WHO ARE THE MULTICHANNEL SHOPPERS AND HOW DO THEY PERFORM?: CORRELATES OF MULTICHANNEL SHOPPING BEHAVIOR

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We develop a conceptual framework, which identifies the customer-level characteristics and supplier factors that are associated with purchase behavior across multiple channels. We also propose that multichannel shoppers provide benefits as measured by several customer-based metrics. We conduct an empirical analysis of our propositions using the customer database of a high technology hardware and software manufacturer. We find that customers who buy across multiple product categories, initiate more contacts with the firm, have past experience with the supplier through the online channel, have longer tenure, purchase more frequently, are larger and receive communication from the supplier through multiple communication channels, especially through highly interpersonal channels. We also find evidence for a nonlinear relationship between returns and multichannel shopping, and that there is a positive synergy towards multichannel shopping when customers are contacted through various communication channels. Customers who shop across multiple transaction channels provide higher revenues, higher share of wallet, have higher past customer value, and have a higher likelihood of being active than other customers. We derive several implications for managers who wish to target customers for a multichannel strategy.

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INTRODUCTION

Organizations are moving towards multiple channel integration (Sawhney, 2001). This phenomenon is widespread, spanning such industry segments as retail, travel, banking, computer hardware and software, and manufacturing. Customers can deal with a single organization to search for information, purchase products, and return products through one or more of the following channels: brick and mortar retail stores, salespersons, mail-order catalogs, telephone sales, and online Web sites. Both supplier-side and customer-side rationales explain the current trend toward multichannel integration.

Supplier-Side Factors

Customer relationship management (CRM) software allows organizations to obtain a single view of each customer across these multiple channels. The various channels vary in their costs of operation and effectiveness. For example, retail banks typically acquire customers through an expensive combination of direct mail, telemarketing, and salespersons (when they set up kiosks on college campuses to attract freshmen). Once they acquire customers, banks expect to retain them through relatively inexpensive means, such as the online channel. Also, research studies show that communication across multiple channels can influence the lifetime value of customers (Venkatesan & Kumar, 2004).

Customer-Side Factors

Several studies conducted recently indicate that customers are using multiple channels to make purchases. For example, in a KPMG-Indiana University study, Boa (2003) found that more than 60% of customers in their sample (sample size = 2,000) want to use multiple channels to make purchases. Shop.org\(^1\) found that 34% of customers in their sample (sample size = 48,000) had used at least three different channels to make purchases. Increasing use of e-commerce and CRM capabilities has exposed customers to the virtues of multichannel shopping.

Providing multichannel facilities for shopping can be considered as a strategy for retaining customers who value the convenience. However, anecdotal evidence conflicts concerning the benefits derived from multichannel shoppers. Shop.org also shows that multichannel shoppers purchase more frequently and spend more than single-channel shoppers. However, a survey of online retail consumers shows that they are more of a liability than single-channel shoppers (Reda, 2002). The survey results also suggest that multichannel shoppers are not necessarily more loyal than single-channel shoppers.

An extensive literature in marketing concerns the organizational and supply-chain issues and consequences of adding a channel to an existing portfolio (Purohit, 1997) and the allocation of resources and products across multiple channels (Venkatesan & Kumar, 2004). However, the academic literature contains almost no empirical research on customer characteristics and supplier factors associated with multichannel shopping. Knowledge of the various correlates of multichannel shopping allows managers to target customers when they add a new channel and for migration of customers across existing channels. In our study, we addressed this void in the literature by using the customer database of a high technology computer hardware and software manufacturer to investigate the correlates of multichannel shoppers. We also evaluated the benefits provided by multichannel shoppers using several customer-based metrics. We expect our study to allow us to resolve some of the contradicting evidence on the benefits multichannel shoppers provided. In the next section, we describe the conceptual background and propositions of the study. Then we proceed to discuss the data and models used in the study. We provide the results from our analyses and discuss the managerial implications in a latter section. Finally, we list the limitations of the study and provide suggestions for future research.

CONCEPTUAL BACKGROUND AND PROPOSITIONS

We defined multichannel shoppers as customers who have made a purchase in more than one channel in the observed time period. Researchers have only recently started investigating strategies to manage multichannel shoppers. Schoenbachler and Gordon (2002) proposed a conceptual framework for understanding the drivers of channel choice. They expected that the risk customers perceived in shopping with a supplier, past communication from the supplier,
customer motivation, and product category would drive multichannel purchase behavior. Stone, Hobbs, and Khaleeli (2002) proposed that in the current competitive environment suppliers run the risk of losing customers if they do not provide purchase options across multiple channels. Further, they thought multichannel customers would provide more value and have lower propensities to churn than single-channel shoppers. They also proposed that customers could benefit from shopping through multiple channels because doing so improves convenience and choice.

**Correlates of Multichannel Shopping**

We classified some of our propositions regarding the correlates of multichannel shopping as customer characteristics and supplier factors. We used the findings from research in customer lifetime value (Bowman & Narayandas, 2001; Reinartz & Kumar, 2003; Venkatesan & Kumar, 2004), theoretical propositions in multichannel shopping (Schoenbachler & Gordon, 2002), and research on online customer behavior (Grewal, Corner, & Mehta, 2001; Lynch & Ariely, 2000) to develop our conceptual framework and propositions (Figure 1).

**Customer Characteristics**

**Cross-Buying.** We defined cross-buying as the number of different product categories that a customer has bought from the firm. It is widely acknowledged that the channel of purchase customers prefer usually depends on the product category (Lynch & Ariely, 2000). For example, banks can offer mutual funds, stock-trading facilities, and home mortgages. Customers may conduct transactions for mutual funds and stocks online and prefer to obtain home mortgages through a salesperson. In addition, customers tend to look for information on complex products (such as computer servers and mutual funds) online but prefer to purchase them after consulting a company representative in person or by telephone sales. Hence, we can expect that customers who exhibit a high degree of cross-buying would be inclined to purchase across multiple channels according to the nature of the different products they purchase. Also, we can reasonably expect customers who exhibit a high degree of cross-buying to be familiar with the firm. Familiarity with a brand or firm tends to reduce the perceived risk in customer purchases, leading to increased multichannel shopping (Schoenbachler & Gordon, 2002). Hence we propose that

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**FIGURE 1**

Conceptual Model of Correlates of Multichannel Shopping Behavior
P1: The higher the degree of cross-buying, the higher the likelihood of multichannel shopping.

Returns. If firms treat customers who return products well and make every effort to solve their problems, these customers can turn out to be very loyal and exhibit positive word-of-mouth behavior (Reicheld, 1998). Loyal customers are more familiar with the firm and its products, which can lead to multichannel shopping (Schoenbachler & Gordon, 2002). Hence, returns can have a positive association with multichannel shopping. However, Venkatesan and Kumar (2004) found that the influence of returns on customer purchase behavior is nonlinear. Specifically, customers who exhibit high levels of return behavior (in other words, the number of their returns exceeds a certain threshold) tend to purchase less frequently. As a consequence, a high level of returns (beyond a certain threshold) can increase the risk customers perceive and decrease their motivation to purchase products through multiple channels of the firm (Schoenbachler & Gordon, 2002). Hence, we expect returns to be positively associated with multichannel shopping up to a certain threshold, beyond which an increase in the number of returns can lead to a decrease in the motivation to shop across multiple channels. We therefore expect an inverted U-shaped relationship between returns and multichannel shopping.

