US Federal Reserve Board's website (http://www.federalreserve.gov/releases/h10/Hist/, retrieved 07/01/2007).

data on project characteristics include project type (development or maintenance), contracting type (fixed price or time and materials), project technology (whether low level or high level, including Caper Jones language level indicator), client id, project duration, and project domain. The personnel data include PM and team members' performance ratings as well as details on their total work experience. The data also contain client feedback reports for these projects, which are on a scale of 1 (very dissatisfied) to 7 (very satisfied).

The data allow us to directly measure project size in terms of effort (e.g., Boehm, 1983; Gopal, 2003), team size, average team experience at the beginning of the project, etc. We used the baseline measure spreadsheets provided by the vendor to compute project size in terms of function points. We averaged historical performance ratings data for each PM at the start of the project. We developed team familiarity measure following Espinosa et al. (2002). For this, we assigned a count variable for each team member. We then examined the allocation data, and increased the count variable by one if a team member had worked with another prior to the current project. We did this for each team member, summed it up at the project level, and normalized it by the team dyads.[2]

Because we had detailed allocation data, we were able to assess PM's prior exposure to the technology, domain, or methodology as required by the project. The client identification for each project enables us to compute whether it was a new client for the vendor, and also whether the PM was familiar with the client or not.

**Critical incidents data**

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[2] For example, let a team contain members A, B, and C. Suppose A and B have worked together 3 times in the past, and A& C have worked twice in the past, the familiarity variable for the current project is 5. Normalizing it by the team dyads, we obtain a normalized team familiarity measure as 2.5.

While the importance of practical intelligence and soft skills in IT/IS professionals is well established, these are not easily assessed. Following the approach of Wagner and Sternberg (1985) and Joseph et al. (1999), we use the critical incident methodology to measure these skills along the seven dimensions defined by Wagner and Sternberg: managing tasks, self, career, peers, subordinates, superiors, and clients.

For PMs, managing tasks relates to soft skills that they utilize while performing project management related activities, such as costing and project planning. In managing careers, PMs display acumen in managing short and long term career growth goals. In managing self, PMs manifest self-regulation strategies of applying self-motivation and self-organizational aspects of individual performance with the objective of improving one's productivity, for example, prioritizing project activities. Finally, because management is an interactive activity, the most important soft skill dimension for PMs is managing others. PMs have to manage not only their team members, but also collaborate with their peers and their superiors. This skill is further demonstrated when interacting with external entities like clients, especially in the outsourcing scenario. Joseph et al. (1999) include superiors, subordinates (permanent or contract), peers, users, clients and vendors in their definition of "others." We find, however, that for most IT vendors, "others" include superiors, subordinates, peers, and clients.

**Critical incident collection:** The critical incidents were gathered from an expert panel at the research site along each of dimensions mentioned above. These experts had executed at least 5 projects as project managers. We had a total of 32 questions in our incident bank. We created 8 separate surveys, where we randomized the survey question for each dimension from our incident bank. We then randomly administered one of eight surveys to the PMs corresponding to the projects. Each PM in the sample was thus asked to respond to seven critical incidents (corresponding to the dimensions mentioned above). The survey responses were in a detailed essay type format.

**Evaluation:** We received 209 completed surveys.[3] At the time of incident collection, we had asked the expert panel for a sample good, average, and bad response. Detailed evaluation instructions were prepared using the expert panel's response guidelines. The detailed survey responses were evaluated by a panel of four experts with requisite credentials. Each evaluator had considerable experience in IT as well as project management, in addition to having worked in or being exposed to outsourcing projects; the evaluators also had graduate degrees. We computed inter rater reliability measures for each of the respondents in each dimension, and found that these were over 0.96 (Table 3), suggesting substantial agreement among evaluators. We conducted a factor analysis of the evaluations, using a varimax rotation (Harman, 1967). One factor emerged from this analysis; we used the factor loadings in our analysis as a measure of soft skills.

## Measurement

**Measuring Project Outcomes**

IT projects have multi-dimensional outcomes. Project performance is often measured in financial terms. In the context of outsourcing, where maintaining client relationship is a key to success in the vendor market (Ethiraj et al., 2004), client feedback on a project also becomes an important dimension of project success. Many IT outsourcing vendors view this as a crucial measure, as it can lead to further

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[3] Not all 300 PMs in our original data set responded to the survey. We conducted statistical tests to check for any non-response bias. T-tests of means for experience and performance ratings for the PMs in our sample and the larger population of PMs at the research site indicated no significant differences, suggesting that there was no selection bias in the response to our survey.

assignments with the same client.[4] All of these outcome measures are closely related to efficient project management, and hence appropriate in the context of the current study.

Financial outcomes can be measured in two ways, project margins or profits, and costs (Deephouse et al., 1995). A discussion with industry experts revealed that actual project profits depend on numerous factors beyond the control of the PM. For example, sales people often offer discount to new clients, and hence project profit may not be a suitable project outcome measure in our context. On the other hand, given a project size, project costs can be controlled to a large extent by the PM (Nidumolu and Knotts, 1998). Project costs directly impact a vendor's bottom line, and can define whether a project is successful or not. Projects that have cost overruns can be deemed failures despite having achieved other quality and engagement level goals. Hence we use project costs as one of the key variables that measure project performance.[5]

Client satisfaction is also an important dimension of project performance (e.g., Kekre et al., 1995; Aladwani, 2000). In an outsourcing scenario, where good client feedback may mean further projects with the same client or renewal of outsourcing contracts, client satisfaction is extremely crucial. In a typical development project, clients are asked for feedback at the end of project lifecycle or at an end of an important project phase. For maintenance projects, these feedbacks are solicited to gauge the health of the project so that appropriate action can be taken with regard to project renewal, etc.

**Measuring PM's skills**

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[4] As marketing wisdom proclaims, it takes considerable lesser outlay costs to woo an existing client than to engage a new client. The same holds true for IT outsourcing industry.

[5] However, since an increase in costs is akin to a decrease in performance, cost measurements are hard to interpret, especially when we have interaction terms as our explanatory variables. We follow Espinosa et al. (2007), and use -1*log(Cost) as our cost performance variable.

We measure PM's skill set across two dimensions, hard and soft skills (Kirsch, 2000). Soft skills are assessed as stated previously. As stated earlier, we conceptualize hard skills as task familiarity. Although the CMM maturity level of the vendor may moderate the impact of such PM skills (Kemerer, 1997), in our sample, the projects had been assessed at the same CMM level. Furthermore, Kirsch (2000) suggests that the processes designed to aid project management in mature organizations can complement PM's experience and skill level.

We assess PM's average prior experience in project technology, domain and methodology in number of years, and use that as a measure of hard skills or PM's task familiarity (Krishnan, 1998). Discussions with industry experts reveal that domain expertise is crucial when interacting between the client and the design team. As Lee et al. (1995) point out, the focus of IS activities centers around the effective application of IS to meet business needs. When the client outsources, a PM with an in-depth business functional knowledge necessary for the project is an important asset to the team. IT systems are often seen as strategic assets (Ethiraj et al., 2004), and hence clients need their IT systems to align to their organizational structure and processes to maximize the value of these systems. Domain or functional knowledge is essential not only from the vendor's perspective but is also prized by clients. In addition to domain expertise and project management skills, a PM has to manifest technological expertise appropriate to the project requirements. One of the PM's activities is to make the technology accessible to the client, and also to examine what business needs and functional requirements from the IT system can or can not be handled by the technology being employed by the project. For example, if the PM has had experience in only mainframe technology, it is difficult for her to comprehend the capabilities offered by internet or web based technology. Further, literature has suggested that maintenance and development projects may require different framework and management styles (Swanson and Beath, 1990, Gopal et al., 2003); therefore we include methodology experience in our hard skills measure.

**Project contingency factors and controls**

We measure project contingency factors as follows:

**Project uncertainty** is measured in terms of project type (whether maintenance or development), or project technology. Shenhar (2001) expounds on project scope and related uncertainty. Maintenance projects are thought of as additive projects (Brooks, 1995); we can thus think of more routine projects, as opposed to innovative projects, to be associated with lower uncertainty. Thus, development projects would be considered more uncertain than maintenance projects. A similar argument can be made for project technology. Proven technologies are perceived as being less uncertain. A lower level language, such as COBOL, which has an established base, would be less uncertain than a high level language.

**Project complexity** is assessed in terms of project size, project duration, and team size. Prior literature suggests that project size, measured in function points, is indicative of project complexity (Kemerer, 1987 and 1993; Shenhar, 2001). Duration is also a measure of complexity, as longer projects inevitable require more effort, and may also experience coordination issues. Further, as team size increases, coordination and other issues arise, requiring more complex management skills (e.g., Kraut and Streeter, 1995; Nidumolu, 1995; Koushik and Mookerjee, 1995).

**Project familiarity** is measured with two constructs: team and client familiarity. The literature suggests that prior familiarity between team members enhances coordination and hence impacts project performance (for example, Crowston and Kammerer 1998; Curtis et al. 1988; Faraj and Sproull 2000; Espinosa et al., 2007). Interviews at the research site confirmed that clients are indeed the most crucial external entities that a PM has to deal with. A PM's prior experience with the same client may thus ameliorate project outcomes, especially client feedback, for the better (Ethiraj, et al., 2004; Duncan, 1996). Hence we include PM's prior client experience to control for client familiarity. We also include a dummy to indicate whether the client was familiar to the vendor before the current project execution, because an older client would need less hand holding; the vendor may have a rapport with the client which can also ease communication, understanding, and problems with the client.

**Other controls:** We control for other PM and project characteristics in our analysis. Joseph et al. (1999) find that soft skills are also correlated with the work experience of the IT professional. Thus we control for the PM's IT and project management experience (at the start of the project).

Project and team characteristics, such as average team experience, also impact project outcomes. Factors such as project contracting types may also impact project outcomes (Gopal et al., 2003). For example fixed price contracts are usually very closely monitored, and hence a tighter control over budget may be exercised, leading to lower project costs. Similarly, time and materials contracts are usually maintenance or repeat contracts with an existing client, with whom the vendor may already have established a rapport, and hence may lead to favorable feedback. We also control for average IT experience within a team and PM's performance ratings.

The archival data variables are described in detail with the descriptive statistics in table 1. Table 2 shows the correlation matrix between the explanatory and control variables. Variables such as project cost and function point were transformed using logs. Further, prior to analysis, we centered each of the non categorical variable that had an interaction terms (log(FP), duration, team size, team familiarity, PM's client experience, hard and soft skills), to avoid collinearity issues in estimation (Aiken and West, 1991).

## 4.  Analysis and Results

We develop the following model to test our hypotheses for project *i* and PM *j*:

$$Performance_i = \alpha_0 + \alpha_1.\log(FP)_i + \alpha_2.Duration_i + \alpha_3.AvgTeamExp_i + \alpha_4.TeamSize_i + \alpha_5.TeamFamiliarity$$
$$+\alpha_6.ContractType_i + \alpha_7.ProjectTechnology_i + \alpha_8.ProjectType_i$$
$$+\alpha_9.PMRating_{ij} + \alpha_{10}.ITWorkEx_{ij} + \alpha_{11}.PMWorkEx_{ij} + \alpha_{12}.SoftSkills_j$$
$$+\alpha_{13}.ClientExp_{ij} + \alpha_{14}.HardSkills_{ij}$$
$$+\alpha_{15}.\log(FP)_i\,XSoftSkills + \alpha_{16}.Duration_i XSoftSkills$$
$$+\alpha_{17}.TeamSize_i XSoftSkills + \alpha_{18}.TeamFamiliarity_i XSoftSkills$$
$$+\alpha_{19}.ProjectTechnology_i XSoftSkills + \alpha_{20}.ProjectType_i XSoftSkills$$
$$+\alpha_{21}.ClientExp_{ij} XSoftSkills_j + \alpha_{22}.HardSkills_{ij} XSoftSkills_j + \varepsilon_{1i}$$

$$Feedback_i = \beta_0 + \beta_1.\log(FP)_i + \beta_2.Duration_i + \beta_3.AvgTeamExp_i + \beta_4.TeamSize_i + \beta_5.TeamFamiliarity$$
$$+\beta_6.ContractType_i + \beta_7.ProjectTechnology_i + \beta_8.ProjectType_i$$
$$+\beta_9.PMRating_{ij} + \beta_{10}.ITWorkEx_{ij} + \beta_{11}.PMWorkEx_{ij} + \beta_{12}.SoftSkills_j$$
$$+\beta_{13}.ClientExp_{ij} + \beta_{14}.HardSkills_{ij}$$
$$+\beta_{15}.\log(FP)_i\,XSoftSkills + \beta_{16}.Duration_i XSoftSkills$$
$$+\beta_{17}.TeamSize_i XSoftSkills + \beta_{18}.TeamFamiliarity_i XSoftSkills$$
$$+\beta_{19}.ProjectTechnology_i XSoftSkills + \beta_{20}.ProjectType_i XSoftSkills$$
$$+\beta_{21}.ClientExp_{ij} XSoftSkills_j + \beta_{22}.HardSkills_{ij} XSoftSkills_j + \beta_{23}.dVendorClient_i + \varepsilon_{2i}$$

We assume that the error terms in the two equations are correlated, and estimate the model using Seemingly Unrelated Regression (SUR) technique.[6] The results are provided in the appendix (Table 4). We inspected the model for multicollinearity by conducting regression diagnostics; we computed condition indices (Belsley et al., 1970) and variation inflation factors (Marquardt, 1970). These collinearity statistics are reported in table 4. Further, we tested for heteroskedasticity using White's test, and for autocorrelation using the Durbin-Watson test (Greene, 2002). These tests did not reveal any problems.

