Chapter 25
Multichannel Customer Management

Abstract Nowhere is the potential – and challenge – for database marketing more acute than in the "brave new world" of multichannel customer management. Whereas many companies historically interacted with their customers through one channel – the bricks-and-mortar retail store, the bank branch, the company catalog, the financial advisor – today almost all companies are multichannel. This gives rise to several key questions and management issues; for example, "Is the multichannel customer a better customer?" "If so, why?" "Should we encourage our customers to be multichannel?" We have just begun to understand questions such as these, and this chapter reviews what we know and do not know. We discuss the multichannel customer in depth, including the association between multichannel usage and sales volume. We also discuss the factors that influence customers' channel choices, the phenomenon of research shopping and the impact of channel introductions on firm revenues. We present a framework for developing multichannel customer strategies, and conclude with industry examples of multichannel customer management.

One of the most promising applications for database marketing is the management of customers over multiple marketing channels. These channels include the Internet, call centers, sales forces, catalogs, retail stores, and in the near-future, interactive television. Neslin et al. (2006b, p. 96) define multichannel customer management as "the design, deployment, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development." As Neslin et al. note, marketers have always considered channel management to be a fundamental component of the marketing mix (e.g., Stern and El- Ansary 1972; Webster 1991). However, while traditional channel management has taken the perspective of the firm (Rangaswamy and Van Bruggen 2005), multichannel *customer* management centers on the customer, on the creation of customer value as a means to increase firm value (Payne and Frow 2005; Boulding et al. 2005).

25.1 The Emergence of Multichannel Customer Management

25.1.1 The Push Toward Multichannel

Company adoption of multichannel customer strategies has been driven by company, customer, and competitive forces. Companies have developed enhanced technological capabilities, particularly in data management and the Internet. The Internet has created an entirely new channel; one that naturally links to other channels. For example, customers can research products on the Internet and purchase them in the store (see Sect. 25.2.5).

Customers have rapidly expanded their channel experiences beyond the traditional store or sales call. They are also comfortable with catalogs, the Internet, ATM's, and call centers. They therefore expect companies to have a presence in all these channels.

Lastly is the impact of competition. Driven by company and customer factors, Company A initiates a multichannel strategy, and Company B has to follow suit. Whether this precipitates a Prisoner's Dilemma is a major issue (see Sect. 25.3.3.1).

25.1.2 The Pull of Multichannel

Companies have also been *pulled* toward multichannel management by potential improvements in loyalty, sales growth, and efficiency. Loyalty may benefit from increased satisfaction or higher switching costs. Sales may grow simply because the brand is more available. See Sect. 25.2.2.2 on sales growth and Sect. 25.2.7 on loyalty.

The promise of improved efficiency is driven by the Internet and call centers (see Sect. 25.3.4.1). Both channels are highly automated and may seem antithetical to enhancing customer relationships. However, the choice may not be between personal and automated contact, but rather, between automated or no contact. The customer's *need* for company contact has risen dramatically. Consider the multitude of features that now accompany a cell phone. These stimulate customers to contact the company, to inquire about a feature or determine why it isn't working. The challenge is to develop effective yet low-cost channels for dealing with this skyrocketing demand for service.

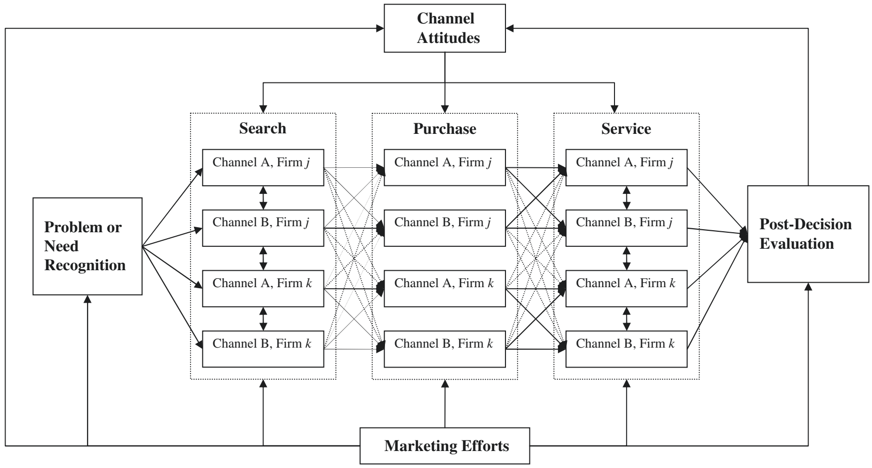

Fig. 25.1 A general model of customer channel choice.

25.2 The Multichannel Customer

25.2.1 A Framework for Studying the Customer's Channel Choice Decision

Figure 25.1 presents a framework for studying the customer channel choice decision. The framework weds the customer's decision process (Engel et al. 1995; Peterson et al. 1997) with the firm's marketing efforts (see also Neslin et al. 2006b). The customer recognizes a need, searches for information for a product that addresses the need, purchases the product, and then seeks after-sales service. Along the way, the customer can access various channels at various companies. The process is guided by the customer's attitudes toward the various channels, by the firms' marketing efforts, and by the outcomes of previous stages in the process. Finally, the customer evaluates the experience and updates his/her attitudes.

For example, stimulated by a Sony advertisement, a customer realizes he/she might want a high-definition television (HDTV). The customer requires information, and accesses Circuit City's and Best Buy's websites. Now the customer can talk intelligently to an expert. The customer decides to visit a store to gather more information, and chooses Best Buy because the store is closest. Now the customer knows what kind of HDTV he or she wants. Having recently seen a Wal-Mart ad claiming brand-name HDTVs at lower prices, the customer goes to Wal-Mart and purchases the product. After purchasing the HDTV, the customer has trouble installing it and goes back to Wal-Mart for help. Finally, the HDTV is successfully installed and the customer evaluates the process. One sees in this example the complexity

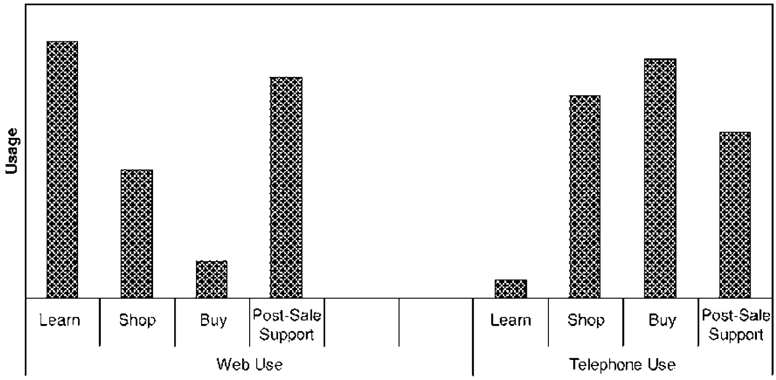

Fig. 25.2 Customer self-reported use of marketing channels (From IOMA 2002).

of the process, the choice between channel and firm, and the dynamics of search ⇒ purchase ⇒ after-sales.

Figure 25.2 compares B2B customer preference for the Internet versus telephone for various stages of the buying process (IOMA 2002). The search stage is divided into "learning" and "shopping." Learning is gathering information about general product attributes. Shopping is specifying exactly what product is wanted at what price. The Internet excels on learning and after-sales; the telephone is preferred for shopping and actual purchase. The figure is clear evidence that customers prefer different channels for different stages of the decision process (see also Verhoef et al. 2007).

25.2.2 Characteristics of Multichannel Customers

25.2.2.1 Demographic and Psychographic Characteristics

Individual difference variables have been shown to describe customers who use multiple rather than single channels. Ansari et al. (2008) found the multichannel shopper to be younger and higher income. Kumar and Venkatesan (2005) found that customer size and annual sales, purchase frequency, tenure as a customer, number of customer-initiated contacts, and the level of cross-buying were positively associated with multichannel usage. In addition, the number of returns had an inverse U-shaped relationship to multichannel usage. These findings show that multichannel shoppers have different personal characteristics than single-channel shoppers.

25.2.2.2 Purchase Volume and Profitability

An emerging generalization in multichannel research is that multichannel shoppers purchase higher volumes (Neslin et al. 2006b). Figure 25.3 shows

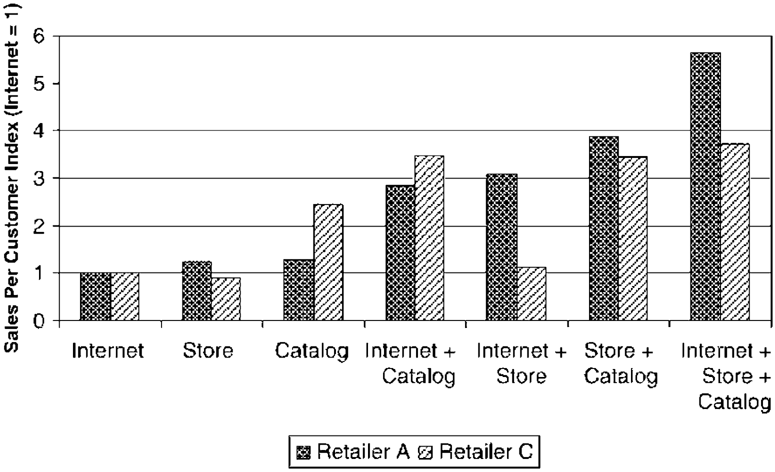

Fig. 25.3 Channel usage and purchase volume (From Retailer A: DoubleClick 2004a; Retailer C: Thomas and Sullivan 2005a).

the evidence for two US retailers. Note, it may not be that every multichannel combination exceeds every single channel, but the customer who purchases from channels A *and* B purchases more than the customer who purchases only from channel A *or* B. Further evidence on the association between multichannel buying and purchase volume can be found in Kumar and Venkatesan (2005), Myers et al. (2004, p. 1), Kushwaha and Shankar (2005), and Ansari et al. (2008). One interesting exception to this generalization is the work of Campbell and Frei (2006). These authors find that adoption of online banking is associated with higher transaction volume, but a net decrease in revenues, which they conjecture may be due to customers managing their balances more effectively and avoiding various fees.

There are three reasons why the multichannel customer might buy more: (1) loyalty, (2) self-selection, and (3) marketing. Identifying which of these explanations applies is very important because of the implications for whether companies should encourage customers to be multichannel.

The loyalty explanation is that purchasing from multiple channels increases customer service and satisfaction, resulting in higher loyalty to the firm and therefore higher sales volume. Another possibility is that the multichannel customer purchases more products from the company and hence would incur higher switching costs for leaving. If higher loyalty is indeed a natural consequence of multichannel usage, this would favor companies encouraging customers to become multichannel.

The self-selection explanation is that high volume customers have more complex needs and more purchase occasions, so naturally use more channels. Self-selection says that multichannel does not grow the business – it simply allows high-volume customers to purchase from more convenient outlets.

Self-selected multichannel shopping may still increase profits if it decreases costs, e.g., as customers spend more time on the Internet.

The marketing explanation works in three ways: First, multichannel customers may receive more marketing because they are higher volume and hence targeted with more marketing. If this is the case, whether multichannel should be encouraged depends on customer response to marketing. Second, the multichannel customer may be exposed to more marketing *as a consequence* of being multichannel. The customer who only uses the firm's retail store is exposed to in-store merchandising, whereas the customer who uses the firm's store and catalog is also exposed to the advertising value of the catalogs. Third, multichannel is a form of increased distribution and hence makes the company's products more easily available. If increased marketing occurs as a consequence of multichannel shopping or availability, then multichannel shopping should be encouraged.

