



## Marketing Science

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To cite this article:

Elisa Montaguti, Scott A. Neslin, Sara Valentini (2016) Can Marketing Campaigns Induce Multichannel Buying and More Profitable Customers? A Field Experiment. Marketing Science 35(2):201-217. <https://doi.org/10.1287/mksc.2015.0923>

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# Can Marketing Campaigns Induce Multichannel Buying and More Profitable Customers?

## A Field Experiment

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One of the most intriguing findings in the multichannel customer management literature is the positive association between multichannel purchasing and customer profitability. The question is whether this finding can be put into action. That is, can a firm develop a marketing campaign to increase multichannel purchasing and hence average customer profitability, and if so what are the key factors that enable success. We design and implement a randomized field experiment to investigate this question. The field experiment tests four marketing campaigns that vary in the communications message and the provision of financial incentives. We find that the multichannel/profitability relationship is actionable. A properly designed marketing campaign increases the number of multichannel customers and increases average customer profitability. That campaign's message emphasizes the benefits of multichannel shopping but does not rely on financial incentives. Moreover, we use propensity score matching to show that, after accounting for self-selection, multichannel customers are more profitable than they would be if they were not multichannel. A post-test analysis suggests that the multichannel/nonfinancial incentive campaign succeeded in inducing customers to become multichannel because it decreased customer reactance and increased perceived behavioral control.

Data, as supplemental material, are available at <http://dx.doi.org/10.1287/mksc.2015.0923>.

**Keywords:** multichannel shopping; customer profitability; field experiment; treatment effect on the treated

**History:** Received: August 19, 2013; accepted: February 27, 2015. Preyas Desai served as editor-in-chief and Gary

Lilien served as associate editor for this article. Published online in *Articles in Advance* June 29, 2015.

### 1. Introduction

The ever-expanding multiplicity of channels through which customers can purchase from firms has produced the multichannel customer, i.e., the customer who purchases through more than one of the firm's channels. An intriguing finding is that multichannel customers buy more and are more valuable than nonmultichannel customers (see [Neslin and Shankar 2009](#) for a review). This suggests a multichannel customer strategy for the firm, i.e., undertake marketing campaigns that produce more multichannel customers. This should produce higher average revenues and profits per customer, and thereby increase overall firm profits.

In this paper we seek to determine whether this multichannel customer strategy is actionable, that is, can it be successful and if so what factors determine its success. We conduct a field experiment wherein we randomly assign newly acquired customers to one of four marketing campaigns, and compare results to a control group that does not receive any one of these campaigns. We develop a framework to guide

the design of the campaigns and help investigate the reasons for the results, which we diagnose using a post-test survey of the firm's customers.

The logic behind the multichannel customer strategy is: (1) Marketing campaigns induce more customers to become multichannel; (2) Multichannel customers are more profitable than they would have been if they were not multichannel, and as a result; (3) Average profits per customer and hence total profits increase when we induce more multichannel shopping. It is also important to understand the factors that contribute to the success of this strategy. Accordingly, we address four research questions:

1. Can a marketing campaign induce customers to become multichannel?
2. Are multichannel shoppers more profitable than they would be had they been multichannel?
3. Can a marketing campaign increase average customer profitability?
4. What types of multichannel marketing campaigns work best, and why?

We answer questions 1 and 3 using test-versus-control comparisons from the field test. Question 2 asks for a counterfactual, i.e., how valuable would a multichannel customer have been had that customer not been multichannel. We address this by using propensity score matching (PSM) to estimate the average treatment effect on the treated (TT) (Wooldridge 2002, pp. 614–621). We answer question 4 by analyzing a post-test survey of the firm's customers.

The field experiment involves a cohort of 30,710 newly acquired customers. The design of the four marketing campaigns is motivated by our framework. The campaigns differ in terms of message and incentive. The message is an explicit invitation for the customer to become multichannel or a general message stating the value proposition of the firm. The incentive is the provision of price discount coupons or no coupons provided.

We find that the multichannel message not coupled with coupons produces more multichannel customers and increases profit. We estimate the profit (return on investment (ROI)) of this strategy to be 93%. The post-test survey suggests that this strategy induces more multichannel shopping because it generates less customer reactance and greater perceived behavioral control (as in Fitzsimons and Lehmann 2004, Ajzen 1991, to be discussed later).

The PSM analysis reveals that multichannel purchasing increases customer profit an average of €28.39 per year among multichannel customers compared to what they would have generated as nonmultichannel customers. The positive TT is substantiated by several robustness checks, including a switching regression. These results suggest that higher profits for multichannel customers are not due to self-selection.

We proceed with a discussion of theory and evidence as to the multichannel-profitability link. This leads to our proposed framework (§2). We then present our research design (§3). We next discuss our analysis approach and our results (§4). Then we conduct post-test analyses to diagnose these results (§5). We conclude with a summary and implications for future research (§6).