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[6] We use a dummy variable to indicate vendor's client experience and use it in the feedback equation. This strategy renders the parameters in the two equations are different; hence the SUR model is identified, and provides more efficient estimates than estimating these models separately.

**Hierarchical regression**

As is consistent with models using interaction effects (Aiken and West, 1991), we analyzed the model by entering variables in blocks. We first tested the baseline model, without adding any of the skills variables. The baseline model thus included all project uncertainty, complexity, and familiarity variables, as well as the control variables. Next, we added the skills variables (soft skills, client experience, and hard skills) into the skills model. This increased the explanatory power of the model significantly, especially for feedback equation (Performance: $\Delta R^2 = 0.0137$, $F_{\Delta R^2} = 4.554$, $p = 0.0037$; feedback: $\Delta R^2 = 0.1313$, $F_{\Delta R^2} = 29.199$, $p < 0.001$). This suggests that PM's skills are important predictors of project outcomes like performance and feedback. Finally, we added all the interaction variables to estimate the full model. Again, we find that the predictive power of the model increased (Performance: $\Delta R^2 = 0.0216$, $F_{\Delta R^2} = 2.767$, $p = 0.0053$; feedback: $\Delta R^2 = 0.0963$, $F_{\Delta R^2} = 8.693$, $p < 0.001$); leading us to believe that the interaction variables explain significant variation in both performance and feedback over the baseline or skills models.

**Results of the baseline model**

The baseline model estimates show that the effect of the uncertainty, complexity, and control variables are largely as expected. Both project size and duration significantly decrease performance (increase costs; $\alpha_1 = -0.425$, $p < 0.001$; $\alpha_2 = -0.082$, $p < 0.001$); however, we find that project size is associated with an increase in feedback ($\beta_1 = 0.089$, $p = 0.018$). This perhaps is indicative of the fact that although executing more complex projects decreases project performance with respect to budget constraints, the final delivery resulted in higher client satisfaction.[7] Team size is associated with an increase in cost

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[7] This result led us to examine whether project costs could be an explanatory factor in client feedback. We estimated a simultaneous equation model to control for the endogeneity in the resultant model. However, we found

performance but a decrease in feedback ($\alpha_4 = 0.009$, $p = 0.001$; $\beta_4 = -0.003$, $p = 0.089$), although the effect is small. Surprisingly, we also find that project manager's ratings are poor predictors of both project performance and client feedback.[8] Likewise, we find that the PM's total IT or project management experience did not significantly impact project cost performance but the latter did help with client feedback ($\beta_{11} = 0.071$, $p = 0.001$). We find that older technology projects are associated with poorer project outcomes, although the effect is not significant for client feedback ($\alpha_7 = -0.302$, $p = 0.032$; $\beta_7 = -0.122$, $p = 0.110$). One explanation could be the difficulty in finding people who are willing to develop expertise in older technologies, leading to poor performance in these project types.[9]

Maintenance projects were significantly associated with better cost performance ($\alpha_8 = 0.604$, $p < 0.001$). This suggests that long term relationship with the client, as is the case with most maintenance projects, is beneficial for both the client and the vendor, in terms of project costs. It reduces uncertainty and also builds up trust. In addition, we find that client familiarity at the firm level is significantly correlated with higher feedback ($\beta_{23} = 0.815$, $p < 0.001$).

**Results of the skills model**

The addition of the PM's skills to the model did not significantly change the estimates significantly, except that the coefficient for team familiarity became significant for the cost performance equation ($\alpha_5$

that although project costs increase client satisfaction, the effect is not significant. Hence we do not report it in the current study. The results are available by request from the authors.

[8] A discussion with the vendor revealed that factors other than PM's performance may influence ratings, and hence they may not be reliable indicators of project performance.

[9] Talks with the developers at site revealed that even when the base system is a mainframe, many of the clients were developing or in the process of developing internet or open system enabled applications; hence there was a high attrition from the projects using older technologies, leading to longer development or knowledge transfer costs.

= -0.662, p = 0.031), although in the opposite direction to that expected. The skills variables added to this model included measures for hard and soft skills as well as control for client familiarity, which was computed at the PM level. We find that PM's skills, especially soft skills, significantly improve project outcomes.

Hypothesis 1 predicted that hard skills, or task familiarity, would improved project outcomes, that is, increase cost performance as well as client feedback. We find that these skills do help in improving cost performance, but they do not have any significant impact on client feedback ($\alpha_{14}$ = 0.110, p = 0.005; $\beta_{14}$ = -0.013, p = 0.541). Thus, hypothesis 1 is partially supported.

Hypothesis 2 predicted that soft skills would also improve project outcomes. We find support for this hypothesis ($\alpha_{12}$ = 0.212, p = 0.012; $\beta_{12}$ = 0.368, p < 0.001). Soft skills significantly impact both cost performance and client feedback.

Hypothesis 3 predicted that a PM's soft skills would impact project outcomes more than her hard skills. We find that a one tailed test failed to reject the hypothesis that soft skills impacts project performance more than hard skills ($\chi^2$ = 26.09, p = 0.03). Likewise, a one tailed test supported the hypothesis that soft skills impacts feedback more than hard skills ($\chi^2$ = 51.56, p < 0.0001). Intuitively, hard skills are both more observable and readily if not perfectly substitutable. Hence, if a PM lacks, say technical or domain expertise, it can always be compensated by appropriate team allocation. On the other hand, a PM needs soft skills in managing the team as well as the client, and these skills are tacit in nature and hence may not be as easily substituted. This suggests that soft skills rather than hard skills may be more valuable for a PM.

In addition, the results suggest that prior experience with the client helps the PM in better managing client satisfaction ($\beta_{13} = 0.05, p = 0.013$). We also find that experience as a project manager helps a PM

manage client expectations better ($\beta_{11} = 0.076, p < 0.001$). Again, we find that the PM's ratings are poor predictors of project outcomes.

**Results of the interactions model**

We now discuss the results of the full model that includes interaction effects. Note that apart from the coefficients for team familiarity variable, the direction and significance of other variables did not change significantly. The effect of team familiarity on performance was negative and significant, it now becomes positive and significant ($\alpha_5$=0.476, p = 0.084). This suggests that team familiarity helps in containing costs, and is consistent with prior research. However, the effect of team familiarity is negative and significant on client feedback.

The interactions model continues to provide partial support for hypothesis 1 ($\alpha_{14}$ = 0.111, p = 0.005; $\beta_{14}$ = -0.025, p = 0.214). Hypothesis 2 is again fully supported ($\alpha_{12}$ = 0.288, p = 0.002; $\beta_{12}$ = 0.345, p < 0.001). Hypothesis 3 is also fully supported, the one tailed failed to reject the hypothesis that (i) soft skills impact performance more than hard skills ($\chi^2$ = 39.61.09, p = 0.012), and that (ii) soft skills impact client feedback more than hard skills ($\chi^2$ = 59.81, p < 0.0001).

We now analyze the interaction effects. For ease of interpretation, we illustrate these effects in figures 1, 2, and 3 (complexity, uncertainty, and familiarity respectively). We find mixed support for hypotheses 4, 5, and 6. Hypothesis 4 stated that soft skills would help more complex projects in improving project outcomes. We find that this may not always be so. For example, figure 1A and 1C show that soft skills help projects that are high in complexity, such as those with higher function points or bigger team sizes, improve outcomes more than they do low complexity projects. This holds for both performance and client feedback. However, we find that soft skills help shorter duration projects more than longer duration projects, for both performance and client feedback (figure 1B). We offer an alternative explanation here. With longer duration projects, team members develop longer term relationships, and

hence there is more coordination within the team. Thus, there is less need of active management and coordination on part of the PM, and hence a decreased need of soft skills. In contrast, for shorter term projects, a PM may need to intervene more and oftener to ensure that project runs along smoothly. Thus, duration and soft skills may be substitutive.

Hypothesis 5 stated that PM's soft skills will help moderate the effects of project uncertainty on project outcomes. We find that soft skills do help when the technology is new or unproven. However, soft skills help maintenance projects more than they development projects. Because maintenance projects are ongoing, there is an increased amount of interaction between client and the project team. This is in contrast to development projects, where typically the team interacts with the client only at the beginning (requirements gathering) or the end of the project (implementation). Hence, for maintenance projects, the increased client interface necessitates higher soft skills in the PM.

Similarly, hypothesis 6 stated that soft skills should help projects with less familiarity, with respect to task, team, and client. We find that familiarity – both task and team – may indeed be substitutive with soft skills, at least sometimes. We find that low team familiarity can be offset by soft skills, as can be low hard or technical/domain skills. However, we find mixed response for client familiarity. While client familiarity and soft skills are substitutive for client satisfaction, the effect is not significant for cost performance.

We also investigated how an increase in firm-specific human capital would impact project costs and client satisfaction. Ceteris paribus, we find that an increase of one unit in soft skills enhances project performance by approximately $64,000 and increases client feedback by 0.60 (on a scale of 1 to 7).

## 5. Discussion and conclusion

How do PM skills affect IT outsourcing projects, and how should PMs be allocated to these projects? We provide a rigorous empirical answer to these questions in the current study. While prior research has

predicted that project manager's skills should impact IT project performance, our study is one of the first to provide unequivocal evidence that a project manager's skills do indeed improve project cost performance and client satisfaction. Consistent with prior research on project complexity and uncertainty, we use detailed archival data to find that both complexity and uncertainty lead to impaired project performance.

However, the most significant contributions of the current study are thus. We first develop a rigorous measure for assessing PM's soft skills. We then relate this measure to project outcomes. Our findings provide support that both hard (technical, general) and soft (non-technical, tacit) skills enhance project outcomes. We find that soft skills significantly improve both cost performance and client satisfaction feedback. We further show that their impact is much stronger compared to that of hard skills.

Next, we explore the contingent impact of soft skills. We find that in general, soft skills help moderate the negative effects of project complexity and uncertainty. They improve coordination not only within a project, but also with external stake holders like clients. These skills also help in developing and implementing better management practices. Contrary to our expectation, we find that soft skills are more beneficial for shorter projects than for longer projects. An analysis of the data revealed that there may not be any correlation between project duration and project size, and shorter term projects may also be complex. Moreover, with longer term projects, team members get an opportunity to interact with each other, and develop familiarity as well as ease in coordination. Therefore, our results suggest that soft skills would better moderate team friction or coordination issues in shorter term projects.

We further find that soft skills are to a large extent substitutive with familiarity. When there is low task familiarity, such as PMs with lower hard skills, soft skills can substitute for these. Because hard skills may be surrogated with greater ease than soft skills, a project or technical lead with the requisite hard skills may fulfill the role of technical leader within the project, and vice versa.