Ansari et al. (2008) support the marketing explanation. They find that multichannel customers receive more marketing and are more responsive to it. They find that using the Internet is associated with lower, not higher, purchase frequency in the long run. They also find that at the beginning of their data, the customer group that eventually became multichannel was equal in purchase volume to the group that stayed single channel. These results tend to refute the loyalty and self-selection hypotheses. Hitt and Frei (2002), however, support the self-selection hypothesis. They find that while customers who adopt online banking (and presumably are multichannel) acquire new products at a faster rate, the magnitude is only about 10% of the overall difference between online and offline customers (p. 746). The authors conjecture that self-selection therefore plays a large roll in differences between on and offline customers.

A related issue is the relationship between multichannel behavior and customer profitability. Three studies have investigated this.

Venkatesan et al. (2007) use a two-equation model where the first equation regresses current period customer profits versus lagged multichannel purchasing. The second equation regresses the probability of being a multichannel shopper versus lagged multichannel purchasing. Their results are that the coefficient for *lagged* multichannel shopping in the first equation is statistically significant and positive.

Hitt and Frei (2002) and Campbell and Frei (2006) analyze the impact of adoption of online banking services. Hitt and Frei (2002) use cross-sectional analyses to infer that online customers are more profitable than their offline counterparts. Campbell and Frei (2006) analyze per-period data of banking customers over an 18-month period. They find that online customers increase the number of transactions after adoption. These customers substitute online transactions for ATM and automated as well as human call-center transactions, but slightly increase their usage of the bank branch. The net increase in transactions, however, results in increased costs. The authors then find that revenues actually decrease, as reported earlier. The net result is a decrease in profits. However, the authors find that online adoption leads to higher retention rates, so the net result may be higher customer lifetime value.

Clearly more work is needed to sort out why the multichannel shopper is higher volume, and ultimately, whether adoption of new channels yields more profitable customers. There are challenging methodological issues (Sect. 25.2.4.3), and we need to gather more empirical evidence to generalize the initial findings reviewed above.

25.2.3 Determinants of Channel Choice

25.2.3.1 Overview

Much work has been conducted on the determinants of channel choice. Figure 25.4 draws on Neslin et al. (2006b) to list six major determinants: (1) marketing, (2) channel attributes, (3) social influence, (4) channel integration (5) situational factors, and (6) individual differences. We review what is known about these determinants.

25.2.3.2 Individual Differences

As reported by Neslin et al. (2006b), several individual difference variables are associated with channel choice, including age, gender, education, income, family size, and region (Ansari et al. 2008; Gupta et al. 2004b; Inman et al. 2004; Kushwaha and Shankar 2005; Verhoef et al. 2007). Interestingly, Thomas and Sullivan (2005b) find that stage in the customer lifecycle determines channel choice.

Another important individual-difference variable is channel experience. Montoya-Weiss et al. (2003), Inman et al. (2004), and Ansari et al. (2008) find that experience in using a particular channel makes it more likely the customer will use that channel in the future. Whether this is due to mindless inertia or to cognitive learning has not been explored.

Ward (2001) provides a theory for the role of channel experience. He proposes that customers make human capital investments in learning to use particular channels. If the skills gained through these investments "spillover" to other channels, customers can become multichannel users. For example, a skill in using a catalog is the ability to determine the best product without actually touching it. This skill spills over to using the Internet, and as a result, the catalog and Internet become substitutes.

To measure spillover, Ward obtains data on customer purchases, by channel, in several product categories. The author estimates an equation of the customer's propensity to purchase a category in each channel as a function of channel-specific and category-specific dummies. The residuals from these

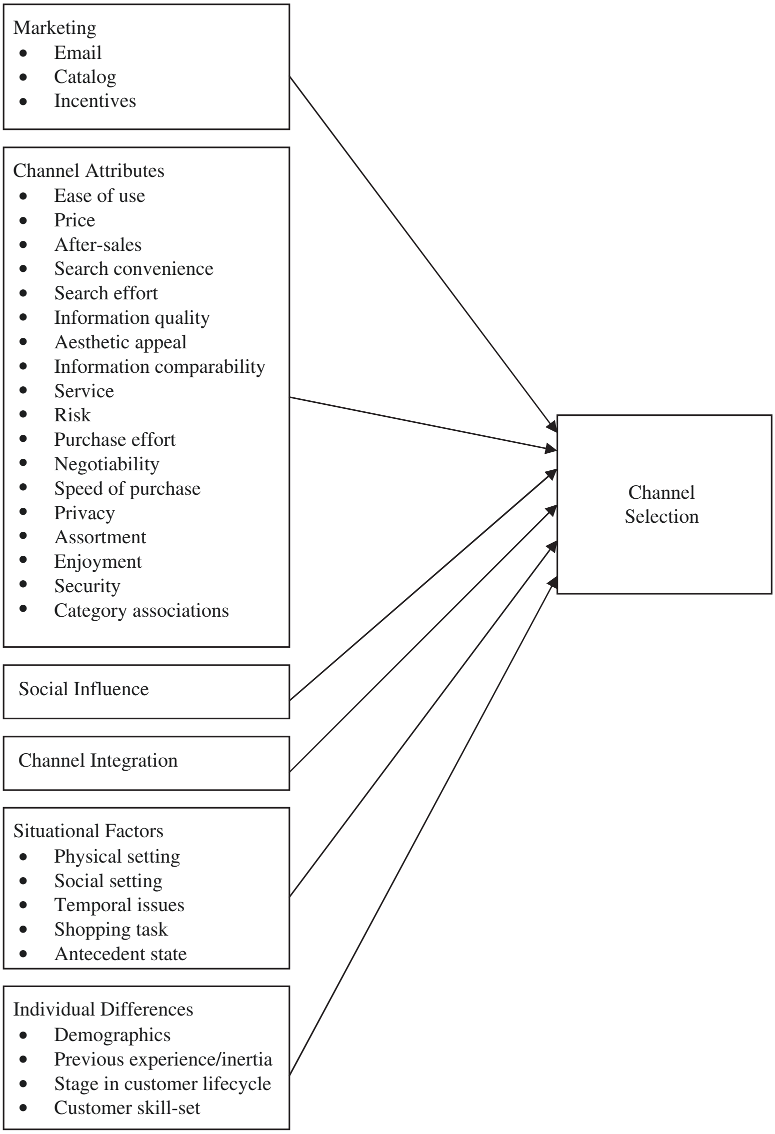

Fig. 25.4 Determinants of customer channel selection (From Neslin et al. 2006b).

regressions represent effects that cause deviations from which channel we would expect the customer to use on average. By correlating these residuals between channels, the author estimates spillover.

The results suggest that the spillover effects are largest between online and direct marketing. The spillover between retail and direct or between retail and online is lower. However, there is somewhat more spillover between retail and direct than retail and online. Overall, Ward's work is quite interesting because it provides theory as to why certain channels might be substitutes for each other.

25.2.3.3 Situational Factors

Neslin et al. (2006b) cite five situational factors suggested by Nicholson et al. (2002): (1) physical setting (e.g., weather), (2) social setting, (3) temporal issues (time of day, urgency of the purchase, (4) task definition (e.g., type of product), and (5) antecedent state (e.g., mood). Neslin et al. note that particular attention has been devoted to task definition, hypothesizing for example that experience goods are more likely to be purchased at a store, while search goods are more likely to be bought on the Internet (Mathwick et al. 2002), and customizable products are more likely to be purchased on the Internet (Mahajan et al. 2002).

25.2.3.4 Channel Integration

Integrated channels make it easy for the customer to choose whichever channel is more convenient under the circumstances. Companies can enhance this effect through incentives and their design of the channels. Neslin et al. (2006b) cite the case where the Internet includes store locators and in-store pick-up that allow the customer to search on the Internet but make the purchase at the store.

Bendoly et al. (2005) survey customers regarding their perceptions of whether channels were integrated, and their use of the Internet and the retail store. They identify two types of integration – information integration, such as advertising local stores on the Internet, and physical integration, such as purchases made via the Internet being returnable at the store. The authors found these dimensions interacted with perceived product availability. For example, if the product was perceived as available at the store, *and* the store and Internet were perceived as being integrated, the customer was more likely to purchase the product on the Internet. These results suggest that to the extent channels are integrated, they are perceived as equally desirable for purchase. This shows how integrated channels breed multichannel shopping.

25.2.3.5 Social Influence

The theory of reasoned action (e.g., Fishbein and Azjen 1975; Sheppard et al. 1988) suggests that consumers make decisions based not only on their own perceptions of the decision, but their perceptions of whether peers, friends, spouses, etc. perceive the decision is a good one, and whether these others' opinions matter to the decision-maker. Accordingly, one would expect that channel usage would depend on the influence of significant others.

This has been verified. Keen et al. (2004) utilized "Norm" as a factor in a conjoint analysis of channel choice. Norm was defined at two levels ("85% of people important to you have made an online purchase like this," and "5% ..."). The authors found that Norm was an important factor in channel choice, although channel format and price were most important. Verhoef et al. (2007) modeled customers' channel preferences as a function of several attributes, including "Clientele" – the belief that the customer's acquaintances used the channel. The authors found that Clientele particularly influenced customers' choice of the Internet. This makes sense in that the Internet is a new channel and one would expect consumers to model their behavior after peers when they personally have less experience. It also could relate to the "community" concept behind the Internet. Nicholson et al. (2002) found in an ethnographic study that a mother decided to purchase a gift for her child at a store rather than the Internet because the effort in using the store was consistent with the mother's devotion to her child.

25.2.3.6 Channel Attributes

As Fig. 25.4 shows, perceived channel attributes play an important role in channel choice. This follows from the theory of reasoned action. Neslin et al. (2006b) cite several papers that investigate these attributes, including Keen et al. (2004), Nicholson et al. (2002), Burke (2002), Montoya-Weiss et al. (2003), Kacen et al. (2003), Teerling and Huzingh (2005), Jing and Rosenbloom (2005), Thomas and Sullivan (2005b), Ancarani and Shankar (2004), Tang and Xing (2001), Morton et al. (2001), Pan et al. (2002a), Gupta et al. (2004b), Inman et al. (2004), Kushwaha and Shankar (2005), and Verhoef et al. (2007) (see also Teerling 2007). As Fig. 25.4 shows, the list of potential attributes is long and varied.

Figure 25.5, from Verhoef et al. (2007), shows how the Internet, Store, and Catalog are "positioned" in terms of customer perceptions of 15 attributes. The store is strong on lack of risk, service, assortment, and after-sales support. It is also strongly positioned on privacy. The Internet excels on search convenience and information comparison, but lags on service, privacy, after-sales support, and risk. The catalog is similar to the Internet, not as convenient but without the privacy concerns. The privacy result is interesting. The catalog is not anonymous, especially when used for purchase. However, the lack of privacy is transparent. The catalog buyer knows the firm knows who they are; with the Internet, there is no telling who is monitoring one's actions.