P2: An inverted U-shaped relationship exists between returns and the likelihood of multichannel shopping.

P3: The higher the level of customer-initiated contacts, the higher the likelihood of multichannel shopping.

Customer-Initiated Contacts. Bowman and Narayandas (2001) found that customer-initiated contacts are a good indicator of customer loyalty. Especially in business-to-business markets, customer-initiated communication in channels strengthens a relationship, indicates customer involvement, and increases the interdependence of channel members (Ganesan, 1994; Mohr & Nevin, 1990). Moorman, Deshpande, and Zaltman (1993) found timely communication improves relationships between channel members. Also, customers who initiate many contacts with a firm can be expected to have greater familiarity with the firm and the various channels of communication with the firm than those who do not (Schoenbachler & Gordon, 2002). Hence, we can expect a high degree of customer-initiated contacts to be associated with multichannel shopping. Therefore,

P4: The higher the frequency of Web-based, contacts the higher the likelihood of multichannel shopping.

Frequency of Web-Based Contacts. In our study, we analyzed Web-based contacts separately from other forms of customer-initiated contacts because customers’ awareness of a supplier’s Web site indicates their willingness to use new technology. Grewal et al. (2001) found that organizations enter and actively participate in electronic markets if they wish to improve their efficiency in transactions. Participation in electronic markets (or use of Web-based initiatives) improves transaction effectiveness and efficiency (Rindfleisch & Heide, 1997). Also, to improve their efficiency, customers generally prefer to conduct transactions through particular channels depending on the product category (Boa, 2003). Hence we hypothesize that

P5: The longer the tenure of a customer, the higher the likelihood of multichannel shopping.

Customer Tenure. Customers with longer tenure have a higher level of inertia than those with shorter tenure. They value the convenience of shopping across multiple channels, which could also increase their motivation to do business with the supplier. Customers who have been purchasing from a firm for a long time are familiar with the brand and the firm. This familiarity reduces the risk they perceive in making purchases (Schoenbachler & Gordon, 2002). Also, these customers can be expected to be aware of the multiple channel options available for purchasing products. Hence, we propose that

Purchase Frequency. Customers who have a high frequency of purchases can be expected to be willing to improve the efficiency of their transactions, and can be expected to be more familiar with the products and brands of the firm than those who seldom purchase. Morgan and Hunt (1994) argue that, to the extent that the interactions are satisfactory, frequent interactions might increase trust (in other words, reduce perceived risk). Researchers have found that increased frequency of interactions increases the trust between organizations and between individuals

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(Becerra & Mehta, 2003; Heide & Miner, 1992). Given that a customer’s increase in trust in the supplier and hence reduction in the customer’s perceived risk in purchasing leads to multichannel shopping, we propose that

**P6:** The higher the customer’s purchase frequency, the higher the likelihood of multichannel shopping.

### Supplier Factors

**Number of Channels Used for Contact.** Suppliers can initiate contacts with customers through multiple channels, such as direct mail, telemarketing, e-mail, sales personnel, and retail stores. Supplier contacts through multiple channels can inform customers about the multitude of options available for purchasing products. In addition, suppliers can use their contact strategy in one channel to motivate customers to migrate to other channels. For example, salespeople can use their contacts to educate customers about the online channel and in the process reduce the customers’ perceived risk of using the online channel to make purchases (Keltner, 2000). Hence, we propose that

**P7:** The higher the number of communication channels a supplier uses to contact a customer, the higher the likelihood of that customer shopping through multiple channels.

**Type of Contact Channel.** The various communication channels differ in effectiveness. Contact channels such as salespersons, telemarketing, and direct mail can be classified as more or less interpersonal (Mohr & Nevin, 1990). Salesperson contacts, which are at one extreme of the communication continuum, are dyadic in nature, offer the supplier the ability to customize messages, enable rich interaction, and build for personal relationships (Stewart & Kamins, 2002). Another notable aspect of salesperson contacts, which relates to their high level of interpersonal interaction, is the explicit physical nature of the communication. This is in contrast to telephone sales interactions, which can be very interpersonal, like sales calls but lack the face-to-face interaction. On the other extreme of the communication continuum, such instruments as direct mail are unidirectional, limited in content, and impersonal. Firms can improve their understanding of customers’ needs and preferences, educate customers about channels available for making transactions, and respond to customers’ predilections when communications are two-way; it follows that the more interpersonal contact channels are likely to be more effective than the less interpersonal contact channels.

In fact, highly interpersonal channels can reduce risk customers perceive in conducting transactions through new channels. For example, Vanguard has used telephone sales contact with customers successfully (through its customer-service center) to educate customers about the advantages of using its Web site to buy shares in its mutual funds. In fact, the service representatives in the call center also educate customers on how to use Vanguard’s Web site for most of their needs. This strategy has enabled Vanguard to move customers to its Web site fairly easily, and thus reducing its costs. Based on the relative effectiveness of the different contact channels, we suggest that contacts via the more interpersonal channels have a greater positive impact on multichannel shopping than contacts via the less interpersonal channels. Therefore, we propose that

**P8:** Highly interpersonal contact channels have a greater association with multichannel shopping than less interpersonal contact channels.

**Contact Mix Interactions.** At the simplest level, different contact channels may be seen as having independent effects on multichannel shopping. This approach would be reflected in a pure main effects model. However, an interaction effect among channels is likely. Investigating interaction effects between different promotional vehicles is complex, and researchers rarely attempt it (Sethuraman & Tellis, 1991). Farris (2003) believes we need to develop models that reflect media synergies and interactions. For example, Jagpal (1981) studied radio and print advertising for a commercial bank and was the first to present empirical evidence of synergy in multimedia advertising. Berger and Nasr-Bechwati (2001) accounted for the possibility of media interaction effects in their deterministic model of customer equity. Naik and Raman (2003) found empirical evidence for the existence of synergistic effects between TV and print media. Overall, surprisingly little empirical research has concerned this conceptually appealing effect. In addition, until now, researchers have looked at the impact of sales but have found no
empirical evidence for media interaction effects on multichannel shopping.

Interaction effects among contact channels may be positive or negative, and they may be smaller or larger than the main effects. For example, contacting a prospect via telemarketing and via direct mail at the same time may have a stronger effect than administering the two at different times because the different contact channels delivering the same message at the same time reinforce each other. However, a supplier delivering contradictory messages across the different channels could have negative effects. To the extent that the supplier synchronizes its communications across the channels, we propose that the messages will have a positive synergistic effect on multichannel shopping.

P9: Contacting customers through more than one channel has a positive synergistic effect on multichannel shopping.

Control Variables. We used several customer organizational variables, including size, annual sales, and industry category of the customer as control variables. Because we lack prior theory, we have no expectations for the directions of these variables. However, we included them in our framework as components of observed heterogeneity. In addition, these variables can be used for profiling customers who are most likely to purchase from multiple channels.