This has important implications for senior managers, as they advise and groom potential candidates for PM positions. We find that IT or project management experience may not be indicative of an individual's true potential as a PM, the experience may not always be commensurate with increased soft skills. Hence it may be necessary for senior management to provide tailored training to PMs.

Our study does have some limitations. The data were collected from a single vendor, though the vendor and projects we chose were fairly representative of the IT outsourcing projects that are currently being executed. Hence, although a single site gives us better control in terms of model identification, the results may be indicative of practices prevalent at the vendor site and organizational peculiarities. These findings could also hold true only in the case of large IT outsourcing vendors, and may not apply to in-house IT projects or non-IT projects. Further, we have a post-hoc measure of soft skills that, although we control for relevant project management experience, may indicate that the perfection of hindsight. We hope that future studies will be able to mitigate these data issues and validate our results.

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**Appendix I**

**I Data characteristics and model estimations**

**Table 1: Average prices on e- versus p-channel**

| Channel | Average Unit Sales Price |
|---|---|
| Electronic | $9.254 |
| Physical | $8.632 |

**Table 2: Sample Statistics**

| Variables | Mean or Frequency | | Explanation |
|---|---|---|---|
| **Firm** | | | |
| *Channel* | 0.2485 | | When the electronic sales channel was used by the firm. |
| *Electronics* | 0.4668 | | The product category. The two categories are toys and electronics. Electronics =1 indicates that the product category is electronics |
| *Log of Price* | 7.4280 | | log of the final sales price for the BoL |
| *log of Pallets* | 1.9268 | | log of the number of pallets in the BoL |
| *Unit Sales Price for the e-Channel* | | | This is the unit sales price for the electronic channel in USD |
| **Buyer** | | | |
| *Category* | *Toys* | *Electronics* | |
| *Retail Unit Price* | 19.856 | 81.185 | This is the 'worth' or the retail unit price for a particular BoL. This is indicative of the price that the salvage dealer can get. |
| *Unit Sales Price* | 2.730 | 15.704 | This is the unit sales price for a BoL |
| *# Units* | 1214.100 | 449.616 | These are the number of units in a BoL. |
| *Bidders* | 2.049 | 1.989 | These are the number of distinct bidders when e-channel is used for sales. |
| *Bids* | 5.488 | 7.737 | These are the number of distinct bids when e-channel is used for sales. |

**Table 3: Logit Estimation for Firm's Channel Decision**

| | P(Channel) |
|---|---|
| Electronics | -0.533 (0.04)** |
| Log of firm's expected price | 0.246 (0.04)** |
| e-channel inertia | 9.806 (0.30)** |
| log of #Pallets | -0.231 (0.07)** |
| Standard errors in parentheses | |
| + significant at 10%; * significant at 5%; ** significant at 1% | |

**Table 4: Regression Estimation for Unit Purchase Price**

| | Unit Purchase Price | | | |
|---|---|---|---|---|
| | Toys | | Electronics | |
| | **E-Channel** | **P-Channel** | **E-Channel** | **P-Channel** |
| Unit Retail Cost | 0.17(0.00)** | 0.14(0.00)** | 0.35(0.00)** | 0.23(0.00)** |
| Purchase Price at (t-1) | 0.01(0.00)** | 0.05(0.00)** | 0.01(0.00)** | 0.05(0.00)** |
| Purchase Price at (t-2) | 0.01(0.00)** | 0.00(0.00) | 0.04(0.00)** | 0.04(0.00)** |
| #Bidders at (t-1)\|E-Channel | 0.14(0.00)** | | 3.42(0.02)** | |
| R-Squared | 0.95 | 0.94 | 0.94 | 0.80 |
| Standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1% | | | | |

**Table 5: Probit Estimation for Purchase Decision**

| | Benchmark model I: Without loyalty or heterogeneity | Benchmark model II: With loyalty but without heterogeneity | Proposed Model (Posterior distribution of $\beta_i$) |
|---|---|---|---|
| Electronics | 0.124(0.014)** | 0.155(0.014)** | 0.542(0.009)** |
| E-Channel | 0.061(0.012)** | 0.037(0.012)** | 0.775(0.027)** |
| log(Net Inventory) | 0.151(0.002)** | 0.153(0.002)** | -0.052(0.001)** |
| log(Expected Purchase Price) | - 0.018(0.005)** | -0.016(0.005)** | -0.006(0.002)** |
| E-Channel Loyalty | | 0.427(0.017)** | 2.758(0.165)** |
| Log likelihood | -24482.487 | -24206.303 | -16738.680 |
| Standard errors in parentheses | | | |
| + significant at 10%; * significant at 5%; ** significant at 1% | | | |

**Table 6: Posterior distribution of Δ, showing the estimates of the heterogeneity model**

| Covariates | INTERCEPT | SIZE | DIVERSITY |
|---|---|---|---|
| Electronics | 0.528(0.008)** | -0.397(0.014)** | -0.567(0.007)** |
| E-Channel | 0.781(0.009)** | -0.950(0.017)** | 0.428(0.009) |
| log(Net Inventory) | -0.053(0.002)** | 0.030(0.003)* | -0.010(0.001)** |
| log(Expected Purchase Price) | 0.001(0.001)** | -0.077(0.002)** | 0.116(0.001)** |
| E-Channel Loyalty | 2.905(0.018)** | -1.939(0.033)** | 0.060(0.013)** |
| Intercept | -5.767(0.014)** | 2.904(0.021)** | -0.817(0.010)** |
| Standard errors in parentheses | | | |
| + significant at 10%; * significant at 5%; ** significant at 1% | | | |
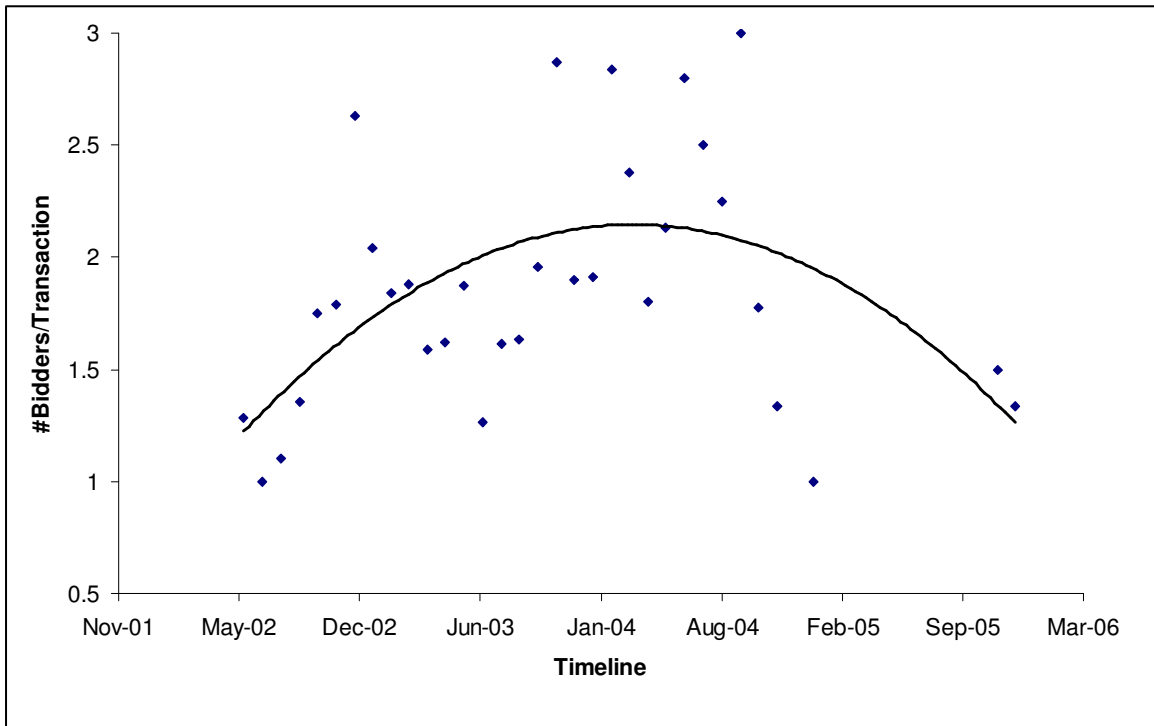
**Figure 1A: Buyers' adoption of e-channel over time (Current allocation)**
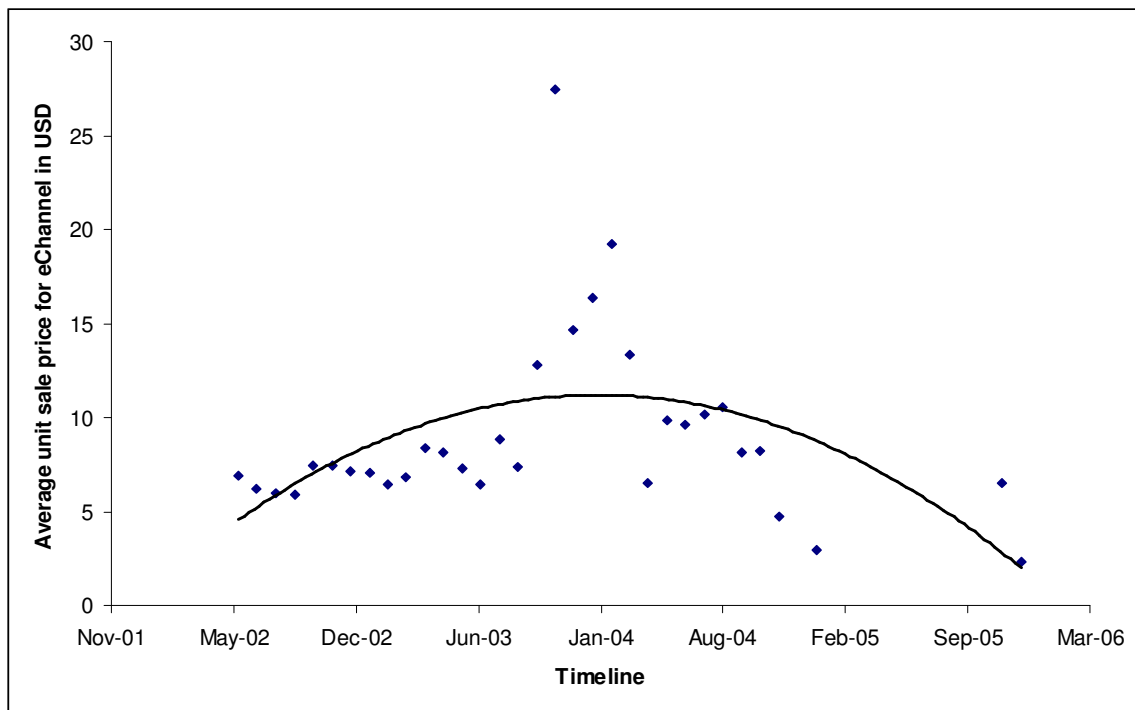


