Drivers and Consequences of Multichannel Shopping

Hasan Tolga Bilgicer

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ABSTRACT

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Previous research has investigated what happens when customers start utilizing more than a single sales channel (i.e., become multichannel). This research stream has identified two key consequences of multichannel usage. First, Shankar et al. (2003) and Hitt and Frei (2002) determine that customers using an internet channel in addition to the traditional brick-and-mortar channel are more loyal than customers who use a single channel. Sousa and Voss (2004) explain that these higher customer retention rates are because of increased coordination between channels; the coordination among channels increases customer satisfaction, which improves retention rates. Second, Neslin et al. (2006), Thomas and Sullivan (2005), Kumar and Venkatesan (2005), Venkatesan et al. (2007), Ansari et al. (2008), and Kushwaha and Shankar (2008) determine that on average multichannel customers spend more than single channel customers. Although plenty of research exists about multichannel customer management, there is relatively little known about the drivers that induce customers to adopt a new channel. Additionally, previous research has mainly focused on the short term effects and has not attempted to quantify, if any, the long-term effects of multichannel usage.

This dissertation examines multichannel customers' decisions. Specifically, I address the following questions: (1) What factors lead customers to adopt new sales channels? and (2) What is the long-term effect of multichannel shopping on customers' spending?

The first essay investigates the drivers of new sales channel adoption. In this essay, I propose a conceptual framework grounded in diffusion theory, and test this framework on

longitudinal data from a major catalog company using a discrete-time, hazard model. This essay contributes to the marketing literature by providing empirical evidence that social influence impacts the timing of new channel adoption. I find that longer tenured customers are more eager to adopt a new channel and less impacted by social influence. I also find that customers adopt a physical store at a faster rate than an Internet store. Moreover, social influence and customer tenure play more important roles when customers adopt an Internet channel than a brick-and-mortar channel. In contrast, marketing activities play a more important role in customers' adoption of the physical store than in the customer's adoption of the internet channel. These new findings have implications for identifying early adopters and accelerating the diffusion of a new channel.

The second essay is the first study to look at how multichannel shoppers' spending pattern changes over time, and is distinctive from past research which examines multichannel customers' spending only in the short term. For this study, I examine longitudinal data from a major U.S. retailer. My empirical analysis is likely to be affected by self-selection bias because heavy users may self-select themselves into using more than one channel. To control for such bias, I combine different panel data econometrics techniques with the propensity score matching method. The results provide empirical evidence that multichannel customers increase their spending when they initially start to use a new channel. In the long run, however, I find that the difference between multichannel and mono-channel customers' spending disappears. The findings have implications for predicting revenue streams from multichannel customers over time. Methodologically, this study is the first to combine dynamic panel data estimation with the propensity score matching. In addition, several papers in social sciences rely on aggregate level data (for example, zip code level demographics from U.S. Census), to create matched pairs.

These papers are criticized as some scholars (Gensler et al., 2012) argue that zip code level data do not provide sufficient information to construct functional matched pairs. To address this issue, I create matched pairs based on U.S. Census data and household level data. The findings show that the estimates obtained by both matching procedures are exceptionally similar results.

Table of Contents

List of Figures

Essay 1:

List of Tables

Essay 1:

Essay 2:

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always been there to cheer me up and stood by me through the good and bad times. I cannot be more grateful for her unconditional love.

Dedication

For my family and friends.

1. Introduction

Recent technological advances and fierce competition have lead many companies to expand their channel structures. According to the Direct Marketing Association's 2005 report on multichannel customers, 42 percent of retailers in U.S. sell through two channels, while 40 percent sell through three or more channels. These channels typically include catalogs, websites, physical retail stores, sales force, apps for smart phones, and call centers (Neslin and Venkatesh, 2009).

Ample evidence suggests that multichannel customers are more loyal (Shankar et al., 2003; Hitt and Frei, 2002) and on average spend more than single channel customers (Neslin et al., 2006; Thomas and Sullivan, 2005; Kumar and Venkatesan, 2005; Venkatesan et al., 2007; Ansari et al., 2008; Kushwaha and Shankar, 2008). However, what makes customers adopt new channels is far less clear and investigations on the drivers of new channel adoption have been scant. Furthermore, pertinent research has mainly focused on the short term effects and has not attempted to quantify, if any, the long-term effects of multichannel shopping. To address these issues, this dissertation concentrates on two questions: (1) What factors lead customers to adopt new sales channels? and (2) What is the long-term effect of multichannel shopping on customers' spending? These questions are managerially relevant because executives need to understand how they can accelerate the diffusion of their new sales channels, and predict future revenue streams from multichannel customers over time.

The first essay examines the drivers of new sales channel adoption. In this essay, I posit a conceptual framework that is grounded in diffusion theory. To test this framework, I utilize longitudinal data from a major catalog company using a discrete-time, hazard model. The first essay contributes to the marketing literature by providing empirical evidence that social influence shortens the duration of a new channel adoption. Additionally, I find that longer tenured customers are more eager to adopt a new channel, and less impacted by social influence. I also find that customers adopt a physical store at a faster rate than an Internet store. Moreover, social influence and customer tenure play more important roles when customers adopt an Internet channel than a brick-and-mortar channel. In contrast, marketing activities play a more important role in customers' adoption of the physical store than in their adoption of the internet channel.

The second essay is the first to look at how multichannel shoppers' spending pattern changes over time. Empirically testing this research question on customer-level transaction data is likely to be affected by self-selection bias. That is, heavy users may self-select themselves into using more than one channel. To control for such bias, I combine different panel data econometrics techniques with the propensity score matching method. The results show that multichannel customers increase their spending when they initially start to use a new channel. In the long run, however, I find that the difference between multichannel and mono-channel customers' spending disappears. Methodologically, this study is the first to combine dynamic panel data estimation with the propensity score matching.

Past Research: Multichannel Customer Management

This dissertation contributes to the literature in marketing that investigates multichannel customer management. This section provides a background on research in marketing and other fields that is pertinent to this dissertation.

Customers' New Sales Channel Adoption

A relatively limited number of studies examine what factors impact customers' sales channel adoption decision. Venkatesan et al. (2007) investigate such factors empirically and find that basket size, cross-category purchase volumes, and customer satisfaction (with previously used channels) influence the timing of new channel adoption. The authors also determine that marketing efforts and customer demographics (such as age and income) are additional important factors. Ward (2001) studies consumer substitution behavior among different channels, and reports that once a customer learns to adopt a new channel, the customer is more likely to adopt other new channels. Similarly, Venkatesan et al. (2007) find that customers adopt new channels at faster after these customers become multichannel.

Social Influence on Channel Choice

Two recent articles investigate empirically how neighborhood effect impacts usage patterns of an online store. Bell and Song (2007) and Choi et al. (2010) assess the neighborhood effect (i.e., previous trials in adjacent zip codes) on trial rates of a new online grocery store. The authors find that the neighborhood effect is positive and significant.

Two previous studies rely on survey data to examine how social influence impacts customers' channel selection decisions. Verhoef et al. (2007) show that customers' channel choice is impacted by the belief that people similar to them use that channel. Similarly, Keen et al. (2004) examine customers' channel choice in a conjoint analysis setting and report that social norms influence channel decisions. For example, when a mother shops for her baby, she prefers to use a brick-and-mortar store rather than an Internet store. This is because shopping at the brick-and-mortar store requires the mother to exert more effort, and the mother sees such effort as an opportunity to show her dedication to her child.

Consequences of Multichannel Shopping

There is a consensus in the marketing literature that, on average, multichannel customers purchase more than single channel users. Ansari et al. (2008), Neslin et al. (2006), Thomas and Sullivan (2005), Kumar and Venkatesan (2005), and Kushwaha and Shankar (2008) find that multichannel customers buy more than mono-channel customers. Thomas and Sullivan (2005), however, highlight that using any combination of two channels does not necessarily result in higher purchase volume than a single channel. For example, consumers using catalog and online channels could buy (on average) less than customers using only a brick-and-mortar store. However, these customers purchase more than only online or catalog channel users.

Multichannel customers could buy more because they are exposed to more marketing efforts. Blattberg et al. (2008) argue that multichannel customers are exposed to heavy marketing activities, simply because these customers utilize multiple channels. For example, multichannel customers see online advertising banners while they shop online, and are exposed to promotions while they browse a brick-and-mortar store. In addition, Pauwels and Neslin (2010) suggest that marketing efforts are endogenous for a multichannel household. In other words, multichannel customers are exposed to more advertising, because they purchase in higher volumes and thus companies target them more heavily.

Self-Selection

In an ideal scenario, I would conduct an experiment to measure the effects of multichannel shopping. This way, I would have a set of households that were required to use more than one channel (i.e., the treatment group) and another group that were enforced to stay as a single channel user (i.e., the control group). Examining such data would provide results that are free of bias stemming from unobserved variables. Unfortunately, it is not possible to run such an experiment and empirical research relies on transaction data. Using transaction data raises concerns of self-selection bias: a heavy user is more likely to select a multichannel firm over a single channel company. It is highly possible that customers using more than one sales channel are inherently different than customers who use a single channel. Campbell and Frei (2009) find that customer retention rates are positively influenced by multichannel usage. After controlling for the self-selection problem using instrumental variable estimation, the authors conclude that their results are robust. Nevertheless, there are conflicting results when the relationship between customers' spending and multichannel usage is explored. Ansari et al. (2008) find that customers who become multichannel were purchasing in similar amounts compared to customers who stay as single channel customers. This implies that self-selection problem may not exist. Hitt and Frei (2002), on the other hand, conclude that consumers who adopt online banking channel have always been more profitable. These results contradict each other. Hence, the literature can benefit from further work quantifying the relationship between customer spending and multichannel usage, while addressing the self-selection problem.

The Long-Term Effects of Multichannel Usage

A limited number of studies have examined the long-term consequences of multichannel usage on a firm's revenues at aggregate level. Avery et al. (2009) investigate the cannibalization and complementarily effects of adding brick-and-mortar stores to internet stores, focusing on total revenues. The authors find that at the aggregate level, opening retail stores reduce sales in catalog channels in both the short and long run. However, new brick-and-mortar stores cannibalize the sales in online channel in the short term, but produce a complementary effect (i.e., increasing sales) in the long run. Pauwels and Neslin (2008) determine that catalog mailings enhance sales not only through the catalog channel, but through the online and retail store channels in both short and long run.

Several papers look at the relationship between customer loyalty and multichannel usage. Shankar et al. (2003), and Hitt and Frei (2002) conclude that customers who use the internet channel and a retail store were more loyal than mono-channel users. Sousa and Voss (2004) explain these higher customer retention rates based on coordination between channels. The coordination among channels increases customer satisfaction, which improves customer retention rates. Ansari et al. (2008), on the other hand, show that increased internet usage decreases customer loyalty for a multichannel firm. Blattberg el al. (2008) explain this result as follows: When customers use the internet, they can easily gather information, and compare competitors' products. Therefore, in the long run customers who use online channel are more likely to leave the firm than customers who do not.

Essay 1 Summary

The first essay explores social influence and other drivers of customers' timing to adopt new sales channels. This essay makes four main contributions. First, most research (Keen et al., 2004; Verhoef et al., 2007) relies on survey data to determine how social influence impacts channel adoption. In contrast, I use customer-level transaction data to empirically show that social influence, measured by the percent of neighboring customers who have already adopted the channel (Bass, 1969), accelerates the diffusion of a new sales channel.

Second, I demonstrate that longer tenured customers adopt new channels faster, but they are less impacted by social influence compared to relatively new customers. Tenured customers perceive less risk when adopting a new channel and seek less information (Arndt, 1967), as they are more familiar with the firm (Kumar and Venkatesan, 2005). The first essay also shows that education and number of children within a household are more influential on a customer's timing to adopt the Internet channel than the brick-and-mortar channel.

Third, my unique data enable me to compare and contrast the adoption patterns of Internet and brick-and-mortar store channels. The results show that social influence and customer tenure have greater impact on customers' timing to adopt the Internet channel than the brick-and-mortar channel. The physical store has a faster adoption rate than the Internet channel, as the latter channel is more complex, riskier, and less compatible with consumer habits, and because customers are less familiar with it (Rogers, 2003; Holak and Lehmann, 1990; Verhoef et al., 2007).

Finally, this paper is the first to discriminate between product returns made for refunds from those made for product exchanges in the context of channel choice. I find that returns for refunds have a nonlinear effect on customers' timing to adopt a new channel. Product exchanges, however, only influence customers' timing of adopting a brick-and-mortar store.

Essay 2 Summary

The second essay empirically examines the long-term consequences of multichannel usage on consumers' spending, while controlling for potential self-selection through a variety of statistical methods. To address the self-selection problem, I combine several panel-data econometrics techniques with the propensity score matching. The propensity score matching creates matched pairs between multichannel customers and observational control groups.

The second essay contributes to the literature in marketing by assessing the long-term effects of multichannel purchasing. My results confirm the results of past research: multichannel customers spend more on average. Nonetheless, this increased spending diminishes over time. That is, the difference between a multi- and mono-channel customer's spending disappears in three years after a consumer becomes multichannel. These results can be explained by the novelty theory. According to the novelty theory, customers derive value from learning new ways of doing things (Philstrom and Brush, 2008). This value is referred as novelty or epistemic value (Donthu and Garcia, 1999; Duman and Mattila, 2005). Customers who are motivated by epistemic value typically return to their regular consumption patterns after satisfying their need for change (Sheth et al., 1991). Similar empirical evidence has been documented in research examining sporting events (Howard and Crompton, 2003), business-to-business markets (McQuiston, 1989), and consumers' reactions to cause-related marketing efforts (La Ferle et al., 2013).

Methodologically, I combine different panel data econometrics techniques with the propensity score matching methodology. To the best of my knowledge, this study is the first to estimate a dynamic panel data model on matched data based on propensity scores. In addition, several papers in social sciences rely on aggregate level data (for example, zip code level demographics from U.S. Census), to create matched pairs. These papers are criticized by some scholars (Gensler et al., 2012) who argue that zip code level data do not provide sufficient information to construct functional matched pairs. By creating matched pairs based on U.S. Census data (at zip code level) as well as household level data, I find that there are no significant discrepancies in the results obtained by matching methods relying on zip code and individual level data and address this concern.

The rest of this document is organized as follows: Essays 1 and 2 appear in the next two sections. Following the essays, the final chapter contains general commentary and discussion of future research directions.

2. Essay 1: Social Influence and Customer Adoption of New Sales Channels

Abstract

While innovations in technology have led firms to expand their channel structures, less is known about the drivers that induce customers to adopt a new channel. I propose a conceptual framework grounded in diffusion theory that identifies the factors associated with new channel adoption. I test this framework on longitudinal data from a major catalog company using a discrete-time, hazard model. The results provide empirical evidence that social influence impacts the timing of new channel adoption. Additionally, longer tenured customers are both more eager to adopt a new channel and less impacted by social influence. I also find that customers adopt a physical store at a faster rate than an Internet store. Moreover, social influence and customer tenure play a more important role when customers adopt an Internet channel than a brick-and-mortar channel. In contrast to social influence, marketing activities play a more important role in customers' adoption of the physical store than in their adoption of the internet channel. These findings have implications for identifying early adopters and accelerating the diffusion of a new channel.

Introduction

Offering a multichannel structure is challenging, but very widespread among retailers. According to the Direct Marketing Association's 2005 report on multichannel customers, 42 percent of retailers in U.S. sell through two channels, while 40 percent sell through three or more channels. These channels typically include catalogs, websites, physical retail stores, sales force, and call centers (Neslin and Venkatesh, 2009).

Researchers have identified two main benefits to companies of offering new channels. First, Ansari et al. (2008), Neslin et al. (2006), Thomas and Sullivan (2005), Kumar and Venkatesan (2005), Nielsen Research (2008), and Kushwaha and Shankar (2013) report that multichannel customers typically spend more than single channel customers. Second, Shankar et al. (2003), Hitt and Frei (2002), and Campbell and Frei (2009) find customers who use an online channel along with a traditional channel (i.e., a bank's branch) are more loyal than customers who use a single channel.

Given these benefits, it is important to understand what factors impact customers' decisions to adopt a new channel. Managers can use such information to estimate the time a customer takes to adopt a new channel, to identify early adopters based on customer demographics and past company-customer interactions, and to accelerate the diffusion of the new channel by efficiently targeting early adopters who spread word-of-mouth about the new channel and influence other customers to adopt.

Accordingly, I propose and empirically test a conceptual framework grounded in diffusion theory (Rogers, 1962, 2003; Bass, 1969) to identify the key drivers of new channel adoption. To test my hypotheses, I implement a discrete time survival analysis model on Internet and brick-and-mortar store adoption data from a major U.S. catalog company that sells consumer apparel products. Apparel companies generate massive revenues: In 2007, U.S. customers purchased 20.1 billion garments and 2.4 billion pairs of shoes, representing $371 billion in revenue (Anderson and Simester, 2011). Additionally, the apparel category has the highest volume of Internet and catalog orders (DMA, 2006). Thus, my data are relevant to a significant portion of the U.S. economy. For each household and quarter, the data include channel-specific sales amounts, marketing activities, returns, exchanges, recency, frequency, and monetary value (RFM) type measures, and demographics.

This paper makes four main contributions. First, most research (Keen et al., 2004; Verhoef et al., 2007) relies on survey data to determine how social influence impacts channel adoption. In contrast, I use customer-level transaction data to empirically show that social influence, measured by the percent of neighboring customers who have already adopted the channel (Bass, 1969), accelerates the diffusion of a new sales channel. Social influence is significant even when I control for observed and unobserved customer heterogeneity (Thomas and Sullivan, 2005; Ansari et al., 2008), marketing activities (Venkatesan et al., 2007; Ansari et al., 2008; Knox 2006), and proxies for customer satisfaction with incumbent channels (Reicheld, 1998; Venkatesan and Kumar, 2004; Venkatesan et al., 2007).

Second, I find that customers who have longer relationships with the catalog company (longer customer tenure) are more eager to adopt the new channel but are less impacted by social influence compared to relatively new customers. Because tenured customers are more familiar with the firm (Kumar and Venkatesan, 2005), they perceive less risk when adopting a new channel and seek less information (Arndt, 1967). In addition, education and number of children within a household are more influential on a customer's timing to adopt the Internet channel than the brick-and-mortar channel.

Third, I compare and contrast the adoption patterns of Internet and brick-and-mortar store channels. My results show that social influence and customer tenure have greater impact on customers' timing to adopt the Internet channel than the brick-and-mortar channel. Additionally, I show that the physical store has a faster adoption rate than the Internet channel. This occurs because the latter channel is more complex, riskier, and less compatible with consumer habits, and because customers are less familiar with it (Rogers, 2003; Holak and Lehmann, 1990; Verhoef et al., 2007).

Finally, previous research examining the relationship between product returns and consumer behavior does not discriminate between product returns made for refunds and those made for product exchanges. I find that returns for refunds have a nonlinear effect on customers' timing to adopt a new channel. Product exchanges, however, only influence customers' timing of adopting a retail store.

Overall, my results show that marketing activities (social influence) play a more (less) important role in customers' adoption of the brick-and-mortar store than in their adoption of the internet channel. Marketing activities (social influence) account for 70% (19%) and 48% (47%) of the total number of adopters of the brick-and-mortar store and Internet channel, respectively.[1] In addition, I find that different types of customers are likely to adopt different channels. I also find that product returns and exchanges, if managed successfully, can increase customer satisfaction and therefore accelerate the adoption rates of new channels.

[1] The rest of the effects are baseline sales levels that one obtains without marketing effort or social influence.

The rest of the paper is organized as follows. First, I briefly review the literature and then present a set of hypotheses about the expected effects of social influence, marketing activities, customer characteristics and past purchase behavior on new channel adoption based on the channel literature and diffusion theory. Next, I describe the data, develop a survival analysis model to empirically test my hypotheses and present my results. Finally, I discuss managerial implications and suggest directions for future research.