Performance of Multichannel Shoppers

We analyzed how multichannel shoppers differ from single-channel shoppers using several customer-based metrics, including revenues, past customer value, share of wallet, and predicted propensity to stay in the relationship. Stone et al. (2002) proposed that multichannel customers provide a higher value per customer to suppliers than single-channel customers, and have reduced churn rates. In addition, anecdotal evidence from practitioners suggests that multichannel shoppers are bigger spenders, more loyal, and are less likely to quit buying than single-channel shoppers (Cyr, 2001). Based on the findings of Cyr and Stone et al., we proposed that multichannel shoppers provide higher revenues and higher share of wallet, have higher past customer value, and have a greater likelihood remaining active than single-channel shoppers. Hence,

P10: The higher a customer’s propensity for multichannel shopping, the higher the revenues from that customer.

P11: The higher a customer’s propensity for multichannel shopping, the higher the supplier’s share of the customer’s wallet.

P12: The higher a customer’s propensity for multichannel shopping, the higher the past customer value to the supplier.

P13: The higher a customer’s propensity for multichannel shopping, the higher the likelihood the customer will stay active.

DATA AND METHOD

Data

We used the customer database of a large multinational manufacturer of computer hardware (servers, workstations, and PCs) and software (integration and application) to test our propositions. The company’s database largely concerns business customers. The firm allows customers to purchase products via multiple channels, including salespersons, direct mail, telephone sales, and online. The products the firm manufactures are available for purchase through all four channels. We used customer purchase history from 1998 to 2001 as our calibration sample. We restricted our population to customers who made at least three purchases during the calibration period. Customers who shopped across multiple channels by definition would have made at least two purchases. Therefore, in the calibration sample, we used only those customers who made enough purchases (at least two) to shop across multiple channels. We randomly sampled 3,578 and 3,721 customers at random from the calibration set to create Sample 1 and Sample 2, respectively. To create the holdout sample, we used customer purchase history data through 2002. From this set, we first removed customers who were already in the calibration sample and customers who made fewer than three purchases. We then extracted a random sample of 3,200 customers to create our holdout sample. We used the holdout sample to evaluate the predictive accuracy of the proposed model. We scored the holdout sample using the
estimates obtained from the model we built using the calibration sample. We then evaluated the accuracy of the predictions of the model for the holdout sample by comparing them to the actual observed behavior of the holdout sample. Specifically, we used the model to predict whether customers in the holdout sample would buy using multiple channels and then compared the model predictions to what was observed in the holdout sample. Testing the model's predictive accuracy using the holdout sample was necessary because we hoped our framework would allow managers to target customers likely to shop across multiple channels. In addition, the process we used to create the holdout sample ensures that our model is generalizable across different sets of customers and across different time periods.

In Table 1, we list the variables we used in our study, their operationalization, and their descriptive statistics. In Table 2, we provide the correlation matrix of the correlates of multichannel shoppers. We operationalize the inverted U-shaped relationship between returns and multichannel shopping by using both the number of returns and the square of returns in the model to predict the likelihood that a customer would purchase from multiple channels. The Appendix contains a detailed description of the operationalization of past customer value and likelihood to be active because the computation of these variables is more involved than the rest.

**Method**

**Correlates of Multichannel Shopping.** Our objective in this study was to evaluate empirically the association of various customer specific and supplier-specific factors with multichannel shopping. We used an ordered logistic regression for this purpose. Ordered logistic regression is used when the dependent variable of interest is categorical and an inherent ordering exists among the various categories. We used the number of channels a customer used for making purchases as the dependent variable. Four channels are available for customers to use in making purchases. Hence, using an ordered logistic regression, the probability that a particular customer would shop in \( Y \leq j \) channels is given by the following:

\[
\text{Prob}(Y \leq j) = \frac{1}{1 + e^{-U_j}}
\]  

(1)

\[
U_{ij} = \beta_{0j} + \beta_1 \text{cross-buying} + \beta_2 \text{returns} + \beta_3 \text{returns}^2 + \beta_4 \text{customer-initiated contacts} + \beta_5 \text{Web-based contacts} + \beta_6 \text{tenure} + \beta_7 \text{purchase frequency} + \beta_8 \text{number of different channels of contact} + \beta_9 \text{salesperson contacts} + \beta_{10} \text{telephone contacts} + \beta_{11} \text{direct-mail contacts} + \beta_{12} \text{salesperson telephone sales} + \beta_{13} \text{salesperson direct mail} + \beta_{14} \text{telephone sales direct mail} + \beta_{15} \text{size} + \beta_{16} \text{annual sales} + \sum \beta_{17j} \text{industry category} + \text{error}
\]  

(2)

where the \( \beta_s \) are the coefficients estimated from data and \( \beta_{0j} \) is the intercept term specific to \( j \), the number of channels. Specific to our case, the model can be expanded as follows:

\[
\text{Prob}(Y \leq 1) = \frac{1}{1 + e^{-u_{1j}}}, \quad \text{and}
\]

\[
\text{Prob}(Y \leq 2) = \frac{1}{1 + e^{-u_{2j}}}, \quad \text{therefore;}
\]

\[
\text{Prob}(Y = 2) = \text{Prob}(Y \leq 2) - \text{Prob}(Y \leq 1).
\]

We can obtain the probability that a customer would shop in three channels and four channels similarly. We estimate this model using the maximum-likelihood procedure.

**Performance of Multichannel Shoppers.** In addition to the antecedents of multichannel shopping, we were also interested in knowing if customers who shop across multiple channels are different from single-channel shoppers in terms of such customer-based metrics as revenues, share of wallet, past customer value, and likelihood of being active. We evaluated this using a combination of test procedures. First, we tested for each customer-based metric, whether the mean of at least one group (where the groups are determined by the level of multichannel shopping—shopped in one channel, in two channels, in three channels, or in four channels) is significantly different from the rest of the groups using a MANOVA procedure. We then conducted a post-hoc analysis of the difference in means of the customer-based metrics for all four groups. This analysis allowed us to understand where the differences are in the customer-based metrics across the various groups. Specifically, we wanted to know whether customers who shopped in a
## TABLE 1
**Variable Operationalization and Descriptive Statistics**