**Figure 1B. Average unit sale prices in the e-channel over time (Current allocation)**
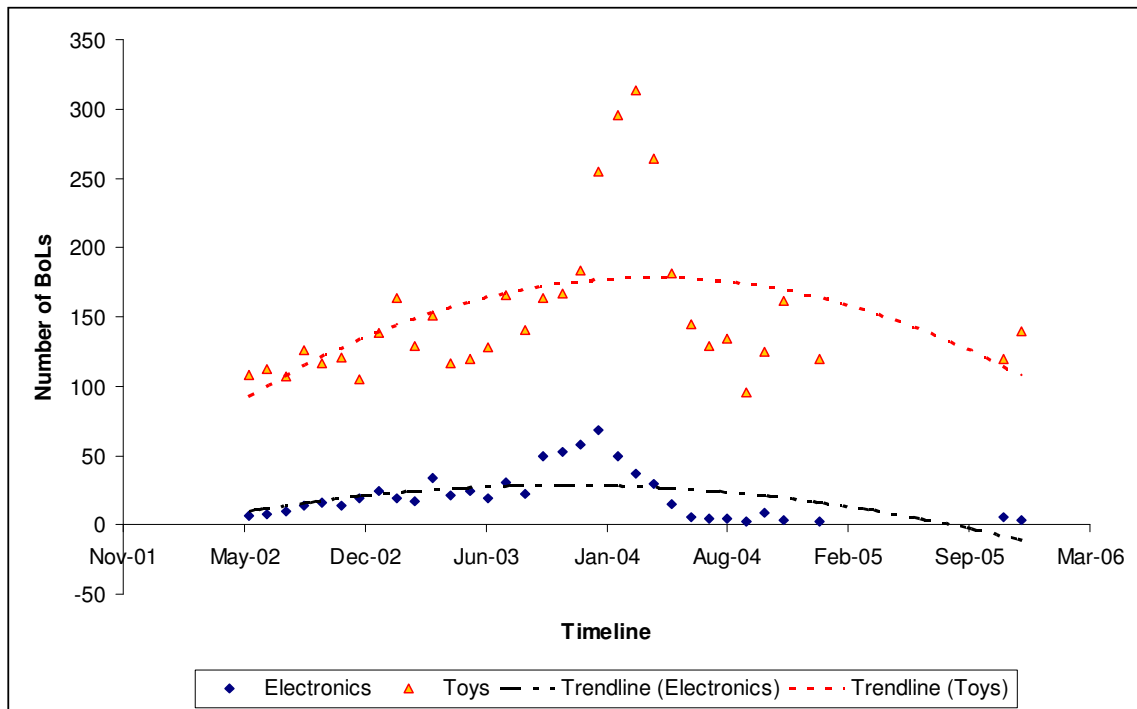
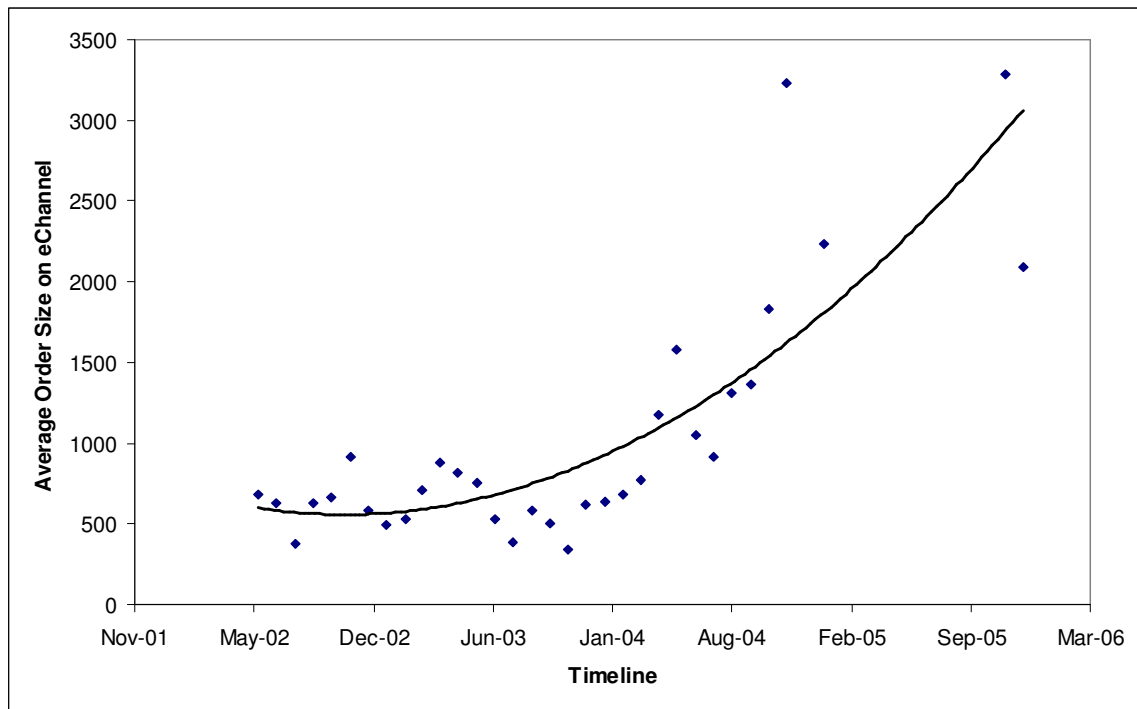**Figure 1C: Number of Products Allocated to E-Channel (Current Allocation)**



**Figure 1D. Average Order Size Allocated to E-Channel (Current Allocation)**
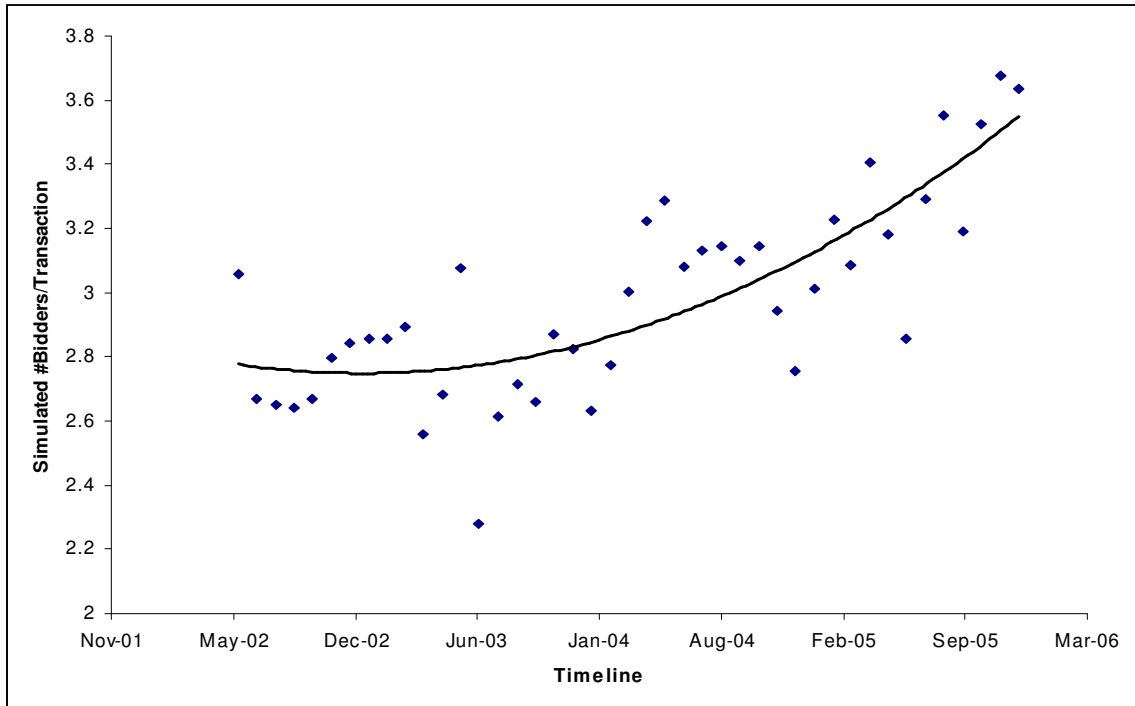
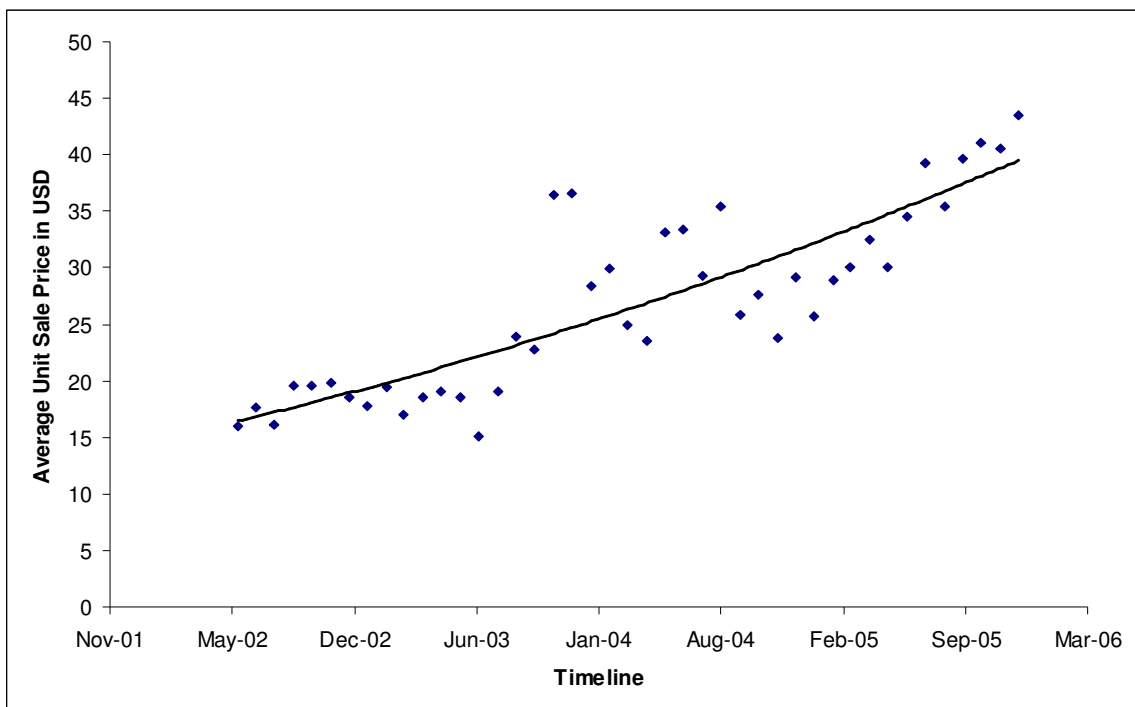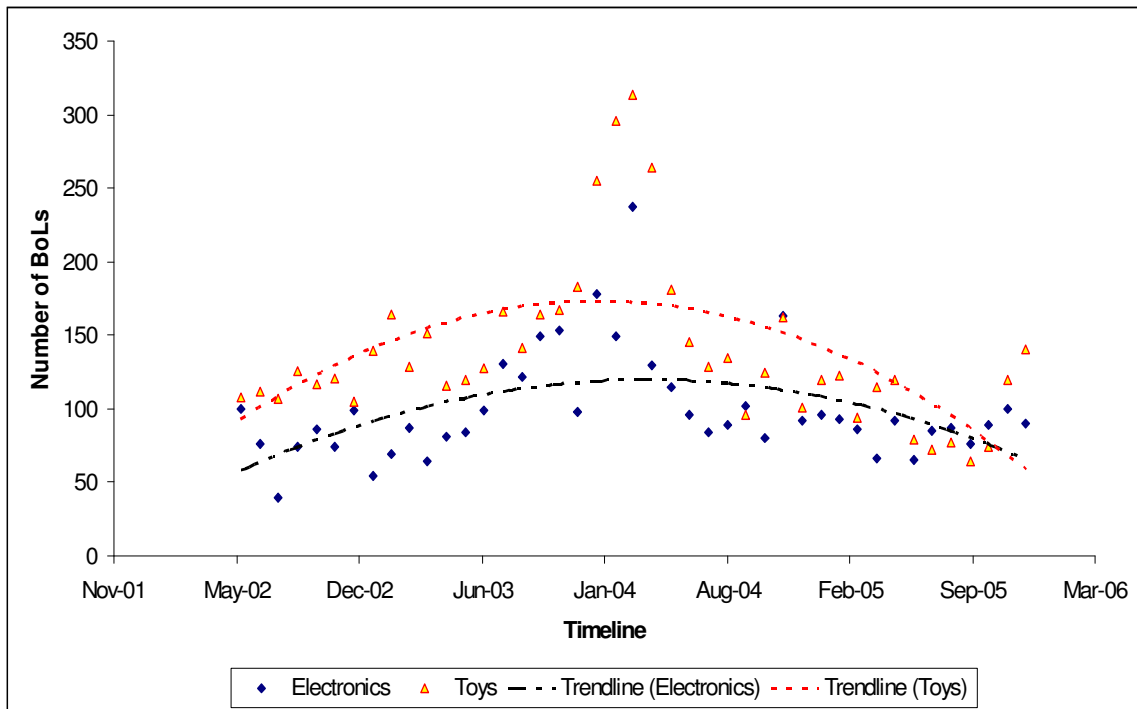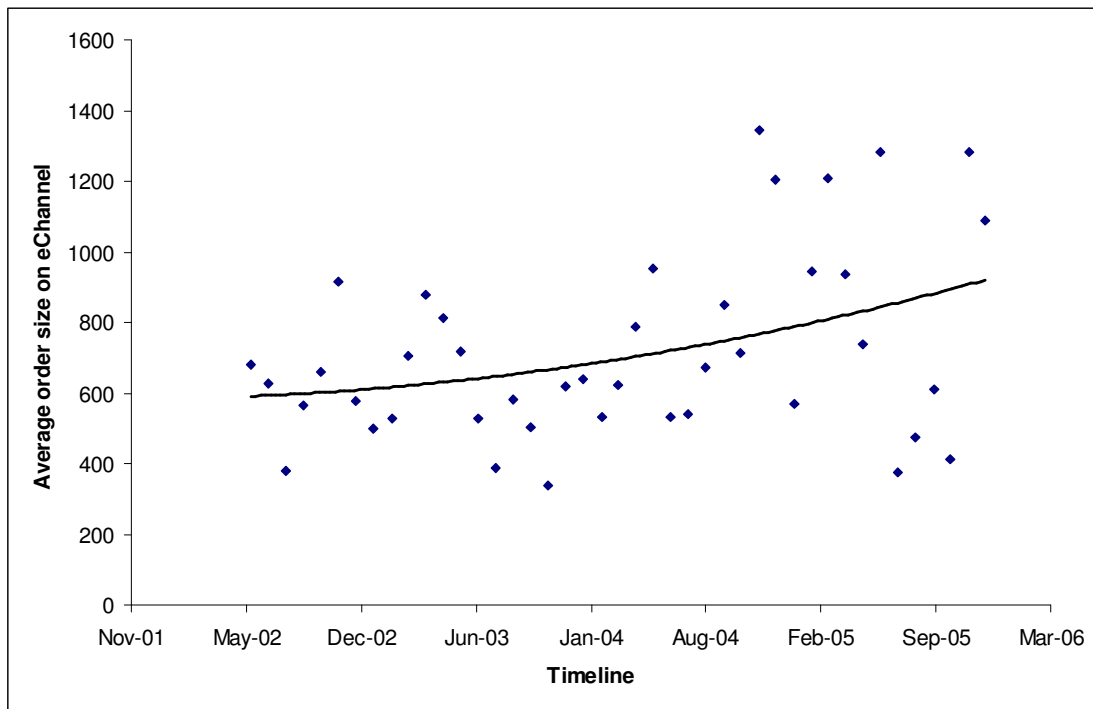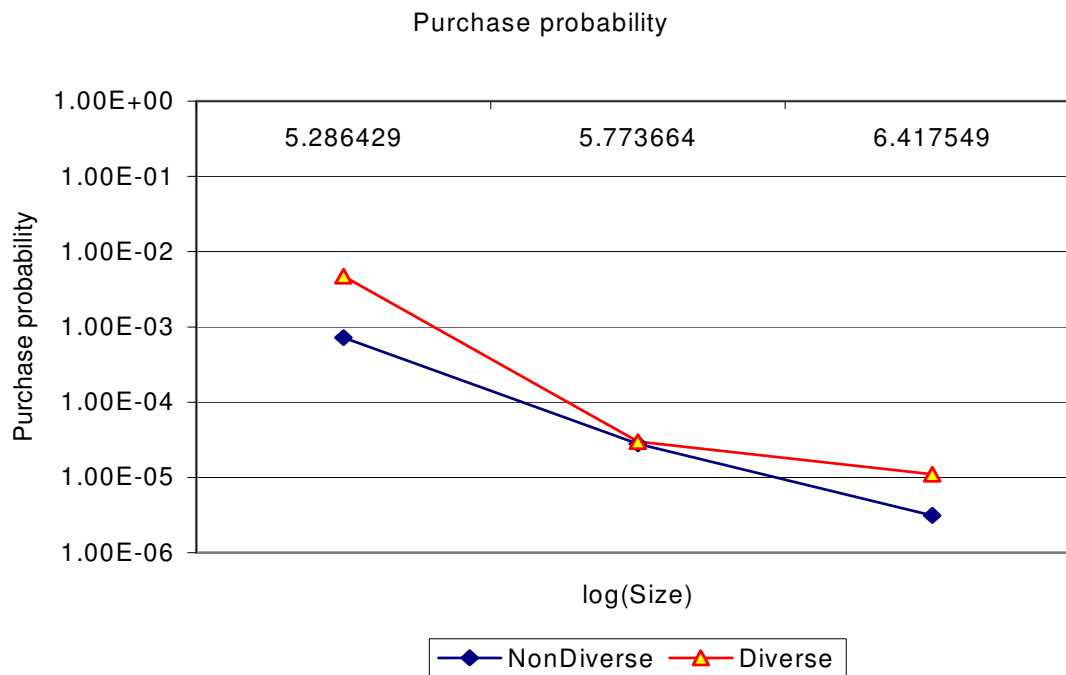**Figure 2A: Buyers' adoption of e-channel over time (Simulated allocation)**