Literature

Relevant research identifies two important benefits for companies offering multiple channels: heavy spending and increased customer loyalty. Scholars find that on average multichannel customers spend more than single channel customers (Ansari et al., 2008; Neslin et al., 2006; Thomas and Sullivan, 2005; Kumar and Venkatesan, 2005; Kushwaha and Shankar, 2008). Moreover, multichannel customers are more loyal than mono-channel customers (Shankar et al., 2003; Hitt and Frei, 2002; Campbell and Frei, 2009). Given the empirical evidence showing that offering customers multiple channels is beneficial to companies, it is essential to understand what factors influence customers' decision to adopt new channels.

Customers' New Sales Channel Adoption

Relatively small number of studies examines factors impacting customers' new sales channel adoption decision. Venkatesan et al. (2007) investigate such factors empirically by using a hazard model. The authors conclude that basket size, cross-category purchase volumes, and customer satisfaction (with previously used channels) are the major drivers of new channel adoption. The authors also find that marketing efforts and customer demographics impact the duration of new sales channel adoption. Ward (2001) studies consumer substitution behavior among different channels and find that once a customer learns to adopt a new channel, the customer is more likely to adopt other new channels. Likewise, Venkatesan et al. (2007) find that customers adopt new channels at faster rates after these customers become multichannel. These studies provide important insights on understanding how customers decide to adopt new channels, but they do not ask whether social influence has any role in the context of new channel adoption.

Social Influence on Channel Choice

Two previous studies rely on survey data to examine how social influence impacts customers' channel selection decisions. Verhoef et al. (2007) show that customers' channel choice is impacted by the belief that people similar to them use that channel. Similarly, Keen et al. (2004) examine customers' channel choice in a conjoint analysis setting and report that social norms influence channel decisions. For example, when a mother shops for her baby, she prefers to use a brick-and-mortar store rather than an Internet store. This is because shopping at the brick-and-mortar store requires the mother to exert more effort, and the mother sees such effort as an opportunity to express her dedication to her child. Verhoef et al.'s and Keen et al.'s research provide interesting insight on how social influence affects customers' channel choice, however, these studies rely on survey data. In this study, I use transactional data.

Two recent articles investigate empirically how neighborhood effect impacts usage patterns of an online store. Bell and Song (2007) and Choi et al. (2010) assess the neighborhood effect (i.e., previous trials in adjacent zip codes) on trial rates of a new online grocery store. The authors find that the neighborhood effect is positive and significant. However, Bell and Song (2007) and Choi et al. (2010) examine the data of a new online grocery store. As a result, each trial in their study represents new customer acquisition. Furthermore, the units of analysis in these studies are zip codes, not customers. I, on the other hand, examine a firm's incumbent customers' decision to adopt new channels.

Hypotheses

I draw on findings in the literatures on innovation and product diffusion, multichannel customer management, and channel choice to develop hypotheses on the impact of social influence, customer tenure and their interaction on customers' timing of adopting a new channel. I also propose hypotheses about how the channel type moderates these relationships. Finally, I examine the effects of marketing activities, customers' behavioral and demographic variables on channel adoption while controlling for unobserved customer heterogeneity.

Figure 1. Conceptual Framework

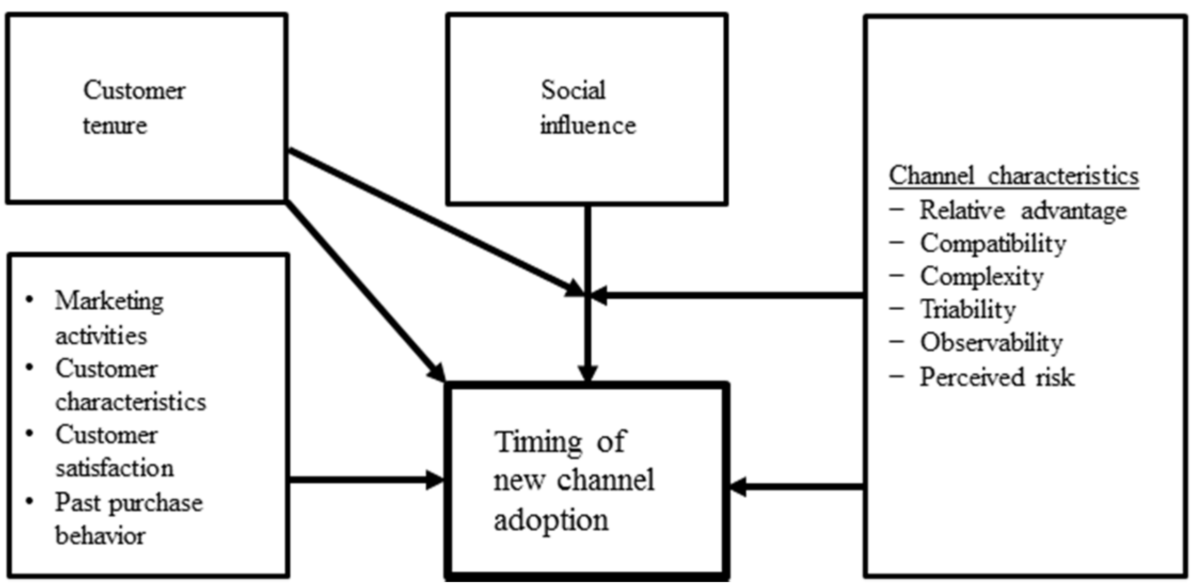


Figure 1 presents my conceptual framework for examining the effects of social influence, customer characteristics, and marketing activities on channel adoption. Social influence impacts customers' channel adoption through word-of-mouth communications, visual imitation, and homophily.[2] Customers can communicate via both direct (face-to-face contact) and indirect word-of-mouth such as electronic communication (Godes and Mazylin, 2004) or simply by observing packages at their neighbor's houses. Such interactions raise awareness of the new channel and its characteristics, reduce the perceived risk from channel adoption, and may persuade non-adopters to use the new channel based on adopters' recommendations.

Table 1. Channel Charactheristics

Channel Type	Diffusion Factors					
	Relative Advantage	**Compatibility**	**Complexity**	**Triability**	**Observability**	**Perceived Risk**
Online Channel	✓ - Excellent search convenience - Easy to compare information - High assortment	✓ - Only for limited number of transactions	✓$^+$ - High purchase effort	✓	No	✓ - High purchase risk
Brick-and-Mortar Store	✓$^+$ - High assortment - Good service - Quickly obtain product - Good after sales support - Enjoyable experience - Excellent privacy	✓$^+$ - Familiar channel type	No - Familiar channel type	✓	✓ - "Billboard effect"	No

The magnitude of the impact of social influence on channel adoption depends on the new channel's characteristics. Rogers (1961; 2003) proposes that five characteristics regulate an innovation's rate of diffusion: (1) relative advantage, (2) compatibility, (3) complexity, (4) trialability (or divisibility), and (5) observability (or communicability). Holak and Lehmann (1990) identify "perceived risk" as an additional factor impacting the adoption of new products.

In this paper, I consider two new channels: online and brick-and-mortar. Table 1 evaluates these two channels on Rogers's adoption factors. Though both channels have advantages, Verhoef et al. (2007) find that customers perceive the online channel as more

[2] Given the limitation of my data, I do not distinguish between word-of-mouth, visual imitation and homophily, and refer to their combined effect as social influence.

complex and associate it with higher perceived risk. Van Birgelen et al. (2006) show that the compatibility of different channels stems from their functional similarities. Bank customers, for example, perceive that the online channel has limited functionality (Hitt and Frei, 2002) and they use it only for a limited number of routine tasks (e.g., paying bills and checking account balances). Consequently, the online channel may be relatively less compatible than a brick-and-mortar store. Moreover, Avery et al. (2011) find that the presence of a physical store provides repeated exposure to customers, making this type of channel highly observable.

The relationship between social influence and channel adoption is also moderated by past purchase behavior. Customers with a long purchase history (i.e., longer tenure) are expected to be less influenced by social influence when adopting a new channel than newer customers. Besides social influence, a customer's adoption of a new channel depends on consumer characteristics, past purchase behavior, customer satisfaction, and marketing activities. I now formally state my hypotheses.

Impact of Social Influence, Customer Tenure, and their Interaction

The impact of social influence on the diffusion of new products has been an integral part of the academic literature for decades. Rogers (1962) and Katz et al. (1963) posit that the timing of adoption is influenced by the pressure of the social system. They suggest that innovation diffusion is influenced by social communication and that social pressure grows for later adopters as the number of previous adopters increases. Bass (1969) relies on the diffusion theory to model the timing of adoption of new durable products and technologies. His model demonstrates that aggregate diffusion of new durable products is correlated with the number of previous adopters.

Several scholars have highlighted the importance of social influence in the context of channel selection. Verhoef et al. (2007) use survey data to show that customers' channel choice is impacted by the belief that people similar to them use that channel. Similarly, Keen et al. (2004) examine customers' channel choice in a conjoint analysis setting and report that social norms influence channel decisions. Bell and Song (2007) and Choi et al. (2010) empirically estimate the effect of zip code contiguity on trial rates of an Internet grocery store. The authors conclude that the neighborhood effect is positive and significant. Therefore, I posit:

Hypothesis 1: Social influence accelerates the diffusion of a new sales channel.

Xue et al. (2007) empirically study what influences the usage of new self-service channels in retail banking and find no systematic relationship between customer tenure and choice of channel. The authors report that greater customer tenure is associated with less usage of ATMs and online banking. Nonetheless, the authors also observe that customer tenure has positive relationships with the use of some self-service channels, such as voice response unit and automatic clearance house. In contrast, Kumar and Venkatesan (2005) find that customer tenure is positively correlated with multichannel shopping. Relatedly, Thomas and Sullivan (2005) find that the stage of the customer lifecycle determines channel choice. These conflicting results suggest that the marketing literature could benefit from further work examining the relationship between customer tenure and channel adoption. Kumar and Venkatesan (2005) argue that customers who purchase from a firm over a long time period are familiar with the brand, which reduces perceived risk with new product purchases (Schoenbachler and Gordon, 2002; Kumar and Venkatesan, 2005). Therefore, I hypothesize:

Hypothesis 2: Longer tenured customers adopt a new channel faster.

Who is more impacted by social influence when adopting a new channel, a long tenured customer or a relatively new customer? Some classic papers provide insights into this issue.

Bauer (1960) suggests that perceived risk determines an innovation's rate of diffusion. Similarly, Ostlund (1974) reports that high perceived risk is negatively associated with the rate of diffusion. Arndt (1967) concludes that interpersonal communication often leads to an initial purchase of a new product and that potential adopters tend to rely more on word-of-mouth when the perceived risk of the new product is high. As longer tenured customers perceive less risk with new purchases (Schoenbachler and Gordon, 2002; Kumar and Venkatesan, 2005), I hypothesize:

Hypothesis 3: Longer tenured customers are less influenced by social influence than newer customers when adopting a new channel.

Moderating Effects of Channel Type

Verhoef et al. (2007) measure consumers' attitudes towards different channels. The authors report that customers have uniformly positive attitudes towards brick-and-mortar stores. Customers associate physical retail stores with high assortment, better privacy and enjoyable shopping experience. They also perceive minimum risk with their purchases, as they can physically inspect and quickly obtain a product. These positive associations are not surprising considering that customers are highly familiar with the conventional retail stores. Blattberg et al. (2008) suggest that these associations could stem from an "experience halo". Furthermore, retail stores typically offer social interaction with its sales force, provides repeated exposure to a "living billboard" (Avery et al., 2011), and eliminate hassles associated with product returns and exchanges.

Consumers associate an online store with lower compatibility, higher complexity and higher purchase risk (Verhoef et al., 2007). In addition, use of an online store is not readily observable. Thus:

Hypothesis 4: Customers adopt a new brick-and-mortar store faster than a new Internet channel.

Verhoef et al. (2007) find that customers consider Internet stores to be high on purchase risk and lack service and after-sales support. Arndt (1967) determines that consumers rely more on word-of-mouth when they perceive high risk with a purchase. Thus, I expect that:

Hypothesis 5a: Customers are more impacted by social influence when adopting an Internet channel compared to when they adopt a brick-and-mortar store.

Although customers consider online stores to be high on purchase risk, Schoenbachler and Gordon (2002) and Kumar and Venkatesan (2005) argue that familiarity (i.e., customer tenure) decreases such risks. Therefore, customer tenure is less influential when customers adopt a less risky channel, such as a brick-and-mortar store. I hypothesize:

Hypothesis 5b: Customer tenure plays a more important role when customers adopt an Internet channel than when they adopt a brick-and-mortar store.

Other Drivers of Channel Adoption

This section discusses other potential factors influencing a customer's channel adoption, developing hypotheses only for relationships that have not been previously tested in the literature.

Past Adoption Behavior

Ward (2001) found that once a customer learns to adopt one new channel, she is more likely to adopt other new channels. Similarly, Venkatesan et al. (2007) find that customers who adopted a new channel in the past adopt a newer channel at a faster rate.

Customer Satisfaction

Product returns are one way for customers to express dissatisfaction with a product (Venkatesan et al., 2007). In particular, if a company deals with product returns satisfactorily, customers can become loyal to the firm (Reicheld, 1998). Reinartz and Kumar (2003) find a positive relationship between the proportion of returns and customer profitability. This result highlights the importance of a good returns policy as customers who are more comfortable with the seller's policies buy more products over time (Mark et al., 2007). Nevertheless, customers who frequently return items typically have a low level of satisfaction with the company (Venkatesan and Kumar, 2004). Venkatesan et al. (2007) demonstrate that product returns have a nonlinear impact on new channel adoption. Customers who return products at moderate levels adopt a new channel faster. Customers who return products frequently, on the other hand, are less likely to adopt a new channel.

Research investigating the influence of product returns on consumer behavior typically does not discriminate between product returns for refunds and for exchanges (Bower and Maxham, 2012; Venkatesan et al., 2007). While the effort exerted in returning products for refunds is fairly consistent, the effort for exchanging products varies greatly across different channels (Avery et al., 2011). For example, when a customer uses a catalog or Internet channel to exchange a product, there is still a chance that the customer might not be satisfied with the new product. If the customer uses a retail store, however, she has a chance to inspect the product and to exchange it without a waiting period. Thus:

Hypothesis 6a: Customers who return products for refund or exchanges at moderate levels adopt a new channel faster than those with infrequent or frequent returns.

Hypothesis 6b: Customers who exchange products at moderate levels adopt a brick-and-mortar channel faster than an Internet channel.

Marketing Activities

Knox (2006), Ansari et al. (2008), and Thomas and Sullivan (2005), among others, show that marketing efforts impact consumer's channel choice. Similarly, Venkatesan et al. (2007) find that frequent marketing communications can shorten the time untill channel adoption. Typically, firms allocate a limited budget to their marketing activities. Thus, it is important for practitioners to target customers who are more likely to be influenced by marketing efforts and utilize the most effective marketing activities.

Customer Characteristics

Previous research on multichannel customer management and new channel adoption has identified several demographic and socio-economic factors which influence channel selection. Venkatesan et al. (2007), Ansari et al. (2008), and Fox et al. (2002) report that high-income customers are more likely to buy across different channels. In addition, Thomas and Sullivan (2005) and Ansari et al. (2008) conclude that young customers tend to adopt the Internet channel faster. Travel time and cost also influence the appeal of a new physical store; Avery et al. (2011), Bell et al. (1998), Fox et al. (2002), Venkatesan et al. (2007), and Forman et al. (2009) find that proximity to a brick-and-mortar store positively influences the likelihood of using it. Hence, I use distance to the retail store as a proxy for travel cost and time.

The effect of education on the diffusion of innovations has been well documented. Weir and Knight (2004) find farmers with high formal education are earlier adopters of higher-yielding crop varieties and chemical fertilizers. Similarly, Mattilla et al. (2003) show well-educated customers are likely to adopt the Internet channel early. The majority of research on effects of education, however, is in the context of disruptive innovations (Rogers, 2003). Disruptive innovations are more difficult to comprehend and adopt in comparison to continuous innovations. Rogers (2003) suggests that individuals with high levels of formal education are more inclined to learn about new technologies. Therefore, I expect formal education to be a less integral factor in the adoption of retail stores, as customers are already highly familiar with this type of channel:

Hypothesis 7a: Customers with higher levels of education adopt a new channel faster than those with lower levels of education.

Hypothesis 7b: Education is a more important factor when customers adopt an Internet channel than a brick-and-mortar store.

Davis (1976) points out that children have considerable influence on their parents' purchase decisions. Lunsford and Burnett (1992) argue that children are prone to learn about disruptive innovations more rapidly and lead their elderly relatives in adopting new technologies. As a result, they recommend "communication through children" as a solution to the barriers to adoption that new technologies pose for senior customers. Because the Internet is based on less familiar technology (Verhoef et al., 2007), I expect children to be more influential in the diffusion of an Internet channel:

Hypothesis 8a: Customers with more children adopt a new channel faster.

Hypothesis 8b: The number of children is a more important factor when customers adopt an Internet channel than a brick-and-mortar store.

Seasonality

Christmas and back-to-school seasons significantly increase sales of many consumer products. Since there are no convincing theories on the impact of seasonality on diffusion of innovations, I do not have formal hypotheses about seasonality.

Data

My main data source is a major catalog company in the United States that sells durables and apparel in mature categories. This seller gathered quarterly data between January 1, 1997 and September 8, 2004 on more than 5,000 households that reside in United States. For each household and quarter, the data are comprised of channel-specific sales amounts, marketing activities (i.e., emails, catalogs, promotions for the retail store opening, and other promotions), returns, exchanges, and demographics. The catalog company also provided us recency, frequency, and monetary value (RFM) measures for each household *prior* to the beginning of the data. In the clothing and consumer durables industries, the relationship between the customers and company is noncontractual: a household can start and end the relationship with the company at any time. I follow previous research in noncontractual settings (Xue et al., 2007; Kumar and Venkatesan, 2005; Thomas and Sullivan, 2005; Schoenbachler and Gordon, 2002) and assume the relationship between the customer and the firm begins with the customer's initial purchase. Table 2 lists the variables I use and their operationalization.

Table 2. Operationalization of Variables

Variable	Description
Social influence	Percent of neighboring customers who have already adopted
Customer tenure	The natural logarithm of the number of years passed since household's first purchase
Probability of college education	Percent of college educated people in the zip code
Number of kids in household	Number of children within the household
Head of household's age	Head of the household's age in years
Household income	Household's annual income in US Dollars
Within 25 miles of the store	Dummy variable indicating whether the household resides within twenty five miles of the brick-and-mortar store
Whether retail store (Internet channel) is adopted	Dummy variable indicating whether the household adopted a new channel
Past purchase incidences	Household's cumulative number of purchases
Number of refunds	Number of product returns for refunds in the previous time period
Number of exchanges	Number of product returns for exchanges in the previous time period
Number of catalogs received	Number of catalogs received in the current time period
Number of emails received	Number of emails received in the current time period
Number of store opening promotions received	Number of fliers about physical store opening received in the current time period
Number of other promotions received	Number of other promotional activities, including spring sales events, outdoor discovery school (ODS) promotions (such as, discounted kayaking or fishing lessons), and rewards from company's brick-and-mortar store specific loyalty program
Quarter 1	Dummy variable for the first quarter of a year
Quarter 2	Dummy variable for the second quarter of a year
Quarter 3	Dummy variable for the third quarter of a year

As the two new channels open at different times, I create separate datasets to investigate customers' channel adoption behavior for the Internet channel and the brick-and-mortar store. The data for the online channel adoption span the period from January 1, 1997 to September 8, 2004. According to the catalog company, less than one in one thousand households adopted the Internet channel before 1997. I exclude these households from my analysis on the Internet channel adoption. The data for the brick-and-mortar store adoption start on September 1st, 2002 (when the store opened) and end on September 8, 2004. Avery et al. (2011) find that customers are willing to drive for an hour to go to a physical retail store. Hence, I focus on the households who live within seventy five miles of the brick-and-mortar store. [3] I measure social influence by the percent of customers who have already adopted the new channel (Bass, 1969) and test for the robustness of this measurement under different neighborhood assumptions. For both data sets, I exclude households that did not make any purchase from any channel during the entire observation period. As the data for online channel and retail store adoption start at different dates, I examine these data separately.