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>OPERATIONALIZATION</th>
<th>MEAN</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Correlates of Multichannel Shopping</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Customer Characteristics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-Buying</td>
<td>Number of product categories a customer has purchased in his or her lifetime</td>
<td>2.4 (2.6)</td>
<td>1.2 (1.4)</td>
</tr>
<tr>
<td>Returns</td>
<td>Number of products customer returned in his or her lifetime</td>
<td>13.5 (15.8)</td>
<td>12.2 (16.5)</td>
</tr>
<tr>
<td>Customer-Initiated Contacts</td>
<td>Number of contacts customer made with the firm in his or her lifetime excluding Web-based contacts and purchases</td>
<td>12.8 (13.5)</td>
<td>7.3 (7.1)</td>
</tr>
<tr>
<td>Number of Web Site Contacts</td>
<td>Number of times the customer contacted the supplier through the Internet in his or her lifetime excluding purchases</td>
<td>11.5 (12.1)</td>
<td>5.8 (6.2)</td>
</tr>
<tr>
<td>Tenure</td>
<td>Number of years between the customer’s first purchase and the current time period</td>
<td>2.5 (4.1)</td>
<td>3.8 (3.6)</td>
</tr>
<tr>
<td>Purchase Frequency</td>
<td>Number of purchases a customer made in a given month, calculated as the ratio of the number of purchases to the tenure of the customer</td>
<td>0.8 (0.7)</td>
<td>5.1 (4.8)</td>
</tr>
<tr>
<td>Supplier Factors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Channels of Contact</td>
<td>Number of channels the firm used to contact the customer in his or her lifetime</td>
<td>1.5 (1.6)</td>
<td>0.7 (0.8)</td>
</tr>
<tr>
<td>Salesperson Contacts</td>
<td>Frequency of contacts made by salesperson</td>
<td>23.14 (22.8)</td>
<td>5.79 (5.91)</td>
</tr>
<tr>
<td>Telephone Sales Contacts</td>
<td>Frequency of contacts made by telephone</td>
<td>17.4 (18.1)</td>
<td>46.12 (45.62)</td>
</tr>
<tr>
<td>Direct Mail Contacts</td>
<td>Frequency of contacts made by direct mail</td>
<td>27.41 (28.1)</td>
<td>47.12 (48.11)</td>
</tr>
<tr>
<td>Customer Demographics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size(^a)</td>
<td>Average number of employees in the customer firm during the analysis time period</td>
<td>1.7 (1.4)</td>
<td>3.2 (3.3)</td>
</tr>
<tr>
<td>Annual Sales(^b)</td>
<td>Average annual sales of the customer firm during the analysis time period</td>
<td>30.2 (31.8)</td>
<td>29.4 (28.9)</td>
</tr>
<tr>
<td>Industry Category</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aerospace</td>
<td></td>
<td>0.02 (0.05)</td>
<td>0.10 (0.09)</td>
</tr>
<tr>
<td>Consumer Packaged Goods</td>
<td></td>
<td>0.29 (0.31)</td>
<td>0.48 (0.49)</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td>0.06 (0.07)</td>
<td>0.21 (0.22)</td>
</tr>
<tr>
<td>Financial Services</td>
<td></td>
<td>0.17 (0.14)</td>
<td>0.31 (0.32)</td>
</tr>
<tr>
<td>Government</td>
<td></td>
<td>0.07 (0.08)</td>
<td>0.26 (0.29)</td>
</tr>
<tr>
<td>Manufacturing</td>
<td></td>
<td>0.10 (0.09)</td>
<td>0.25 (0.26)</td>
</tr>
<tr>
<td>Technology</td>
<td></td>
<td>0.13 (0.11)</td>
<td>0.30 (0.35)</td>
</tr>
<tr>
<td>Travel</td>
<td></td>
<td>0.02 (0.03)</td>
<td>0.25 (0.26)</td>
</tr>
<tr>
<td>Performance of Multichannel Shoppers</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Revenues(^c)</td>
<td>Lifetime purchases of the customer</td>
<td>280 (257)</td>
<td>141 (143)</td>
</tr>
<tr>
<td>Share of Wallet</td>
<td>Average ratio of the revenues from the customer to the customer’s annual budget for information technology in the analysis time period</td>
<td>0.41 (0.39)</td>
<td>0.35 (0.41)</td>
</tr>
<tr>
<td>Past Customer Value(^d)</td>
<td>Cumulative profits obtained from a customer</td>
<td>274 (270)</td>
<td>133 (133)</td>
</tr>
<tr>
<td>Likelihood of Staying Active</td>
<td>Probability that a customer is still alive</td>
<td>0.33 (0.38)</td>
<td>0.3 (0.4)</td>
</tr>
</tbody>
</table>

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**Note.** Values in parentheses represent sample 2.  
\(^a\) Values reported in thousands; \(^b\) Values reported in $ millions; \(^c\) Values reported in $ thousands.
<table>
<thead>
<tr>
<th></th>
<th>Number of Channels</th>
<th>Cross-Buying</th>
<th>Returns</th>
<th>Customer-Initiated Contacts</th>
<th>Web-Based Contacts</th>
<th>Tenure</th>
<th>Purchase Frequency</th>
<th>Number of Channels Used for Contact</th>
<th>Frequency of Salesperson Contacts</th>
<th>Frequency of Telephone Contacts</th>
<th>Frequency of Direct Mail Contacts</th>
<th>Salesperson* Telephone Sales</th>
<th>Salesperson* Direct Mail</th>
<th>Telephone Sales* Direct Mail</th>
</tr>
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<tr>
<td>Number of Channels</td>
<td>1</td>
<td></td>
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<tr>
<td>Cross-Buying</td>
<td>0.13^c</td>
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<tr>
<td>Returns</td>
<td>0.0096^c</td>
<td>0.02^b</td>
<td>1</td>
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<td>Customer-Initiated Contacts</td>
<td>0.17^c</td>
<td>0.09^a</td>
<td>0.12^a</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Web-Based Contacts</td>
<td>0.07^c</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Tenure</td>
<td>0.22^c</td>
<td>0.14^a</td>
<td>0.09</td>
<td>0.12^a</td>
<td>0.09</td>
<td></td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purchase Frequency</td>
<td>0.19^c</td>
<td>0.18^b</td>
<td>0.001</td>
<td>0.09</td>
<td>0.11^b</td>
<td>0.10^b</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Channels Used for Contact</td>
<td>0.21^c</td>
<td>0.10</td>
<td>0.09</td>
<td>0.07</td>
<td>0.08</td>
<td>0.13^b</td>
<td>0.04</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency of Salesperson Contacts</td>
<td>0.15^c</td>
<td>0.11</td>
<td>0.09</td>
<td>0.04</td>
<td>0.01</td>
<td>0.17^c</td>
<td>0.001</td>
<td>0.50^c</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency of Telephone Contacts</td>
<td>0.14^c</td>
<td></td>
<td></td>
<td></td>
<td>0.001</td>
<td>0.03</td>
<td>0.11</td>
<td>0.09</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency of Direct Mail Contacts</td>
<td>0.11^c</td>
<td></td>
<td></td>
<td></td>
<td>0.005</td>
<td>0.10^b</td>
<td>0.004</td>
<td>0.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Salesperson* Telephone Sales</td>
<td>0.21^c</td>
<td>0.18</td>
<td>0.01</td>
<td>0.04</td>
<td>0.001</td>
<td>0.20^c</td>
<td>0.06</td>
<td>0.6^c</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Salesperson* Direct Mail</td>
<td>0.18^c</td>
<td>0.10</td>
<td>0.08</td>
<td>0.02</td>
<td>0.06</td>
<td>0.13^b</td>
<td>0.001</td>
<td>0.68</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telephone Sales*</td>
<td>0.15^c</td>
<td>0.09</td>
<td>0.06</td>
<td>0.04</td>
<td>0.007</td>
<td>0.14^b</td>
<td>0.03</td>
<td>0.10^c</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significant at α < 0.10;  ^ Significant at α < 0.05;  ^^ Significant at α < 0.01.
single channel differ from customers who shopped in two, three, or four channels.