**Figure 2B. Average unit sale prices in the e-channel over time (Simulated allocation)**

**Figure 2C: Number of Products Allocated to E-Channel (Simulated Allocation)**



**Figure 2D. Average Order Size Allocated to E-Channel (Simulated Allocation)**

**Figure 3. Average purchase probability for small versus large and diverse versus non diverse buyers**

## II Priors and Conditional Posteriors for Estimation of the Purchase Probability Model

Following Rossi et al. (1996), following three priors are assumed:

a) Prior on $\sigma_\zeta^2$: $\sigma_\zeta^2 = 1$ (The identifying assumption for a binomial probit model)

b) Prior on $V_\beta$: $V_\beta^{-1} \sim Wishart(v_{bo}, V_{bo}); v_{bo} = 2 + 5(7); V_{bo} = v_{bo}I_2$

c) Prior on $\Delta$: $\delta = vec(\Delta) \sim N(\overline{d}, (V_\beta \otimes A_d^{-1}))$; assume $\overline{d} = 0, A_d = 0.01I_d$

Conditional posteriors: We use Gibbs sampler for the following 4 sets of conditional posteriors:

a) $U_{ijkt} \mid \beta_i, W_{ijkt}, \Delta, V_\beta, U_{ijkt} = \beta_i.W_{ijkt} + \zeta_{ijkt}, \zeta_{ijkt} \sim N(0, \sigma_\zeta^2), \sigma_\zeta^2 = 1$. Draws for $U_{ijkt}$ can be generated

using a truncated normal distribution ($U \sim N(W\beta, \sigma_\zeta^2)$), using a rejection sampler

b) $\beta_i \mid Z_i, \Delta, V_\beta$ - using standard (Bayesian) linear regression, i.e., $\overline{\beta}_i = \Delta Z_i; \hat{\beta}_i = (W_i'W_i)^{-1}W_i'U$;

here $W_i'$ is a stacked matrix ($2T_i$ X 5) of $W_{it}$

$\Delta \mid \{\beta_i\}, V_\beta; \delta = vec(\Delta) \sim N(\tilde{d}, (V_\beta \otimes A_d^{-1}))$;

c) $\tilde{d} = vec(\tilde{D}), \tilde{D} = (Z'Z + A_d)^{-1}(Z'Z\hat{D} + A_d\overline{D})^{-1}$;
$\hat{D} = (Z'Z)^{-1}Z'B,$

Where B is the I X 5 matrix with $\beta_i^i$ as a row, Z is the corresponding matrix with $Z_i$ as a row, and $\overline{D}$

is the stack ($\overline{d}$).

$V_\beta \mid \{\beta_i\}, \Delta; V_\beta^{-1} \sim W(v_{bo} + I, V_{bo} + S); S = \Sigma_i(\beta_i - \overline{\beta}_i)(\beta_i - \overline{\beta}_i)^{-1}; \overline{\beta}_i = \Delta Z_i$; and *I* is the total number of
buyers.

**Appendix II**

| | P(Claim) |
|---|---|
| RFID | -0.6382 |
| | (0.1262)** |
| log(Offer) | 0.0516 |
| | (0.0498) |
| log(Offer Amount/#Units) | 0.1978 |
| | (0.0760)** |
| Electronics? | -0.0868 |
| | (0.1656) |
| log(Total Monthly Shipments) | 0.5960 |
| | (0.2777)* |
| log(Buyer's Total Prior Shipments) | 0.0231 |
| | (0.0362) |
| log(Buyer's Total Prior Claims) | 0.1404 |
| | (0.0929) |
| Observations | 5607 |
| Std errors in parentheses. [+] significant at 10%; [*] significant at 5%; [**] significant at 1% | |

Table 1: We show the probit model results for ascertaining the probability of claims.



RFID Tag          Radio Waves          RFID Reader          Middleware          Database

Figure 1: The basic elements of RFID technology are tags, readers, and middleware.
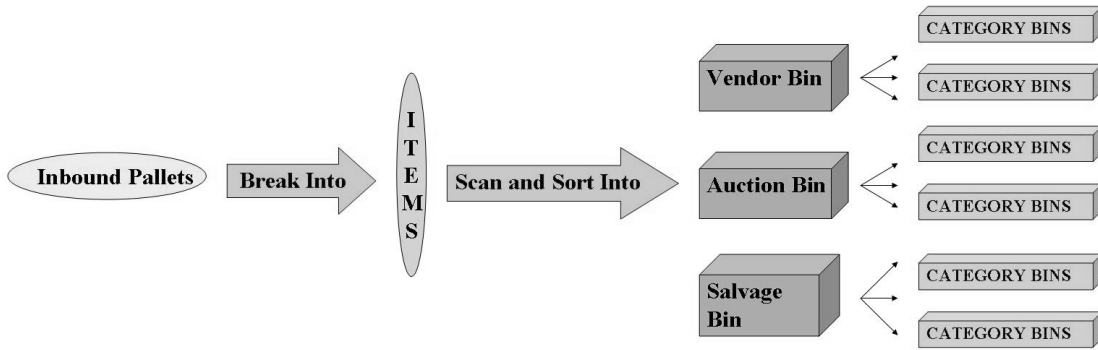
Figure 2: Inbound materials at the RC are scanned and then sorted into vendor, auction, and salvage
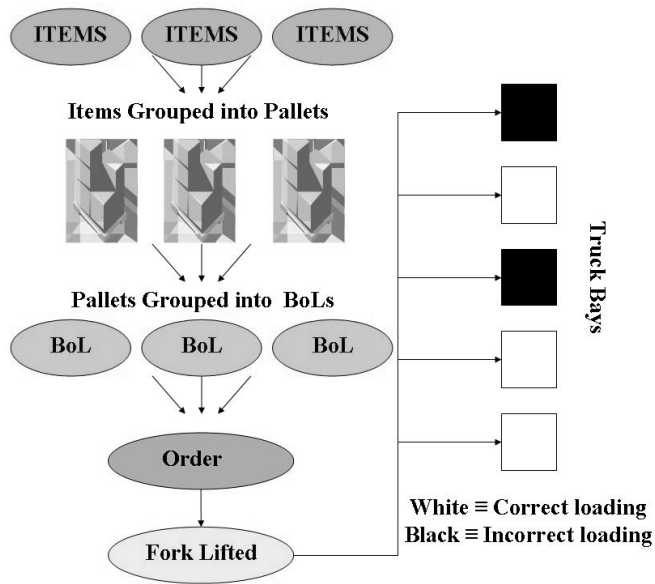
bins.



Figure 3: Outbound material flow at the RC before the RFID implementation demonstrates some
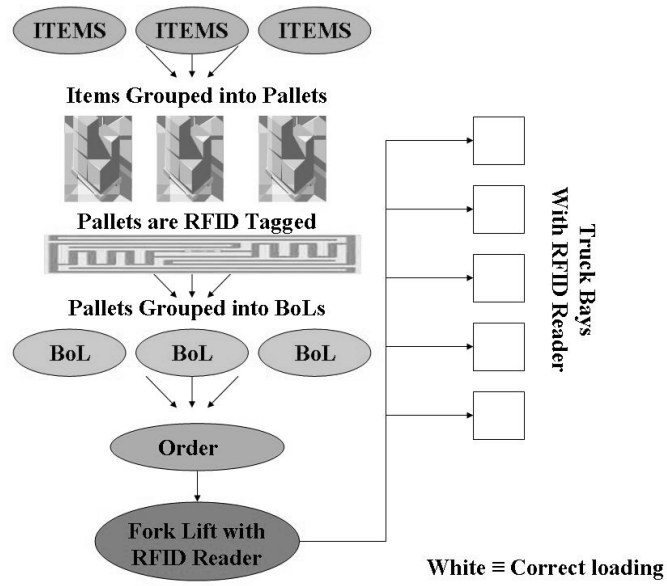
incorrect loadings that lead to claims.