Figure 25.6 shows attribute importances inferred by Verhoef et al. by a regression of overall attitude versus attribute perceptions. Attributes differ markedly in their importance and importance differs by channel. Purchase risk, after-sales support, assortment, and enjoyment are important

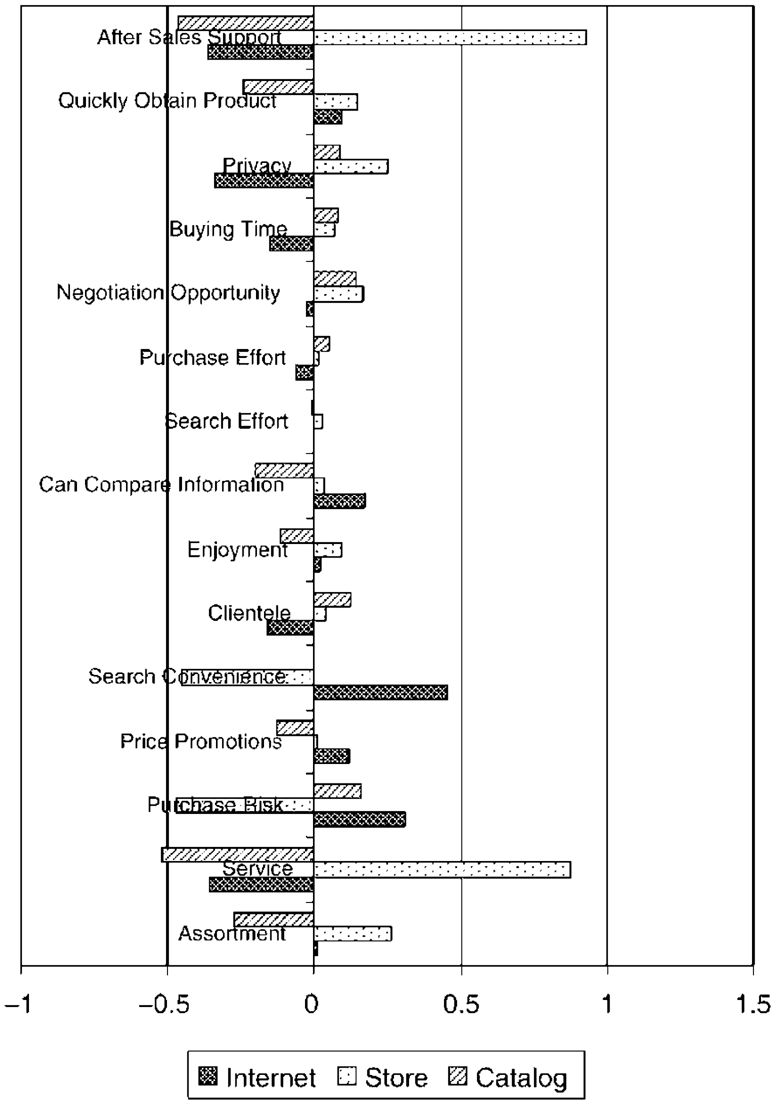

Fig. 25.5 Attribute positioning of channels (From Verhoef et al. 2007).

determinants of attitudes toward using the Internet for purchase, whereas negotiation opportunity and purchase effort are less important. Privacy is an important attribute for using the Internet for purchase, but less so for the catalog and of no concern for the store. The Internet and catalog are more "attribute-driven" than the store. In Verhoef et al.'s sample, customers had uniformly high attitudes toward the store, perhaps due to an experience "halo".

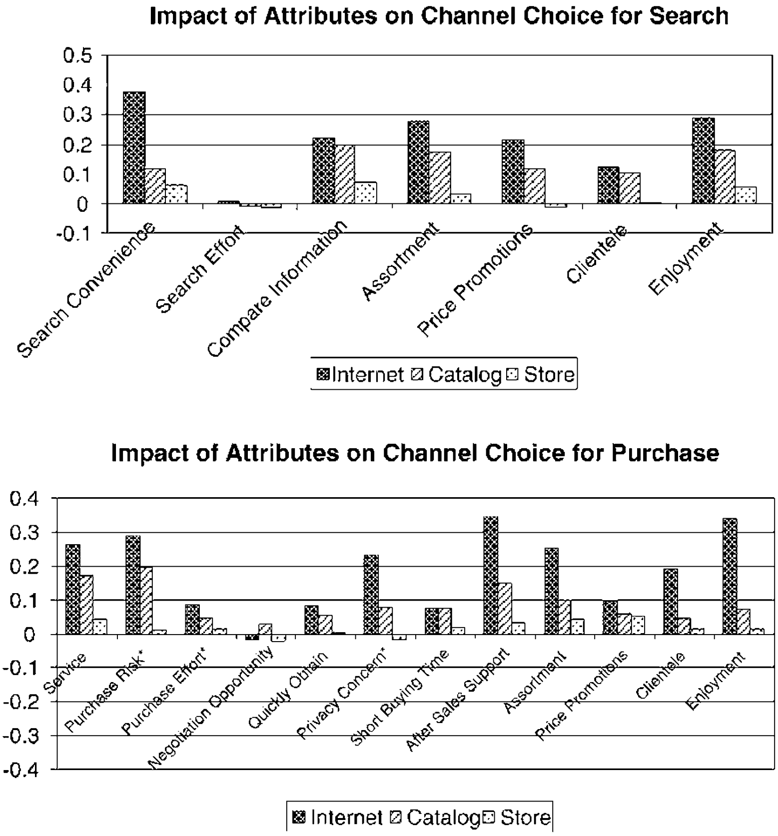

Fig. 25.6 Attribute importances for search and purchase (From Verhoef et al. 2007).
* Signifies that the attribute is reverse-coded. That is, purchase risk has a negative impact on channel choice, as does purchase effort. Privacy concern has a negative impact for Internet and catalog; the impact for store is nominally positive, but was not statistically significant.

In summary, channels are "positioned" much in the way products are. An extension of the Verhoef et al.'s research would be to create a positioning map for each channel, for each decision stage, for each *firm.*

25.2.3.7 Marketing

Recent work has verified that marketing can drive channel choice. Thomas and Sullivan (2005a) found that direct marketing influenced choice of store, catalog, or Internet. They found two segments. For one segment, direct marketing expenditures migrated customers to the Internet at the expense of the store. For the other segment, direct marketing expenditures moved customers to the store rather than the Internet. The main finding is that marketing determines migration, and segments respond differently, even in opposite directions. Ansari et al. (2008) reach the same conclusion.

Venkatesan et al. (2007) studied the time it took customers to adopt new channels, given they had bought earlier from another channel. They found that marketing communications (direct mail and e-mail) had an inverse U-shaped relationship with the timing of new channel adoption. Up to a point, increasing communications would shorten the time till adoption; however, after that threshold, increasing communications would actually lengthen the time till adoption.

Ansari et al. (2008) found that e-mails were strongly associated with choice of the Internet. This makes sense – e-mails and the Internet are basically the same technology, and the availability of a click-through URL in an e-mail would encourage movement to the Internet. This is supported by Knox (2005), who found that newly acquired customers evolve toward online, offline, and multichannel segments. The online segment was highly responsive to e-mails and this appeared to guide them toward the Internet.

In summary, marketing efforts influence channel choice, and the influence is heterogeneous across customers. Ansari et al. (2008), and Knox (2005), have also found that marketing influences purchase incidence. As a result, marketing influences sales volume as well as the channel that produces that volume. Avenues for future work include: (1) Is there a "channel/marketing congruency," whereby marketing and channels link well if they use similar technology (e.g., e-mails and the Internet)? (2) How effective are direct incentives in influencing channel choice? For example, how effective is free shipping in getting customers to buy online? (3) Much more needs to be learned about customer heterogeneity. What types of customers respond to marketing by moving to one channel versus the other?

25.2.4 Models of Customer Channel Migration

Researchers have begun to model the customer channel "migration" process. Migration can be thought of simply as channel choice, but we use it to convey choices over time. This is particularly important to managers who wish to route customers to different channels over time, or learn how to create multichannel customers.

25.2.4.1 Integrating Channel Choice with Purchase Frequency and Order Size

Models developed for consumer scanner data are being adapted to study customer channel migration. Analogous to the brand choice/purchase incidence/purchase quantity (e.g., Bell et al. 1999), we now have channel choice/

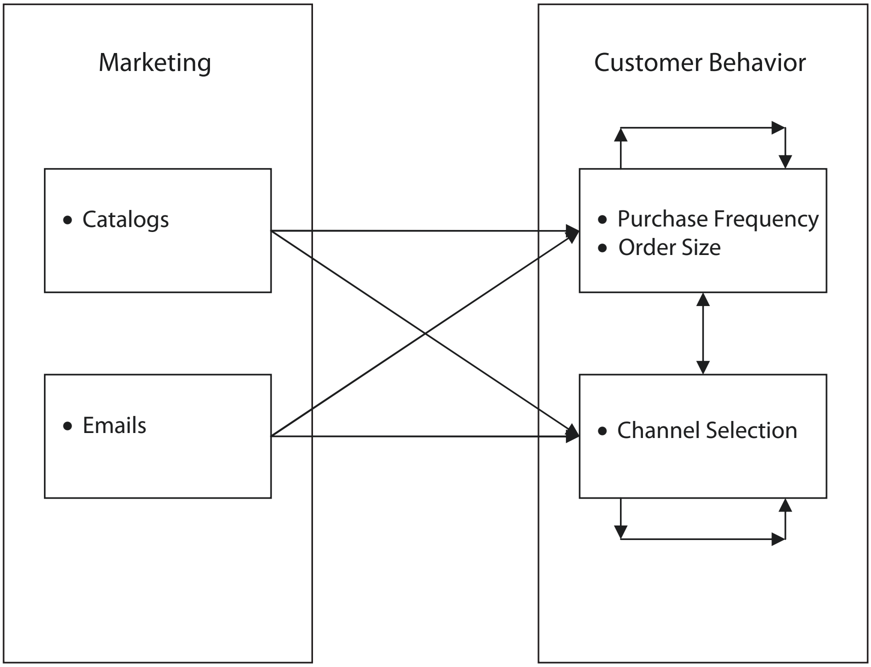

Fig. 25.7 Impact of marketing on channel migration (From Ansari et al. 2008).

purchase frequency/order size. Since data are available typically for a given firm, brand choice cannot be modeled. Purchase frequency therefore entails purchase of the focal firm's products. Order size is the amount spent on the firm's products, given incidence.

The advantages of studying purchase frequency/order size/channel choice holistically are twofold: First, we learn not only the factors that determine migration, but explicitly link that migration to sales volume. Second, some researchers (Keane 1997; Sun et al. 2003) suggest that stand-alone choice models can mis-estimate choice effects: The impact of marketing on choice construed by a stand-alone choice model might also represent the impact on purchase incidence.

Ansari et al. (2008) use the framework depicted in Fig. 25.7. Marketing communications determine customer behavior, in the form of channel selection (choice), purchase frequency, and order size. These behaviors are related contemporaneously and reinforced over time through "experience effects." The authors utilize a type-2 tobit model of purchase frequency and order size, and integrate it with a binary probit model of choice between catalog and Internet. The model is as follows:

$$b_{it} = \begin{cases} Purchase & if\, b_{it}^* > 0 \\ No\ Purchase & Otherwise \end{cases} \tag{25.1a}$$

$$q_{it} = \begin{cases} e^{q^*_{it}} & if\ b^*_{it} > 0 \\ 0 & otherwise \end{cases} \tag{25.1b}$$

$$w_{it} = \begin{cases} Use\ catalog & if\ w^*_{it} > 0\ and\ b^*_{it} > 0 \\ Use\ Internet & if\ w^*_{it} \leq 0\ and\ b^*_{it} > 0 \end{cases} \tag{25.1c}$$

The un-starred variables (b, q, and w) are observations of whether the customer purchases from the firm in period t (b_{it}), if so, how much is spent (q_{it}), and which channel is chosen (w_{it}). The starred variables (b^*, q^*, and w^*), are customers' latent utilities that drive the observed data. These are linear functions of customer characteristics, previous behavior or experience, marketing, and seasonality/trend:

$$\begin{aligned} b^*_{it} &= Customer\ Characteristics_{bi} + Experience_{bit} + Marketing_{bit} \\ &\quad + Time\ Effects_{bt} + e_{bit} \\ q^*_{it} &= Customer\ Characteristics_{qi} + Experience_{qit} + Marketing_{qit} \\ &\quad + Time\ Effects_{qt} + e_{qit} \\ w^*_{it} &= Customer\ Characteristics_{wi} + Experience_{wit} + Marketing_{wit} \\ &\quad + Time\ Effects_{wt} + e_{wit} \end{aligned} \tag{25.2}$$

Customer characteristics include demographics, etc., that remain constant over time. Experience effects include variables such as expenditures in the previous period, channel choice in the previous period, etc. The authors also include cumulative Web usage – since the Internet was new at the time, they wanted to investigate permanent learning that might occur. Marketing includes catalogs and e-mails, modeled as stock variables and interactions described in Chapter 28. Time effects include seasonality and trend.