Figure 2. Adoption Patterns of the Internet Channel and the Brick-and-mortar Store

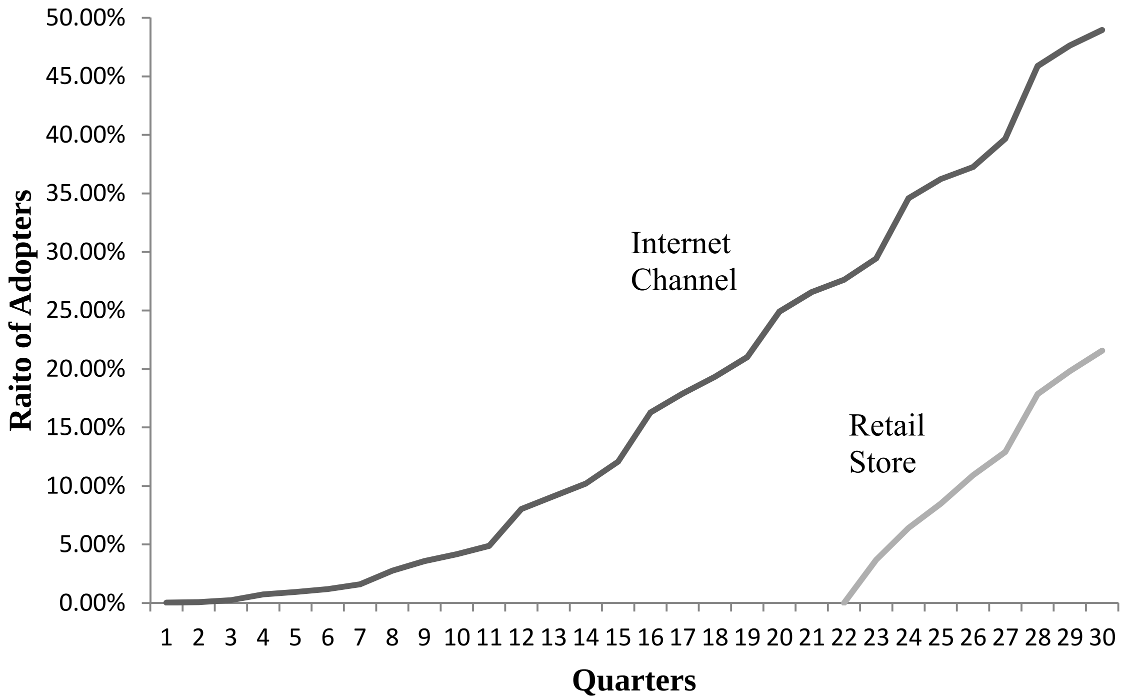


Figure 2 shows the adoption patterns of the Internet channel and the physical retail store. Adoption of the Internet store was relatively slow in the beginning. After the third year, the Internet channel's client base began to expand at a faster rate. The physical retail store, on the

[3] As a robustness check, I also ran an analysis on the households living within thirty miles of the retail store. The results are consistent. See Appendix A for more details.

other hand, had fairly rapid adoption rate early on, consistent with Hypothesis 4. By the end of my observation period, nearly 48% of households had adopted the Internet channel, whereas approximately 23% had adopted the retail store.

The catalog company has records of the number of emails, catalogs, and other type of promotions sent in each quarter. The company sent fliers to inform the households about the opening of the physical store. In addition, the firm kept track of its "other promotions", which include spring sales events, special activity events, and rewards from its brick-and-mortar store specific loyalty program. The company increased the number of emails sent to its customers over time.

The company also has survey-based demographics data on their customers (basic descriptive statistics are given in Table 3). Most of the demographic statistics are similar to the national averages, except for household income, which is higher (the average household income according to 2000 U.S. Census is $56,604 whereas it is about $95,000 in the sample). The households in the data reside in a relatively wealthy region. Nonetheless, within my data the households' incomes vary substantially. Unfortunately, the catalog seller does not have any information on households' formal education. Hence, I integrate data from the National Center for Environmental Health (NCEH) website[4] (http://www.cdc.gov/nceh/) into the primary dataset. NCEH's data provide the distribution of formal education levels for adults older than twenty five years at the zip code level. I use the percent of college educated people within a zip code as a proxy for the probability that the head of the household in a given zip code has a college degree.

[4] This zip-code level dataset can be obtained from the NCEH's website free of charge.

Table 3. Descriptive Statistics

Variable	Online Channel: Means for All Households	Online Channel: Means for Adopters	Online Channel: Means for Non-Adopters	Retail Store: Means for All Households	Retail Store: Means for Adopters	Retail Store: Means for Non-Adopters
Customer tenure (in years)	12.22	12.30	12.08	10.38	10.65	9.72
Probability of college education	.37	.39	.36	.37	.38	.37
Number of kids in household	.48	.62	.41	.49	.56	.49
Head of household's age (in years)	48.09	44.19	50.01	47.15	43.19	47.15
Household income (in thousand US Dollars)	97.29	105.01	93.33	96.57	103.37	95.60
% of households living within 25 miles of the retail store				.53	.56	.51
Past purchase incidences	10.09	12.04	9.14	10.37	12.26	9.52
Number of refunds per period	.06	.09	.05	.06	.08	.04
Number of exchanges per period	.02	.02	.01	.02	.02	.01
Number of catalogs received	4.15	5.31	3.59	3.62	4.52	3.42
Number of emails received	1.83	4.03	.83	3.91	7.78	3.74
Number of store opening promotions received	.02	.02	.01	.03	.03	.02
Number of other promotions received	.02	.04	.02	.07	.09	.04
Sample size	169261	69830	99431	74675	17664	57011

For each channel, Table 3 depicts sample means for the overall sample, adopters, and non-adopters. Adopters of the Internet and brick-and-mortar channels tend to be younger, well-educated, and have higher income and more children compared to non-adopters. In addition, new channel adopters tend to be longer tenured customers, more frequent buyers, and are exposed to more marketing activities. This latter result suggests a potential endogeneity issue, which I address in my empirical analysis. It is interesting to note that Internet and retail store adopters return more products for refunds and exchanges than non-adopters. Not surprisingly, adopters of the brick-and-mortar store live in closer proximity to the retail store. As the sample size is large for both channels, all mean differences between adopters and non-adopters are significant ($p < 0.05$).

Model

I use discrete time survival analysis to determine which factors influence the timing of new channel adoption. My model is designed for right-censored data, where households are observed for a limited period of time and not every household adopts the new channel during this time period. I assume the target event is non-repeatable (i.e., once a household adopts a new channel, it cannot re-adopt it again).

Cox (1972) shows that hazard probabilities can be parameterized as logistic probabilities. As demonstrated by Brown (1975), Allison (1982), Laird and Oliver (1981), and Singer and Willett (1993), maximizing the likelihood function of a discrete time survival function on right-censored data, given the hazard probabilities are modeled as logistic probabilities, is equivalent to maximizing the likelihood function of logistic probabilities.

I parameterize the hazard probabilities as the probability of channel adoption occurring at time *t* by household *i* (given that household *i* did not adopt the channel before *t*) as:

$$h_{it} = 1 \Bigg/ \left(1 + \exp\left(\gamma + \sum_{m=1}^{M} \beta_m x_{mit} + \mu_i \right) \right) \qquad (1)$$

where γ is the intercept and the vector $\boldsymbol{x}_{it} = (x_{1it}, \ldots x_{Mit})'$ includes all the M independent variables (i.e., customer tenure, social influence, their interaction, past adoption behavior, customer satisfaction, marketing variables, customer characteristics, and seasonality; see Table 2, column 1). $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_M)'$ is a vector of regression parameters and μ_i denotes the unobservable, time-invariant, household-specific, random effect, which I assume to be i.i.d. normally distributed, N(0, σ_μ^2).

When Rogers (2003, p. 11) explains the elements of diffusion, he states: "an innovation that is communicated through certain channels over time among the *members of a social system*". In my study, I measure the social influence as a percent of people who already adopted the new channel within a market. I define this market (or social system in Rogers' terms) as people living within a 75-miles radius. It is possible that such market may be too broad. For example, while adopting a brick and mortar store, a typical household may communicate only with its neighbors. I address this concern with a robustness check in the results section. Moreover, the adoption of the online channel may be confounded by Internet availability in different neighborhoods. I control this concern in the 'Robustness Check' section of this essay.

Marketing variables are likely to be endogenous in the data. Catalog firms typically target their marketing efforts to their best customers (Blattberg et al., 2008). This means heavy and frequent users are subject to heavy advertising by the catalog firm. In the data the number of catalogs a household receives is highly correlated with the household's previous number of purchases ($r = 0.65$, $p < 0.05$). Similarly, retailers can be strategic when opening a new store by placing the brick-and-mortar store close to their most profitable customers. To control for such endogeneity, Blattberg et al. (2008; p.652) and Ansari et al. (2008) suggest including variables used by the firm to target marketing activities in the model. Accordingly, I include two sets of targeting variables in my model to control for endogeneity: the cumulative number of previous purchases (an RFM variable) and household demographics.[5] As an additional robustness check, I use lagged marketing variables as instruments in Appendix D. The results are very robust and show that my conclusions do not suffer from endogeneity bias.

My model accounts for both observed and unobserved household heterogeneity. To capture observed household heterogeneity, I include household income, education level, head of household's age, and number of children as well as behavioral variables (for example, customer tenure and number of product returns). To capture unobserved household heterogeneity, I use a

[5] It is possible that price-sensitive consumers adopt sales channels that offer price discounts. The prices are consistent across all channels in the data. Therefore, this concern is not relevant to my model.

random effects model specification (the μ_i terms in Equation 1). I use Stata to estimate the model parameters.

Empirical Results

I estimate the model using maximum likelihood estimation on both the Internet channel and the brick-and-mortar store adoption datasets. Both models fit the data well. McFadden Rho^2 statistics are 40.6% and 37.2% for the Internet channel and retail store adoption data, respectively.[6] Table 4 reports the maximum likelihood estimation results separately for the Internet channel and retail store adoption.

Impact of Social Influence, Customer Tenure, and their Interaction

The results in Table 4 indicate that social influence (the percent of neighboring customers who had already adopted the new channel) significantly affects the timing of consumer adoption of both the internet and brick-and-mortar channels (β= 0.456 and β = 0.143, respectively; $p < 0.001$). These effects are non-linear and characterized by diminishing returns; the coefficients of squared social influence are negative and significant (β = -0.004 and β = -0.004, respectively; $p < 0.001$). These findings suggest that neighboring households' adoption of the Internet and the retail store accelerates the diffusion of the new channel (supporting Hypothesis 1) with diminishing returns. The results also show that longer tenured customers are more eager to adopt a new internet or retail store (β = 2.803 and β = 0.686, respectively; $p < 0.001$), which contradicts Hypothesis 2. The interaction between customer tenure and social influence is significant and negative for both channel types (β = -0.029 and β = -0.032, respectively; p <

[6] Rho-squared values of 0.2 to 0.4 are considered highly satisfactory (see Whitmore et al., 2007, p. 602).

0.001). This result supports Hypothesis 3 and indicates that newer customers are more influenced by social influence when adopting a new channel.

To assess the overall significance of the impact of social influence on channel adoption, I re-estimate both of my models without the three social influence variables (i.e., social influence, social influence squared and the interaction between social influence and customer tenure). As indicated in Table 4 (bottom panel), the log-likelihood of my full model is -6811.18 and -3653.87 for online and retail store channels adoption, respectively. Without the social influence variables, these values are -7265.88 and -3678.13, respectively. The likelihood ratio test indicates that social influence significantly impacts customers' adoption of the online channel (χ^2=909.4; $p < 0.001$) and the brick-and-mortar channel (χ^2=48.5; $p < 0.001$).

Moderating Effects of Channel Type

To compare the magnitude of the estimates across the two channels, I test for parameter invariance. A commonly used test in academic literature is the Chow Test (Chow, 1960), which is designed for linear models. For my non-linear estimation, I use the likelihood ratio based-test developed by Andrews and Fair (1988). One advantage of this test is that it can test the stability within a subset of coefficients. The results of the Andrews and Fair (1988) test indicate that the coefficients of intercept, social influence, and customer tenure in the Internet channel adoption model are all significantly different from those in the retail store adoption model ($p < 0.001$). The coefficients of the squared social influence and the interaction between customer tenure and social influence variables are not statistically different across the two models.

As an Internet channel is associated with higher risk than a conventional retail store (Verhoef et al., 2007), customers are more hesitant to adopt it compared to a physical store (ceteris paribus). The intercept term of the online channel adoption model is negative and significantly larger in magnitude than that of the retail store adoption model ($\beta = -24.224$ vs. $\beta = -9.518$, $p < 0.001$), consistent with Hypothesis 4.

As expected, the impact of social influence is significantly larger for the online channel adoption as compared to the retail store adoption ($\beta = 0.456$ vs. $\beta = 0.143$, $p < 0.01$). This supports my argument that customers associate the online channel with higher risk (Verhoef et al., 2007) and attend to social influence (Arndt, 1967), supporting Hypothesis 5a. Finally, as familiarity with the firm reduces the perceived risk with purchases (Schoenbachler and Gordon, 2002; Kumar and Venkatesan, 2005), and the Internet channel is associated with higher risk than a conventional retail store (Verhoef et al., 2007), customer tenure is more impactful for the Internet store adoption model than the brick-and-mortar store model ($\beta = 2.803$ vs. $\beta = 0.686$, $p < 0.01$), supporting Hypothesis 5b.

Table 4. Maximum Likelihood Estimates

Variables	Hypothesized Effect	Expected Moderating Effect of Channel Type	Internet Channel Adoption: Parameter Estimate (Standard Error)	Retail Store Adoption: Parameter Estimate (Standard Error)
Intercept	Control variable	Greater negative intercept when adopting an Internet channel (H4)	-24.224 (2.176)***	-9.518 (1.093)***
Customer Characteristics				
Log-customer tenure	No impact (H2)	Greater parameter when adopting an Internet Channel (H5b)	2.803 (.374)***	.686 (.114)***
Probability of college education	Positive (H7a)	Greater parameter when adopting an Internet Channel (H7b)	1.618 (.566)**	-.519 (.301)
Number of kids in household	Positive (H8a)	Greater parameter when adopting an Internet Channel (H8b)	.264 (.072)***	-.017 (.038)
Head of household's age	Control variable	-	-.120 (.008)***	-.001 (.003)
Log-household income	Control variable	-	.370 (.170)*	.185 (.083)*
Past purchase incidences	Control variable	-	.080 (.006)***	.003 (.004)
Within 25 miles to the store	Control variable	-	–	1.803 (.141)***
Social Influence				
Social influence	Positive (H1)	Greater parameter when adopting an Internet Channel (H5a)	.456 (.030)***	.143 (.034)***
$(\text{Social influence})^2$	Control variable	-	-.004 (.000)***	-.004 (.001)**
Log-customer tenure * social influence	Negative (H3)	-	-.029 (.008)***	-.032 (.007)***
Customer Satisfaction				
Number of refunds	Positive (H6a)	-	1.604 (.198)***	1.387 (.211)***
$(\text{Number of refunds})^2$	Negative (H6a)	-	-.350 (.082)***	-.325 (.094)**
Number of exchanges	Positive (H6a)	Greater parameter when adopting a retail store (H6b)	-.377 (.406)	1.174 (.396)**
$(\text{Number of exchanges})^2$	Negative (H6a)	-	.045 (.235)	-.207 (.250)
Marketing Efforts				
Number of catalogs received	Control variable	-	.481 (.056)***	.173 (.034)***
Number of emails received	Control variable	-	.521 (.013)***	.013 (.008)
Number of store opening promotions received	Control variable	-	.006 (.210)	1.235 (.187)***
Number of other promotions received	Control variable	-	-.464 (.166)**	1.192 (.105)***
Log-customer tenure * catalogs received	Control variable	-	-.107 (.021)***	-.052 (.012)***
Past Adoption Behavior				
Whether the retail store is adopted	Control variable	-	-.996 (.263)***	–
Whether the Internet channel is adopted	Control variable	-	–	-.169 (.100)
Seasonality				
Quarter 1	Control variable	-	-1.724 (.100)***	-.283 (.116)*
Quarter 2	Control variable	-	-1.460 (.102)***	-.107 (.118)
Quarter 3	Control variable	-	-1.474 (.094)***	-.129 (.114)
σ_μ			7.201 (.178)	.869 (.294)
Log-likelihood			-6811.184	-3653.865
McFadden's Rho^2			.406	.372
Sample size			125967	44660

Note: *p < .05, **p < .01, ***p <.001.

Other Drivers of Channel Adoption

Past Adoption Behavior

The "Whether the retail store is adopted" variable has a negative sign ($\beta = -0.996$; $p < 0.001$) for Internet store adoption, which contradicts my expectation and suggests a cannibalization effect: Households who adopted the retail store adopt the Internet channel late. This can be explained as follows: the conventional store opened after more than six years from the launch of the Internet channel. Thus customers who adopted the conventional store without adopting the Internet channel exhibit stronger resistance to the online channel than those who did not adopt. Internet store adoption has also a slightly negative effect on retail store adoption, but it is not significant ($\beta = -0.169$; $p > 0.05$).

The coefficient of the cumulative number of previous purchases included in my analysis to control for endogeneity of marketing efforts is statistically significant and positive only for the online store adoption ($\beta = 0.08$; $p < 0.001$). This result is intuitive: customers' familiarity with the company lowers perceived risk associated with the adoption of a new technology.

Customer Satisfaction

As anticipated, refunds have a positive impact on customers' timing of adopting both online and retail channels (Venkatesan et al., 2007), supporting Hypothesis 6a ($\beta = 1.604$ and $\beta = 1.387$; $p < 0.001$). The negative coefficients of the squared terms suggest that refunds have diminishing, and at some point negative, influence ($\beta = -0.35$; $p < 0.001$) on Internet channel adoption, and on retail store adoption ($\beta = -0.325$; $p < 0.01$).

Product exchanges have no significant impact on Internet channel adoption ($\beta = -0.377$; $p > 0.05$). However, they have a positive and significant effect on physical store adoption ($\beta =$

1.174; $p < 0.01$), suggesting that exchanges are easier to cope with through a conventional store than through an online store, supporting Hypothesis 6b.

Marketing Activities

Most marketing activities (catalogs, emails, and retail store specific promotions) are significant and shorten the time to adopt the physical channel. E-mails, on the other hand, are not (statistically) influential on the retail store channel adoption. For the Internet channel, emails and catalogs lessen the adoption duration. Other promotions, however, seem to increase the channel adoption duration, implying that the brick-and-mortar store specific loyalty program cannibalizes sales at the Internet store. The interaction term between catalogs and the customer tenure is significant and negative for both channels ($\beta = -0.107$; $p < 0.001$ for Internet channel adoption, and $\beta = -0.052$; $p < 0.001$ for retail store adoption), indicating that shorter tenured customers are more impacted by catalog mailings.

Customer Characteristics

Consistent with Venkatesan et al. (2007), Ansari et al. (2008), and Fox et al. (2002), I find that higher income households adopt the Internet and retail stores faster. Close proximity to the retail store also accelerates the retail store adoption (Avery et al., 2011; Bell et al., 1998; Fox et al., 2002; Venkatesan et al., 2007; Forman et al., 2009). An increase in the head of household's age slows the time to adopt the online store, indicating that senior customers wait longer to adopt a new technology (Venkatesan et al., 2007; Ansari et al., 2008).

College education lessens the time to adopt the Internet channel, supporting Hypothesis 7b ($\beta = 1.618$; $p < 0.01$), but has no statistically significant impact on the physical store adoption

($\beta = -0.519$; $p > 0.05$). As a result, I have partial support for Hypothesis 7a. These results suggest that people with higher education adopt new technologies at faster rates.