RESULTS AND DISCUSSION

Results

Correlates of Multichannel Shopping. We show the results of the logistic regression in Table 3. The pseudo $R^2$ for the ordered logistic regression is 0.61 in Sample 1 and 0.64 in Sample 2. The coefficients reported in Table 4 are standardized coefficients. Overall, we see that all our propositions were supported by the results of our analyses of Sample 1 and Sample 2. For the sake of brevity, we discuss only the results from Sample 1.

Customer Characteristics. The coefficient of cross-buying is positive and significant ($\beta_1 = 2.81$, $\alpha < 0.01$), hence supporting P1. The coefficient of returns is positive and significant ($\beta_2 = 0.51$, $\alpha < 0.01$) and the coefficient of square of returns is negative and significant ($\beta_3 = -0.09$, $\alpha < 0.05$), hence supporting the inverted U-shaped relationship proposed in P2. The coefficient of customer-initiated contacts is positive and significant ($\beta_4 = 2.34$, $\alpha < 0.01$), hence supporting P3. We found that Web-based contacts and customer tenure are positively associated with multichannel shopping ($\beta_5 = 1.04$, $\alpha < 0.01$, and $\beta_6 = 5.08$, $\alpha < 0.01$), hence supporting propositions P4 and P5. Finally, the coefficient of purchase frequency is positive and significant ($\beta_7 = 4.75$, $\alpha < 0.01$), hence supporting proposition P6.

Supplier-Specific Factors. With respect to supplier-specific factors, the analyses show that the number of channels the supplier chooses to contact the customer is positively associated with multichannel shopping ($\beta_8 = 4.45$, $\alpha < 0.01$), therefore supporting P7. In addition, we found that the coefficients of salesperson, telephone sales and direct-mail contacts are positive and significant ($\beta_9 = 3.51$, $\alpha < 0.01$, $\beta_{10} = 2.01$, $\alpha < 0.01$, and $\beta_{11} = 1.56$, $\alpha < 0.01$, respectively) as expected. Also, our comparison of the standardized coefficients shows that salesperson contacts have the highest association ($\beta_9 = 3.51$) with multichannel shopping, followed by telephone sales ($\beta_{10} = 2.01$), and finally direct mail ($\beta_{11} = 1.56$), hence supporting P8. Finally, all the interactions among the various contact channels are positive and significant ($\beta_{12} = 4.51$,

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### TABLE 3
Results From the Ordered Logistic Regression of the Correlates of Multichannel Shopping

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>EXPECTED EFFECT</th>
<th>SAMPLE 1 (N = 3,578)</th>
<th>SAMPLE 2 (N = 3,721)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept 1</td>
<td>-1.55***</td>
<td>-0.66***</td>
<td></td>
</tr>
<tr>
<td>Intercept 2</td>
<td>-1.85***</td>
<td>-1.59***</td>
<td></td>
</tr>
<tr>
<td>Intercept 3</td>
<td>-3.54***</td>
<td>-3.29***</td>
<td></td>
</tr>
<tr>
<td><strong>Customer Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-Buying</td>
<td>+</td>
<td>2.81***</td>
<td>2.72***</td>
</tr>
<tr>
<td>Returns</td>
<td></td>
<td>0.51***</td>
<td>0.49***</td>
</tr>
<tr>
<td>Square of Returns</td>
<td></td>
<td>-0.09***</td>
<td>-0.08***</td>
</tr>
<tr>
<td>Customer-Initiated Contacts</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used for Contact</td>
<td>+</td>
<td>4.49***</td>
<td>4.48***</td>
</tr>
<tr>
<td>Frequency of Salesperson Contact</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telephone Sales Contact</td>
<td>+</td>
<td>3.51***</td>
<td>3.49***</td>
</tr>
<tr>
<td>Sales Contact</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency of Direct Mail Contact</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telephone Sales*Direct-Mail Contact</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct-Mail Contact</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Supplier Factors</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Channels</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual Sales</td>
<td></td>
<td>2.67E-1***</td>
<td>3.21E-1***</td>
</tr>
<tr>
<td><strong>Industry Category</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aerospace</td>
<td>n.s.</td>
<td>n.s.</td>
<td></td>
</tr>
<tr>
<td>Financial Services</td>
<td>0.06***</td>
<td>0.08***</td>
<td></td>
</tr>
<tr>
<td>Manufacturing</td>
<td>n.s.</td>
<td>n.s.</td>
<td></td>
</tr>
<tr>
<td>Technology</td>
<td>0.1***</td>
<td>0.09***</td>
<td></td>
</tr>
<tr>
<td>Consumer Packaged Goods</td>
<td>n.s.</td>
<td>n.s.</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>0.09***</td>
<td>0.12***</td>
<td></td>
</tr>
<tr>
<td>Travel</td>
<td>n.s.</td>
<td>n.s.</td>
<td></td>
</tr>
<tr>
<td>Government</td>
<td>n.s.</td>
<td>n.s.</td>
<td></td>
</tr>
</tbody>
</table>

*Reported coefficients are standardized values. *Significant at $\alpha = 10\%$; **Significant at $\alpha = 5\%$; ***Significant at $\alpha < 1\%$. 

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CORRELATES OF MULTICHANNEL SHOPPING BEHAVIOR 53
The prediction accuracy of the model is significantly different from the prediction that would be based just on chance. The likelihood of our ordered logit model for Sample 1 is \(1,251.2\). The ordered logit model is a discrete model, meaning likelihoods are equivalent to probabilities. The overall log likelihood of the data is given by the following:

\[
L(\text{Data} \mid \text{estimates}) = \log \left[ \sum_{j=1}^{N} L(\text{data}_j \mid \text{estimates}) \right] = \log \left[ \sum_{j=1}^{N} p(o_j \mid x_j, \text{estimates}) \right]
\]

where \(o_j\) and \(x_j\) are the outcome and explanatory variables for observation \(j\), \(p(o_j \mid x_j, \text{estimates})\) means the probability that outcome \(o_j\) is observed conditional on the values of \(x_j\) along with the estimated coefficients, and \(N\) is the sample size of the data.

Thus, the probability of observing a category (the category corresponding to the number of channels a customer uses to shop) conditional on the estimates is given by \(\exp(L(\text{data} \mid \text{estimates})/\text{sample size})\) (this is equivalent to the geometric average of \(p(o_j \mid x_j, \text{estimates})\)). In our study, the probability of observing a category that is true without any information (i.e., assuming a uniform random probability of observing a category) is given by \(1/4 = 0.25\). Based on the log-likelihood, the probability of observing a category that is true is given by \(\exp(-1,251.2/3578) = 0.45\). Hence, the model provides an improvement in the probability of observing a category that is true by approximately 0.2 (an improvement of approximately 80%).