The error terms are assumed to follow a multivariate normal distribution, correlated across equations. The correlations are considered during the estimation process, which means that selectivity effects driven by unobserved variables influencing two or more of the three dependent variables are controlled for.

The authors found that catalog choice exhibited strong inertia, i.e., spending a lot of money on a catalog in the previous month increased the likelihood the catalog will be chosen if a purchase were made this month. E-mails were associated with choosing the Internet, although with decreasing returns to scale. Catalogs did not influence catalog choice at low levels, although did so at high levels. The authors found several significant effects in their purchase frequency model, while they find very few significant parameters in the order size equation. This is quite interesting, suggesting that purchase frequency is malleable, whereas order size is stable. Perhaps most importantly, the authors found a negative association between cumulative use of the Internet and purchase incidence, suggesting that Internet purchasing may undermine customer retention.

Knox (2005) developed a similar model to capture purchase frequency, order size, and choice. He used a nested logit to capture incidence and channel choice. The main focus of Knox's work, however, is on modeling the process whereby consumers evolve to form three channel usage segments: Online-oriented, Off-line oriented, and Multichannel. We discuss this in Sect. 25.2.4.2.

While we mentioned that estimating stand-alone choice models may be problematic when variables in the model might also affect purchase incidence, this needs more study and replication before one can say that stand-alone choice models are taboo! An example of a very interesting stand-alone logit model of channel choice is by Thomas and Sullivan (2005a), discussed earlier. These authors model the choice among the bricks-and-mortar store, the catalog, and Internet. The authors include channel-specific effects of all the independent variables and find that marketing can affect the choice of Channel A vs. B differently than it affects the choice of Channel A vs. C. This is an important notion – that marketing can affect various channel migrations differently.

25.2.4.2 Channel Adoption Models

An important issue is the *process* by which customers become loyal to certain channels, or choose to adopt certain channels. Knox models channel adoption as a hidden Markov process. The customer is assumed to be in an (unobserved) segment at any point in time. The possible segments include the initial or "learning" segment, as well as the ultimate online, offline, and multichannel segments. The transition matrix assumed to govern migration between segments is shown in Table 25.1. Knox assumes that offline, online, and multichannel are absorbing states – once customers evolve to one of those segments, they stay there. This of course is debatable, but useful to study the initial evolution of segments. The probabilities of migrating from the learning segment (the P's) depend on marketing (m). This is modeled using a Dirichlet distribution for each marketing instrument combination (received catalog, received e-mail, received both, received neither). This captures heterogeneity in transition likelihood across customers depending on what if any marketing communications are received. Knox finds that customers migrate to one of the three segments, that marketing influences the migration probabilities, and that the multichannel segment accounts for the highest sales volume.

Table 25.1 Tansition matrix governing migration between customer segments (From Knox 2005)

		State (Segment) at time $t+1$			
		Learning	**Offline**	**Online**	**Multichannel**
State (Segment) at time t	Learning	$P_{11}(m)$	$P_{12}(m)$	$P_{13}(m)$	$P_{14}(m)$
	Offline	0	1	0	0
	Online	0	0	1	0
	Multichannel	0	0	0	1

Venkatesan et al. (2007) model the time until the adoption of a second channel, given the customer is initially using one channel, and then the time until the adoption of a third channel, given the customer is using two channels. The authors consider a retailer using a full-priced store, discount-priced store, and the Internet. The authors define t_{ij}, where j equals either 2 or 3, as the time taken to adopt the second or third channel. The authors formulate a hazard model of t_{ij} as follows:

$$h(t_{ij}, X^*_{ij}) = h_0(t_{ij}) \bullet \psi(X^*_{ij}, \beta) \bullet w_i \tag{25.3}$$

where:

X^*_{ij} = A set of variables including customer characteristics, customer behavior, and marketing variables for customer i, that occur between the adoption of the $j-1$th and jth channel.
$h(t_{ij}, X^*_{ij})$ = The instantaneous "hazard" probability that customer i will adopt his or her jth channel at time t_{ij} since the adoption of the $j-1$th channel ($j = 2, 3$).
$h_0(t_{ij})$ = Baseline hazard rate, i.e., that part of the hazard probability that is influenced only by the passage of time. The authors use a flexible Weibul distribution to capture this influence.
$\psi(X^*_{ij}, \beta)$ = The impact of the X variables on the hazard probability.
w_i = "Shared Frailty" impact on the hazard probability for customer i. This picks up unobserved but stable heterogeneity across customers in their time to adopting the next channel.

The authors find that marketing encourages faster channel adoption, although with decreasing returns. The authors find that cross-buying and purchase frequency shortens the time of channel adoption, presumably because these customers need more channels. Note this supports the self-selection hypothesis (Sect. 25.2.2.2) that high-volume shoppers seek out more channels. The authors find the number of returns especially increases the length of time to adopt the third channel. Once customers are using two channels, they have to be shopping at least at one type of store, so their returns needs are satisfied. Another finding involves the baseline hazard – all else equal, customers adopt their second channel less quickly than their third. This suggests that once the customer learns to adopt a second channel, they have acquired the skill to shift channels (cf. Ward 2001).

25.2.4.3 Challenges in Modeling Customer Channel Migration

There are several challenges in modeling channel migration. Selectivity bias (Chapter 15) can arise regarding the level of marketing received or regarding channel usage. With respect to marketing, Ansari et al. (2008) include e-mails as an independent variable in their channel choice equation. However, there may be unobserved variables, e.g., "Internet orientation," that generate the receipt of e-mails, and these same variables generate channel choice. The result would be a biased estimate of the e-mail ⇒ channel choice coefficient. We use Ansari et al. as an example, but this problem could occur in any customer migration model.

With regard to channel usage, customers may select channels due to unobserved factors – e.g., customer involvement with the category – that drive both channel usage and total revenues or profits. An observed relationship between channel usage and profits may be spurious, due not to channel usage but to these unobserved factors.

There are two ways to address selectivity. First is to include all variables that generate marketing contacts or channel usage. For example, companies use RFM variables to target catalogs; if those variables are included in the model, this helps to address selectivity in the form of marketing received. Ansari et al. include several "experience" variables that implicitly measure RFM. A second alternative is statistical. One might specify a formal selection model (Chapter 15; Wooldridge 2002; Maddala 1983) or use instrumental variables or two-stage least squares to purge the endogenous channel selection or marketing variables of their endogeneity.

Ansari et al. (2008), and Knox (2005), control for selectivity in channel usage by allowing the error terms for purchase, order size, and channel selection equations to be correlated and incorporate that in estimation. Including an unobserved heterogeneity intercept does not control for selectivity bias because the term is still unobserved and could be correlated with the receipt of marketing, thus the results would still be biased unless this information is incorporated in the estimation (Chamberlain 1980).

Gönül et al. (2000) address selectivity bias due to marketing, and Campbell and Frei (2006) address selectivity in channel choice, using instrumental variables. They find in both cases that the use of this technique does not change their results. However, these are just two instances and more work is needed.

Other methodological challenges in modeling channel migration include (1) the use of single-equation choice models that do not incorporate purchase incidence (see Sect. 25.2.3.1) and (2) detail in specifying the marketing variables ("catalogs sent" is a very gross measure, given that firms send so many different kinds of catalogs (Ansari et al. 2008). A final challenge is to model the research ⇒ purchase ⇒ service process. Verhoef et al. (2007) investigate this, but their model is cross-sectional. A dynamic model is needed since the process is temporal.

25.2.5 Research Shopping

Research shopping is the propensity of consumers to gather information (search) on one channel but purchase on another. Kelley (2002) reports roughly half of online shoppers search on the Internet and then purchase "offline." This is particularly common in consumer electronics, computer hardware, toys, books, and automobiles. Figure 25.8 reports a DoubleClick

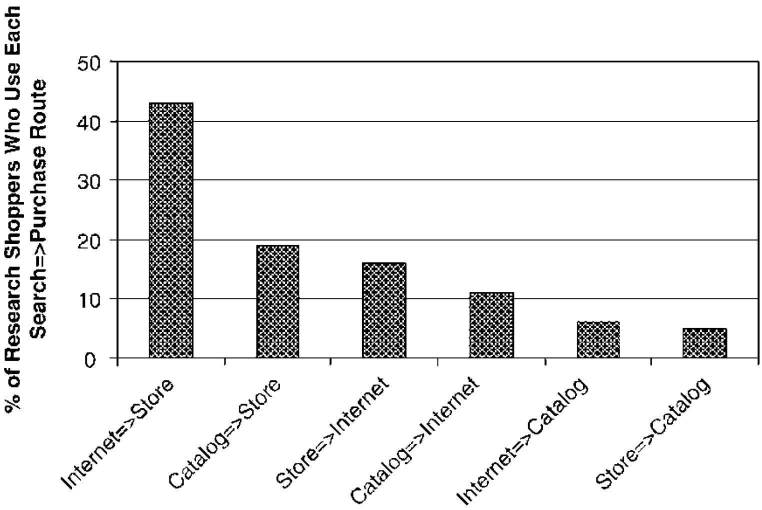

Fig. 25.8 Frequency of various types of research shopping (From DoubleClick 2004b).

(2004b) study documenting the extent of various types of research shopping. The study shows that Internet ⇒ Store is the most common form (see Ward and Morganosky 2002, and Farag et al. 2005).

Research shopping has strategic implications because the customer can search at competitors' channels yet buy from Firm A. The probability a customer buys from Firm A is:

$$\begin{aligned}&\text{Prob(BuyA)} = \text{Prob(BuyA|Search A only)} \bullet \text{Prob(Search A only)}\\&+\text{Prob(Buy A|Search competitors only)} \bullet \text{Prob(Search competitors only)}\\&+\text{Prob(Buy A|Search A and competitors)} \bullet \text{Prob(Search A and competitors)}\end{aligned} \tag{25.4}$$

The first term represents a loyal customer, i.e., the customer searched for the product at one of Firm A's channels and purchased from Firm A.[1] The last two terms represent customers who bought from Firm A despite searching at other firms. Kelley (2002) shows these quantities differ significantly by retailer. For example, Wal-Mart does a good job of attracting the research shopper, especially in consumer electronics, computer hardware, computer software, and small appliances. In books, Barnes and Noble does the best, whereas Best Buy is best in CD's. Inside 1 to 1 (2003) reports that Coach, Neiman Marcus, and J. Crew are particularly successful with the first term in Equation 25.4, i.e., they are particularly successful of directing their Internet researcher to purchase from their store.