The number of children in the household shortens the online store adoption duration, supporting Hypothesis 8b ($\beta = 0.264$; $p < 0.01$). This result is intuitive: children are inclined to learn about and convince their parents to start using new technologies. In addition, they contribute to greater overall family spending. This variable, on the other hand, is not significant for the adoption of brick-and-mortar store ($\beta = -0.017$; $p > 0.05$). As a result, Hypothesis 8a is partially supported.

Seasonality

For the Internet store adoption, all seasonal dummy variables are significant. The Christmas season (the fourth quarter) unsurprisingly leads to higher sales. For the retail store adoption, however, the difference between the quarters is much smaller.

Predictive Validity

To assess the out-of-sample predictive validity, I calculate mean absolute deviation (MAD) for Internet channel and retail store adoption. I use estimated parameters for both channel types to examine my model's predictive validity for holdout samples (i.e., the last eight quarters of the Internet channel adoption data and the last four quarters of the retail store adoption data). The MAD for the percent of households adopting the Internet channel in the last 8 quarters is 2.2% and that for the brick-and-mortar store in the last 4 quarters is 0.9%.

Figure 3a contrasts actual and predicted percentages of Internet channel adopters, and Figure 3b compares actual and predicted percent of retail store adopters. The figures show that my out-of-sample predictions capture movements in Internet and brick-and-mortar store adoption fairly well.

Figure 3a. Actual vs. Predicted Internet Channel Adopters

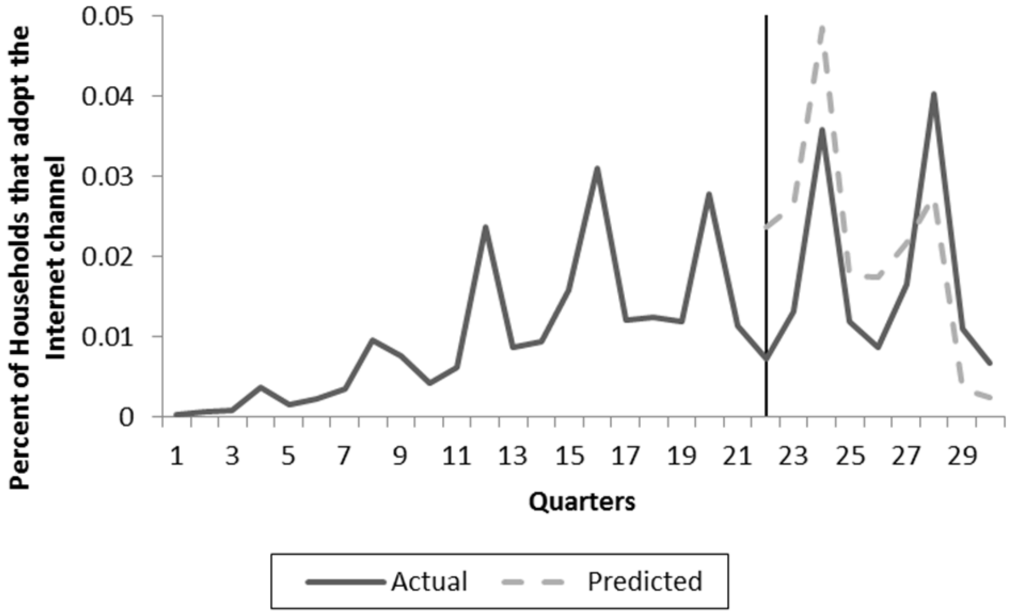
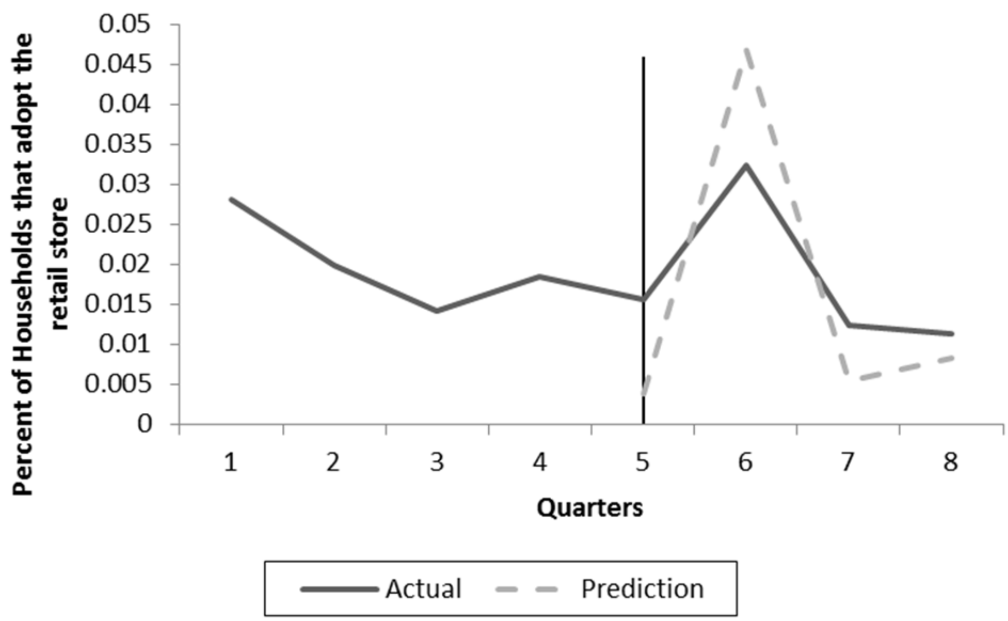


Figure 3b. Actual vs. Predicted Retail Store Adopters



Robustness Check

In this study, I measure social influence by the percentage of customers who already adopted the new channel within a 75-miles radius. It is possible that such a definition is too broad. For example, while adopting a brick-and-mortar store, a customer could communicate primarily with her immediate neighbors. I check for the robustness of my results by measuring social influence in two additional ways. The first measure considers only the people who already adopted the new channel within a customer's county as a source of influence. The second measure uses the geographical proximity of the customers to define social influence. Accordingly, I cluster customers based on their zip code (GPS) coordinates and measure social influence by the percent of people who already adopted the new channel within a customer's cluster. The cluster analysis (Proc KMEANS in SAS) retained thirty clusters based on the pseudo R-squared criterion and visual inspection of the results.

Table 5a. Robustness Check Results
Online Channel Adoption

Variables	Social Influence Based on Counties: Parameter Estimate	Social Influence Based on Counties: Standard Error	Social Influence Based on Clusters: Parameter Estimate	Social Influence Based on Clusters: Standard Error	Social Influence Based on 75 Miles Radius: Parameter Estimate	Social Influence Based on 75 Miles Radius: Standard Error
Social influence	.515	(.040)***	.593	(.045)***	.456	(.030)***
(Social influence)^2	-.005	(.000)***	-.006	(.000)***	-.004	(.000)***
Log-customer tenure * social influence	-.038	(.011)***	-.045	(.011)***	-.029	(.008)***
McFadden's Rho^2	.404		.404		.406	

Table 5a and 5b report the estimation results for each the two alternative measures of social influence and my measure based on the whole population. I focus on the social influence parameters. All the other coefficients are virtually identical to those reported in Table 2. Appendix C presents these estimates. The results in Tables 5a and 5b show that the three sets of parameter estimates are quite consistent with each other, which provides support for the robustness of my empirical results. In addition, the McFadden Rho^2 fit statistics are almost equal across these models.

Table 5b. Robustness Check Results
Retail Store Adoption

Variables	Social Influence Based on Counties		Social Influence Based on Clusters		Social Influence Based on 75 Miles Radius	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Social influence	.169	(.013)***	.135	(.016)***	.143	(.034)***
(Social influence)^2	-.003	(.000)***	-.004	(.001)***	-.004	(.001)**
Log-customer tenure * social influence	-.028	(.004)***	-.023	(.004)***	-.032	(.007)***
McFadden's Rho^2	.396		.373		.372	

Managerial Implications

The results show that marketing activities are effective for accelerating the diffusion of new channels and that their importance varies across different customers. This suggests that managers should target their marketing resources differentially across customers. For example, tenured customers rely less on social influence and are less influenced by marketing efforts. They are also more likely to adopt a new channel earlier than new customers. This suggests that managers should focus their limited resources by targeting newer customers to accelerate their channel adoption. Further, a differential link exists across channels between customer demographics and channel adoption. For an Internet-based channel, managers should focus on customers with high education, high income, and larger number of children. For a retail store, on the other hand, managers should target higher income customers who live in close proximity to the store.

Product returns and exchanges are opportunities for managers to increase customer satisfaction and, thus, influence the adoption of a new channel. Consistent with the results in previous research, I find that if customers are satisfied with the product return service, they adopt a new channel faster. Successfully managed product exchanges, on the other hand, only enhance the adoption of a retail store.

To quantify the relative impact of marketing activities with respect to social influence on channel adoption, I use my parameter estimates to simulate adoption patterns for the Internet and retail store under three different scenarios. In the first (baseline) scenario, I assume that the firm employs no marketing activities and operates in a world with no social influence. (That is, I set social influence and the quarterly marketing activities to zero and predict channel adoption for the whole duration of the data.) In the second scenario, I still assume no marketing activities, but allow social influence to impact new channel adoption. The difference between the adoption levels that I predict under these two scenarios captures the impact of social influence on channel adoption. In the last scenario, I allow both social influence and marketing activities to affect channel adoption. The difference between the adoption levels under this scenario and the previous one captures the additional impact of marketing activities beyond social influence.

Figure 4a depicts the simulation results for the online channel adoption. These results indicate that social influence and marketing activities contribute 47% and 48% of the total adoption effect, respectively. Figure 4b presents the simulation results for the brick-and-mortar store adoption. In this case, social influence contributes only 19% of the total controllable diffusion. Marketing activities, on the other hand, play a more important role in the adoption of the conventional retail store and contribute 70% of the total adoption effect.

Figure 4a. Assessing the Impact of Social Influence and Marketing on Online Channel Adoption

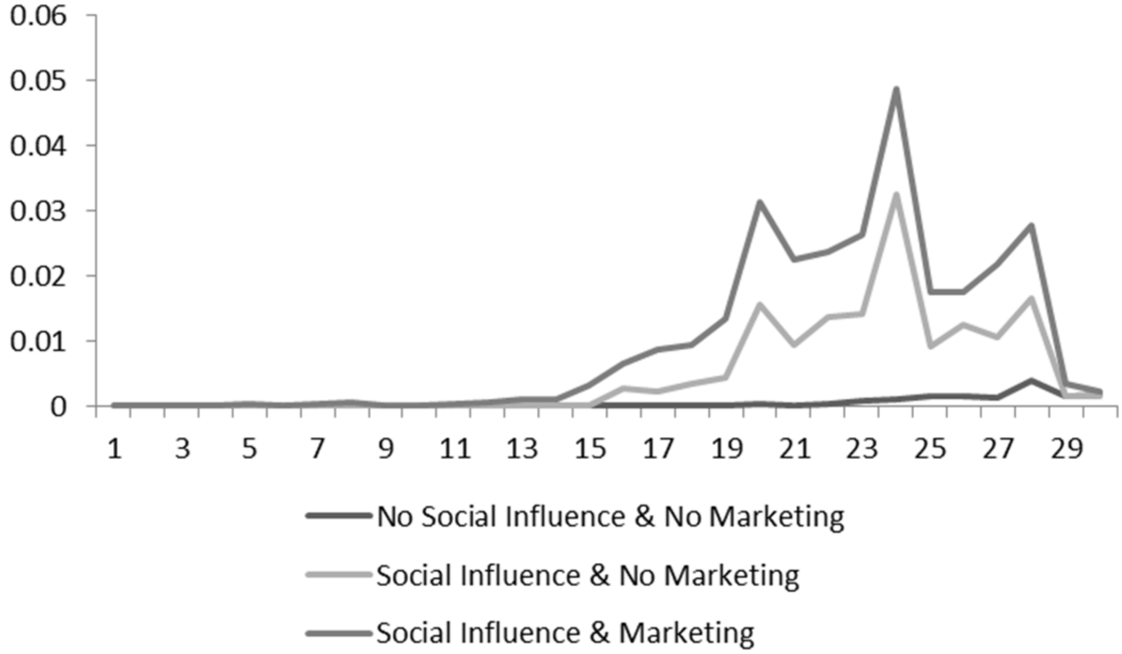
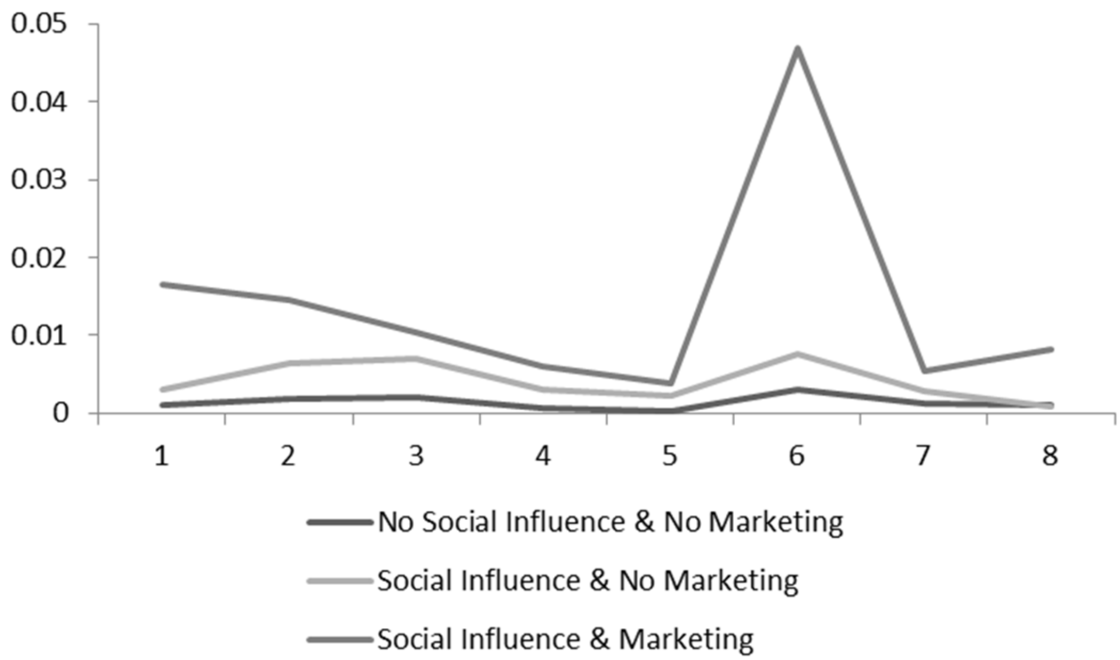


Figure 4b. Assessing the Impact of Social Influence and Marketing on Retail Store Adoption



In these simulations, I first calculate baseline adoption, then the impact of social influence, and finally the additional impact of marketing activities. It is possible that the results could be biased due to this order effect. To address this, I change the order by first calculating the impact of marketing on adoption in the absence of social influence and then measure the additional impact of social influence. For the online channel adoption, I find that social influence and marketing efforts contribute 41% and 54% of total adoption, respectively. For the retail store adoption, social influence and marketing activities account for 16% and 75% of retail store adoption, respectively. Thus, regardless of the order, social influence contributes between 41% to 47% of the total adoption effect for the online channel and between 16% to 19% for the retail store channel.

Summary and Conclusions

This paper examines factors that impact new channel adoption. I find that social influence accelerates the diffusion of a new sales channel. Moreover, I conclude that longer tenured customers rely less on social influence and are less influenced by marketing activities, but adopt new channels faster. My unique data enable me to compare and contrast adoption patterns of online and brick-and-mortar store channels. The results show that social influence and customer tenure have greater impact on customers' timing to adopt the Internet channel than the brick-and-mortar channel. Additionally, I find that while refunds are influential for Internet channel and conventional stores, product exchanges are only associated with the adoption of brick-and-mortar stores. To the best of my knowledge, this paper is the first to distinguish the effects of product returns for refunds and exchanges in the context of channel adoption.

My study contributes to the marketing literature demonstrating demographics, marketing activities and customer satisfaction influence the timing of a new channel adoption. Education and number of children in household are more impactful on customers' timing of adopting the Internet channel than a conventional store. In contrast to earlier work, I determine that customers who adopt a different new channel earlier are less likely to adopt a third channel. This novel result can be explained by a cannibalization effect and by a tendency on the part of customers to pick their favorite channel. More empirical work on this subject is needed.

Managerially, I discuss how my findings can be used to accelerate customers' adoption of new channels through the targeting of marketing resources. I also quantify the contribution of social influence and marketing activities in generating channel adoption. I find that marketing activities are quite influential for the diffusion of new channels, particularly conventional retail stores. Simulation results indicate that marketing efforts (social influence) contribute 48% (47%) and 70% (19%) to the adoption of the online channel and the brick-and-mortar store, respectively.

I acknowledge that this paper has limitations. First, the data come from a single firm that operates in mature markets. While the data are highly relevant to a substantial component of the U.S. economy as the data provider is one of the biggest catalog companies in U.S., my findings may not generalize to other markets. Second, I do not have an explicit measure of social influence or word-of-mouth. Nonetheless, my measure, the percent of previous adopters, has been extensively used in diffusion literature as a proxy for social influence. Third, catalog firms typically use RFM variables to target their marketing efforts. This means heavy and frequent users are subject to heavy marketing by the firm. To address this potential endogeneity issue, I included the number of past purchases (an RFM variable) in my model. Other approaches to dealing with endogeneity are worth exploring. Fourth, the results on the online channel adoption may be affected by a potential omitted variable bias: availability of Internet. To check for such bias, I run an additional regression controlling for the presence of high speed Internet providers in each household's zip code. Appendix B shows that the results presented in this study are robust. Finally, I define the initial purchase from a new channel as 'adoption'. It is important to distinguish between trial purchases and full adoption of new channels (i.e., repeated purchases). Ansari et al. (2008) and Knox (2006) report that customers' channel choice evolves over time. Valentini et al. (2008) conclude that a newly acquired customer's purchase decisions are shaped by trials, and a customer's choice process evolves after the customer learns more about her preferences and becomes familiar with a firm's marketing efforts. Additional work aimed at understanding differences between channel adopters and triers would be beneficial. More broadly, I hope the paper stimulates additional work on the adoption and use of multiple channels by customers.

3. Essay 2: The Long-Term Effect of Multichannel Usage on Sales

Abstract

Past research finds that on average multichannel customers spend more than mono-channel customers. This research stream, however, fails to examine multichannel shoppers' consumption patterns over time. I empirically investigate how customers' overall spending changes over several years after these customers start using a new sales channel besides their regular channel (i.e., become multichannel). Consistent with the previous research, I find that multichannel customers increase their overall spending when they adopt a new sales channel. I also find that multichannel consumers revert to their typical consumption pattern in the long-run. My empirical analysis is likely to be affected by the self-selection bias. That is, heavy users may self-select themselves into using more than one channel. To control for such a bias, I use several panel data econometrics techniques in conjunction with propensity score matching methods. My key results are robust across all specifications, providing evidence for their validity. In addition, I find that matching methods based on U.S. census data at the zip-code level produce similar results using household-level data and therefore can be used to control for self-selection.

Introduction

Neslin et al. (2006) define channel as a customer contact point or a medium through which firms and customers interact. Recent technological advances and fierce competition have lead many companies to expand their channel structures. In many product categories, customers have a broad range of channels to choose from, such as catalogs, call centers, Internet stores, apps for smart phones, or brick-and-mortar stores.

Previous research has investigated what happens when customers start using more than a single channel (i.e., become multichannel). This research stream has identified two key consequences of multichannel usage. First, Shankar et al. (2003) and Hitt and Frei (2002) determine that customers using internet channel in addition to the traditional brick-and-mortar channel are more loyal than customers who use a single channel. Sousa and Voss (2004) explain the higher customer retention rates by increased coordination between channels: the coordination among channels increases customer satisfaction, which improves retention rates. Second, Neslin et al. (2006), Thomas and Sullivan (2005), Kumar and Venkatesan (2005), Venkatesan et al. (2007), Ansari et al. (2008), and Kushwaha and Shankar (2008) determine that on average multichannel customers spend more than single channel customers. This research stream, however, has mainly focused on the short term effects and has not attempted to quantify, if any, the long-term effects of multichannel usage on household spending.