Figure 4: Outbound material flow at the RC after the RFID implementation demonstrates all correct loadings.
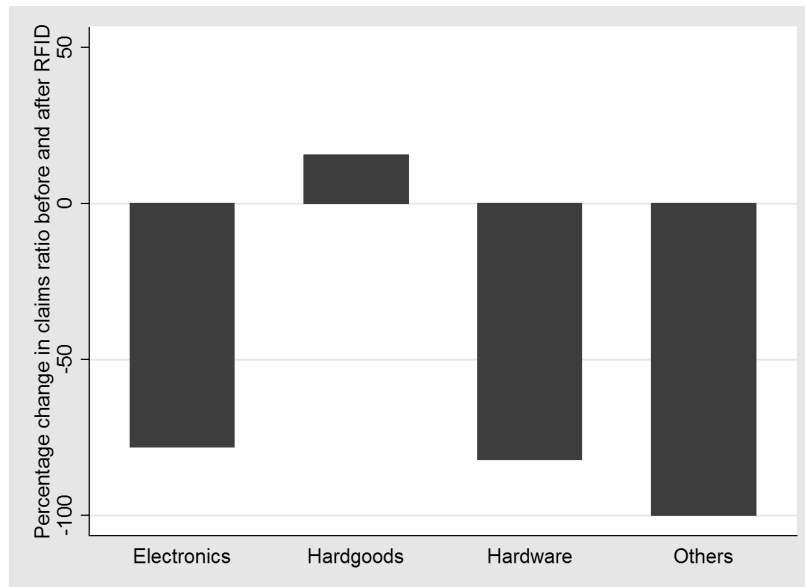


Figure 5: After the RFID implementation, claims in almost all categories decreased dramatically.
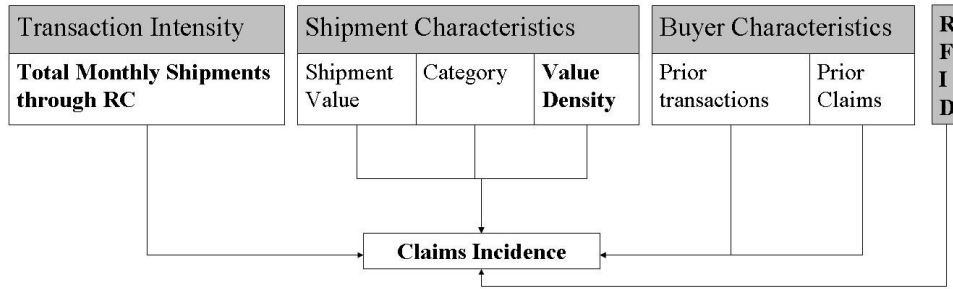
| Transaction Intensity | Shipment Characteristics | | | Buyer Characteristics | | R F I D |
|---|---|---|---|---|---|---|
| **Total Monthly Shipments through RC** | Shipment Value | Category | **Value Density** | Prior transactions | Prior Claims | |

**Claims Incidence**

Figure 6: The figure summarizes the factors affecting claims; we show the significant variables in a bold font.
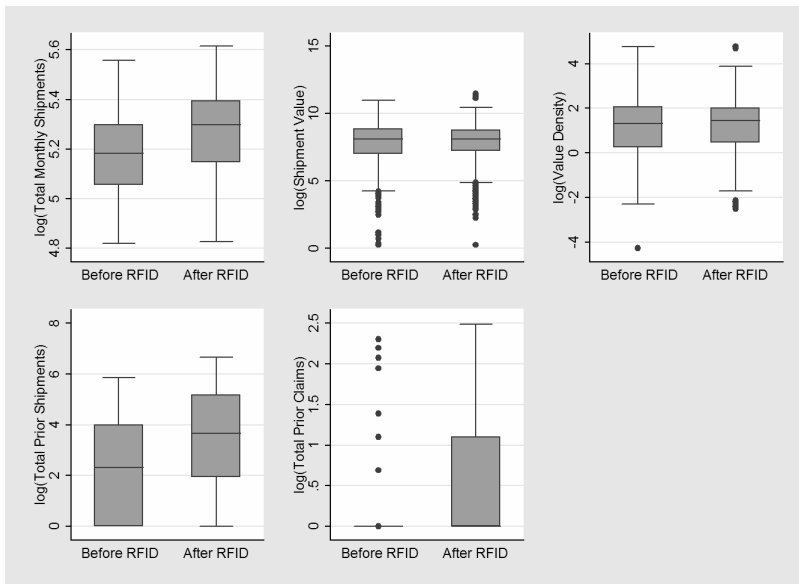


Figure 7: Box plots for explanatory variables show little change in their distributions before and after the RFID implementation.
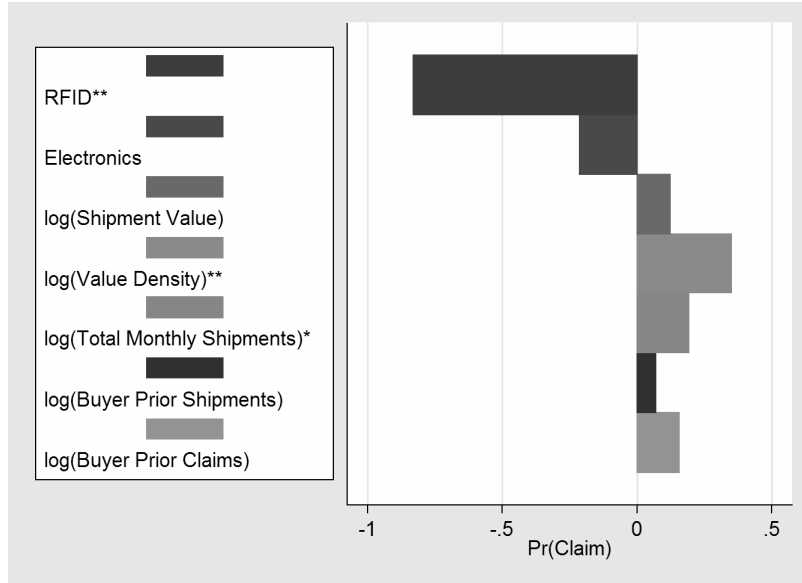
Figure 8: The graph shows how changes in each of the explanatory variables influence the probability of

claims. We indicate the significant variables by * (5% significance) or ** (1 % significance) and show
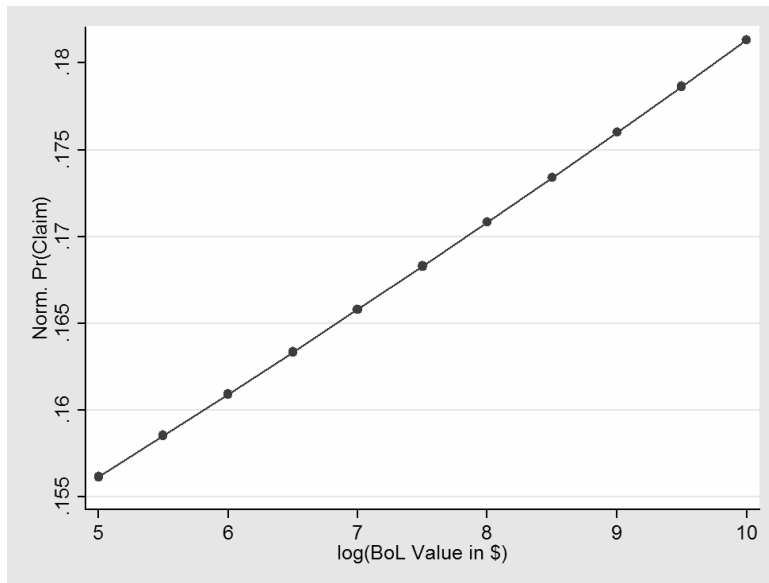
that RFID has the most significant impact.



Figure 9: RFID implementation reduces the probability of a claim; however, it may have less impact as
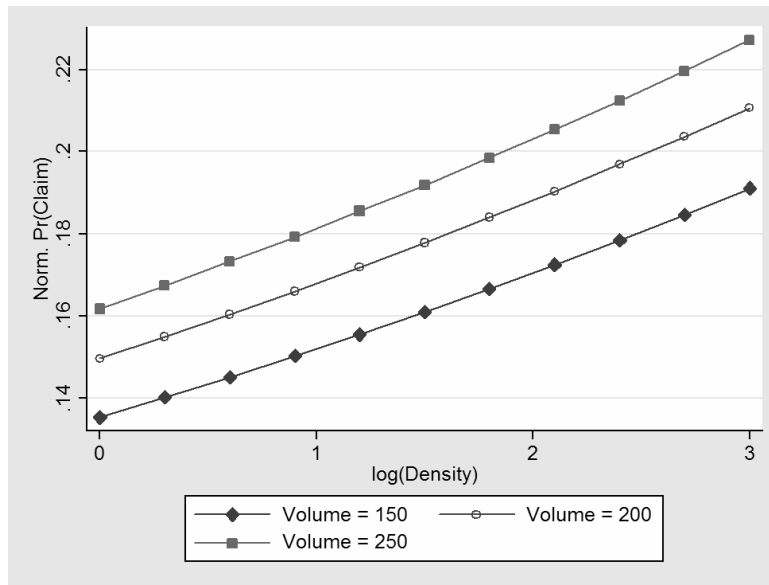
the total BoL value increases.

Figure 10: RFID reduces the likelihood of claims for all shipments; however, this is more evident for

lower-valued items at low volumes than for higher-valued items at higher volumes.

**Appendix III**

**Table 1: Data Dictionary**

| Variable name | Variable description | Mean (SD) |
|---|---|---|
| Performance | log(Cost) is the log transformation of project cost (in USD). Performance is −1*log(Cost) (See Espinosa et al., 2007). | −12.59(2.12) |
| Feedback | This is the client feedback for at the project level. The feedback ranges from 1 (poor) to 7 (excellent) | 5.68(0.87) |
| log(FP) | This is the log transformation of function points associated with the project. For maintenance projects, these were summed up for major enhancements, minor enhancements, and bug fixes, during the PM's tenure. | 8.11(2.14) |
| Duration | Project duration in months. | 14.67(13.78) |
| AvgTeamExp | Average team experience. This variable is computed by averaging the team members' experience at the start of the project, at the project level. | 863.08(424.10) |
| TeamSize | Team size. This is the number of people who have been allocated to the project, and the number is derived from project allocation data. | 42.01(39.87) |
| TeamFamiliarity | This is a computed variable measuring normalized team familiarity. To measure this, we first computed raw team familiarity, that is, whether two team members have worked with each other before or not, and if yes, how many times. This count is then summed up at the project level. Thus for a 3 member team (A/B/C), if A and B have worked together twice before and A and C have worked together once before, this variable would be 3 at the project level. We then normalize this sum by the team size dyad, which in turn is obtained from a combination algorithm. Thus for a 3 member team, suppose raw team familiarity is 3, then TeamFamiliarity would be 3/(3C2) = 1. | 0.15(0.25) |
| ContractType | Variable indicating whether the contract is fixed price (FP) or times and materials (TM). | FP: 16% TM: 84% |
| ProjectTechnology | Variable indicating whether the project technology is low level (L) or high level (H). | L: 57% H: 43% |
| ProjectType | Variable indicating whether the project is development (D) or maintenance (M). | D: 28% M: 72% |
| PMRating | Average rating of the PM at the start of the project. This is computed from primary data. The rating ranges from 1 (poor) to 4 (excellent). | 1.90(0.40) |
| ITWorkEx | Total IT work experience in years at the start of the project. Each survey respondent was asked for their total IT work experience in years. We then computed this measure based on the survey input and project start date. For example, if the respondent stated that her IT experience in April 2007 is 10 years, for a project started in 2000, this would be 3 years | 7.91(2.80) |
| PMWorkEx | Total experience as PM in years at the start of the project. Each survey respondent was asked for their total work experience as PM in years. We then computed this measure based on the | 3.27(2.89) |

| Variable name | Variable description | Mean (SD) |
|---|---|---|
| | survey input and project start date. For example, if the respondent stated that her PM experience in April 2007 is 3 years, for a project started in 2000, this would be 0 years. | |
| ClientExp | Experience with the client in years. This is computed based on the allocation data. This experience need not be as a PM. | 1.24(1.55) |
| dVendorClient | Dummy variable indicating whether client is familiar to the vendor (1) or not (0), at the firm level. | 0.97 (0.18) |
| SoftSkills | Factor loadings from mean survey evaluations. For obtaining this, we first calculated the mean from all four evaluations for each project manager. Next, we did a factor analysis using varimax rotation. We found that the means load to a single factor, which we use as our measure of soft skills. | 0.16(0.91) |
| HardSkills | This is a computed variable. We calculated the prior experience in years that the PM has for the current project's technology, domain, or methodology, and then averaged it to obtain our measure for hard skills. | 3.27(2.60) |