Verhoef et al. (2007) propose three mechanisms that enable research shopping: attribute advantage, channel lock-in, and cross-channel synergy. At-

[1] For simplicity, we do not specify channel in Equation 25.4. However, as Fig. 24.1 indicates, the full equation would include terms such as B_{A1}, meaning purchase from retailer A, channel 1, and S_{A2}, meaning search at Retailer A, channel 2.

tribute advantage is the perceived advantage of one channel over another in terms of attributes related to search or purchase. For example, the Internet may be superior to the store in "search convenience," but inferior in "service." This suggests Internet ⇒ Store research shopping. Channel lock-in pertains to the intrinsic ability of a channel to hold onto its customer. Stores have high channel lock-in because a sales person courts the customer and the customer pays a high switching cost to walk out of one store and go to another. The Internet has low lock-in, because there is little to prevent "cart abandonment." Low lock-in encourages research shopping. Cross-channel synergy pertains to the benefit searching on Channel A has for purchasing at Channel B. The catalog may be a good search channel because it gets the customer 90% through the decision of what product to buy. This sets the customer up to interact effectively with in-store personnel. Cross-channel synergy encourages research shopping.

Verhoef et al. measure attribute advantage, channel lock-in, and cross-channel synergy using a cross-customer model of the research and purchase channel choice decisions. Table 25.2 summarizes their results. The authors find that the Internet has an attribute advantage over the store for search, while the store has an attribute advantage over the Internet for purchase. As expected, the Internet has low lock in. The authors find a marginally significant cross-channel synergy between searching on the Internet and purchasing in the store. As a result, attribute advantage, lack of lock-in, and cross-channel synergy are all at work and Internet ⇒ Store was the most common form of research shopping they observed, collaborating the DoubleClick study.

The above shows that research shopping is a real phenomenon that can be managed. Research is needed on exactly how to do this. The phenomenon needs to be studied at the firm-channel level rather than just the channel level. In this way the components of Equation 25.4 could be quantified. Finally, the competitive ramifications of research shopping need to be examined (see Balasubramanian 1998).

Table 25.2 The determinants of research shopping as applied to various research shopping patterns (Verhoef et al. 2007)

		Determinant of research shopping				
Research shopping pattern		**Attribute differences**				
Search channel	**Purchase channel**	**Search channel advantage**	**Purchase channel advantage**	**Search channel lock-in**	**Cross-channel synergy**	**Observed research shopping**
Internet	Store	$\surd$	$\surd+$	Low	Positive	50%
Catalog	Store	No	$\surd+$	High	No	34%
Catalog	Internet	No	No	High	Positive	7%
Store	Internet	$\surd$	No	High	No	6%
Store	Catalog	$\surd$	No	High	Negative	2%
Internet	Catalog	$\surd$	No	Low	No	1%

25.2.6 Channel Usage and Customer Loyalty

In Sect. 25.2.2.2 we noted that one possible explanation for multichannel customers being higher volume is that multichannel shopping breeds higher loyalty. Neslin et al. (2006b) report the evidence on this is mixed but leaning positive. Wright (2002, p. 90), in referring to the banking industry, states that new technologies had "loosened the banker–customer relationship." However, Shankar et al. (2003) find that Internet usage is associated with higher loyalty, as do Hitt and Frei (2002) and Campbell and Frei (2006). Danaher et al. (2003) find that Internet usage enhances the loyalty enjoyed by high-share brands. Wallace et al. (2004) find that multichannel usage is associated with enhanced attitudes toward the firm's product. However, as mentioned earlier, Ansari et al. (2008) find that repeated use of the Internet is associated with lower purchase frequency.

Much of the question hinges on the impact of the Internet. The potential problems with the Internet are: (1) Switching costs are low – the mildly dissatisfied customer can easily switch to another website. (2) The Internet is inherently transaction-oriented with little human contact. Ariely et al. (2002) find in a lab experiment that customers who used the Internet but thought they were interacting with a human "on the other side" developed higher loyalty to the website than those who thought they were interacting with a computer-generated recommendation engine.

Managers can take steps to combat both problems. They can increase switching costs by storing important information (e.g., credit card number) so the customer is disadvantaged by switching to another site. Managers can also humanize their website through the use of "shopping advisors" – sales representatives who engage in an "Instant-messenger" type conversation with the online shopper. Perhaps even the use of pictures of people on a website can humanize it. The humanization of the Internet is an important area for future research, because the evidence is mixed as to whether the Internet currently enhances loyalty. Ironically, many of the changes one might propose to enhance the website increase its cost, and for some companies, the attractiveness of the Internet is lower cost.

25.2.7 The Impact of Acquisition Channel on Customer Behavior

The key issues in the use of channels for customer acquisition are cost per acquired customer and quality of acquired customer. Acquisition cost should obviously vary by channel. That the quality of customer acquired would differ is less obvious. It is on this topic that we are beginning to learn more.

Villanueva et al. (2003) use a vector autoregression (VAR) to compare the return on investment for various channels used for customer acquisition.

a

		Level of Contact	
		Personal	**Broadcast**
Level of Intrusiveness	**High**	Direct Marketing Catalogs E-Mail Telemarketing	Advertising Television Radio Print Online
	Low	Word of Mouth Among Friends From Search Engines	Public Relations Print Articles Online Articles

b

			Level of Contact	
			Personal	**Broadcast**
Level of Intrusiveness	**High**		Direct Marketing	Advertising
		Increased Logins Acquisition $/Customer+ Logins/$	9.22 $27 0.34	30.51 $323 0.09
	Low		Word of Mouth	Public Relations
		Increased Logins Acquisition $/Customer+ Logins/$	14.03 * *	16.58 $82 0.20
+ These numbers were obtained by the authors from a third-party source; see Table 4 of Villenueva et al (2003).			* Could not be directly calculated. Breakeven Acquisition Cost is $149 vs. advertising, $41 versus direct marketing, and $69 versus public relations	

Fig. 25.9 Classification of acquisition channels and ROI per channel (From Villanueva et al. 2003). (a) Classifications (From Villanueva et al. 2003); (b) ROI (From Villanueva et al. 2003)

They classify acquisition channels into the matrix shown in Fig. 25.9**a**. The two dimensions are level of contact (personal versus mass-market broadcast) and level of intrusiveness (high versus low). The authors use data from a website-hosting company that had asked acquired customers to reveal the channel through which they had been acquired. This yielded a time series of number of acquisitions per channel. The company also kept track of subsequent contribution from each acquired customer, measured as the number of subsequent logins to the website. This is an appropriate measure because it relates to advertising revenue that can be generated by the firm.

The results showed that each acquisition channel contributed differently. Figure 25.9**b** shows contribution (short-term plus long-term increase in logins), acquisition cost, as well as increased logins per acquisition dollar

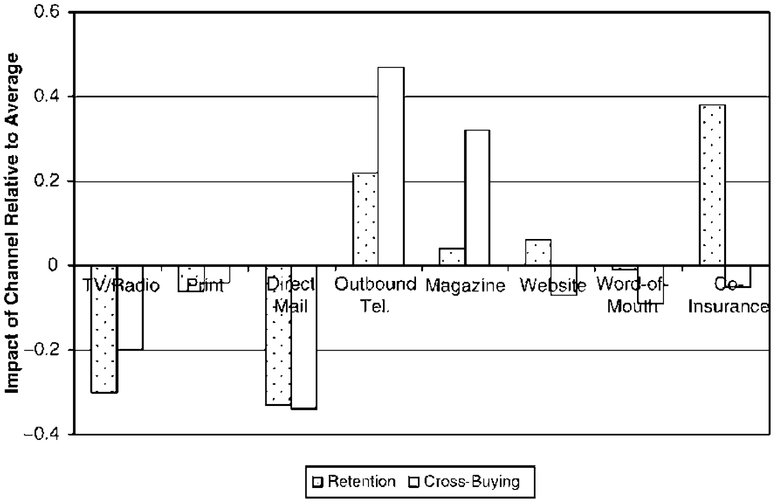

Fig. 25.10 Relationship between acquisition source and retention and cross-buying rate (From Verhoef and Donkers 2005).

(ROI). Broadcast advertising (AD) acquires the most valuable customers, but its cost per acquisition is so high that ROI is the lowest. Conversely, direct marketing (DM) attracts the least valuable customers, but its acquisition cost is so low that its ROI is quite high. Villanueva et al. (2008) expand on these results and find that customers acquired through marketing efforts tend to add more short-term value compared to word-of-mouth, but customers acquired through word-of-mouth add more long-term value.

Verhoef and Donkers (2005) study the impact of acquisition channel on customer quality in the insurance industry. They model retention and cross-buying as a function of acquisition channel as well as several control variables such as customer characteristics. Figure 25.10 displays the logit coefficients for each channel relative to the average coefficient across channels. Retention and cross-buying differ appreciably by acquisition channel, *after* controlling for customer characteristics. Direct Mail and TV/Radio perform poorly on both retention and cross-buying. Outbound telephone is good for both retention and cross-buying. Co-insurance (where customers obtain the insurance through their employer) is very good for retention, but less so for cross-buying. The Internet is a little better on average for retention, and a little below average for cross-selling.

25.2.8 The Impact of Channel Introduction on Firm Performance

As the competition to provide multiple channels heats up, a fundamental question is, what is the impact of adding channels on firm revenues and performance?

Biyalogorsky and Naik (2003) estimate a time series model using data from Tower Records, which had introduced an Internet channel. The authors find that current Web purchases encouraged future Web purchases. They also find the point estimate for cannibalization of store sales was only \$0.89 and only marginally significant ($t = 1.2$). However, store sales were autoregressive – the lagged store sales coefficient was 0.95 in the store sales equation. To illustrate, if we take the point estimate for cannibalization as "true," the total impact of the Internet would be $\$0.89/(1 - 0.95) = \$17.80$, suggesting that of the average Web purchase of \$32.06, roughly half is taken from current and future store sales. Again, this is just an exploratory calculation since the statistical significance of the cannibalization effect is marginal, but illustrates the importance of short and long-term cannibalization effects.

Deleersnyder et al. (2002) use time series analysis to analyze the performance of British and Dutch newspapers during the time in which they introduced a website version. They analyze both the *level* and *trend* in performance of two measures – circulation and advertising revenue. They find that the introduction of the website had a nominally negative impact on circulation trend for 35 newspapers, but the result was statistically significant in only five instances. The authors found a nominally positive impact of website on circulation trend for 32 newspapers, 10 of which were statistically significant. Results were similar for advertising, as well as for *levels* as opposed to trends. Overall, the predominant effect seems to be that the introduction of a website did not influence newspaper circulation or advertising, although for a minority of cases the effect can be either positive or negative.

Pauwels and Dans (2001) examine the impact of the regular print newspaper on visits to the newspaper website. Newspapers with larger print readership obviously experience greater website visit levels, but also, newspapers whose demographic profile matches that of the Internet-browsing public also experience greater website visits. This reinforces the impact that individual characteristics have on Web usage.

In a time series analysis of 106 firms during 1992–2000, Lee and Grewal (2004) found that early adoption of the Internet as a *communications* channel improved stock market performance as measured by Tobin's q, but adoption as a *sales* channel had no impact. This could due to the market perceiving synergies due to communications but potential inter-channel cannibalization from another sales channel (at least in the early days of the Internet). Consistent with this, Geyskens et al. (2002), in an event analysis of firms in the newspaper industry, found that the stock market reacted positively to Internet introductions on average, especially for firms that did not currently have a strong direct market channel presence.

Coelho et al. (2003) examined 62 UK financial services companies. They find multichannel companies have higher levels of customer acquisition, market share, and sales growth, but lower levels of customer retention, profit, service, and cost control. The retention results are consistent with Ansari et al. (2008).