## 2. Theory, Evidence, and Framework

### 2.1. Why Multichannel Customers May Become More Profitable

Blattberg et al. (2008) and Neslin and Shankar (2009) enumerate three reasons that multichannel customers might be more profitable: (1) self-selection, (2) marketing, and (3) customer satisfaction. The self-selection explanation is that high volume customers have more purchase occasions; hence they naturally use more channels if available. The marketing explanation is that multichannel shoppers naturally receive more

or different marketing because they interact with the firm through several channels. The customer satisfaction explanation views multichannel use as additional service, so the multichannel customer is happier and therefore more valuable. A related perspective is that multichannel shoppers pay a set-up cost to learn how to use various channels and hence would incur a switching cost to defect to another company.

A fourth possible reason is that the multichannel customer purchases from higher margin channels (e.g., see Campbell and Frei 2010). For example, the multichannel customer may be more likely to use the Internet, which may be a lower cost, higher margin channel.<sup>1</sup>

The positive relationship between multichannel shopping and profitability has received considerable empirical support (Thomas and Sullivan 2005, Kumar and Venkatesan 2005, Venkatesan et al. 2007, Ansari et al. 2008, Boehm 2008, Campbell and Frei 2010, Xue et al. 2011). Thomas and Sullivan (2005) show that multichannel shoppers generate more revenue, purchase more items in more categories, and purchase more frequently than nonmultichannel shoppers. Venkatesan et al. (2007) show that lagged multichannel purchasing relates positively to current profits. Kushwaha and Shankar (2013) add the proviso that the multichannel/profits relationship is more likely to occur in hedonic product categories. Ansari et al. (2008) attribute the positive relationship to additional marketing and higher responsiveness to marketing.

Whereas these studies are important for establishing a positive link between multichannel buying and customer value, they do not show that a proactive marketing campaign geared toward creating multichannel customers can induce customers to become multichannel and, in turn, increase profitability per customer. We address this using a one-year field experiment, providing strong internal as well as external validity.

### 2.2. Inducing Multichannel Customer Buying Behavior

Venkatesan et al. (2007) find that “Frequency-related interaction characteristics (purchase frequency and frequency of marketing communication) have the greatest influence on second-channel adoption...” (p. 129). Purchase frequency has a positive impact. Marketing has a positive impact up to a point, but “overcommunicating to customers can have dysfunctional consequences...” (p. 129).

The theory of reasoned action (Fishbein and Ajzen 1975) provides an explanation for why purchase frequency and marketing can induce customers to become

<sup>1</sup> We thank the editor for suggesting this possibility and for encouraging us to explore it.

multichannel. This theory posits that behavior is determined by consumer perceptions (i.e., cognitions) and attitudes toward the behavior. In our study the relevant behavior is multichannel shopping. Therefore cognitions such as the belief that multichannel shopping is convenient should influence behavior.

Purchase frequency influences these cognitions because it increases customer familiarity with the firm's channels. Marketing can also inform the customer about channel attributes, through its message or by influencing the customer to use a particular channel. Ansari et al. (2008) find that email communications route the customer to the Internet to make a purchase. Significantly, they also find that marketing increases purchase frequency.

The role of marketing in influencing channel choice has been documented in several studies (Thomas and Sullivan 2005, Ansari et al. 2008, Venkatesan et al. 2007). Although the marketing efforts investigated in these studies were not designed to induce multichannel shopping behavior, the findings suggest that if marketing can influence channel choice, it can convince customers to become multichannel.

The above literature has mainly focused on nonfinancial communications rather than financial incentives. For example, Gedenk and Neslin (1999) found that financial incentives are relatively detrimental to brand loyalty, compared to nonfinancial incentives. Furthermore, an attempt to influence consumers in a way they may interpret as restricting their freedom can induce reactance (Brehm 1966). As a result, consumers resist marketing activities explicitly directed to influence their behavior (Fitzsimons and Lehmann 2004;

see Trampe et al. 2014 for reactance to a firm's efforts to induce consumers to use the Internet). Reactance theory predicts potential negative consumer reactions to marketing efforts overtly trying to turn them into multichannel shoppers, particularly when these efforts involve financial incentives that too explicitly limit freedom of choice.