## Table 2: Correlation matrix

| | Performance | Feedback | log(FP) | Duration | Avg TeamExp | Team Size | Team Familiarity | Contract (TM) | Project Tech(L) | Project Type(M) | PM Rating | IT WorkEx | PM WorkEx | Soft Skills | Client Exp | Hard Skills | dVendorClient |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Performance | 1.000 | | | | | | | | | | | | | | | | |
| Feedback | -0.015 | 1.000 | | | | | | | | | | | | | | | |
| log(FP) | -0.281 | 0.075 | 1.000 | | | | | | | | | | | | | | |
| Duration | -0.607 | 0.021 | 0.193 | 1.000 | | | | | | | | | | | | | |
| Avg TeamExp | 0.137 | 0.014 | -0.497 | -0.018 | 1.000 | | | | | | | | | | | | |
| Team Size | -0.022 | 0.005 | 0.713 | 0.008 | -0.375 | 1.000 | | | | | | | | | | | |
| Team Familiarity | 0.002 | -0.021 | -0.261 | -0.041 | 0.158 | -0.269 | 1.000 | | | | | | | | | | |
| Contract(TM) | -0.344 | -0.028 | -0.008 | 0.264 | -0.123 | -0.278 | -0.047 | 1.000 | | | | | | | | | |
| Project Technology(L) | -0.080 | -0.070 | 0.149 | -0.009 | -0.130 | 0.201 | -0.122 | 0.005 | 1.000 | | | | | | | | |
| Project Type(M) | -0.054 | 0.075 | -0.023 | 0.265 | 0.169 | -0.173 | -0.119 | 0.145 | -0.061 | 1.000 | | | | | | | |
| PM Rating | -0.087 | -0.006 | -0.014 | 0.190 | -0.081 | -0.079 | -0.060 | 0.027 | -0.159 | 0.149 | 1.000 | | | | | | |
| IT WorkEx | -0.139 | -0.026 | 0.016 | 0.172 | -0.054 | -0.038 | 0.076 | 0.096 | -0.041 | -0.023 | 0.242 | 1.000 | | | | | |
| PM WorkEx | -0.093 | 0.074 | -0.017 | 0.151 | -0.018 | -0.062 | 0.032 | 0.110 | -0.074 | -0.024 | 0.233 | 0.774 | 1.000 | | | | |
| Soft Skills | 0.173 | 0.338 | -0.204 | -0.062 | 0.222 | -0.144 | 0.123 | -0.046 | -0.141 | 0.141 | 0.051 | -0.049 | -0.027 | 1.000 | | | |
| Client Exp | -0.048 | 0.078 | 0.092 | 0.056 | -0.052 | 0.033 | 0.236 | -0.043 | 0.006 | 0.008 | -0.072 | 0.109 | 0.022 | -0.015 | 1.000 | | |
| Hard Skills | 0.106 | 0.071 | 0.010 | -0.082 | 0.025 | -0.013 | 0.278 | -0.146 | -0.031 | -0.052 | -0.057 | 0.091 | -0.005 | 0.007 | 0.742 | 1.000 | |
| dVendorClient | -0.026 | 0.167 | 0.129 | -0.022 | -0.036 | 0.095 | -0.075 | 0.054 | 0.036 | 0.122 | 0.047 | -0.076 | -0.035 | 0.042 | 0.065 | 0.066 | 1.000 |

**Table 3: Sample critical incident methodology survey**

| Dimension | Survey question |
|---|---|
| Task | You are the offshore PM for a project. The project faced some delays in the timelines, eventually cutting into the time for testing the product thoroughly. On one hand, you need to make an on-time delivery as promised to the client. On the other hand, you are sure that the deliverable is not of the quality it should be. Describe what actions you would take? |
| Self | You have been in the client-server and web technology for a few years. Because of some visa issues, you are asked to head the onsite team for a data warehousing project. The responsibilities are challenging - you are expected to quickly learn the new technology, tools, procedures, and hit the ground running - at the client side! You of course have the option to take up a lead role in another project which is in the same technology area that you are comfortable in. What would you do? |
| Career | You have been excited to join ITV[21] as a PM via a lateral entry. You have been at ITV for sometime, and there has been a delay in the timing of your promotion, recognition and rewards for all the hard work you have put in. What would you do? |
| Superiors | You are project leader for an incident and a change management team. You have been brought into the team with the prospect of you becoming the PM for the change management team. However, after the successful delivery of the project, you are sidelined and a new PM is brought in. How would you approach your superiors about this situation? |
| Peers | You are the offshore PM for a team. Your onsite coordinator turns out to be a client pleaser - he interprets the client requirements in his own way, and suggests enhancements that are not even within the scope. The resultant scope creep may get out of hand, resulting in missed deadlines. How would you resolve this situation? |
| Subordinates | Your hard work has paid off, and you have been promoted to be the project manager of your existing team. You are excited, but there is hitch: your old team members view you as one of them, and forget that you are their PM now. At the same time, the senior most team member feels that he has been sidelined, and that he should have been the PM instead of you. All these undercurrents make the transition turbulent, and you are concerned about their impact on project performance and client relationship. Your managers are looking at you to brave this storm and deliver results as you have always done. What should you do? |
| Clients | You are the onsite PM for a project which is being transitioned from another vendor. Unfortunately, the knowledge transfer necessary for the transition is not happening, and the other vendor has support from client middle management. What would you do to ensure that you take on the project smoothly? |

**Table 3: Inter rater reliability for survey response evaluations shows significant agreement amongst evaluators.**

|  | Task | Self | Career | Superiors | Peers | Subordinates | Clients |
|---|---|---|---|---|---|---|---|
| Avg Variance | 0.53 | 0.84 | 0.52 | 0.55 | 0.60 | 0.60 | 0.79 |
| Null Variance | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 |
| Avg/Null Variance | 0.13 | 0.21 | 0.13 | 0.14 | 0.15 | 0.15 | 0.20 |
| 1-avg/null | 0.87 | 0.79 | 0.87 | 0.86 | 0.85 | 0.85 | 0.80 |
| J | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 |
| J*(1-avg/null) | 6.08 | 5.54 | 6.09 | 6.03 | 5.95 | 5.94 | 5.61 |
| Rwg(J) | 0.98 | 0.96 | 0.98 | 0.98 | 0.98 | 0.98 | 0.97 |

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[21] ITV is "IT Vendor," our research site. For confidentiality purposes, we do not reveal the name of the vendor.

**Table 4: SUR estimation results show significant direct as well as contingent impact of soft skills on project outcome measures.**

| | Baseline model | +Skills | + Interactions | VIF |
|---|---|---|---|---|
| **Project outcome measure: Performance** | | | | |
| log(FP) | -0.425(0.073)** | -0.423(0.073)** | -0.434(0.074)** | 2.67 |
| Duration | -0.082(0.005)** | -0.079(0.005)** | -0.078(0.005)** | 1.36 |
| Avg Team Exp | 0.000(0.000) | -0.000(0.000) | -0.000(0.000) | 1.60 |
| Team Size | 0.009(0.003)** | 0.009(0.003)** | 0.010(0.003)** | 2.74 |
| Team Familiarity | 0.459(0.300) | -0.662(0.307)** | 0.476(0.326)+ | 1.24 |
| Contract=TM | -1.071(0.215)** | -0.989(0.214)** | -0.985(0.213)** | 1.36 |
| Language=L | -0.302(0.141)* | -0.262(0.140)+ | -0.213(0.141)** | 1.11 |
| ProjType=M | 0.604(0.165)** | 0.561(0.165)** | 0.548(0.163)** | 1.27 |
| PM's Avg Rating | -0.020(0.181) | -0.054(0.179) | -0.025(0.178) | 1.20 |
| PM's IT WorkEx at Project Start | -0.045(0.038) | -0.052(0.038) | -0.053(0.039) | 2.22 |
| PM's PM WorkEx at Project Start | 0.045(0.038) | 0.052(0.037) | 0.047(0.037) | 2.12 |
| Soft Skills | | 0.212(0.044)* | 0.288(0.044)** | 5.91 |
| Customer Known to PM (in years) | | -0.110(0.065)+ | -0.123(0.064)* | 2.32 |
| Hard Skills | | 0.110(0.039)* | 0.111(0.040)** | 2.33 |
| log(FP) X Soft Skills | | | 0.074(0.086)* | 2.42 |
| Duration X Soft Skills | | | -0.019(0.006)** | 1.24 |
| Team Size X Soft Skills | | | 0.005(0.003)+ | 2.25 |
| Team Familiarity X Soft Skills | | | -0.326(0.044)* | 1.21 |
| Language=L X Soft Skills | | | -0.099(0.175) | 2.18 |
| ProjType=M X Soft Skills | | | 0.318(0.178)+ | 4.05 |
| Customer Known to PM (in years) X Soft Skills | | | -0.049(0.102) | 2.56 |
| Hard Skills X Soft Skills | | | -0.031(0.053)* | 2.39 |
| **Project outcome measure : Feedback** | | | | |
| log(FP) | 0.089(0.038)* | 0.125(0.035)** | 0.174(0.035)** | 2.69 |
| Duration | 0.001(0.003) | 0.001(0.003) | -0.001(0.003) | 1.35 |
| Team Size | -0.002(0.001)+ | -0.003(0.001)+ | -0.003(0.001)* | 2.72 |
| Team Familiarity | -0.010(0.161) | -0.252(0.156) | -0.422(0.157)** | 1.47 |
| Contract=TM | -0.203(0.114)+ | -0.135(0.107) | -0.182(0.102)+ | 1.34 |
| Language=L | -0.122(0.076) | -0.050(0.071) | -0.085(0.068) | 1.14 |
| ProjType=M | 0.104(0.089) | 0.002(0.083) | 0.082(0.079) | 1.26 |
| PM's Avg Rating | -0.104(0.097) | -0.121(0.090) | -0.080(0.085) | 1.18 |
| PM's IT WorkEx at Project Start | -0.056(0.021)** | -0.056(0.019)** | -0.038(0.019)* | 2.84 |
| PM's PM WorkEx at Project Start | 0.071(0.020)** | 0.076(0.019)** | 0.062(0.018)** | 2.67 |
| Firm's Client Experience | 0.815(0.226)** | 0.596(0.213)** | 0.591(0.200)** | 1.11 |
| Soft Skills | | 0.368(0.043)** | 0.345(0.091)** | 5.62 |
| Customer Known to PM (in years) | | 0.050(0.020)** | 0.066(0.019)** | 3.02 |
| Hard Skills | | -0.013(0.021) | -0.025(0.020) | 2.82 |
| log(FP) X Soft Skills | | | 0.211(0.040)** | 2.45 |
| Duration X Soft Skills | | | -0.003(0.003) | 1.26 |
| Team Size X Soft Skills | | | 0.005(0.001)** | 2.30 |
| Team Familiarity X Soft Skills | | | -0.884(0.209)** | 1.38 |

| | Baseline model | +Skills | + Interactions | VIF |
|---|---|---|---|---|
| Language=L X Soft Skills | | | 0.150(0.084)[+] | 2.53 |
| ProjType=M X Soft Skills | | | -0.054(0.089) | 3.51 |
| Customer Known to PM (in years) X Soft Skills | | | -0.079(0.025)[**] | 3.42 |
| Hard Skills X Soft Skills | | | 0.013(0.029) | 3.45 |

| Model Fit Statistics | Baseline model | + Skills | + Interaction vars |
|---|---|---|---|
| N | 530 | 530 | 530 |
| R2 (Performance) | 0.4699 | 0.4836 | 0.5052 |
| R2 (Feedback) | 0.0703 | 0.2016 | 0.2979 |
| Change in R2 (Performance) | 0.4699 | 0.0137 | 0.0216 |
| Change in R2 (Feedback) | 0.0703 | 0.1313 | 0.0963 |
| F Test for change in R2 (Performance) | 41.7431 | 4.5543 | 2.7666 |
| F Test for change in R2 (Feedback) | 3.5608 | 29.1988 | 8.6925 |
| pVal of F Test (Performance) | < 0.0001 | 0.0037 | 0.0053 |
| pVal of F Test (Feedback) | 0.0001 | < 0.0001 | < 0.0001 |
| Condition index (collinearity) | 12.1094 | 12.1505 | 12.2167 |