In addition to the in-sample fit provided by the pseudo-\(R^2\) and the log-likelihood, we tested the out-of-sample predictive accuracy of the model in the holdout sample using a hit rate. In Table 4, we provide a cross-tabulation of the predictions of our model versus the observed data in the holdout sample. Table 4 shows that our model can predict the membership of customers in various groups significantly better than a model that is just based on chance. We used the \(t\)-test recommended by Frank, Massy, and Morrison (1965) to compute the significance of the improvement in prediction accuracy our model provided.

**Analysis of Fit and Predictive Accuracy.** The log-likelihood of our ordered logit model for Sample 1 is \(-1,251.2\). The ordered logit model is a discrete model, meaning likelihoods are equivalent to probabilities. The overall log likelihood of the data is given by the following:

\[
\text{Expected to Shop in One Channel} \quad 1,870^a \\
\text{Expected to Shop in Two Channels} \quad 180 \\
\text{Expected to Shop in Three Channels} \quad 25 \\
\text{Expected to Shop in Four Channels} \quad 2
\]

<table>
<thead>
<tr>
<th>SHopped IN A SINGLE Channel</th>
<th>SHopped IN Two Channels</th>
<th>SHopped IN Three Channels</th>
<th>SHopped IN Four Channels</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected to Shop in One Channel</td>
<td>1870^a</td>
<td>268</td>
<td>18</td>
<td>0</td>
</tr>
<tr>
<td>Expected to Shop in Two Channels</td>
<td>180</td>
<td>560^a</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Expected to Shop in Three Channels</td>
<td>25</td>
<td>10</td>
<td>155^a</td>
<td>1</td>
</tr>
<tr>
<td>Expected to Shop in Four Channels</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>95^a</td>
</tr>
<tr>
<td>Total</td>
<td>2077</td>
<td>839</td>
<td>188</td>
<td>96</td>
</tr>
</tbody>
</table>

In addition to the in-sample fit provided by the pseudo-\(R^2\) and the log-likelihood, we tested the out-of-sample predictive accuracy of the model in the holdout sample using a hit rate. In Table 4, we provide a cross-tabulation of the predictions of our model versus the observed data in the holdout sample. Table 4 shows that our model can predict the membership of customers in various groups significantly better than a model that is just based on chance. We used the \(t\)-test recommended by Frank, Massy, and Morrison (1965) to compute the significance of the improvement in prediction accuracy our model provided.

**Sensitivity Analysis.** In addition to evaluating the directional effect of the various correlates of multi-channel shopping, we also wanted to evaluate the magnitude of the association. In other words, we wanted to evaluate the elasticity of the various customer and supplier characteristics on the probability of shopping in multiple channels using a simulation analysis. In the simulation analysis, we computed the probability that a customer shops in four channels (the highest number of channels possible) at three different levels of each driver: at the mean, one standard

---

\(^a\)The prediction accuracy of the model is significantly different from the prediction that would be based just on chance.

\(^2\)We also investigated the magnitude of the effects for the probability that a customer would shop in two and three channels. The results were similar to those reported and can be obtained from the author(s).
deviation below the mean, and one standard deviation above the mean. This procedure is widely used to evaluate the cumulative effects of moderators (Aiken & West, 1996; Kumar & Periera, 1995). For example, if we were interested in evaluating the magnitude of effects of cross-buying, we would compute three probabilities as follows:

\[ P_{\text{low}} = 1 - P(Y \leq 3 | \text{Cross-buy}_{\text{low}}, \text{rest}_{\text{mean}}); \]
\[ P_{\text{mean}} = 1 - P(Y \leq 3 | \text{Cross-buy}_{\text{mean}}, \text{rest}_{\text{mean}}); \]
\[ P_{\text{high}} = 1 - P(Y \leq 3 | \text{Cross-buy}_{\text{high}}, \text{rest}_{\text{mean}}) \]

where, Cross-buy_{\text{mean}} = Mean value of cross-buy in the sample,

Cross-buy_{\text{low}} = Value of cross-buy one standard deviation below the mean,

Cross-buy_{\text{high}} = Value of cross-buy one standard deviation above the mean,

rest_{\text{mean}} = Vector of the mean value of all other correlates of multichannel shopping,

\[ P_{\text{low}} = \text{Probability that a customer would shop in four channels, given Cross-buy}_{\text{low}}, \text{and rest}_{\text{mean}}. \]
\[ P_{\text{mean}} = \text{Probability that a customer would shop in four channels, given Cross-buy}_{\text{mean}}, \text{and rest}_{\text{mean}}. \]
\[ P_{\text{high}} = \text{Probability that a customer would shop in four channels, given Cross-buy}_{\text{high}}, \text{and rest}_{\text{mean}}. \]

We show the results from our simulation analyses in Figure 2a–c. We provide the results for the top five correlates of multichannel shopping in Figure 2a. With regard to the top customer behavior variables, the probability that a customer shops across four channels varies from 0.07 to 0.99, from 0.25 to 0.99, and from 0.48 to 0.84 depending on the tenure of the customer, the frequency of customer purchases, and customer initiated contacts, respectively. Similarly, with regard to the top managerial intervention variables, the probability that a customer shops in four channels varies from 0.45 to 0.87 and from 0.52 to
FIGURE 2B
Effect Slopes for Correlates (Middle 5) of Multichannel Shopping

FIGURE 2C
Effect Slopes for Correlates (Bottom 3) of Multichannel Shopping
0.79 depending on the level of interaction between salesperson and telephone sales contacts, and the number of different channels used for contact.

In Figure 2b, we provide the results for the middle five correlates of multichannel shopping. With regard to the customer behavior variables, the probability that a customer shops across four channels varies from 0.60 to 0.72 depending on the level of cross-buying the customers exhibited. Similarly, with regard to the managerial intervention variables, the probability that a customer shops in four channels varies from 0.53 to 0.79 depending on the level of interaction between salesperson and direct-mail contacts, and from 0.59 to 0.73 depending on the level of salesperson contacts. In addition, the probability that a customer shops in four channels varies from 0.60 to 0.72 and from 0.61 to 0.71 depending on the level of interaction between telephone sales and direct mail contacts and the level of telephone sales contacts.

In Figure 2c, we provide the results for the bottom three correlates of multichannel shopping. With regard to the customer behavior variables, the probability that a customer shops across four channels varies from 0.64 to 0.68 and from 0.66 to 0.65 depending on the level of Web-based contacts and returns made by the customer. Similarly, among the managerial intervention variables, the probability that a customer shops in four channels varies from 0.62 to 0.70 depending on the level of direct-mail contacts.

In summary, based on our simulation analysis, we can infer that customer tenure, purchase frequency, and customer-initiated contacts are the customer characteristics associated with the highest variation in multichannel shopping, and highly interpersonal communication channels, such as salesperson contacts and telephone sales and the width of communication channels the supplier employed are the supplier factors associated with the highest variation on multichannel shopping.