Blattberg et al. (2008) point out that multichannel customers could buy more due to self-selection: a heavy user is more likely to be able to take advantage of the availability of several channels. Note that in this argument, multichannel usage does not cause (or lead to) higher revenues; the heavy users self-select into using multiple channels. Thus, the direction of causality between increased overall spending and utilizing more than one channel is not clear.

This study empirically examines the long-term consequences of multichannel usage on consumers' spending, while controlling for potential self-selection through a variety of statistical methods. To address the self-selection problem, I use five different panel data econometrics techniques (i.e., pooled OLS, random effects, first-difference, lagged dependent variable, and Arellano-Bond GMM estimation). Further, I also implement propensity score matching methodology to create datasets consisting of matched pairs. This matching method is a commonly used technique to cope with self-selection problems in social sciences (Dehejia and Wahba, 1999; Heckman et al., 1998). By artificially creating observational control groups and treatment groups, propensity score matching enables us to compare single channel and multichannel customers with similar observed characteristics.

In line with prior research, I find that multichannel customers spend more on average even when I control for the self-selection bias. However, I contribute to the literature by showing that this increased spending decays over time. Specifically, the difference between multi and mono-channel customers' spending disappears after three years of being multichannel customers. This result can be explained by the novelty theory: According to the novelty theory, customers derive value from learning new ways of doing things (Philstrom and Brush, 2008), but they return to their regular consumption patterns in the long-run (Sheth et al., 1991; Howard and Crompton, 2003; McQuiston, 1989; La Ferle et al., 2013). Alternatively, this decay could be related to the type of the new sales channel that consumers begin to use as well: Blattberg et al. (2008) posit that online channel usage in the long-run lead customers to compare competitors' products and prices and become more price-sensitive over time. Ansari et al. (2008) provide empirical support for this argument. In my main analysis, I investigate when consumers start to use an online channel besides a catalog channel and, therefore, my results could be a consequence of online channel usage. To analyze whether customers buy less frequently from my data providing retailer in the long-run and switch to competitors, I conduct three supplementary studies (see Appendix E and F). The results of these supplementary studies support my explanation based on the novelty effect.

This decay in spending has important implications for managers. Many companies expand their channel structures because their managers expect a boost in sales and react to the competitive environment. It is well-known that adding new channels has its drawbacks in the short-run: opening new sales channels generates new fixed cost to firms. For instance, Campbell and Frei (2010) find that adding an online channel increases a bank's operating costs substantially and, thus, decreases its profitability in the short-run. However, it is generally accepted in the literature that adding new channels is beneficial to firms: Multichannel customers are more loyal than mono-channel users, which increases these customers' lifetime value (Shankar et al., 2003; Hitt and Frei, 2002). Sousa and Voss (2004) explain these higher customer retention rates based on enhanced coordination between channels. The coordination among channels increases customer satisfaction, which improves customer retention rates. In this study, I point out that potential limitation of opening new sales channels: the increased sales associated with multichannel usage are not sustainable in the long-run. As a result, practitioners should take this new insight into consideration while managing their channel structures.

The rest of the paper is organized as follows. I first describe relevant research and highlight my contributions. Next, I discuss data and present key methodologies I use to analyze the data. I then present empirical results. Finally, I conclude with a discussion on managerial implications and directions for future research.

Literature

The main objective of my research is to examine how the spending patterns of multichannel customers evolve over time as compared to mono-channel customers. In this section, I review the pertinent literature and highlight my research contributions. Specifically, this study contributes to the literature in the following ways:

I. Impact of Multichannel Usage on Revenues

Most findings in the marketing literature suggest that multichannel customers purchase more than mono-channel customers (e.g., Ansari et al., 2008; Neslin et al., 2006; Thomas and Sullivan, 2005; Kumar and Venkatesan, 2005; and Kushwaha and Shankar, 2008). However, Thomas and Sullivan (2005) point out that using any combination of two channels does not necessarily result in higher purchase volume than a single channel. For example, consumers using catalog and online channels could buy (on average) less than customers using only a brick-and-mortar store. However, these customers typically purchase more than only online or catalog channel customers.

Few scholars have examined the long-term consequences of multichannel usage on customers' spending habits. Avery et al. (2009) investigate the cannibalization and complementarily effects of adding brick-and-mortar stores to existing Internet and catalog channels. The authors find that opening retail stores reduce sales in catalog channels in both short- and long-run. However, new brick-and-mortar stores cannibalize the sales in online channel in the short term, but produce a complementary effect (i.e., increasing sales) in the long-run. Pauwels and Neslin (2008) find that catalog mailings enhance sales not only of the catalog channel, but also the online and retail store channels in both short- and long-run. All these researchers, however, report aggregate channel sales effects and do not distinguish between increases in sales stemming from newly acquired customers and those stemming from existing customers. In this paper, I use household-panel data to investigate the sales effect of multichannel behavior on existing customers over time.

II. Self-Selection

A heavy user is more likely to select a multichannel firm over a single channel company. It is highly possible that customers using more than one sales channel are inherently different than customers who use a single channel. For example, Hitt and Frei (2002) find that consumers who adopt online banking channel have always been more profitable. In contrast, Ansari et al. (2008) find no differences in the spending of multichannel and mono-channel customers. This implies that self-selection problem may not be present in their case. As these results are contradictory, the literature can benefit from further work quantifying the relationship between customer spending and multichannel usage, while addressing the self-selection problem. In addition, while these papers have examined only the short-term effects of multichannel usage, I examine both short- and long-run impact of multichannel usage in this study.

III. Methodology

To address the self-selection problem, researchers typically use different panel data econometrics techniques, instrumental variable estimation, or matching methods (Heckman and Navarro-Lozano, 2004). In this study, I estimate five different panel data econometrics models on ‘matched’ data based on observed customer characteristics. To the best of my knowledge, this study is the first to combine a dynamic panel data model with the propensity score matching method.

Several papers in social sciences rely on aggregate level data (such as U.S. Census data or demographics at zip code) to create matched pairs. These papers are criticized as some scholars (Gensler et al., 2012) argue that zip code level data do not provide sufficient information to construct functional matched pairs. My household-level data enable us to create matched pairs based on U.S. Census and household level data. Therefore, I compare the estimation results using data generated by both matching scenarios and address previous criticisms.

To summarize, I contribute to the marketing literature by examining both short- and long-term effects of multichannel usage on consumers' spending. As my analysis is likely to suffer from self-selection bias, I address this concern by using panel data econometrics techniques and the propensity score matching method. Methodologically, my paper is the first study using dynamic panel data econometrics techniques in conjunction with propensity score matching. Further, I compare and contrast the estimation results obtained using matched pairs based on aggregate and household level data.

Data

The data provider is a major retailer in the United States that sells durables and apparel in mature categories predominantly through catalog channel. The panel data are reported yearly at the household level, starting on January 1, 1997, and ending on December 31, 2001. The retailer has introduced an online channel in 1996. However, the vast majority of customers (i.e., more than 99.9%) did not try the Internet channel before 1997, when I begin to observe them.[7]

The data include channel-specific sales amounts, marketing activities (catalogs and e-mails), and household specific demographics. The catalog company also provides us with recency, frequency, and monetary value (RFM) measures for each household *prior* to the beginning of the data. Table 1 lists the variables I use and their operationalization.

Table 1. Operationalization of Variables

Variable	Description
Total Spending	Household's total spending in the current year
First year of multichannel usage	Dummy variable for the first year that a household becomes multichannel user
Second year of multichannel usage	Dummy variable indicating that a household became multichannel user two years ago
Third year of multichannel usage	Dummy variable indicating that a household became multichannel user three years ago
Fourth year of multichannel usage	Dummy variable indicating that a household became multichannel user four years ago
Five year of multichannel usage	Dummy variable indicating that a household became multichannel user five years ago
Customer tenure	Years passed since household's first purchase; we use the natural logarithm of the customer tenure to capture the nonlinear effect of customers' familiarity
Probability of college education	Percent of college educated people in the zip code
Number of kids in household	Number of children within the household
Head of household's age	Head of the household's age in years
Household income	Household's annual income in US Dollars
Past purchase incidences	Household's cumulative number of previous purchases
Number of catalogs received	Number of catalogs received in the current year
Emails subscription	Whether the household subscribed to receive emails from the company
Number of emails received	Number of emails received in the current year
Year 3	Dummy variable for the third year of sample data
Year 4	Dummy variable for the fourth year of sample data
Year 5	Dummy variable for the fifth year of sample data

The company has survey-based demographics data about their customers (Table 2 depicts households' descriptive statistics across all the years I observe them). To add information regarding customers' formal education level, I integrate data from the National Center for

[7] We exclude the households that tried the Internet channel prior 1997 from the analysis.

Environmental Health (NCEH) website into the primary dataset.[8] NCEH's data provide the distribution of formal education levels for adults older than twenty five years at zip code level. By calculating the percent of college educated people within each zip code, I create a proxy for the probability that the household head has a college degree.

Table 2. Descriptive Statistics

Variable	Means for All Households	Means for Multichannel Households	Means for Single Channel Households
Total spending (in US Dollars)	146.95	210.72	128.17
Purchase Frequency	1.20	1.37	1.15
Customer tenure (in years)	12.06	11.93	12.15
Head of household's age (in years)	50.11	45.67	51.38
Household income (in thousand US Dollars)	99.53	108.51	96.90
Number of kids in household	.46	.62	.42
Probability of college education	.38	.41	.38
Number of catalogs received	22.53	27.66	21.04
Number of emails received	2.05	6.61	.73
Sample size	55070	12350	42720

The main analysis is on customers who add the online channel to the incumbent catalog channel that they already use. Table 2 presents the sample means for the overall sample, multichannel, and single channel households. According to this table, multichannel users spend significantly more than mono-channel users. Moreover, multichannel customers are younger, better-educated, and have higher income and more children compared to single channel users. In addition, multichannel households are more frequent buyers, and are exposed to more marketing activities. This latter result suggests a potential endogeneity issue, which I address in my empirical analysis.

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[8] This zip-code level dataset can be obtained from the NCEH's website free of charge at: http://www.cdc.gov/nceh.

Empirical Analysis

In an ideal scenario, I would conduct an experiment to measure the long-term effects of multichannel usage on consumers' total spending. This way, I would randomly assign a set of households to the treatment group (multichannel) and another set to the control group (mono-channel) and track their purchase behavior over time. Analyzing such experimental data would provide clean results that are free of bias stemming from the self-selection problem. Unfortunately, it is difficult to run such an experiment since it is impossible to force customers to use multiple channels. This explains why most empirical researchers rely on observational data to study multichannel issues. However, using observational data suffers from self-selection bias: The households who use multiple channels may be different from those who use a single channel from the beginning. For example, the multichannel households could differ in their usage level even before becoming multichannel and any difference in purchase behavior cannot solely be attributed to being multichannel. This is quite possible in my empirical application since customers with higher predisposition to become multichannel are more likely to be heavy users (Blattberg et al., 2008). Econometrically, the self-selection bias induces a correlation between customer decision to becoming multichannel and the model error term. Failure to control for such an endogeneity problem will lead to biased empirical results.

There are several econometric approaches for addressing the self-selection problem, such as panel data econometrics, instrumental variable estimation, and matching methods (Heckman and Navarro-Lozano, 2004). In this section, I briefly review the panel data econometrics models that I use to address the self-selection problem. I then discuss the propensity score matching method and explain how I implemented it in my study. As I do not have valid instruments, I do not use instrumental variable estimation in my analysis.

Panel Data Econometrics Models

I. Pooled Ordinary Least Squares

I use pooled ordinary least squares (POLS) regression as a benchmark model. To reduce the self-selection bias in POLS, Angrist and Pischke (2008, chapter 3) suggest including customer demographics as independent variables. To control for period effects, I include year-specific dummy variables in the model, as I are not interested in the non-parametric relationship between multichannel usage and household spending. Let y_{it} be household i's total spending in year *t* in U.S. Dollars. Let YEARSMC_{ijt} be a dummy variable that indicates whether at time *t*, household *i* is (=1) a multichannel user for *j* years (j=1, ..., 5) or not (=0). For example, in the first year that household *i* starts using the online channel, YEARSMC_{i1t} =1. In the next year, YEARSMC_{i1t+1}=0 and YEARSMC_{i2t+1}=1 indicating that the household is a second-year multichannel user, and so forth. I use the set of dummy variables YEARSMC_{ijt} (j=1, …, 5) to capture the short and long term effects of multichannel usage. Previous research did not study the sales impact of multichannel usage over time (i.e., it only examined the effect of YEARSMC_{i1t} on sales). Note that all the households in my sample use the catalog channel for purchase. Thus I consider the adoption of the new online channel as equivalent to becoming a multichannel household.

The POLS model is specified as follows:

$$y_{it} = \gamma + \sum_{j=1}^{5} \rho_j \text{YEARSMC}_{ijt} + \sum_{m=1}^{M} \beta_m x_{mit} + \lambda_t + \varepsilon_{it} \tag{1}$$

where γ is an intercept term, ρ_j (j=1, …, 5) are the parameters of interest that measure the long-term effects of multichannel usage on consumers' total spending. The vector $\boldsymbol{x}_{it}$ =

$(x_{1it}, \dots x_{Mit})'$ includes the M independent control variables that are listed in Table 1 and discussed in detail below. $\boldsymbol{\beta} = (\beta_1, \dots, \beta_M)'$is a vector of parameters and λ_t denotes a set of period effects that capture common trends in all consumers' total spending. ε_{it} is an error term for capturing all other omitted factors. I assume that ε_{it} normally distributed with mean zero and variance σ^2 for all i and t.

I include the following control variables in my analysis: the firm's marketing efforts, consumer demographics and socio-economic factors. Marketing activities have considerable impact on consumers' spending (Venkatesan et al., 2007; Ansari et al., 2008) and channel choice (Venkatesan et al., 2007; Ansari et al., 2008; Knox, 2006). Further, marketing variables are likely to be endogenous, as companies target their marketing efforts to their best customers (Blattberg et al., 2008). To control for such endogeneity issues, including variables that generate marketing activities is effective (Ansari et al., 2008; Blattberg et al., 2008; p.652). Here, I include a RFM variable (i.e., cumulative purchase incidences) to control for potential endogeneity of the marketing variables. Demographic and socio-economic factors impact consumers' spending as well propensity to become multichannel. Venkatesan et al. (2007) and Ansari et al. (2008) find that younger customers with high income tend to spend more. Such customers are also more likely to try new channels (Fox et al., 2002). As formal education is highly correlated with income, and influences consumers' channel choice (Mattilla et al., 2003), I include my proxy for education level in my analysis. The number of children within a household also directly influences the household's disposable income. Therefore, number of children impacts consumers' spending (Ansari et al., 2008) and a household's inclination to become multichannel. Finally, customer tenure is associated with multichannel shopping (Kumar and Venkatesan, 2005; Thomas and Sullivan, 2005), and therefore included in my framework.

The POLS model does not fully control for the self-selection problem. By including demographic variables as covariate in the model, the POLS model only controls for observed heterogeneity. Nonetheless, Angrist and Pischke (2003) point out that the POLS model impressively minimizes self-selection and causality biases, when the customer demographics are included as explanatory variables. To control for unobserved household heterogeneity, I utilize the random effects (RE) specification as my next model.

II. Random Effects

The RE model extends POLS by specifying a customer-specific random effects component to account for unobserved customer heterogeneity.[9] This model can effectively address the self-selection problem if unobserved heterogeneity or omitted time-invariant household characteristics underlie the self-selection process. For example, the households may have different levels of "ability," which influences their spending levels and their propensity to become multichannel users. Obviously, if customer "ability" evolves over time, then the RE model will suffer from endogeneity (i.e., correlation between the random effect component and the model covariates) due to omitted time-varying components.

The RE model is specified as follows:

$$y_{it} = \gamma + \sum_{j=1}^{5} \rho_j \text{YEARSMC}_{ijt} + \sum_{m=1}^{M} \beta_m x_{mit} + \lambda_t + \mu_i + \varepsilon_{it} \tag{2}$$

where μ_i denotes the unobservable, time-invariant, household-specific random effect, which I assume to be i.i.d normally distributed, N(0, σ_μ^2) and uncorrelated with the model covariates and ε_{it}.

[9] An alternative to the RE model is to estimate a fixed effect model (FE). However, given our relatively large sample (i.e., 7,779 households) and small number of time periods (i.e., 4 years), the FE model is not ideal to implement (Angrist and Pischke, 2008). Nevertheless, we estimate the FE model for robustness check and we find consistent results.

The assumption of zero correlation between μ_i and the independent variables in the model is particularly strong. In my data, it is highly possible that household with high "ability" will also have high income and education. The first-difference specification addresses this issue.

III. First-Difference

The first-difference (FD) model "differences out" the customer-specific random component by subtracting the (t-1)th equation from the tth equation. Similar to the RE model, the FD model controls for time-invariant, unobserved heterogeneity. An advantage of the model over RE is that it does not make the assumption of zero covariance between the person-specific random component and the covariates in the analysis (William H. Greene, 2003, chapter 20; Card and Krueger, 1994; 2000; Wangenheim and Bayón, 2007). The FD model is specified as follows:

$$y_{it} - y_{it-1} = \sum_{j=1}^{5} \rho_j (\text{YEARSMC}_{ijt} - \text{YEARSMC}_{ijt-1}) + \sum_{m=1}^{M} \beta_m (x_{mit} - x_{mit-1}) + \lambda_t + (\varepsilon_{it} - \varepsilon_{it-1}) \qquad (3)$$

The FD model has two disadvantages. First, its specification wipes out all of the time-invariant household specific characteristics, such as demographics and socio-economic factors from the model. Moreover, the standard errors estimated by ordinary least squares method will be biased, as the error terms in the FD model are correlated across observations. Therefore, I use Huber-White sandwich estimators to remedy this problem.

IV. Lagged Dependent Variable

Both the RE and FD models do not account for time-varying, unobserved heterogeneity. To control for this potential source of bias, I use a lagged dependent variable (LDV) model as my fourth model. Unobserved heterogeneity (or "ability") may change over time as a result of learning or maturation. The LDV model captures this changing unobserved heterogeneity by using the lagged dependent variable as a proxy. The LDV model specification is:

$$y_{it} = \gamma + \alpha y_{it-1} + \sum_{j=1}^{5} \rho_j \text{YEARSMC}_{ijt} + \sum_{m=1}^{M} \beta_m x_{mit} + \lambda_t + \varepsilon_{it} \tag{4}$$

where the lagged value y_{it-1} is included in the model to capture persistence in a household's spending and also to control for the self-selection in multichannel usage since multichannel users tend to be heavy users (Blattberg et al., 2007; Hitt and Frei, 2002). The advantage of a lagged dependent variable model is that it controls for both time-invariant and time-variant unobserved heterogeneity. However, such a control comes with a heavy price: the lagged dependent variable and the model error term are correlated and consequently the results will be biased. To address this, I use the Arellano-Bond generalized method of moments (A-B GMM) estimation as my final model.

V. *Arellano-Bond GMM*

This method (also referred as the dynamic panel data estimation) combines the essence of the lagged dependent variable and the RE models. This model accounts for the unobserved time-invariant household characteristics, does not require these latent characteristics to be uncorrelated with other covariates, and allows for dynamic structure (i.e., including the lagged dependent variable in the regression). This model is specified as:

$$y_{it} = \gamma + \alpha y_{it-1} + \sum_{j=1}^{5} \rho_j \text{YEARSMC}_{ijt} + \sum_{m=1}^{M} \beta_m x_{mit} + \lambda_t + \mu_i + \varepsilon_{it} \tag{5}$$

Note that y_{it-1} is persistently correlated with the error structure in Equation (5). In addition, because μ_i appears in each time period, the model cannot be estimated through simple least square estimation procedures. Anderson and Hsiao (1982) suggest first differencing the equation to remove fixed household effects and using lagged explanatory variables as instruments to create moments for estimation. Arellano and Bond (1991) suggest using deeper lags (i.e., 2 or more periods) to use as instruments for GMM estimation and to achieve more efficiency.