**Figure 1 Effect of soft skills on project complexity**
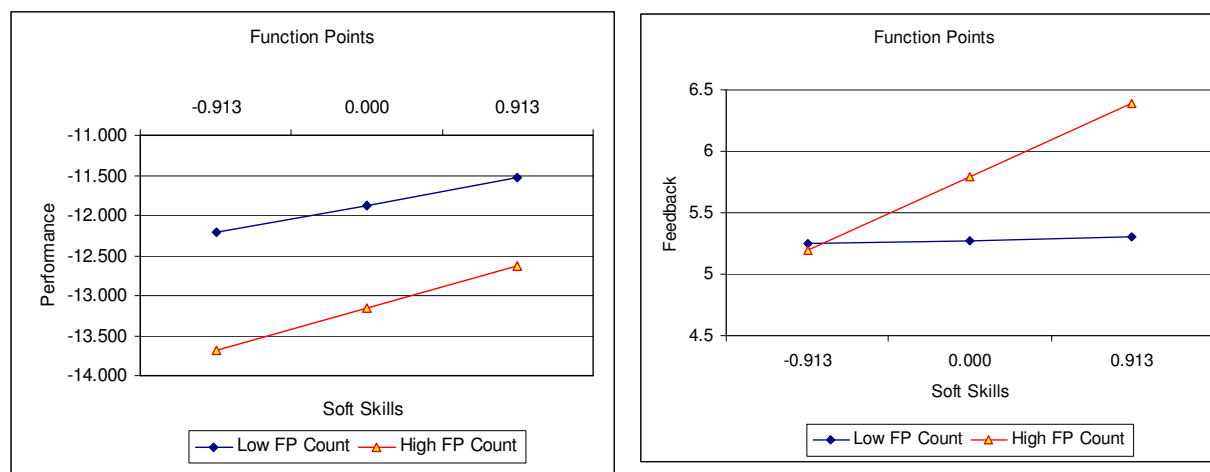


Figure 1A: An increase in soft skills helps projects with higher FP count more and significantly, both in terms of cost performance and feedback.
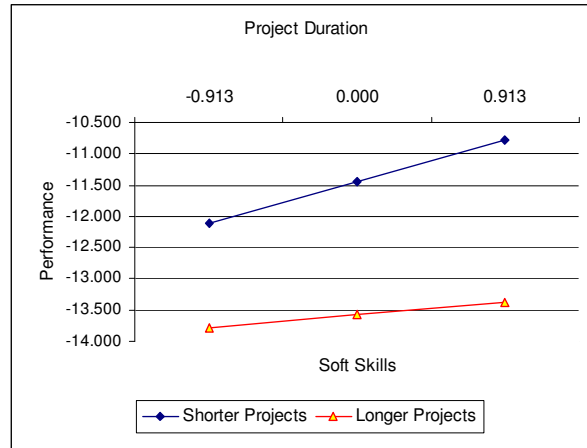
Figure 1B: An increase in soft skills helps improve cost performance for shorter duration projects more.
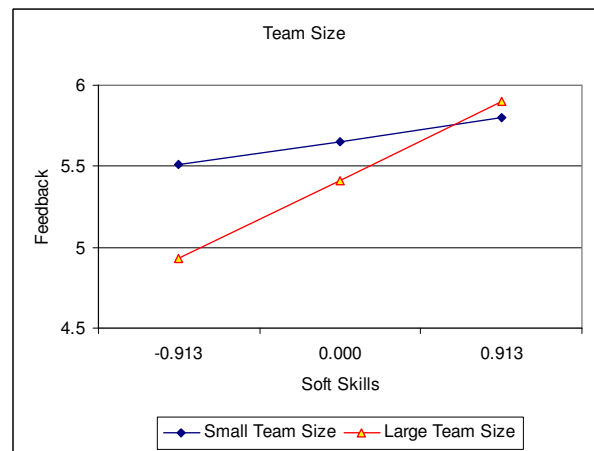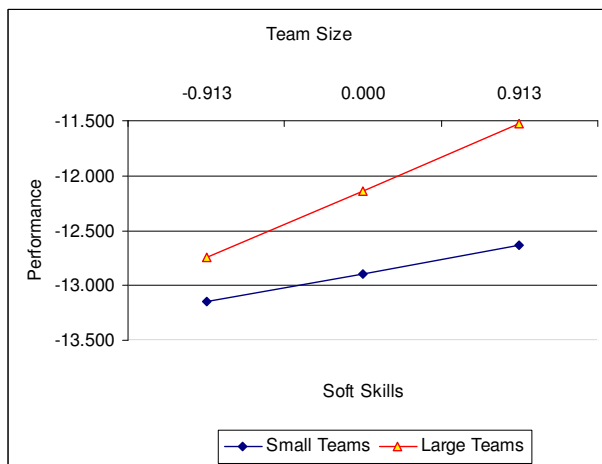


Figure 1C: An increase in soft skills helps projects with larger teams more, both in terms of cost performance and feedback.

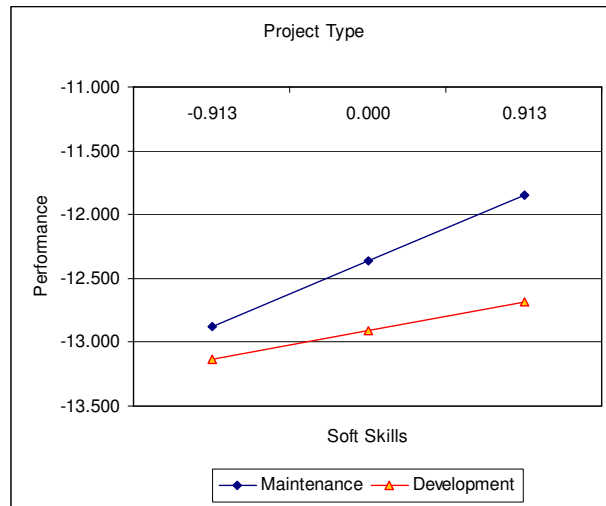**Figure 2 Effect of soft skills on project uncertainty**



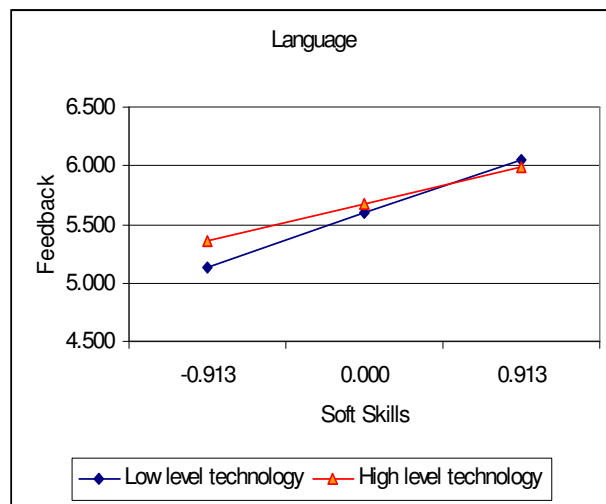Figure 2A: An increase in soft skills helps maintenance projects more for cost performance.



Figure 2B: An increase in soft skills helps low level technology projects achieve higher feedback.

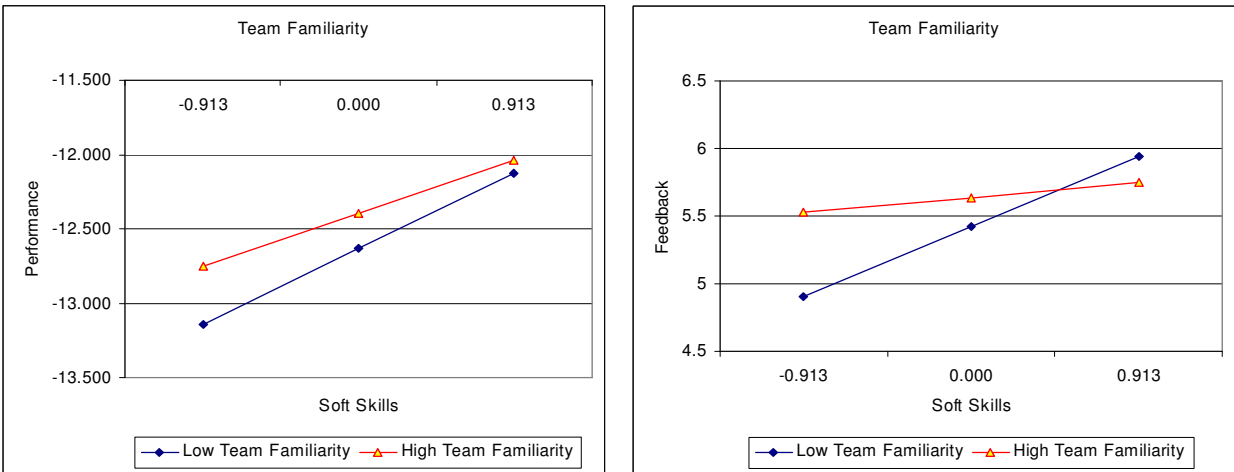**Figure 3 Effect of soft skills on project familiarity**



Figure 3A: An increase in soft skills helps projects with low team familiarity more, both in terms of cost performance and feedback.
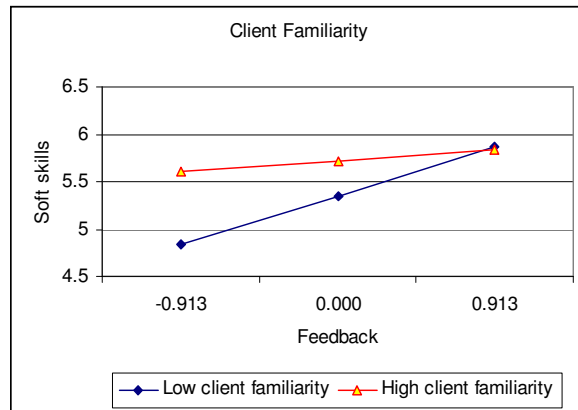


Figure 3B: An increase in soft skills helps PMs with less client familiarity achieve higher feedback.
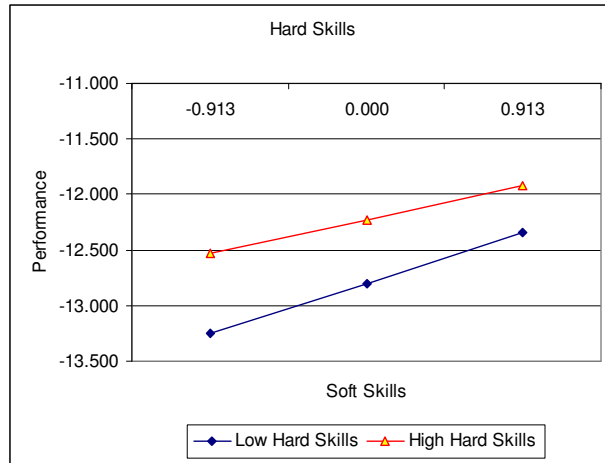
Figure 3C: An increase in soft skills helps PMs with lower levels of hard skills attain better project cost performance.