**Performance of Multichannel Shoppers**

We used a MANOVA procedure to evaluate, for each of the four customer-based metrics, whether the mean of at least one group (where the groups are based on the level of multichannel shopping) is significantly different from the means of other groups. The results from the MANOVA indicated that for all four customer-based metrics; the mean of at least one of the groups was significantly different from the means of the other groups. We then conducted post-hoc tests of the mean of each group (Table 5). The mean revenue ($60,076) and past customer value ($94,456) for customers who shop in four channels are significantly different from the mean revenue and past customer value of customers who shop in three channels (mean revenue = 13,250; past customer value = 22,472) in other groups. Additionally, the mean revenue and past customer value of customers who shop in three channels are significantly higher than the mean revenue and past customer value of customers who shop in two channels (mean revenue = 5,736; and past customer value = 10,874). Finally, the mean revenue and past customer value of customers who shop in two channels are significantly higher than the mean revenue and past customer value of customers who shop in a single channel (mean revenue = 4,262; and past customer value = 6,671).

The share of wallet of customers who shop in three channels (share of wallet = 0.48) is significantly higher than the share of wallet of customers who shop in two channels (share of wallet = 0.35) and the share of wallet of customers who shop in two channels is significantly higher than the share of wallet of customers who shop in a single channel (share of wallet = 0.11). In addition, the share of wallet of customers who shop in four channels (share of wallet = 0.72) is significantly higher than the share of wallet of customers who shop

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**TABLE 5** Comparison of Means of Customer-Based Metrics

<table>
<thead>
<tr>
<th>SHOPPED IN SINGLE CHANNEL</th>
<th>SHOPPED IN TWO CHANNELS</th>
<th>SHOPPED IN THREE CHANNELS</th>
<th>SHOPPED IN FOUR CHANNELS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenues ($)</td>
<td>4,262$</td>
<td>5,736$</td>
<td>13,250$</td>
</tr>
<tr>
<td>Share of Wallet</td>
<td>0.20$</td>
<td>0.35$</td>
<td>0.48$</td>
</tr>
<tr>
<td>Past Customer Value ($)</td>
<td>6,671$</td>
<td>10,874$</td>
<td>22,472$</td>
</tr>
<tr>
<td>Likelihood of Staying Active</td>
<td>0.11$</td>
<td>0.15$</td>
<td>0.38$</td>
</tr>
</tbody>
</table>

*a,b,c,d* Means with the same letter are not significantly different from each other at $p = 0.05$. 

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CORRELATES OF MULTICHANNEL SHOPPING BEHAVIOR 57
in three channels. Finally, the likelihood of staying active increases monotonically with the number of channels customers used for transactions. Specifically, the likelihood of staying active for customers who shop across four channels \( (P(\text{alive}) = 0.67) \) is significantly higher than for customers who shop across three channels \( (P(\text{alive}) = 0.38) \). Similarly, the likelihood of staying active for customers who shop across three channels is significantly higher than for customers who shop across two channels \( (P(\text{alive}) = 0.15) \) and the likelihood of staying active for customers who shop across two channels is significantly higher than for customers who shop in only one channel \( (P(\text{alive}) = 0.11) \).

**DISCUSSION**

Our objectives in this research study were to find the customer characteristics and supplier factors that are associated with multichannel shopping and also to evaluate the benefits multichannel shoppers provide to the supplier. We proposed a conceptual framework for the correlates of multichannel shopping and the performance of multichannel shoppers and conducted an empirical test of our conceptual framework in a business-to-business setting, using the customer database of a large multinational manufacturer of high-technology products.

**Correlates of Multichannel Shopping**

**Customer-Specific Factors.** In our study, we found that several customer characteristics and supplier factors are associated with multichannel shopping. Researchers have consistently found cross-buying to be a good predictor of lifetime duration (Reinartz & Kumar, 2003), purchase frequency (Venkatesan & Kumar, 2004), and customer equity (Rust, Zeithaml, & Lemon, 2004). We found that cross-buying is also associated with multichannel shopping. Based on the results from our study and the findings from previous research, we can infer that customers who purchase across multiple product categories are good targets for any new channel initiation efforts and for eliciting channel migration.

Consistent with recent findings (Reinartz & Kumar, 2003; Venkatesan & Kumar, 2004), we also found that customer returns are an important phenomenon. We found that returns are related in a nonlinear fashion to multichannel shopping. In our sample, returns beyond 47 in number are negatively associated with multichannel shopping. Managers can use the return occasions to educate customers about the various channel options available for making purchases. This can also help them to motivate customers to migrate into channels that suit their profiles.

We also found that customers who initiate contacts with the supplier are more inclined to shop across multiple channels. Similar to returns, customer-initiated contacts provide suppliers with a low-cost mechanism for educating customers about the purchasing options available in multiple channels. Customers can initiate contacts for new needs the supplier might be able to meet and for invitations to training programs the supplier firm may be conducting at the buyer’s site (Cannon & Homburg, 2001). Hence, customers who initiate contacts with suppliers can be expected to have a high degree of loyalty and may also prove to be good candidates for spreading positive word-of-mouth for the supplier and for educating other customers about the various channels available for making purchases.

We found that customers who use the online medium are also inclined to shop across multiple channels. However, suppliers who plan to add an online channel or who manage customers across multiple channels including the online channel should synchronize product and customer information across their various channels. Suppliers should be aware that customers prefer multichannel shopping for the convenience it provides, and inconsistency in information across channels can lead to negative consequences because it creates inconvenience.

Old customers are more likely to shop across multiple channels than new customers. Finally, we found that high purchase frequency is associated with multichannel shopping. Our results provide managers with critical customer behavioral indicators of customers who can be targets of any new channel strategy. Managers in the midst of adding a new channel can use our findings to design programs that focus on targeting customers for channel migration.

**Supplier Factors.** Regarding supplier-specific factors, we found support for contacting customers...
across multiple channels. Recently, the literature has revealed a growing consensus that customer contacts are an important tool for improving the lifetime value of retained customers (Venkatesan & Kumar, 2004) and improving product choice (Ansari, Mela, & Neslin, 2003). In addition, we found that contacting customers across multiple channels can serve to inform customers about the various channels available for purchasing products, while simultaneously reducing their perceived risk of purchasing in new channels. Hence, we believe that while too much communication to prospects can be dysfunctional (Fournier, Dobcha, & Mick, 1997), multichannel communication can be a good tool for educating retained customers. We also found that interpersonal channels of communication, such as salesperson contacts, are more strongly associated with multichannel shopping than such channels as telephone sales and direct mail. Finally, we found a potential for positive synergy when customers are contacted through multiple channels.

**Impact of Customer and Supplier Factors on Multichannel Shopping.** We found that customer duration, customer activity, breadth of supplier contacts, and contacts through interpersonal channels have the highest association with multichannel shopping behavior. This implies that trust in the supplier is more strongly associated with multichannel shopping than other factors such as familiarity with the transaction process in new channels (as evident through the low impact of Web-based contacts). Based on our results, we concluded that customers who have deeper relationships with a firm are better targets for migration to new channels than customers who do not. The results also highlight the importance of interpersonal communications in influencing multichannel shopping.

**Control Variables.** Our framework also provides managers with several demographic variables and several variables concerning the customer firms that they can use to profile customers who are likely to shop across multiple channels. While the demographic and firm variables are not good candidates for developing theoretical models that can be generalized, they are particularly useful for acquiring new customers (past purchase-behavior variables are not available for prospects).