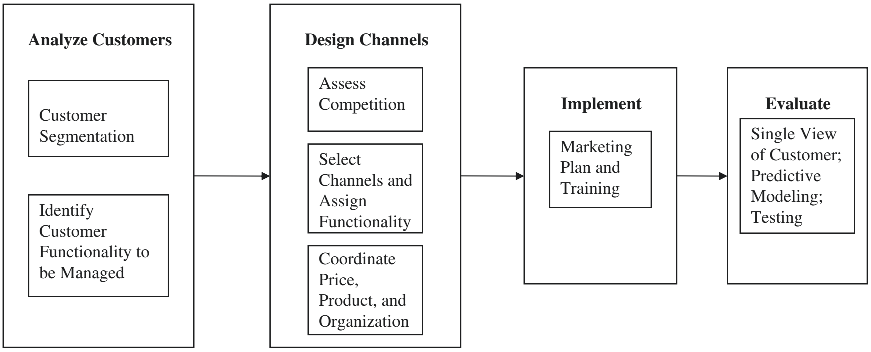

Fig. 25.11 Multichannel design process (drawn heavily form Rangan 1994).

Most recently, Pauwels and Neslin (2007) study the impact of introducing a retail store channel on total company revenues and on revenues from the company's catalog and website. They find that the store channel increases total company sales, mostly through increasing customer purchase frequency. Pauwels and Neslin hypothesized and found that the stores cannibalized the catalog somewhat, but had virtually no impact on website sales.

In summary, we have just begun to learn the impact of channel additions on total firm performance. Most of the work has been on the impact of adding the Internet channel. Obviously more work is needed to flesh out the complete cross-impact matrix showing the impact of adding Channel A on Channel B, C, D, etc.

25.3 Developing Multichannel Strategies

25.3.1 Framework for the Multichannel Design Process

A multichannel customer strategy entails the selection of channels, the assignment of channels to functions and customers, implementation of the strategy, and evaluation. Figure 25.11 proposes a framework for this process, drawing heavily on Rangan (1994).

25.3.2 Analyze Customers

25.3.2.1 Customer Segmentation

The goal is to segment customers with an eye toward possibly serving each segment with different channels. Bases for segmentation include customer profitability and customer channel preferences. Highly profitable customers

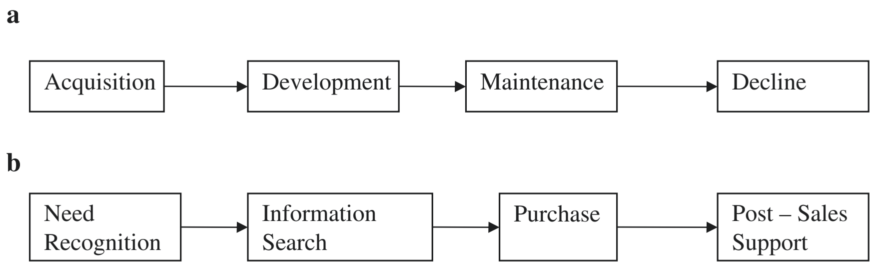

Fig. 25.12 Alternative definitions for customer functionality to be managed. (a) Custome-life-cycle; (b) Custome decision process.

might be given access to personal service channels or routed to more sophisticated call-centers.

Companies can use surveys and then predictive models to measure preferences and "assign" customers to channels. Keen et al. (2004) use the part-worths from a conjoint analysis, followed by a cluster analysis, to derive four segments: "generalists," who care about all issues, "formatters," who have a particular channel preference, "price sensitives," who care about price and find the channel with the lowest price, and "experiencers," who are creatures of habit, selecting the channel they used last. Konus et al. (2007) use survey results to derive three segments: "enthusiastic multi-channel shoppers, unenthusiastic multi-channel shoppers, and store shoppers. Segmentation based on channel preference is therefore feasible, although Knox (2005) suggests these preferences evolve over time.

Note the key issue is not the *current* level of profits or channel preferences, but how the customer will *respond* to using a particular channel – will it enhance customer value? This is where purchase frequency/order size/channel choice models would be useful for segmentation (Sect. 25.2.4).

25.3.2.2 Identifying Customer Functionalities to Be Managed

This stage identifies the functions or customer needs that channels must serve. Figure 25.12 displays two models for identifying these functions (see also Urban 2004, pp. 119–120). Figure 25.12**a** is based on stage in the customer life-cycle: acquisition, development, maintenance, and decline. Figure 25.13**b** is based on the customer decision process: need recognition, information search, purchase, and after-sales.

Customer life-cycle and customer decision functionality could be combined. For example, one could primarily define functions as acquisition, development, maintenance, and decline, and then *within* each of these functions, subdivide into search, purchase, and after-sales. Customers in the development stage might be encouraged to use a certain set of channels for search, purchase, and after-sales, while customers in the decline stage might be encouraged to use a different set of channels.

25.3.3 Design Channels

25.3.3.1 Assess Competition

Competitive effects are particularly salient for multichannel design. The mantra of "We must have a Web presence" was spurred by competition. Neslin et al. (2006b) question whether competitive multichannel strategies may just be a form of Prisoner's dilemma, as follows:

		Firm B	
		Single channel	**Multiple channel**
Firm A	**Single channel**	\$100, \$100	\$60, \$120
	Multiple channel	\$120, \$60	\$80, \$80 or \$120, \$120?

If both firms pursue the single-channel status quo, they each earn \$100. If Firm A adds a channel while Firm B stands pat, Firm A earns \$120 while Firm B decreases to \$60. If Firm B matches Firm A, the result is the lower-right cell. Here there are two crucial possibilities: (1) competition is exacerbated because the firms compete on several fronts. Prices decline but the market does not grow, and both firms are left with lower profits. (2) Multichannel engenders loyalty, or grows the market (e.g., it is quite possible that opening stores in shopping malls helped grow the market for cell phones). In this case, both firms benefit.

How this competition plays out in the real world is a crucial question. Chu et al. (2007) shed light on it. They study the personal computer market and develop a logit demand model with a no-purchase option. This enables the market to grow depending on prices as well as the channels available. The authors model equilibrium pricing by considering competition among manufacturers as well as downstream pricing of indirect channels, i.e., retailers. The authors use their model to calculate the profits for various channel configurations. They find through policy simulation that Dell, for example, made the correct decision to exit the retail channel in 1994. That is, in equilibrium, they made higher profits by exiting the retail channel.

Chu et al.'s (2007) work is a significant step forward. The work can be expanded in several ways. First would be to incorporate the channel decision as a strategic variable-equilibria could change if the channel decision were made endogenous. Second would be to consider the impact of market segmentation. Third would be to consider channel functionality, either via the customer life-cycle or the customer decision process. These are exciting areas for future work.

Price competition between multichannel (MC) and single channel (PP for "pure play") retailers has received particular attention. Tang and Xing (2001) find that Internet prices are higher for MC than PP DVD retailers, and that price dispersion is lower among PP retailers. Pan et al. (2002a) find that customers perceive MC Internet prices to be higher than PP Internet prices. They develop a Hotelling model and find that a bricks-and-mortar retailer should launch an online presence and charge higher prices, *if* that online store can be superior to pure play online retailers. This may work if the multichannel retailer can use the Internet and the bricks-and-mortar store *in combination* to provide a superior customer experience.

As a follow-up, Pan et al. (2002b) study *actual* prices and find that prices are lower for PP Internet compared to MC Internet for CD's, DVD's, desktop computers, and laptop computers, while they are similar for PDA's and electronics. Interestingly, they found prices are higher for PP Internet for books and software.

Ancarani and Shankar (2004) compare MC Internet, PP Internet, and PP Store prices. They find that PP Store prices are the highest, followed by MC Internet and PP Internet. However, when shipping and handling is figured in, the order is MC Internet > PP Internet > PP Store. This differs from Brynjolfsson and Smith (2000), who find Internet prices net of shipping are generally lower than in bricks-and-mortar stores. They however did not break out the results by pure play versus multichannel.

In summary, it appears that MC Internet prices are greater than PP Internet prices. Perhaps multichannel Internet retailers leverage their bricks-and-mortar store to create monopoly power. Ancarani and Shankar (2004) find two instances – books and software – where MC Internet < PP Internet. Perhaps these pure play Internet retailers have built monopoly power through higher customer loyalty (e.g., Amazon). Indeed, in an important review paper, Pan et al. (2004) find that price dispersion, i.e., differences in prices across retailers, is often higher on the Internet than off-line. This suggests that Internet retailers have been able to differentiate themselves.

25.3.3.2 Select Channels and Assign Functionality

This stage is a mix-and-match process of assigning channels to segments and functionalities. Figure 25.13 suggests three strategies. Figure 25.13**a** is the "Multi-Contact Strategy." This does not emphasize segmentation or functional assignment – all channels are available to all customers. The question of which channels the firm should use would be dictated by competitive considerations and cost and revenue impact.

Figure 25.13**b** shows a "Functional Strategy," where customer segmentation is still not considered, but channels are assigned to specific functionalities. A wireless phone company might use outbound telemarketing to stimulate customer awareness of new features. Customers may then be directed to the company's website to learn about the specifics and "design" their optimal phone. Purchase may be made through the Internet or the company's store. Post-sales support would be provided by a company representative reachable through the call center.

Figure 25.13**c** shows the "Segmentation Strategy." This involves assigning segments to different channels for different functions. For example, Segment 1 may be low value and hence assigned to the Internet for all functions. An e-mail may stimulate need recognition and encourage the customer to click

Need recognition	Information search	Purchase	Post-sales support	
		(a) Multi-contact strategy		
X	X	X	X	Internet
X	X	X	X	Call center
X	X	X	X	Catalog
X	X	X	X	Store
X	X	X	X	Representative
		(b) Functional strategy		
–	X	X	–	Internet
X	–	–	–	Call center
–	–	–	–	Catalog
–	–	X	–	Store
–	–	–	X	Representative
		(c) Segmentation strategy		
Segment 1	Segments 1, 3	Segments 1, 3	Segment 1	Internet
–	–	–	Segment 2	Call center
Segment 2	Segment 2	–	–	Catalog
–	–	Segment 2	–	Store
Segment 3	–	–	Segment 3	Representative

Fig. 25.13 Matching functionality with segments: Three generic strategies.

through to the website, design their optimal telephone, purchase it, and receive after-sales support. Segment 3 might consist of high value customers. They would be contacted by a company representative who would carefully explain the new services. The customers would be invited to seek further information, design their telephone, and purchase it over the Internet, because the visuals provided online make things easier for the customer. The particular website for these customers would include an "instant-messenger" type facility for interacting with a company representative if desired. After the purchase, the same representative would contact the customer for after-sales support.

Zettelmeyer (2000) analyzes competitive equilibria in channel functionality and prices when customers are heterogeneous in their preferences (i.e., there are segments) and online and offline channels can be used for search and/or purchase. He finds that information provision is one way that firms can differentiate. For example, if a medium number of customers prefers the Internet for purchase, firms differentiate themselves in terms of the information they provide as well as price. This is very promising work that supports the segmentation strategy to multichannel design.

The functionality/segment assignment decision lends itself to an optimization. The decision variables would be what channel to assign to what segment for what function. Required of course would be customer response to these assignments. Knox (2005), Thomas and Sullivan (2005a), or Ansari et al. (2008) would be useful in this regard. While optimizing the entire decision might be too ambitious, one could isolate one stage. Villanueva et al. (2003) formulate a model to allocate financial resources to different channels for customer acquisition, as follows:

$$\underset{x_k}{Max}\,\Pi = \sum_k m_k n_k(x_k) - B \tag{25.5a}$$

$$\text{s.t.} \sum_k x_k \leq B \tag{25.5b}$$

where:

Π = Profits.
x_k = Dollar expenditures allocated to channel k for customer acquisition.
m_k = Profit contribution per customer acquired through channel k.
n_k = Number of customers acquired through channel k. This is a function of the dollar expenditures allocated to channel k.
B = Acquisition budget.