Matching Methods

The goal of matching methods is to mimic experimental designs by pairing treated and untreated customers who have comparable characteristics but not treatments (Heckman and Navarro-Lozano, 2004). That is, the objective of the matching methodology is to artificially create treatment and control groups. These methods rely on the assumption that the observed characteristics are informative enough that controlling for them is sufficient to remove any self-selection effect, referred to as the "conditional independence assumption". A rich dataset on observed heterogeneity is required to meet the conditional independence assumption (Angrist and Pischke, 2008).

The most commonly used matching methods are (i) covariate matching (Avery et al., 2012; Degeratu et al., 2000; Hitt and Frei, 2002) and (ii) propensity score matching (Campbell and Frei, 2010; Mithas et al., 2005; Wangenheim and Bayon, 2007; Gensler et al., 2012a; 2012b; Smith et al., 2005). The covariate matching pairs multichannel and mono-channel households based on observed household demographics and socio-economic factors. This method, however, comes with inherent problems: utilizing too many customer characteristics to find similar treated and untreated customers is tremendously challenging (Hitt and Frei, 2002; Degeratu et al., 2000; Shankar et al., 2003). One way to cope with this problem is to reduce the dimensions of data by using the propensity score matching (PSM).

To create matched pairs, PSM uses the conditional probability that a customer with particular observed characteristics becomes multichannel user. A logistic model estimates the propensity score for each household to become multichannel shopper. Because PSM reduces each consumer's propensity to a single score, a matched pair with highly similar propensity scores may, in fact, have different household characteristics (Heckman and Navarro-Lozano, 2004; Angrist and Pischke, 2008). Moreover, Smith et al. (2005) find that PSM performs vastly better than the covariate matching method. Therefore, I use PSM to pair multichannel and single channel households.

Let MC_i indicate if household *i* is multichannel user by the last period of the data (MC_i =1), or not (MC_i=0). Following previous research, I use the following logistic regression model to estimate the propensity scores:

$$\mathrm{P}(\mathrm{MC}_i = 1) = 1 \Bigg/ \left(1 + \exp\left(\eta + \sum_{j=1}^{J} \delta_j z_{ij} \right) \right) \tag{6}$$

where $\mathrm{z_i} = (\mathrm{z_{i1}}, \ldots \mathrm{z_{iJ}})'$ are J observed household characteristics (discussed below), η is an intercept, and $\delta = (\delta_1, \ldots, \delta_J)'$ is a vector of regression parameters.

I perform two kinds of propensity score estimations. The first is based on household characteristics measured at the zip code level (i.e., U.S. Census data on education, median age, median income, and average family size). The second uses household-level characteristics (i.e., head of household's age, household income, and number of kids in the household). As Heckman et al. (1997) point out, only variables that are unaffected by the treatment should be included in the logistic model of matching. As the data provider surveyed its customers prior to opening the new channel, the household-level characteristics were measured before the household became multichannel. Similarly, census level characteristics are not likely to be affected by the observed households' decision to become multichannel, as I observe only a small subset of households living in each zip code.

I use the logistic parameter estimates to predict the propensity score for each household and implement the nearest neighbor algorithm to create matched pairs.[10] There are several variants of the nearest neighbor algorithm, such as with or without replacement. I select the algorithm without replacement, where a household can be matched only once, and therefore, I eliminate the risk of artificially giving more weight to some households in my analysis. Any unmatched household is dropped from the dataset and not included in the regressions. To ensure there are no ordering effects during the matching process, I randomize the order of data before matching.

Combining Panel Data Econometrics with Propensity Score Matching

Several papers in social sciences rely on aggregate level data to create matched pairs. For example, Avery et al. (2012), and Degeratu et al. (2000) use U.S. census data at zip code level to generate matched pairs. Gensler et al. (2012a; 2012b), and Heckman and Navarro-Lozano (2004) criticize the use of aggregate level data for matching purposes. They argue that aggregate level data do not provide enough information to construct functional matched pairs. Fortunately, my data contain household level demographics. By adding U.S. Census variables to the main data, I create two scenarios of matching: The matched pairs are either based on U.S. Census data (measured at the zip code level) or household level demographics. Thus, I compare the results obtained by analyzing datasets created under these two scenarios.

[10] These estimation results are available upon request from the corresponding author.

In sum, I estimate the five different econometric specifications (pooled OLS, random effects, first-difference, lagged dependent variable, and Arellano-Bond GMM) on three different dataset: (i) no matching, (ii) matched pairs based on zip-code level demographics, and (iii) matched pairs based on household-level characteristics. When I do not use any type of matching, I regress the econometrics models on the whole data. When I use PSM based on zip-code level demographics, the resulting data is roughly 44% of the original data. As PSM based on household-level characteristics puts the most restrictive form of matching and therefore creates the smallest dataset, the resulting matched pairs are approximately 31% of the original data. Using panel data econometrics techniques in conjunction with matching methods is relatively new and, to the best of my knowledge, my study is the first one combining a dynamic panel data econometrics model with the propensity score matching.

Empirical Results

Most of the econometrics specifications fit the data well. Adjusted R^2 statistics of POLS, lagged dependent variable, and RE models are between 37% and 58% across the three datasets.[11] Table 3, 4, and 5 report the estimation results on the full data, matched pairs based on U.S. Census variables, and matched pairs relying on household factors, respectively.

1 Results Based on Full Data

Table 3 depicts the results when the econometrics models are estimated on the full data. The results are consistent across all econometrics specifications.

The Effect of Multichannel Usage

[11] As FD model examines the changes in differences between the dependent and independent variable, this method provides much lower Adjusted R^2 statistics. In addition, as the Arellano-Bond estimation uses GMM to estimate parameters, R^2 statistic is not calculated for this method (see for example, Acemoglu et al., 2008).

Across all models, multichannel customers spend much more than mono-channel customers in the first year they become multichannel. Across all models, the coefficients pertaining to the first year of multichannel usage are significant ($p < 0.001$) and vary from $\rho_1 = 89.19$ (Pooled OLS) to $\rho_1 = 101.49$ (FD). In their second year of being multichannel, these customers still spend significantly more than mono-channel customers albeit with a lower magnitude. Across all models, the coefficients pertaining to the second year of multichannel usage are significant ($p < 0.001$) and vary from $\rho_2 = 25.16$ (FD) to $\rho_2 = 51.01$ (A-B GMM). On average, multichannel customers spend \$93.37 (\$38.84) more than mono-channel customers in their first (second) year of becoming multichannel. These results are consistent with results in the marketing literature that multichannel customers spend more *on average* than mono-channel customers (Ansari et al., 2008; Neslin et al., 2006; Thomas and Sullivan, 2005; Kumar and Venkatesan, 2005; Kushwaha and Shankar, 2008).

In the long-run (after year two), however, I find that the difference between multichannel and mono-channel customers' spending disappears. Starting from the third year of being multichannel, the spending levels of multichannel and mono-channel customers are not significantly different ($p > 0.05$). This result provides evidence that multichannel customers revert to their regular spending patterns within few years of becoming multichannel. In the Discussion section, I provide potential explanations for why multichannel customers regress to their regular spending pattern over time.

Table 3. Parameter Estimates on Full Data (i.e., No Matching)

Variables	(1) Pooled OLS Parameter Estimates (Standard Error)	(2) Random Effects Parameter Estimates (Standard Error)	(3) First-Difference Parameter Estimates (Standard Error)	(4) Lagged Dependent Variable Parameter Estimates (Standard Error)	(5) Arellano-Bond GMM Parameter Estimates (Standard Error)
Intercept	-28.40 (32.35)	-63.89 (45.33)	-24.12 (2.91)***	-16.73 (30.26)	-69.19 (54.81)
Variables of Interest					
First year of multichannel usage	89.19 (7.41)***	94.04 (6.88)***	101.49 (7.64)***	96.83 (6.93)***	90.31 (9.79)***
Second year of multichannel usage	41.06 (7.74)***	45.33 (7.50)***	25.16 (8.04)**	31.64 (7.24)***	51.01 (12.10)***
Third year of multichannel usage	7.83 (9.81)	7.22 (9.53)	-17.32 (10.05)	-1.14 (9.18)	18.29 (13.52)
Fourth year of multichannel usage	5.92 (12.19)	15.42 (11.94)	-5.36 (12.62)	5.81 (11.40)	8.60 (21.53)
Fifth year of multichannel usage	-24.05 (21.87)	-7.40 (20.56)	-24.14 (22.69)	-21.38 (20.46)	-23.93 (30.08)
State Dependence					
Lagged total spending				.40 (.01)***	-.25 (.03)***
Customer Characteristics					
Past purchase incidences	19.48 (2.08)***	16.20 (2.64)***	-3.55 (7.16)	1.45 (1.97)	37.89 (14.61)**
Log-customer tenure	-7.78 (4.18)	-2.93 (5.82)		-2.53 (3.91)	-2.78 (6.89)
Head of household's age	-.52 (.12)***	-.55 (.17)**		-.35 (.11)**	-.66 (.19)**
Log-household income	3.65 (2.62)	5.80 (3.69)		2.29 (2.45)	5.72 (3.98)
Number of kids in household	-4.22 (1.44)**	-4.04 (2.03)*		-2.51 (1.35)	-4.94 (2.5)*
Probability of college education	24.88 (9.58)**	31.17 (13.50)*		22.27 (8.96)*	30.16 (17.14)
Marketing Efforts					
Number catalogs received	7.84 (0.1)***	6.99 (0.11)***	4.14 (.15)***	4.74 (.1)***	9.09 (.54)***
Email Subscription	65.82 (10.27)***	63.50 (9.21)***	38.45 (8.82)***	67.25 (9.61)***	75.01 (11.94)***
Number of emails received	-2.04 (.26)***	-1.92 (.23)***	-1.97 (.30)***	-2.11 (.24)***	-2.10 (.25)***
Trend					
Year 3	-58.25 (4.01)***	-50.92 (3.40)***	-5.46 (4.19)	-27.72 (3.78)***	-71.44 (5.43)***
Year 4	-49.95 (4.02)***	-44.00 (3.61)***	26.46 (4.16)***	-28.66 (3.77)***	-58.88 (4.75)***
Year 5	-72.75 (4.16)***	-64.99 (3.61)***	6.85 (4.22)	-42.97 (3.91)***	-85.88 (6.24)***
F Value	1078.99		245.41	1411.33	116.24
Chi-square		9509.74			
Adjusted R^2	.37	.56	.09	.45	
Sample Size	31116	31116	31116	31116	31116

Notes: *p < .05, **p < .01, ***p <.001. Under the FD specification, independent variables are differenced between the current year and last year.

The Effect of Control Variables

The estimation results of the control variables are consistent with previous findings in the literature. The Past Purchase Incidence (RFM) variable, which I included to control for endogeneity of marketing efforts, is positively associated with spending, suggesting that more frequent buyers spend more. Its effect is significant ($p<0.01$) in the POLS, RE, and A-B GMM models and ranges from $\beta = 16.20$ (RE) and $\beta = 37.89$ (A-B GMM). Its effect is, however, insignificant ($p>0.05$) for the FD and lagged dependent variable models. This result is perhaps expected since y_{it-1} can be a proxy for past purchase incidence. Across the different models, I find that younger customers spend more than older customers. This effect is significant ($p<0.05$) across models and ranges from $\beta = -0.66$ (A-B GMM) to $\beta = -0.35$ (lagged dependent variable). Similarly, I find the number of children in the household to be negatively associated with customers' spending. Except for the lagged dependent variable model, this effect is significant ($p < 0.05$) and ranges from β = -4.94 (A-B GMM) to β = -2.51 (lagged dependent variable). Education is positively and significantly ($p < 0.05$) correlated with spending, with effects ranging from β = 22.27 (lagged dependent variable) to β = 31.17 (RE). All these results support the previous findings in the literature (Venkatesan et al., 2007; Fox et al., 2002; Ansari et al., 2008). Customer tenure and income are not significantly related ($p > 0.05$) to customer spending.

The number of catalogs received has a positive and significant ($p < 0.001$) impact on customers' spending, with effects ranging from β = 4.14 (FD) to β = 9.09 (A-B GMM). Whether a customer subscribes to receive emails is also positively and significantly ($p < 0.001$) associated with spending. The effects range from β = 38.45 (FD) to β = 75.01(A-B GMM). Interestingly, the number of emails received is negatively and significantly ($p < 0.001$) correlated with consumers' spending. The effects range from β = -2.11 (lagged dependent variable) to β = -1.92 (RE). This result suggests that the company may be over-emailing its customers. Morimoto and Chang (2006) conclude that consumers perceive high number of commercial emails as exceedingly intrusive and irritating.

The state dependence variable show a significant positive effect (β = 0.40, $p < 0.001$) for the lagged dependent variable model, but its effect is negative (β = -0.25, $p < 0.001$) for the A-B GMM model. This suggests that after correcting for the auto-correlated errors and customer observed heterogeneity, a household's current spending is negatively correlated with their previous spending. For illustration, households that made large purchases last year are more likely to make small purchases in the current year. Finally, the dummy variables capturing the time trend indicate that the households in my dataset tend to decrease their spending over time.

2 Results Based on Propensity Score Matching using U.S. Census Data

This PSM method uses U.S. Census data to create matched pairs and the resulting data are approximately 44% of the original, full data. Table 4 depicts the estimates of the same five models using these matched pairs. To the best of my knowledge, this study is the first to estimate a dynamic panel data model on matched data based on propensity scores.

Table 4. Parameter Estimates on Matched Pairs Based on U.S. Census Data

Variables	(1) Pooled OLS Parameter Estimates (Standard Error)	(2) Random Effects Parameter Estimates (Standard Error)	(3) First-Difference Parameter Estimates (Standard Error)	(4) Lagged Dependent Variable Parameter Estimates (Standard Error)	(5) Arellano-Bond GMM Parameter Estimates (Standard Error)
Intercept	-1.70 (51.46)	-44.13 (71.62)	-31.77 (4.16)***	-2.48 (48.50)	-39.79 (78.11)
Variables of Interest					
First year of multichannel usage	83.04 (8.19)***	89.13 (7.63)***	108.53 (7.56)***	91.90 (7.73)***	84.53 (10.28)***
Second year of multichannel usage	33.16 (8.56)***	38.05 (8.42)***	9.98 (7.76)	25.79 (8.07)***	41.48 (12.60)***
Third year of multichannel usage	.96 (10.71)	.56 (10.63)	-2.79 (9.76)	-6.40 (10.10)	9.61 (14.38)
Fourth year of multichannel usage	1.17 (13.09)	9.83 (13.12)	1.71 (12.03)	1.83 (12.33)	3.51 (21.09)
Fifth year of multichannel usage	-27.13 (22.98)	-12.29 (21.92)	-.74 (20.74)	-24.33 (21.66)	-26.87 (30.16)
State Dependence					
Lagged total spending				.38 (.01)***	-.20 (.05)***
Customer Characteristics					
Past purchase incidences	8.18 (3.12)**	6.68 (3.92)	-4.60 (3.41)	5.40 (2.96)	23.96 (13.32)
Log-customer tenure	-13.53 (6.60)*	-1.79 (9.12)		-5.85 (6.22)	-8.55 (9.08)
Head of household's age	-.76 (.19)***	-.79 (.27)**		-.54 (.18)**	-.91 (.30)**
Log-household income	4.34 (4.17)	6.59 (5.83)		2.81 (3.93)	6.43 (6.51)
Number of kids in household	-4.07 (2.10)	-3.66 (2.94)		-2.15 (1.98)	-4.56 (3.89)
Probability of college education	7.56 (14.39)	16.67 (20.13)		9.38 (13.57)	12.37 (25.16)
Marketing Efforts					
Number catalogs received	8.51 (0.14)***	7.61 (0.16)***	-2.13 (.13)***	5.39 (.15)***	9.45 (.53)***
Email Subscription	68.35 (12.49)***	64.05 (11.27)***	9.04 (7.26)	66.60 (11.77)***	78.40 (16.14)**
Number of emails received	-2.04 (.30)***	-1.84 (.27)***	-.59 (.15)*	-2.01 (.28)***	-2.11 (.30)
Trend					
Year 3	-57.06 (6.16)***	-49.12 (5.27)***	48.41 (5.81)***	-22.79 (5.86)***	-69.26 (7.27)***
Year 4	-51.64 (6.26)***	-45.01 (5.41)***	17.89 (5.89)**	-29.70 (5.93)***	-59.23 (6.73)***
Year 5	-78.59 (6.66)***	-70.01 (5.41)***	53.36 (6.73)***	-46.98 (6.32)***	-90.31 (8.20)***
F Value	545.80		66.74	683.03	76.43
Chi-square		5072.85			
Adjusted R^2	.39	.58	.04	.46	
Sample Size	14304	14304	19151	14304	14304

Notes: *p < .05, **p < .01, ***p <.001. Under the FD specification, independent variables are differenced between current year and last year. Matched pair data created by PSM method (based on U.S. Census level charactheristics) are 44% of the whole data.

The Effect of Multichannel Usage

The results in Table 4 show that, except for the FD model, multichannel usage is significantly associated (p <0.001) with increased overall spending in the first two years. Thereafter, the difference between multichannel and mono-channel customers is insignificant (p>0.05). These results are consistent with my previous findings based on the full data. The FD model shows that multichannel customers spend significantly more ($p<0.001$) than mono-channel customers only in the first year. Comparing the PSM results in Table 4 with the full data results in Table 3, I can see that the magnitude of the spending difference between multichannel and mono-channel customers is slightly lower under the PSM models relative to the full data models. On average, under PSM (full data), the first year difference is \$91.42 (\$94.37) and the second year difference is \$29.70 (\$38.84).

The Effect of Control Variables

The only customer characteristics variable that is significant ($p<0.01$) across all five models is the age of the household head, suggesting that younger customers spend more than older one. The effects are similar in magnitude to those obtained using the full data. They range from $\beta = -0.91$ (A-B GMM) to $\beta = -0.54$ (lagged dependent variable). Unlike the full data results, all the other customer characteristics are insignificant ($p<0.05$). There are two exceptions for the POLS model: Past purchase incidence has a significant impact ($p<0.01$) on spending and customer with longer tenure spend significantly ($p<0.05$) less.

For the marketing effort variables, except for the FD model, the results are quite similar to those using the full data. Catalogs have a significant positive impact ($p<0.001$) on consumers' spending with effects ranging from $\beta = 4.74$ (lagged dependent variable) to $\beta = 9.09$ (A-B GMM). Email subscription also has a significant positive impact ($p<0.001$) with estimates ranging from $\beta = 63.50$ (RE) to $\beta = 75.01$ (A-B GMM). The effect of number of emails sent is still significantly negative ($p<0.001$) with a magnitude of about -2 across all the four models. Under the FD model, change in number of catalogs is negatively correlated with change in customers' spending ($\beta = -2.13$, $p < 0.001$). Email subscription has an insignificant effect and number of email received has a significant negative effect ($p < 0.05$) albeit with a lower magnitude.

Similar to the full data analysis, the state dependence variable show a significant positive effect ($\beta = 0.38$, $p<0.001$) for the lagged dependent variable model, but its effect is negative ($\beta = -0.20$, $p<0.001$) for the A-B GMM model. Except for the FD model, the time trend effects have similar decay in customers' spending over time. The FD model, however, shows increased trend over time.

3 Results Based on Propensity Score Matching using Household Characteristics

This PSM method matches households based on their stated demographic and socio-economic factors rather than relying on zip-code level data. As such matching puts the highest restrictions to create matched pairs, the resulting dataset is approximately 31% of the original data. Table 5 presents the results obtained by the five econometric models applied on these data. Overall, the estimation results in Table 5 are quite consistent with those in Table 4. This finding suggests that matching techniques using aggregate level data (such as U.S. Census demographics) minimize self-selection bias and produce similar results to those of matching methods based on individual level data.