**Performance of Multichannel Shoppers**

We found that, at least in business-to-business settings, multichannel shoppers provide better benefits than single-channel shoppers. This implies that customers who shop across multiple channels differ significantly from customers who shop across some of the available channels. Compared to customers who shop through a single channel, multichannel shoppers may have deeper relationships with the supplier and have greater trust and lower perceived risk in their transactions that could motivate them to spend more with the supplier. Also, the depth of a relationship and trust seem to increase as the customers start increasing the number of channels through which they transact with a supplier. Our results imply that organizations adding new transaction channels should first target customers who are already shopping through all the available channels to shop in the new channel.

Our analyses lend support to firms that have invested in integrating information across multiple channels to better manage customers. Several firms, including IBM, Merrill Lynch, and Citibank, have recognized the benefits of providing products directly across multiple channels. In addition, Wells Fargo now allows small businesses to use single online accounts to manage both their business and personal accounts (Grover, 2002). Our results show that multichannel shoppers are more loyal (as measured by share of wallet and likelihood of being active) and more profitable (as measured by past customer value) than single-channel shoppers, possibly because they are aware of options available to them and purchase products in the medium most convenient to them.

**LIMITATIONS AND FUTURE RESEARCH**

The data we used for our study is restricted to the high technology industry and the business-to-business setting. This limits the generalizability of our study results. Future research should investigate the applicability of our conceptual framework in other industry settings. Also, our study focuses on using behavioral data to make inferences. Several attitudinal measures of multichannel shoppers, such as involvement in the purchase process and attachment to the brand image, would help managers understand multichannel shoppers better.
While our research provides a profile of customers who shop across multiple channels, managers are also interested in knowing which customers to select for migration to a new channel or for information about the new channels available for purchasing. In addition, future researchers can identify conditions that make it beneficial for managers to provide incentives in a single channel to all customers, or to provide the identical incentives across all channels to multichannel customers rather than to single-channel shoppers. We did not investigate whether multichannel customers provide a higher lifetime value than single-channel customers. Given the assumption that certain products are more suitable for purchase in a particular channel, future researchers can develop a mapping between product characteristics and the channels most suitable for purchasing various products. The usefulness of online channels as a medium for returning products is also an interesting topic for future research. Finally, given the benefits multichannel customers provide, researchers can investigate the benefit of designing reward programs that offer incentives for purchasing across multiple product categories and across multiple channels over time.

REFERENCES


**APPENDIX A**

**PUTTING CUSTOMER-BASED METRICS INTO OPERATION**

**Past Customer Value**

Using customer-based metrics, we defined past customer value \( (PCV) \) as the historic cumulative profits obtained from a customer. We calculated the cumulative profits annually from a customer’s initial purchase until the current time period. We projected the profit in each year to present day value using a discount factor. We calculate the PCV calculation as follows:

\[
PCV_i = \sum_{x=1}^{X} (CM_{ix} - MC_{ix}) \times (1 + r)^{T-t_x} \tag{A1}
\]

where

- \( CM_{ix} \) = Contribution margin for customer \( i \) in purchase occasion \( x \);
- \( MC_{ix} \) = Marketing costs for customer \( i \) between purchase occasion \( x - 1 \) and \( x \) (we calculate the marketing costs as the cost of the total outbound calls through direct mail, telephone sales, and salespersons);
- \( T = \) current time period, \( t_x = \) time period of purchase occasion \( x \) for customer \( i \),

\( r = \) discount rate (set at 15% for this study), \( x = \) index for purchase occasion of a customer,

\( X = \) number of purchases made by a customer since initial purchase until current time period.

Let us consider a numerical example. Customer 1 has been purchasing over the last two years \( (T = 2) \). During this period, Customer 1 made his first purchase \( (x = 1) \), made two purchases in the sixth month \( (t_{11} = 6 \) months or \( x = 0.5 \) year) and his second purchase \( (x = 2) \) in the 18th month \( (t_{12} = 18 \) months or 1.5 year), respectively. The contribution margins for the first purchase occasion \( (x = 1) \) and second purchase occasion \( (x = 2) \) are equal to \$200,000 \( (CM_{11}) \) and \$150,000 \( (CM_{12}) \), respectively. The marketing costs before \( t_{11} \) and between \( t_{11} \) and \( t_{12} \) are equal to \$4,000 \( (MC_{11}) \) and \$5,000 \( (MC_{12}) \), respectively. We then calculate the past customer value for Customer 1 at the 24th month as follows:

\[
PCV_{Customer\ 1} = (200,000 - 4,000) \times (1.15)^{2-0.5} + (150,000 - 5,000) \times (1.15)^{2-1.5} = \$397,210.
\]

**Likelihood of Staying Active**

In our analysis, we evaluated the probability that a customer is alive or dead in the planning window using the \( P(Alive) \) measure recommended by Schmittlein and
Morrison (1985) and also used by Reinartz and Kumar (2002). The $P(\text{Alive})$ measure uses the past purchase pattern to predict the probability that a customer is still alive at each time period in the prediction window and is defined as follows:

$$P(\text{Alive}) = t^n$$  \hspace{1cm} (A2)

where $t =$ time ratio for the last purchase occasion, and $n =$ number of purchases made by the customer from birth until the current time period.

To calculate $P(\text{Alive})$, we needed to normalize the purchase history data such that the first purchase made by a customer was at time period 0 and the current time period was 1. To do this, we first calculated the interpurchase time for each customer and then divided each interpurchase time by the difference between the current time period and the time of the customer’s first purchase. The $P(\text{Alive})$ measure provides a value between 0 and 1 for all customers. The higher the value of $P(\text{Alive})$, the higher the likelihood of the customer staying alive. Figure A1 portrays the process of calculating $P(\text{Alive})$ for two customers. Customer 1 made four purchases in a 12-month period, the last in the eighth month. Hence for Customer 1, we calculate $P(\text{Alive})$ as follows:

$$P(\text{Alive}) = t^n = (8/12)^4 = (0.67)^4 = 0.2$$

Similarly Customer 2 made two purchases in a 12-month period, the last purchase in the eighth month. Hence for Customer 2, we calculate $P(\text{Alive})$ as follows:

$$P(\text{Alive}) = t^n = (8/12)^2 = (0.67)^2 = 0.45$$

FIGURE A1
Depiction of Customer Purchase History for Calculating $P(\text{Alive})$

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\(^4\) The $P(\text{Alive})$ measure is primarily applied in catalog industries and grocery store purchases where the interpurchase time follows an exponential distribution. Venkatesan and Kumar (2004) show that a generalized gamma distribution is more appropriate for modeling future activity in high technology industries; this is also the case in our study. However, we use the $P(\text{Alive})$ measure in our case to maintain simplicity of exposition. To ensure the face validity of using $P(\text{Alive})$, we also calculated the proportion of customers who made a purchase in 2002 as a proxy measure for $P(\text{Alive})$, and the substantive results of the study did not change. The results are available from the authors.