Profit contribution (m_k) would be available from results such as those shown in Fig. 25.9. The authors propose a particular function for n_k that could be estimated judgmentally, through testing, or through regression models.

25.3.3.3 Channel Coordination

Consider Fig. 25.2, which shows customer preferences for the Internet vs. Telephone. If we use a functional strategy and assign the Internet to be our search channel, the telephone to be our purchase/after-sales channel, *and* provide easy links from the Internet to the telephone (e.g., 800 numbers prominently displayed on the Internet), we have covered the customer decision process and coordinated the two channels.

However, there are many other details to be coordinated among channels, including marketing mix, research shopping, and organization. There is even a question of whether channels *should* be coordinated? Neslin et al. (2006b) list advantages as: (1) economies of scale, (2) ability to assign channels to the functions for which they are efficient and make sense competitively (see Zettelmeyer 2000; Achabal et al. 2005; Sect. 25.3.3.2), (3) Better customer data (Stone et al. 2002), (4) avoidance of channel conflict, (5) improved communications within the firm, (6) stronger customer relationships through better service (Sousa and Voss 2004; Stone et al. 2002; Bendoly et al. 2005), and (7) barriers to entry – an entrant must enter on multiple channels *and* coordinate them. The disadvantages include: (1) loss of flexibility – one cannot opportunistically use a particular channel to solve a problem without re-coordinating all the channels, (2) large investment (see Sect. 25.3.3.1; Sousa and Voss 2004), (3) decreased motivation for non-owned intermediaries who do not see a benefit from channel coordination, and (4) increased skill-requirements for channel mangers.

Assume the firm decides to coordinate its channels. Consider coordination of product assortment. The problem is that carrying the same products in each channel creates channel conflict if some of the channels are non-owned intermediaries. For example, financial services agents (who sell products from several companies) may become less devoted to the firm if the same products are available over the Internet.

One solution, supported by Bergen et al. (1996) is to use "branded variants," where the firm distributes minor variations of its products across channels. This increases customer search costs because customers have to compare more details to decide which product to buy. This creates more monopoly power for each channel. For example, a consumer electronics firm may distribute Model 446G through Best Buy, but Model 446Gb through Wal-Mart. The differences may be minor, but the customer finds it difficult to compare them. Hence, the customer shops only at one channel and focuses on what that channel can offer. Branded variants are a potential way to avoid conflicts between channels. However, there still may be conflicts if various channels vie for the best variants! For example, Wal-Mart may demand that Model 446Gb be the model with extra features, whereas Best Buy would want the model with the extra features.

When channels are owned by the firm, product coordination becomes an issue of targeting. For example, Best-Buy may know that its Internet customers are less quality sensitive and more price sensitive, so may carry a lower tier product line on its website.

Another area of coordination is price. As Neslin et al. (2006b) note, a compelling reason to offer different prices across channels is price discrimination. Lynch and Ariely (2000) and Shankar et al. (2001) suggest that price sensitivity is lower for online customers. Assuming this to be true, prices online should be higher than prices offline. However, the online shopper can learn that the same product can be bought less expensively at the retail store. This has several negative implications. First, the profits from price discrimination are lost. Second, the customer feels cheated and loses trust in the company. Third, more traffic is driven to the store, which is the higher cost channel. Fourth, one solution is branded variants, but this adds costs and confuses customers who expect the Internet and the retail store of the same company to be in sync.

Two ways to charge different prices are price promotions and channel surcharges. The regular price of the same product may be the same at the Internet and the store, but the store can temporarily discount the product. Surcharges are another way to increase prices, particularly on the Internet. For example, the price of the product may be identical on the Web and in the store, but the shipping charges may be significantly higher than needed to cover the marginal shipping cost to the firm. This effectively increases price on the Web (and sets up a strong promotion – free shipping!).

A third area of channel coordination is communications. The argument for coordination is that it reinforces positioning and creates a stronger customer relationship. However, if the firm is using a segmentation strategy (Fig. 25.13**c**), communications perhaps should differ by channel. For example, the website design might highlight low prices if the target group is price sensitive, while retail store communications should emphasize product quality and service if it is targeting the quality-sensitive customer.

Another aspect of communications is how much to spend on communicating through each channel. Berger et al. (2006) develop an analytical model that differentiates three cases: (1) "separation," where the channels are managed as separate entities, (2) "partial integration," where one channel may be considered a separate entity but the firm may be willing to pay some of its costs, and (3) "full integration," in which the firm manages all its channels collectively to maximize total profits. The authors find that the optimal communications expenditures yield highest profit under the full integration strategy. This is a good argument for holistic management of the firm's channels, at least the channels the firm owns.

An important coordination issue is managing the research shopper so as to prevent the customer from searching on Firm A's website but purchasing at Firm B's store. One way to prevent research shopping is to improve purchase attributes of the Internet or increase Internet channel lock-in (Verhoef et al. 2007). However, the customer may still want to research shop. The key then is to make sure the shopping is at Firm A's store and not Firm B's. Actions Firm A can take include: (1) provide store locators on the Internet, (2) offer a coupon on the Web for purchases at the store, (3) offer free product pickup if the product is ordered on the Web but picked up at the store.

A final channel coordination issue is organizational. One example is when a predictive model is used to identify the best customer prospects, say for an insurance company. The most cost-efficient approach might be to send a direct-mail piece to these customers. However, this bypasses the financial agents, who are always looking for prospects. The solution is to divide the top prospects in half and solicit half of them through direct mail, and provide the other half to the financial agents for their own prospecting efforts. This may be less profitable in the short term, but more profitable in the long term because the financial agents' loyalty to the firm is increased.

Another important organizational issue is whether channels should be managed as independent profit centers or one entity. When the Internet channel emerged, many firms set up separate Internet operations and let Internet channel managers "run their own show." However, this does not necessarily maximize total firm profits (cf. Berger et al. 2006). Firms must achieve a balance so that channel managers have the flexibility to pursue opportunities that other channels aren't ready to pursue, while coordinating efforts so for example channel managers don't fight over the same customers.

25.3.4 Implementation

There are several tasks in implementing a multichannel strategy. One of course is the physical design of the channels – i.e., the website design, the store layout, etc. These details are beyond our scope. However, there are two issues – "right channeling" and employee management – that warrant our attention.

25.3.4.1 Right-Channeling

Right-channeling means making sure that the right customers utilize the right channels. This is a crucial part of implementing a Segmentation strategy (Fig. 25.13 **c**). Right-channeling might occur naturally if customer segments self-select into the channels they prefer. However, this may not be the most profitable arrangement for the company. Companies can therefore use a variety of incentives (targeted promotions, etc.), dedicated websites or firm agents, etc., to ensure the right customer uses the right channel.

A particular challenge in right-channeling customers is managing call centers. Companies can provide different levels of service within a call center, making the call center a collection of separate channels. The question is which customers should be routed to which center? This has an impact on immediate as well as future profits.

Sun and Li (2005) develop a dynamic optimization model for deciding whether customer inquiries should be directed to an "on-shore" or "off-shore" call center. The off-shore call center is less expensive; the on-shore call center generates higher satisfaction levels. In addition, there are different types of calls – *transactional* questions involve billing, product news, and product services; *technical* questions involve service, software or installation problems.

Sun and Li (2005) model call duration and customer retention. Duration is a function of previous duration, the type of call, and the call center. Retention depends on previous call duration and variables such as promotions that might have been offered to retain the customer. These models are inserted into an optimization that decides which call center customer i should be routed to at time t for call type k in order to maximize long-term profits. The optimization captures trade-offs such as: the customer prefers on-shore call centers, but the customer tends to take a long time when making an inquiry. This suggests the customer be allocated to the off-shore call center. However, if the consumer is averse to off-shore call centers, the customer might churn and the company will lose its monthly subscription fee. In addition, customer-level parameters are not known in advance, so must be learned over time. This is done by estimating the descriptive models using a latent class approach, and re-classifying each customer in one segment or another after each transaction.

The authors find two segments: Customers in Segment 1 are time-sensitive and dislike off-shore call centers. Customers in Segment 2 are less time-sensitive and less averse to off-shore call center. The optimization therefore tends to allocate Segment 2 customers to the off-shore call center. Policy simulations show that the proposed optimization improves both retention and profits, and the degree of improvement increases over time as the model learns which segment the customer is in.

Sun and Li's research is important because it shows that right-channeling can be achieved through predictive modeling coupled with forward looking optimization. It implements the Segmentation Strategy in Fig. 25.13**c** with respect to after-sales support. While in this situation, the customer was *assigned* to a channel, the model could be expanded to include which channel the customer should be *encouraged* to use, and if so, whether an incentive is needed to get the customer to use the "right channel."

25.3.4.2 Employee Training and Incentives

Employees are key participants in the multichannel strategy. A retailer may want high value customers to use the store and receive special service. Sales personnel need to be trained to recognize a high value customer, and how to service him or her. A catalog company may recognize that its catalog customers who order by phone seek service and conversation, as opposed to its Internet customers, who are more efficiency minded. Accordingly, phone personnel must be trained as sales representatives, not order takers.

Employee incentives can encourage the right employee behavior. For example, rewarding store personnel based on whether the customer cites them at checkout is one technique. The call center representative for the on-shore call center can be rewarded for the brevity of service times, assuming the query is satisfactorily resolved.

25.3.5 Evaluation

25.3.5.1 Single View of the Customer?

Using more channels makes it difficult for the firm to assemble a complete database of the customer's interactions with the company. There are three dimensions to the data picture: (1) channels, (2) stages of the decision process, and (3) competitive information. A true *single view of the customer* would mean the firm knows about the interaction of its customers with all its channels at all stages of the customer decision process, with the firm and with its competitors. Interactions with competitors are extremely difficult to obtain, although recent work by Du et al. (2005) and Kamakura et al. (2003) propose statistical procedures for inferring customer competitive activity.

Given the difficulty in obtaining competitive data, we focus only on decision process and channel. For a three-channel firm, the possible combinations

Table 25.3 Possible data to be assembled by a multichannel firm

	Decision process						
Channel	**Search**	**Purchase**	**Aftersales**	**S + P**	**S + A**	**P + A**	**S + P + A**
Web (W)	Moderate	**Easy**	Moderate	Moderate	Moderate	Moderate	Moderate
Store (S)	Difficult	Moderate	Difficult	Difficult	Difficult	Difficult	Difficult
Catalog (C)	Difficult	**Easy**	**Easy**	Difficult	Difficult	**Easy**	Difficult
W + S	Difficult	Moderate	Difficult	Difficult	Difficult	Difficult	Difficult
W + C	Difficult	**Easy**	Moderate	Difficult	Difficult	Moderate	Difficult
S + C	Difficult	Moderate	Difficult	Difficult	Difficult	Difficult	Difficult
W + S + C	Difficult	Moderate	Difficult	Difficult	Difficult	Difficult	Difficult

of data to be assembled are shown in Table 25.3. The table shows our judgments of how easy it is for firms to assemble each combination. The bottom-right cell signifies a single view of the customer across all channels and all decision stages. It is very difficult to assemble these data. Catalog information is easy to assemble for purchase and after-sales. This is why single-channel catalog companies were the first to apply database marketing. Purchase data are also easy to collect from the Web, because the customer must provide a name and billing address. It is therefore easy to merge these data with the catalog information and create a catalog/Web integrated database of purchase behavior. However, it is not as easy to collect after-sales usage on the Web, because customers may just use the Web for information and not identify themselves. Search behavior is very difficult to obtain for the catalog and store, although a little easier for the Web, since customers may register or have a cookie on their computers if they have previously done business with the firm.