The Effect of Multichannel Usage

The effect of multichannel usage is quite consistent and close in magnitude across the two matching methods. On average, across all the models, the boost in revenues in the first year of being multichannel is \$91.55 and in the second year is \$30.98 (all effects are significant, p<0.001). By the third year, the difference between the multichannel and mono-channel customers' spending is no longer significant (p>0.05).

The Effect of Control Variables

Except for few differences, the effects of the control variables are also similar across the two matching methods. Younger customers spend significantly more than older ones (p<0.05). Number of catalogs and email subscription have a significant positive impact on spending (p<0.00) whereas number of emails sent has a significant negative impact (p<0.001). I also obtain similar persistence and time trend effects. The few differences in the results stem from the POLS model, where the effects of number of kids and customer tenure become significant (p<0.05).

Table 5. Parameter Estimates on Matched Pairs based on Household Level Data

	(1) Pooled OLS	(2) Random Effects	(3) First-Difference	(4) Lagged Dependent Variable	(5) Arellano-Bond GMM
Variables	Parameter Standard	Parameter Standard	Parameter Standard	Parameter Standard	Parameter Standard
Intercept	12.03 (61.95)	-25.84 (87.25)	-33.70 (5.22)***	34.34 (57.14)	-30.38 (107.22)
Variables of Interest					
First year of multichannel usage	82.85 (9.00)***	92.38 (8.35)***	104.96 (9.36)***	94.71 (8.30)***	82.89 (10.59)***
Second year of multichannel usage	31.08 (9.40)**	40.86 (9.21)***	20.02 (9.71)*	25.57 (8.67)**	37.36 (13.04)**
Third year of multichannel usage	-1.35 (11.80)	4.14 (11.65)	-6.77 (12.20)	-6.02 (10.88)	5.42 (14.86)
Fourth year of multichannel usage	-2.10 (14.45)	14.22 (14.43)	7.50 (15.02)	2.94 (13.33)	-2.55 (21.78)
Fifth year of multichannel usage	-30.43 (25.44)	-6.51 (24.13)	-15.24 (26.51)	-22.34 (23.47)	-33.27 (31.07)
State Dependence					
Lagged total spending				.43 (.01)***	-.23 (.05)***
Customer Characteristics					
Past purchase incidences	30.15 (3.27)***	24.61 (4.16)***	-1.90 (3.98)	4.20 (3.06)	49.46 (23.22)*
Log-customer tenure	-9.71 (7.32)	-2.51 (10.21)		-4.61 (6.75)	-4.71 (12.43)
Head of household's age	-.79 (.22)***	-.79 (.32)*		-.51 (.21)*	-.97 (.34)**
Log-household income	.52 (5.17)	2.58 (7.31)		-1.21 (4.76)	2.46 (8.38)
Number of kids in household	-5.63 (2.19)*	-5.70 (3.10)		-3.65 (2.02)	-6.45 (3.50)
Probability of college education	29.80 (16.32)	39.08 (23.08)		23.13 (15.06)	38.34 (30.40)
Marketing Efforts					
Number catalogs received	8.24 (0.15)***	7.39 (.18)***	2.86 (.16)***	4.81 (.16)***	9.57 (.92)***
Email Subscription	64.66 (13.54)***	60.50 (12.13)***	7.02 (8.82)	62.03 (12.49)***	73.17 (15.11)***
Number of emails received	-1.86 (.33)***	-1.69 (.30)***	-.56 (.18)**	-1.86 (.30)***	-1.88 (.29)***
Trend					
Year 3	-63.56 (6.92)***	-56.09 (5.88)***	50.51 (7.29)***	-28.32 (6.42)***	-78.12 (9.39)***
Year 4	-54.94 (7.04)***	-49.57 (6.03)***	18.45 (7.40)**	-32.19 (6.51)***	-64.41 (7.94)***
Year 5	-90.56 (7.50)***	-84.06 (6.70)***	57.74 (8.53)***	-57.65 (6.94)***	-104.85 (11.30)***
F Value	506.71		57.66	698.23	77.07
Chi-square		4488.72			
Adjusted R^2	.38	.56	.05	.47	
Sample Size	13936	13936	13936	13936	13936

Notes: *p < .05, **p < .01, ***p <.001. Under the FD specification, independent variables are differenced between current year and last year. Matched pair data created by PSM method (based on household level charactheristics) are 31% of the whole data.

Discussion

Except for the FD model, all the effects are similar in magnitude across all regressions. This result is expected, as the FD model measures difference in differences, whereas the other regressions examine the relation between the dependent variable and regressors.

My key finding in this paper is multichannel customers spend significantly more than mono channel customers in the short run but revert to their regular spending pattern over time. One potential explanation for this result is the novelty effect. According to the novelty effect, when customers start using a new channel, they derive epistemic (novelty) value from trying and learning new things (Duman and Attila, 2005; Pihlstorm and Brush, 2008). This epistemic value results in excitement (Liu and Khalifa, 2003), positive attitudes towards the purchase (La Ferle et al., 2013), higher customer satisfaction (Liu and Khalifa, 2003), and amplified consumption patterns (Coates and Humphreys, 2008; Feddersen et al. 2006; McQuiston, 1989). These effects are referred to as the novelty effect (Duman and Attila, 2005; Pihlstorm and Brush, 2008). Cantor (1968) and Sheth et al. (1991) find that customers who are motivated by novelty value often return to their regular consumption patterns after satisfying their need for change. For some products and services, reverting to regular consumption patterns may take a few years. For example, Howard and Crompton (2003) find that the boost in attendance and revenues associated with a new stadium may last several years.

Another potential explanation for the no difference between multichannel and mono-channel customers in the long run lies in the consequences of using the online channel. In fact, Ansari et al. (2008) find that when customers use the Internet channel over time, they tend to buy less frequently from the firm. This result suggests that customers may start to compare competitors' products and prices, and become price-sensitive over time (Blattberg et al., 2008).

That is, as multichannel customers (who use an online channel) become more comfortable using the Internet, they start to buy from competitors.

To examine whether customers buy less frequently from the sponsoring firm in the long-run (i.e., switch to other competitors), I conduct three supplementary studies. First, I use data from ComScore (available from Wharton Research Data Services) to examine whether the customers change their purchase behavior over six years (see Appendix E for more details). I find that the online users of my data provider do not switch to competing companies over an extensive period of time (from 2002 to 2008). Second, I examine consumers' online browsing behavior using the ComScore data. The results show that while on average people increase the number of competing websites they visit over time, the majority of consumers (namely, 82%) visit only two competing websites in the last year. Third, I test the framework on a set of catalog customers who start using a conventional retail store channel. Brick-and-mortar stores provide complementary attributes to other types of channels, such as easing the return and exchange processes (Pauwels and Neslin, 2008), providing after sales service (Verhoef et al., 2007), and creating repeated exposure to company's brand (Avery et al., 2012). Hence, it is reasonable to expect that adopting a brick-and-mortar store leads customers to increase their spending over time. Pauwels and Neslin (2008), Avery et al. (2012), and Pancras et al. (2012) find that, at the aggregate level, adding a new retail store increases total revenues of a firm in the long-run. However, if the explanations based on novelty effect are correct, then the increase in aggregate sales is coming from (i) newly acquired customers and (ii) a short-lived spike in existing customers' spending after they start using the physical store. In fact, I find that (i) the multichannel customers increase their spending after they begin to use the physical store, and (ii) revert to their original spending pattern over time (i.e., decrease their total spending in due course).

Conclusion

This paper investigates the consequences of multichannel shopping on consumers' spending. It validates previously established theories suggesting that multichannel customers *on average* spend more. However, I find that new multichannel customers increase their overall spending initially and return to their regular spending pattern over time. These results are consistent with the novelty effect where adopters of new technologies and products increase their consumption for a limited time and regress to their regular spending pattern in due course.

My results are based on observational data which suffer from self-selection: heavy spenders and sophisticated customers are more likely to become multichannel. That is, the direction of causality between multichannel shopping and customers' spending is not clear. To address this issue, I use different panel data econometrics models, and combine them with two kinds of propensity score matching methods. My results are very consistent across all of the analysis methods. Further, I empirically demonstrate that using matched pairs based on aggregate and household level characteristics produces quite similar results. This finding reveals that matching techniques using aggregate level data (such as U.S. Census demographics at zip code) produce reliable results and can control for self-selection bias.

I also validate previous findings that marketing activities, customer demographics and socio-economic factors influence customers' overall spending. Catalogs increase households' spending. Emails, on the other hand, tell a different story: While email subscriptions are positively correlated with spending, number of emails received has negative influence. The latter result implies that the overuse of emails creates irritation among retailer's customers. I find that younger customers with college education tend to spend more. In addition, the number of children in a household is negatively associated with spending, suggesting that having more children decreases a household's disposable income. Alternatively, these households are likely to be more price-sensitive and less loyal to the sponsoring firm.

Managerially, these findings indicate potential drawbacks of expanding channel structures for firms. Although it has been typically accepted in marketing literature that opening and maintaining new channels increases these customers' lifetime value (Shankar et al., 2003; Hitt and Frei, 2002; Sousa and Voss, 2004), my results suggest that managers should be aware that the increased revenues associated with multichannel usage are not sustainable in the long-run.

I acknowledge that this paper is not free of limitations: First, the data provider is a single firm that operates in mature markets. I observe a trend showing a decline in spending across all customers. Such deterioration might not be relevant to companies operating in new and growing industries. Second, catalog firms typically use RFM models to target their marketing efforts. This means heavy and frequent users are subject to heavy advertising by the firm. To address this potential endogeneity issue, I include a RFM type attribute (prior purchase incidences) in the econometrics models. Finally, I do not separate consumers' incidence and purchase amount decisions. Separating these decisions (see for example, Ansari et al., 2008) can provide further insights. My results suggest that marketing literature can greatly benefit from focusing on multichannel shoppers' behavior in the long-run.

4. Discussion

This dissertation investigates what factors lead customers to adopt new sales channels, and the long-term effect of such channel adoption on customers' spending. These questions are managerially relevant as the majority of retailers in United States who interact with their customers via two or more sales channels (The DMA, 2005). Practitioners can benefit from the findings of this dissertation by identifying early adopters, targeting them with marketing efforts, and accelerating the diffusion of their new sales channels. In addition, this dissertation provides insights on how to predict future revenue streams from multichannel customers over time.

The first essay examines the drivers of new sales channel adoption. It highlights the importance of social influence on the timing of a channel adoption. I find that longer tenured customers adopt new channels faster, and are less impacted by the social influence. When I compare the adoption patterns of two types of channels, I find that customers adopt a physical store at a faster rate than an Internet store. Moreover, social influence and customer tenure play more important roles when customers adopt an Internet channel than a retail store. In contrast to social influence, marketing activities play a more important role in customers' adoption of the physical store than in their adoption of the internet channel.

The second essay shows that multichannel customers increase their overall spending when they initially adopt a new channel, but they also regress to their typical consumption pattern in the long run. Methodologically, this essay combines different panel data econometrics techniques with the propensity score matching method to control for self-selection bias, and provides a basis for future academic research to address self-selection problem.

In the following section I present general extensions to this dissertation followed by extensions arising directly from the individual essays.

Future Research Directions

The data provider of both essays is a single firm that operates in mature markets. While the data are highly relevant to a substantial component of the U.S. economy, my findings may not generalize to other markets. As a result, a natural extension to both essays is examination of data from companies operating at new and growing industries.

In the first essay, I do not have an explicit measure of social influence. Using an explicit measure, such as online user reviews (Godes and Mazylin, 2004), can provide further insight on how social influence works in the context of new sales channel adoption. Additionally, I accept the initial purchase from a new channel as "adoption." It is important to distinguish between trial purchases and full adoption of new channels (i.e., repeated purchases). Ansari et al. (2008) and Knox (2006) report that customers' channel choice evolves over time. Valentini et al. (2008) conclude that a newly acquired customer's purchase decisions are shaped by trials, and a customer's choice process evolves after the customer learns more about her preferences and becomes familiar with a firm's marketing efforts. Additional work aimed at understanding differences between channel adopters and triers would be beneficial. More broadly, I hope this essay stimulates additional work on the adoption and use of multiple channels by customers.

In the second essay, I do not separate consumers' incidence and purchase amount decisions. Separating these decisions (for example, Ansari et al., 2008) can provide further insights on how multichannel shopping impacts customers' purchase decisions. In addition, researchers typically use panel data econometrics, instrumental variable estimation, and matching methods to control for the self-selection (Heckman and Navarro-Lozano, 2004). As I do not have valid instruments, I combine panel data econometrics with the propensity score matching method. Developing an instrumental variable estimation to dealing with the self-selection is worth exploring.

Conclusion

In closing, these two essays investigate the causes and consequences of multichannel shopping. First this dissertation explores what factors lead customers to adopt a new sales channel, and how customers' characteristics and social influence play roles in customers' channel adoption decisions. The second essay explores the long-term impact of multichannel shopping on consumers' spending. This essay confirms previous findings in the pertinent literature and concludes that multichannel customers spend more than mono-channel customers. However, this study contributes by focusing on long-term and finds that the increased spending associated with multichannel shopping diminishes in the long run due to the novelty effect.

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6. Appendices

Appendix A: Robustness Check for Essay 1, Distance to the Retail Store

Avery et al. (2011) find that customers are willing to drive for an hour to go to a physical retail store. Hence, in the first essay, the data for the brick-and-mortar store adoption focuses on the households who live within seventy five miles of the retail store. As a robustness check, I also estimate the discrete-time hazard model on the households living within thirty miles of the store. The table below depicts the results from these two regressions. The results are virtually identical.

Robustness Check: Geographical Proximity of the Sample Data to the Brick-and-Mortar Store
Retail Store Adoption

Variables	Hypothesized Effect	Expected Moderating Effect of Channel Type	75 Miles Radius: Parameter Estimate (Standard Error)	30 Miles Radius: Parameter Estimate (Standard Error)
Intercept	Control variable	Greater negative intercept when adopting an Internet channel (H4)	-9.518 (1.093)***	-8.979 (1.131)***
Customer Characteristics				
Log-customer tenure	No impact (H2)	Greater parameter when adopting an Internet Channel (H5b)	.686 (.114)***	.675 (.119)***
Probability of college education	Positive (H7a)	Greater parameter when adopting an Internet Channel (H7b)	-.519 (.301)	-.231 (.322)
Number of kids in household	Positive (H8a)	Greater parameter when adopting an Internet Channel (H8b)	-.017 (.038)	-.001 (.039)
Head of household's age	Control variable	-	-.001 (.003)	-.001 (.004)
Log-household income	Control variable	-	.185 (.083)*	.165 (.088)
Past purchase incidences	Control variable	-	.003 (.004)	.001 (.004)
Within 25 miles to the store	Control variable	-	1.803 (.141)***	1.381 (.182)***
Social Influence				
Social influence	Positive (H1)	Greater parameter when adopting an Internet Channel (H5a)	.143 (.034)***	.162 (.036)***
$(\text{Social influence})^2$	Control variable	-	-.004 (.001)**	-.005 (.002)**
Log-customer tenure * social influence	Negative (H3)	-	-.032 (.007)***	-.033 (.007)***
Customer Satisfaction				
Number of refunds	Positive (H6a)	-	1.387 (.211)***	1.412 (.223)***
$(\text{Number of refunds})^2$	Negative (H6a)	-	-.325 (.094)**	-.327 (.097)**
Number of exchanges	Positive (H6a)	Greater parameter when adopting a retail store (H6b)	1.174 (.396)**	1.195 (.412)**
$(\text{Number of exchanges})^2$	Negative (H6a)	-	-.207 (.250)	-.195 (.257)
Marketing Efforts				
Number of catalogs received	Control variable	-	.173 (.034)***	.172 (.036)***
Number of emails received	Control variable	-	.013 (.008)	.011 (.008)
Number of store opening promotions received	Control variable	-	1.235 (.187)***	1.312 (.197)***
Number of other promotions received	Control variable	-	1.192 (.105)***	1.252 (.118)***
Log-customer tenure * catalogs received	Control variable	-	-.052 (.012)***	-.050 (.013)***
Past Adoption Behavior				
Whether the Internet channel is adopted	Control variable	-	-.169 (.100)	-.205 (.105)
Seasonality				
Quarter 1	Control variable	-	-.283 (.116)*	-.210 (.122)
Quarter 2	Control variable	-	-.107 (.118)	-.045 (.124)
Quarter 3	Control variable	-	-.129 (.114)	-.070 (.121)
σ_μ			.869 (.294)	.792 (.311)
Log-likelihood			-3653.865	-3165.769
McFadden's Rho^2			.372	.343
Sample size			44660	29022

Note: *p < .05, **p < .01, ***p <.001.

Appendix B: Controlling for Potential Omitted Variable Bias for Essay 1

In my analysis on Internet channel adoption, I did not control for the availability of Internet. This naturally raises a concern on whether my results on online channel adoption suffer from a potential omitted variable bias. To address this concern, I added a dummy variable indicating whether there are hi-speed Internet providers within a zip code. Fortunately, the Federal Communications Commission (FCC) provides data on number of high-speed Internet providers at zip code level. However, these data are not perfect for my analysis: The FCC data start at 1999, whereas the catalog company's data start at 1997. Therefore, I created a dummy variable indicating whether there are high-speed Internet providers in each zip code in 1999. This dummy variable should capture a good portion of hi-speed Internet availability for the households.

After adding this new explanatory variable, the results are still very robust and virtually identical to my previous estimates. The table below shows that the coefficient of the availability of high-speed Internet providers is positive, but not statistically significant.

Robustness Check: Checking for Potential Omitted Variable Bias for Internet Channel Adoption

Variables	Hypothesized Effect	Expected Moderating Effect of Channel Type	Model Reported in Essay 1: Parameter Estimate (Standard Error)	Model with a Control Variable for Internet Availability: Parameter Estimate (Standard Error)
Intercept	Control variable	Greater negative intercept when adopting an Internet channel (H4)	-24.224 (2.176)***	-28.421 (2.510)***
Customer Characteristics				
Log-customer tenure	No impact (H2)	Greater parameter when adopting an Internet Channel (H5b)	2.803 (.374)***	3.168 (.419)***
Probability of college education	Positive (H7a)	Greater parameter when adopting an Internet Channel (H7b)	1.618 (.566)**	1.733 (.603)**
Number of kids in household	Positive (H8a)	Greater parameter when adopting an Internet Channel (H8b)	.264 (.072)***	.285 (.077)**
Head of household's age	Control variable	-	-.120 (.008)***	-.145 (.009)***
Log-household income	Control variable	-	.370 (.170)*	.472 (.181)**
Past purchase incidences	Control variable	-	.080 (.006)***	.107 (.006)***
Social Influence				
Social influence	Positive (H1)	Greater parameter when adopting an Internet Channel (H5a)	.456 (.030)***	.516 (.034)***
(Social influence)^2	Control variable	-	-.004 (.000)***	-.005 (.000)***
Log-customer tenure * social influence	Negative (H3)	-	-.029 (.008)***	-.032 (.009)***
Customer Satisfaction				
Number of refunds	Positive (H6a)	-	1.604 (.198)***	1.644 (.205)***
(Number of refunds)^2	Negative (H6a)	-	-.350 (.082)***	-.352 (.085)***
Number of exchanges	Positive (H6a)	Greater parameter when adopting a retail store (H6b)	-.377 (.406)	-.400 (.423)
(Number of exchanges)^2	Negative (H6a)	-	.045 (.235)	.053 (.244)
Marketing Efforts				
Number of catalogs received	Control variable	-	.481 (.056)***	.515 (.059)***
Number of emails received	Control variable	-	.521 (.013)***	.589 (.013)***
Number of store opening promotions received	Control variable	-	.006 (.210)	.042 (.220)
Number of other promotions received	Control variable	-	-.464 (.166)**	-.481 (.170)**
Log-customer tenure * catalogs received	Control variable	-	-.107 (.021)***	-.115 (.023)***
Past Adoption Behavior				
Whether the retail store is adopted	Control variable	-	-.996 (.263)***	-1.149 (.269)***
Internet Availability				
Whether hi-speed Internet providers exist in the zip code	Control variable	-	–	.602 (.866)
Seasonality				
Quarter 1	Control variable	-	-1.724 (.100)***	-1.789 (.103)***
Quarter 2	Control variable	-	-1.460 (.102)***	-1.503 (.106)***
Quarter 3	Control variable	-	-1.474 (.094)***	-1.534 (.098)***
σ_μ			7.201 (.178)	8.410 (.204)
Log-likelihood			-6811.184	-6768.232
McFadden's Rho^2			.406	.410
Sample size			125967	125967

Note: *p < .05, **p < .01, ***p <.001.