Table 25.3 shows the myriad of information required for a single view of the customer. It is for this reason that a firm might be content to consider single view of the customer as obtaining *purchase* information across all channels. Even this is challenging because store purchase data is moderately difficult to obtain unless the customer is a member of the firm's loyalty program and diligently uses his or her loyalty card.

Illustrating the challenges in implementing a single view of the customer (Yates 2001) found that roughly half of 50 retailers they surveyed had learned "nothing" about cross-channel shoppers. Zornes (2004) reports more recently on these challenges and potential solutions. For example, he finds that many firms use "homegrown" customer data integration (CDI) solutions; more than 68% of IT and business professionals he surveyed were planning to evaluate commercial CDI software.

The question then becomes, how much should the firm invest in acquiring a single view of its customers? Neslin et al. (2006b) present a formal model in which the benefits of the percentage of customers for which it has a single view are a concave function of this percentage, and the costs are convex. The benefits of single view are concave because once the company has a single view for a critical mass of customers, it can use predictive modeling to score the rest of its customers for cross-selling programs, churn management, etc. The costs are convex because the costs of tracking down the customer for every single store purchase become astronomical once the "easy" customers, i.e., those who use a loyalty card, are monitored. The result is that a middle range percentage of customers with single view is optimal. Ridgby and Leidingham (2005) reinforce this conclusion in their discussion of the banking industry.

One important study that suggests CDI may pay off is by Zahay and Griffin (2004). These authors survey 209 B2B executives and measure "CIS Development" – the quality and specificity of information available to the company, as well as how easily that data are shared among executives. The authors do not measure data integration *per se*, but companies that self-report high CIS development probably are more likely to have a single view of its customers. Importantly, the research finds a positive relationship between CIS Development and better performance measures related to customer retention, lifetime value, etc., and in turn, these measures relate positively to business growth. This is the most promising indication we have so far that the quality of the data collected leads to improved performance. Obviously, more work is needed that specifically hones in on the performance impact of data integration across channels.

25.3.5.2 Predictive Modeling Implications

The challenge of predictive modeling in a multichannel environment is articulated nicely by Hansotia and Rukstales (2002). Consider the case of a direct mail offer that asks customers to respond via an 800 telephone number. Response is measured through this single channel. However, the predictive model based on these data may be misleading. First, "non-responders" may have bought on another channel. Second, responders possibly would have bought on another channel even if they had not received the offer. The solution is to: (1) assemble data on customer purchases across all channels. (2) include customers who received as well as did not receive the offer. Only then can the predictive model be used to forecast *incremental* sales per customer.

Consider the case (Hansotia and Rukstales 2002) that a company delivers an offer to a subset of its customers (the "treatment group") but not to a "control group." Assume the company has a single view of its customers. Following is a hypothetical decision tree analysis based on the predictor variable X, split on the value "A."

	Split 1	**Split 2**
Predictor variable X	$\leq$ A	$\geq$ A
Treatment group purchase rate	4%	3%
Unadjusted difference in purchase rate due to X	1.0%	
Control group purchase rate	1.5%	1%
Incremental purchase rate for each split	2.5%	2%
Adjusted "Incremental" difference in purchase rate due to X	0.5%	

For X $\leq$ A, 4% of the treatment group purchased from the company in a given time period, across all channels. This compares to 3% for X $\geq$ A. The apparent, "unadjusted" increase in purchase rate due to X is 1%. However, a portion of the treatment group customers might have bought without the offer. Consider the control group that did not receive the offer. For X $\leq$ A, 1.5% of these customers purchased across all channels. That means that only 2.5% (4 − 1.5) of the customers with X $\leq$ A incrementally purchased as a result of the offer. For X $\geq$ A, the incremental response was 2.0% (3 − 1). In conclusion, the true incremental difference in purchase rate between X $\leq$ A and X $\geq$ A is the adjusted 0.5%, not the unadjusted 1%.

Hansotia and Rukstales (2002) discuss a tree-modeling procedure for analyzing incremental response. This can also be accomplished with a regression model:

$$\text{Response} = \beta_0 + \beta_1 \text{X} + \beta_2 \text{D} \tag{25.6a}$$

$$\beta_1 = \delta_0 + \delta_1 \text{D} \tag{25.6b}$$

$$\begin{aligned} \Rightarrow \text{Response} &= \beta_0 + (\delta_0 + \delta_1 \text{D})\text{X} + \beta_2 \text{D} \\ &= \beta_0 + \delta_0 \text{X} + \delta_1 \text{DX} + \beta_2 \text{D} \end{aligned} \tag{25.6c}$$

where Response is customer purchases across all channels, X indicates whether the customer received the offer, and D is a set of predictors. The term $\delta_0 + \delta_1$D measures the extent to which response to the offer is incremental. The term $\beta_0 + \beta_2$D represents baseline sales among customers with demographic profile D. If $\beta_0 = \beta_2 = 0$, baseline sales equal zero, i.e., customers would not have bought had they not received the offer, and we could run a traditional predictive model only among customers who received the offer. However if β_0 or $\beta_2 \neq 0$, Response (among those who receive the offer) $= \beta_0 + \delta_0 + \delta_1\text{D} + \beta_2\text{D} = (\beta_0 + \delta_0) + (\delta_1 + \beta_2)\text{D}$. This estimated equation would be used to score customers, but the resultant rank ordering will be inaccurate because it will confuse incremental response (δ_0 and δ_1) and baseline response (β_0 and β_2).

In summary, in a multichannel environment, traditional predictive models may not predict *incremental* response. One needs multichannel data and data that include customers who received and did not receive the offer. This issue can occur in subtle ways even in a single channel company. A catalog company sends out several catalogs, which are essentially different channels. The typical predictive model includes only those who received Catalog A and considers response only to Catalog A. This may not represent incremental sales generated by Catalog A, since customers might have bought from other catalogs even if they had not received Catalog A.

25.4 Industry Examples

25.4.1 Retail "Best Practice" (Crawford 2002)

Crawford (2002) cites Sears and REI as exemplars of successful multichannel retailers. Sears emphasizes a single "face" to the Sears brand in all channels – Web, catalog, or retail store. Sears coordinates its website and store by allowing customers to order on the Web and pick up the product at the store. This is achieved because Sears has an integrated database between the website and store, so when the customer places an order on the Web, the store sees that order. This linkage pays off because 21% of customers who pick up at the store buy additional product in the store. In addition, Sears has reinforced the centrality of their bricks-and-mortar stores by crediting stores with any purchase picked up at the store, even if "purchased" via the catalog or the Web.[2]

REI specializes in outdoor sporting products, positioned around the expertise and enthusiasm of it store representatives. Similar to Sears, this makes the store the central focus of multichannel management, and the goal is to move customers from the catalog or website to the store. REI does this by emphasizing the stores at the website. REI has an easy-to-use store locator and a "stores and events" tab that promotes special store activities. REI thought at first that the website would replace the catalog, but they found that catalog customers resisted changing their shopping habits to frequent the Web. The entire coordination of catalog, Web, and store is facilitated by data integration – REI has a single view of 80% of its individual customers across channels. It uses this information to target marketing efforts such as e-mails.

25.4.2 Waters Corporation (CRM ROI Review 2003)

CRM ROI Review (2003) reports the experiences of the Waters Corporation, a large chemical company in the liquid chromatography business. The privately held company traditionally emphasized customer relationships, a simple task when the direct sales force was the only channel, and reps could develop relationships and collect all the data needed to monitor that relationship. However, as the company began to rely on additional channels, Waters made a significant investment in information technology to achieve the information integration they desired. They purchased the mySAP system (see Urban 2004), which integrated their customer data. In addition,

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[2] Note there are compensation issues and measurement issues that can ensue because the catalog or Internet may be instrumental in generating the sale, yet they are not "credited" with the sale. Over time, the importance of these channels is less salient and the firm may under-invest in them.

they took the next step to use the data to target marketing efforts more efficiently.

For example, the chemistry group used to implement 15 direct mail campaigns per year targeting 40,000 names, and the HPLC and mass spectrometry groups each implemented 5–6 campaigns targeting 28,000 customers. The first mundane but crucial task was to understand the level of duplication among these separate efforts. Now, the chemistry group mails to 32,000 customers while the HPLC and mass spectrometry groups mail to 25,000 customers, and response rates have risen by 50%. With the savings in marketing budget, the chemistry group implements three additional campaigns per year, yielding an additional $120,000 in revenue.

Data integration is especially important at the acquisition stage. Lead follow-up is more efficient now. No matter how the lead enters the system, the sales rep has access to the data and can follow-up. Service efficiency has improved dramatically because service personnel have complete data on the customer at each service call.

CRM ROI Review (2003) calculates an internal rate of return of 35% on the $5.1 million investment, including benefits of $250,000 from lead follow-up, $3 million in revenue from online sales (net of channel switching), and $750,000 in additional telesales and increased response rates due to better-targeted direct marketing campaigns.

25.4.3 The Pharmaceutical Industry (Boehm 2002)

The pharmaceutical industry has traditionally relied on physicians, retail pharmacies, and managed care organizations to sell its product. It now wishes to add channels such as the Web, mail-order, and call centers. One potential barrier is patients' privacy concerns. While privacy certainly is an issue among many patients, a surprising number of patients support targeted marketing efforts. Boehm (2002) finds that in certain treatment categories (mental health, asthma, gastrointestinal problems), more than 70% of patients would value personalized disease information, more than 50% would share personal information with a drug company to learn more about treatment approaches, and more than 50% do not mind drug marketing as long as it is personalized.

Boehm (2002) emphasizes that the pharmaceutical industry must coordinate its channel efforts across the phases of the patient decision process, including awareness, consideration, physician contact, filling the prescription, and persistence and compliance (loyalty). For example, advertising may be best for generating awareness, while the Web and call centers may work well for facilitating consideration. These channels need to funnel patients to their physicians, where traditional detailing can ensure that the physician is equipped to answer patient questions and prescribe the drug if it suits the patient. Then the Web or e-mail can be used to ensure patient compliance and persistence, i.e., that the patient takes medications as prescribed, and fills prescriptions when they run out. This is an example of a Functional channel strategy (Fig. 25.13**b**).

25.4.4 Circuit City (Smith 2006; Wolf 2006)

Circuit City faces a highly competitive business in retail consumer electronics. However, they recently have improved results dramatically through upgrades in their retail stores and Internet channel, and coordination between the two. In the words of Phil Schoonover, chairman of Circuit City Stores, "Our multichannel marketing efforts drove improved traffic trends in all channels, and we saw an increase in Web-originated sales picked up in our stores." Indeed, not only were online sales up 85% during the first quarter of 2006 versus a year ago, but more than half of all items ordered online were picked up at the store. This of course enabled the customer to obtain the product immediately, and allowed Circuit City staff to cross-sell as appropriate. In fact, a major part of the multichannel strategy was increasing training for store personnel.

25.4.5 Summary

The above industry examples illustrate the importance of channel coordination. Sears, REI and Waters integrate data across channels. This seems to pay off in two ways. First is through better targeted marketing campaigns (Waters). Second is through the ability to offer better services (Sears and REI) such as store pick-up of items ordered on the Web.

In addition, we see in the Circuit City case that right-channeling allows the firm to retain research shoppers. Right-channeling was achieved by encouraging store pick-up of Web orders. This case involves a Functional channel strategy with segmentation occurring on a self-selection basis (e.g., half of Circuit City's Web orders were not picked up at the store). The pharmaceutical industry would like to move in this direction, and there appear to be promising opportunities despite concerns about privacy and the highly traditional ways of doing business in that industry.