Appendix C: Robustness Check for Essay 1, Different Measures of the Social Influence

As an additional robustness check for Essay 1, I create different measures of the social influence variable, and re-estimate the discrete-time hazard model. In the first essay, I calculate the percent of previous adopters based on the general population (i.e., households living within a 75 miles radius). In this section, I also consider different measures. For example, I treat each zip code as a closed market and calculate the percent of people who already adopted the new channel within each zip code separately. Later, I use this new measure to estimate my model. I do the same process for a county-based social influence measure.

I also run a cluster analysis based on the GPS coordinates of each zip code. The cluster analysis (Proc KMEANS in SAS) retained thirty clusters based on the pseudo R-squared criterion and visual inspection of the results. Then, I calculate the percent of previous adopters in each cluster separately. This clustering method has an advantage, as it allows the zip codes within a cluster to be in different counties or even different states. That is, as long as two zip codes are geographically close to each other, they end up in the same cluster.

The next tables present the results estimated on the online channel and brick-and-mortar store adoption, respectively. Despite the measure of social influence changes in each estimation, the results are consistent.

Robustness Check: Different Measures of Social Influence
Online Channel Adoption

Variables	Social Influence Based on Zip Codes: Parameter Estimate (Standard Error)	Social Influence Based on Counties: Parameter Estimate (Standard Error)	Social Influence Based on Clusters: Parameter Estimate (Standard Error)	Social Influence Based on 75 Miles Radius: Parameter Estimate (Standard Error)
Intercept	-14.267 (1.175)***	-23.026 (2.309)***	-24.697 (2.539)***	-24.224 (2.176)***
Customer Characteristics				
Log-customer tenure	1.549 (.248)***	2.809 (.408)***	2.983 (.422)***	2.803 (.374)***
Probability of college education	.072 (.465)	.773 (.581)	2.591 (.640)***	1.618 (.566)**
Number of kids in household	.142 (.072)*	.230 (.073)**	.232 (.080)**	.264 (.072)***
Head of household's age	-.066 (.006)***	-.113 (.009)***	-.120 (.010)***	-.120 (.008)***
Log-household income	.255 (.137)	.337 (.178)	.288 (.194)	.370 (.170)*
Past purchase incidences	.032 (.007)***	.063 (.007)***	.083 (.007)***	.080 (.006)***
Social Influence				
Social influence	.261 (.024)***	.515 (.040)***	.593 (.045)***	.456 (.030)***
(Social influence)^2	-.003 (.000)***	-.005 (.000)***	-.006 (.001)***	-.004 (.000)***
Log-customer tenure * social influence	-.017 (.006)**	-.038 (.011)***	-.045 (.011)***	-.029 (.008)***
Customer Satisfaction				
Number of refunds	1.482 (.173)***	1.585 (.195)***	1.663 (.198)***	1.604 (.198)***
(Number of refunds)^2	-.342 (.075)***	-.352 (.082)***	-.355 (.082)***	-.350 (.082)***
Number of exchanges	-.264 (.361)	-.356 (.402)	-.445 (.417)	-.377 (.406)
(Number of exchanges)^2	.020 (.218)	.052 (.235)	.049 (.243)	.045 (.235)
Marketing Efforts				
Number of catalogs received	.363 (.045)***	.465 (.056)***	.488 (.059)***	.481 (.056)***
Number of emails received	.361 (.016)***	.481 (.015)***	.520 (.017)***	.521 (.013)***
Number of store opening promotions received	.073 (.177)	.097 (.202)	.076 (.205)	.006 (.210)
Number of other promotions received	-.311 (.152)*	-.361 (.165)*	-.325 (.169)	-.464 (.166)**
Log-customer tenure * catalogs received	-.083 (.017)***	-.107 (.021)***	-.113 (.022)***	-.107 (.021)***
Past Adoption Behavior				
Whether the retail store is adopted	-.784 (.245)**	-.964 (.272)***	-1.064 (.282)***	-.996 (.263)***
Seasonality				
Quarter 1	-1.397 (.086)***	-1.476 (.096)***	-1.489 (.098)***	-1.724 (.100)***
Quarter 2	-1.249 (.091)***	-1.247 (.099)***	-1.256 (.102)***	-1.460 (.102)***
Quarter 3	-1.137 (.083)***	-1.225 (.092)***	-1.199 (.094)***	-1.474 (.094)***
σ_μ	3.764 (.184)	6.376 (.190)	7.132 (.233)	7.201 (.178)
Log-likelihood	-7044.305	-6834.037	-6763.410	-6811.184
McFadden's Rho^2	.386	.404	.404	.406
Sample size	125967	125967	124706	125967

Note: *p < .05, **p < .01, ***p <.001.

Robustness Check: Different Measures of Social Influence
Retail Store Adoption

Variables	Social Influence Based on Zip Codes: Parameter Estimate (Standard Error)	Social Influence Based on Counties: Parameter Estimate (Standard Error)	Social Influence Based on Clusters: Parameter Estimate (Standard Error)	Social Influence Based on 75 Miles Radius: Parameter Estimate (Standard Error)
Intercept	-8.783 (.977)***	-9.313 (.963)***	-8.646 (.963)***	-9.518 (1.093)***
Customer Characteristics				
Log-customer tenure	.615 (.074)***	.609 (.074)***	.527 (.075)***	.686 (.114)***
Probability of college education	-.063 (.293)	-.306 (.283)	-.432 (.294)	-.519 (.301)
Number of kids in household	-.002 (.036)	-.012 (.036)	-.014 (.037)	-.017 (.038)
Head of household's age	.000 (.003)	.003 (.003)	.000 (.003)	-.001 (.003)
Log-household income	.150 (.080)	.176 (.079)*	.153 (.079)	.185 (.083)*
Past purchase incidences	.002 (.003)	.003 (.003)	.002 (.003)	.003 (.004)
Within 25 miles to the store	1.389 (.114)***	1.500 (.109)***	1.754 (.119)***	1.803 (.141)***
Social Influence				
Social influence	.106 (.010)***	.169 (.013)***	.135 (.016)***	.143 (.034)***
(Social influence)^2	-.002 (.000)***	-.003 (.000)***	-.004 (.001)***	-.004 (.001)**
Log-customer tenure * social influence	-.027 (.004)***	-.028 (.004)***	-.023 (.004)***	-.032 (.007)***
Customer Satisfaction				
Number of refunds	1.324 (.203)***	1.334 (.203)***	1.330 (.203)***	1.387 (.211)***
(Number of refunds)^2	-.311 (.089)***	-.308 (.091)**	-.307 (.089)**	-.325 (.094)**
Number of exchanges	1.137 (.387)**	1.157 (.386)**	1.120 (.384)**	1.174 (.396)**
(Number of exchanges)^2	-.193 (.244)	-.237 (.246)	-.195 (.244)	-.207 (.250)
Marketing Efforts				
Number of catalogs received	.174 (.031)***	.177 (.031)***	.167 (.031)***	.173 (.034)***
Number of emails received	.013 (.007)	.011 (.007)	.012 (.007)	.013 (.008)
Number of store opening promotions received	1.338 (.158)***	1.430 (.159)***	1.267 (.160)***	1.235 (.187)***
Number of other promotions received	1.186 (.099)***	1.169 (.098)***	1.174 (.099)***	1.192 (.105)***
Log-customer tenure * catalogs received	-.051 (.012)***	-.052 (.011)***	-.050 (.012)***	-.052 (.012)***
Past Adoption Behavior				
Whether the Internet channel is adopted	-.147 (.095)	-.146 (.095)	-.168 (.095)	-.169 (.100)
Seasonality				
Quarter 1	-.219 (.114)	-.225 (.114)*	-.259 (.114)*	-.283 (.116)*
Quarter 2	-.073 (.113)	-.083 (.113)	-.090 (.113)	-.107 (.118)
Quarter 3	-.017 (.113)	-.001 (.113)	-.069 (.113)	-.129 (.114)
σ_μ	.505 (.341)	.426 (.339)	.587 (.283)	.869 (.294)
Log-likelihood	-3557.258	-3513.581	-3609.586	-3653.865
McFadden's Rho^2	.389	.396	.373	.372
Sample size	44660	44660	44466	44660

Note: *p < .05, **p < .01, ***p <.001.

Appendix D: Robustness Check for Essay 1, Endogeneity of the Marketing Variables

The marketing variables in my data may be endogenous, as catalog companies typically use RFM models to target their most profitable customers. To control for this endogeneity problem, I include two sets of targeting variables in my study. As an additional robustness check, I also use lagged marketing variables as instruments to eliminate the endogeneity bias (William H. Greene, 2003, chapter 5). Lagged marketing activities are valid instruments as the catalog company's current marketing activities will be correlated with their marketing efforts in the previous quarter. However, it is reasonable to assume that consumers purchase decisions will not be affected by catalogs or emails they received three months ago. Next table depicts these estimation results and demonstrates that my analysis does not suffer from endogeneity problem.

Robustness Check: Reduced Form Estimation
Controlling for Endogeneity in Marketing Activities

Variables	Hypothesized Effect	Expected Moderating Effect of Channel Type	Internet Channel Adoption: Parameter Estimate (Standard Error)	Retail Store Adoption: Parameter Estimate (Standard Error)
Intercept	Control variable	Greater negative intercept when adopting an Internet channel (H4)	-18.055 (.821)***	-9.866 (1.484)***
Customer Characteristics				
Log-customer tenure	No impact (H2)	Greater parameter when adopting an Internet Channel (H5b)	3.432 (.507)***	.541 (.112)***
Probability of college education	Positive (H7a)	Greater parameter when adopting an Internet Channel (H7b)	.363 (.220)	-.670 (.343)
Number of kids in household	Positive (H8a)	Greater parameter when adopting an Internet Channel (H8b)	.100 (.028)***	-.012 (.043)
Head of household's age	Control variable	-	-.033 (.003)***	-.001 (.004)
Log-household income	Control variable	-	.215 (.066)**	.223 (.094)*
Past purchase incidences	Control variable	-	.015 (.004)***	.017 (.006)
Within 25 miles to the store	Control variable	-	–	2.001 (.252)***
Social Influence				
Social influence	Positive (H1)	Greater parameter when adopting an Internet Channel (H5a)	.639 (.039)***	.127 (.041)**
(Social influence)^2	Control variable	-	-.002 (.000)***	-.004 (.001)**
Log-customer tenure * social influence	Negative (H3)	-	-.007 (.003)**	-.031 (.007)***
Customer Satisfaction				
Number of refunds	Positive (H6a)	-	1.596 (.140)***	1.691 (.223)***
(Number of refunds)^2	Negative (H6a)	-	-.386 (.062)***	-.396 (.096)**
Number of exchanges	Positive (H6a)	Greater parameter when adopting a retail store (H6b)	-.137 (.288)	1.168 (.427)**
(Number of exchanges)^2	Negative (H6a)	-	.022 (.177)	-.149 (.266)
Marketing Efforts				
Lagged number of catalogs received	Control variable	-	.106 (.026)***	.072 (.031)*
Lagged number of emails received	Control variable	-	.400 (.007)***	.003 (.008)
Lagged number of store opening promotions received	Control variable	-	-.278 (.165)	.258 (.203)
Lagged number of other promotions received	Control variable	-	-.387 (.210)	.288 (.154)
Log-customer tenure * lagged catalogs received	Control variable	-	-.031 (.010)**	-.022 (.011)*
Past Adoption Behavior				
Whether the retail store is adopted	Control variable	-	-.254 (.161)	–
Whether the Internet channel is adopted	Control variable	-	–	-.017 (.104)
Seasonality				
Quarter 1	Control variable	-	-1.048 (.074)***	-.733 (.126)***
Quarter 2	Control variable	-	-1.330 (.079)***	-.421 (.121)**
Quarter 3	Control variable	-	-.867 (.073)***	-.105 (.116)
σ_μ			.915 (.177)	1.392 (.447)
Log-likelihood			-7526.343	-3778.263
Sample size			122524	44660

Note: *p < .05, **p < .01, ***p <.001.

Appendix E: Robustness Check for Essay 2, Online Customers' Browsing and Purchasing Behavior over Time

In the second essay, I posit that the initial increase in multichannel shoppers' spending comes from a novelty effect. However, there are alternative explanations that can produce similar empirical results. For example, Ansari et al. (2008) find that when customers use the Internet channel over time, they tend to buy less frequently from the firm. This result suggests that customers may start to compare competitors' products and prices, and become price-sensitive over time (Blattberg et al., 2008). That is, as multichannel customers (who use an online channel) become more comfortable using the Internet, they start to buy from competitors. To examine whether customers switch to other competitors in the long run, I conduct additional studies on ComScore database (obtained from Wharton Research Data Services).

The ComScore data are in bi-yearly and contain online transaction and browsing behavior of more than two million households in the United States. The data span from 2002 to 2008. I focus on seventeen major competing companies' websites (including the focal company of my analysis) selling outdoor gear, clothing lines, and other similar products.

Using the ComScore data, I examine whether consumers' online browsing behavior alter over time. The table below presents the number of channels customers visit each year. This table shows that while on average consumers increase the number of competing websites they visit over the years, the majority of consumers (namely, 82 percent) visit only up to two competing websites in 2008, the last year in the ComScore data.

Consumers' Online Browsing Behavior Over Time

Year	Number of Competing Websites Visited: 1 - 2	3-5	6-10	11-15	Total Number of Consumers Observed
2002	9,652	380	0	0	10,032
	96.21%	**3.79%**	**0.00%**	**0.00%**	
2004	9,232	1,310	63	0	10,605
	87.05%	**12.35%**	**0.59%**	**0.00%**	
2006	23,600	3,414	116	0	27,130
	86.99%	**12.58%**	**0.43%**	**0.00%**	
2008	12,884	2,504	305	7	15,700
	82.06%	**15.95%**	**1.94%**	**0.04%**	

Using the ComScore data, I also investigate whether customers (of the data provider company) change their purchase behavior over the six years. To address this question, I build a switching matrix. In this switching matrix, I focus on three states: (i) solely buying from the data provider (i.e., focal company), (ii) purchasing from competing companies (competition), and (iii) buying from the data provider and a competitor (combination). The table below presents the switching matrix between these states, showing that the focal company's customers are highly loyal.

**Understanding Online Buyers' Purchasing Behavior
Switching Matrix**

	Focal Company	Competition	Combination
Focal Company	71.43%	19.05%	9.52%
Competition	10.42%	68.75%	20.83%
Combination	23.81%	42.86%	33.33%

I also derive the percentages of each state in the steady state. When I compare the percentages in the steady state with the percentages in the last year (i.e., 2008), I find that the online customers of the focal company do not switch to competing companies in the long run. The table below summarizes this result.

Percentages of the Three States

	Focal Company	Competition	Combination
2008	28.30%	52.20%	19.50%
Steady State	33.42%	47.09%	19.49%

Appendix F: Robustness Check for Essay 2, Regression on Brick-and-Mortar Store Users

Similar to Appendix E, in this section I address an alternative explanation: whether my results are driven by the fact that the multichannel customers start to use the Internet channel. Ansari et al. (2008) find that when customers use the Internet channel over time, they tend to buy less frequently from the firm. As a result, it is possible that multichannel users who add other types of channels to their incumbent channel might act differently.

To address this concern, I test my framework on a set of catalog customers who start using a conventional retail store channel. Brick-and-mortar stores provide complementary attributes to other types of channels, such as easing the return and exchange processes (Pauwels and Neslin, 2008), providing after sales service (Verhoef et al., 2007), and creating repeated exposure to company's brand (Avery et al., 2012). Hence, it is reasonable to expect that adopting a brick-and-mortar store leads customers to increase their spending over time. Pauwels and Neslin (2008), Avery et al. (2012), and Pancras et al. (2012) find that, at the aggregate level, adding a new retail store increases total revenues of a firm in the long run. However, if my theory is correct, then this increase in aggregate sales is coming from (i) newly acquired customers and (ii) a short-lived spike in existing customers' spending after they start using the physical store.

The sponsoring retailer has opened a brick-and-mortar store on September 1, 2002 and gathered data until September 1, 2004. These data provide a two-year time period to examine how multichannel customers' (who begin using physical store along with the catalog channel) spending alters.

The table below summarizes the results from the panel data econometrics models I discussed in the second essay. The results show that (i) the multichannel customers increase their spending in the first year they begin to use the physical store, and (ii) significantly lower their spending in the second year of multichannel shopping. These results strongly support the novelty theory.

Parameter Estimates when Customers Adopt a Brick-and-Mortar Store
Matching Is Not Implemented

	(1) Pooled OLS	(2) Random Effects	(3) First-Difference	(4) Lagged Dependent Variable	(5) Arellano-Bond GMM
Variables	Parameter Estimates Standard Error	Parameter Estimates Standard Error	Parameter Estimates Standard Error	Parameter Estimates Standard Error	Parameter Estimates Standard Error
Intercept	-28.59 (37.09)	-46.75 (49.00)	-7.63 (3.56)*	9.95 (34.63)	-42.94 (83.72)
Variables of Interest					
First year of multichannel usage	141.06 (8.02)***	145.28 (7.44)***	140.13 (8.76)***	142.14 (7.49)***	121.70 (18.99)***
Second year of multichannel usage	40.26 (13.40)**	54.66 (12.73)***	26.64 (13.83)	9.43 (12.52)	52.63 (38.66)
State Dependence					
Lagged total spending				.38 (.01)***	-.81 (.06)***
Customer Characteristics					
Past purchase incidences	36.10 (2.24)***	33.87 (2.67)***	-42.78 (2.75)***	14.77 (2.12)***	133.23 (18.63)***
Log-customer tenure	-10.13 (4.77)*	-5.27 (6.27)		-7.49 (4.46)	18.40 (11.64)
Head of household's age	-.64 (.14)***	-.68 (.18)***		-.42 (.13)**	-1.03 (.30)**
Log-household income	-.40 (3.03)	1.01 (4.01)		-.60 (2.83)	2.63 (6.18)
Number of kids in household	-6.50 (1.67)***	-6.15 (2.21)**		-4.76 (1.56)**	-10.16 (3.81)
Probability of college education	21.11 (11.07)	26.39 (14.66)		11.34 (10.34)	50.70 (26.68)
Marketing Efforts					
Number catalogs received	6.81 (0.12)***	6.57 (0.13)***	1.18 (.12)***	3.90 (.12)***	7.33 (1.40)***
Number of emails received	-.23 (.08)**	-.35 (.09)***	-.32 (.09)**	-.34 (.08)***	1.51 (.35)***
Number of store promotions received	72.55 (3.66)***	57.69 (3.31)***	-17.43 (2.66)***	57.70 (3.43)***	73.83 (8.38)***
Trend					
Year 6	4.19 (4.00)	3.47 (3.28)	-9.98 (4.93)*	-6.03 (3.74)	-96.62 (44.18)*
Year 7	7.60 (4.41)	12.22 (3.71)**	7.31 (5.27)	-.03 (4.12)	-82.19 (38.74)*
F Value	997.91		74.94	1309.42	72.77
Chi-square		7872.24			
Adjusted R^2	.36	.49	.03	.44	
Sample Size	23337	23337	23337	23337	23337

Notes: *p < .05, **p < .01, ***p <.001. Under the FD specification, independent variables are differenced between the current year and last year.