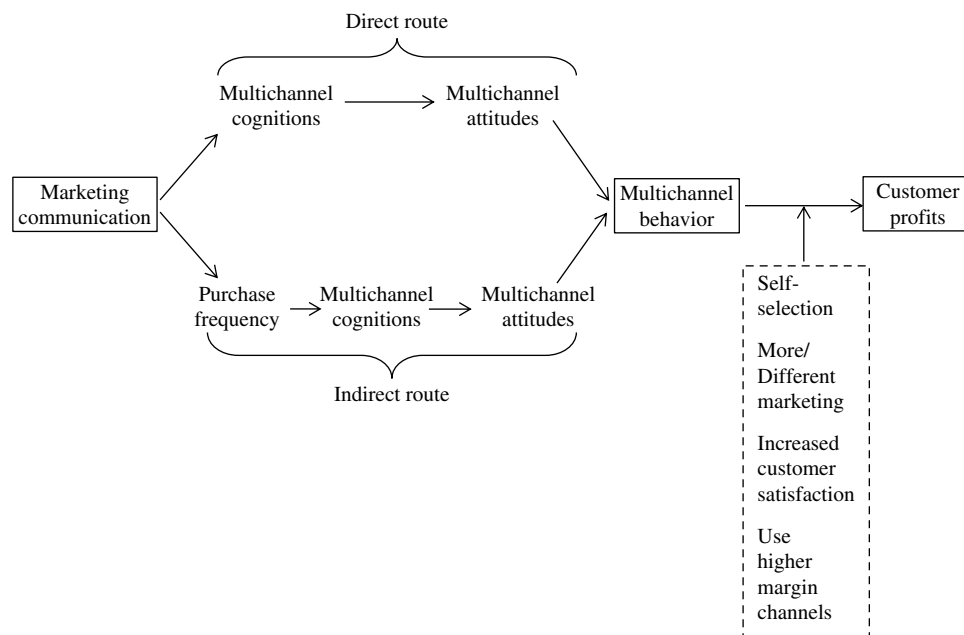
In summary, previous research has found that purchase frequency and marketing can influence multichannel shopping. This happens because both frequency and marketing can affect cognitions and attitudes toward multichannel shopping. This suggests that a campaign to induce multichannel use can succeed if it can activate positive cognitions on multichannel behavior and improve attitudes toward multichannel shopping, despite the risk of reactance. To our knowledge, no previous research has demonstrated that an actionable campaign can be assembled that: (1) induces multichannel shopping, (2) determines the most effective way to do this, and (3) examines the profit implications of such a campaign. This is what we do.

### 2.3. Framework

The above discussion motivates our framework, shown in Figure 1, which illustrates how marketing communication can induce customers to become multichannel shoppers who, in turn, are more profitable.

Drawing on the theory of reasoned action, marketing communications can enhance cognitions for multichannel shopping and hence improve attitudes toward multichannel behavior. The framework identifies two mechanisms by which this can occur. These

Figure 1 Framework: How Communications Can Induce Customers to Become Multichannel, Who, In Turn, Are More Profitable





mechanisms are the direct route and the indirect route. In the direct route, communications directly convince the customer of the benefits of multichannel shopping and hence enhance cognitions and attitudes. The indirect route relies on Ansari et al. (2008) finding that marketing can increase purchase frequency, and then on Venkatesan et al. (2007) finding that purchase frequency leads to multichannel behavior. The indirect route starts by increasing purchase frequency. The customer becomes more familiar with the firm, learns more about its channels, and trusts the firm to deliver a satisfactory experience on these channels. This enhances the customer's multichannel cognitions and attitudes. In summary, the direct route convinces the customer directly that multichannel shopping is a good idea, whereas the indirect route places the customer in a position to learn on his own about the merits of multichannel shopping.

Once the customer becomes multichannel, the framework includes the four mechanisms identified earlier that translate multichannel behavior into profitability: self-selection, more/different marketing, higher satisfaction, and use of higher margin channels.

The framework is valuable in two ways. First, it motivates the communications we use in the field test. We develop two communications to test the direct route and two to test the indirect route. Second, as we find that direct route communication works best, we use a post-test survey based on a detailed elaboration of the direct route to examine why.

### 3. Research Design

#### 3.1. Experimental Setting

We obtained the cooperation of a major multichannel European book retailer to conduct the field experiment. The company sells books through stores, mail-order, phone, and the Internet. Each channel shares the same assortment and price. The company operates on a subscription business model. Each customer must become a member (i.e., subscriber) to purchase. Subscription requires the customer to buy at least one book per quarter. If the customer does not buy a book by the end of each quarter, the featured selection for that quarter (the "book-of-the-month") is shipped and the customer is charged the regular price.<sup>2</sup> The company did not consider the book of the month a purchase channel because it is only used when the customer does not make an explicit channel choice.

The firm mails its main catalog five times per year. Its other marketing activities are managed around each

mailing, i.e., special promotions, price changes, etc. Consequently, customers make purchase decisions in a shopping context created by the current catalog. Significantly, none of the firm's marketing activities is targeted by customer. Thus the firm's marketing activities are the same for all customers. Our field test delivers, on a randomized basis, additional communications and incentives to drive multichannel buying. Also, newly acquired customers had never been encouraged to change their channel use before the field test. So the communications used in our test were entirely new to these customers.

#### 3.2. Marketing Communications Campaigns

Following the framework in Figure 1, we created two communications corresponding to the direct route and two corresponding to the indirect route. Corresponding to the direct route, we used a "multichannel" message promoting multichannel shopping and ensuring that the customer is aware of the available channel choices. By promoting multichannel behavior, the multichannel message should increase cognitions and attitudes toward multichannel shopping, as stipulated by the direct route. Corresponding to the indirect route, we used a "value proposition" message emphasizing the key selling points of the company. This message, which included assortment, service, and special promotions, urged the customer to buy more. If the indirect route works, this should encourage the customer to buy more frequently and thus learn about the benefits of multichannel shopping.

For each message, we included a financial incentive or not. Financial incentives can work through the direct route by increasing the economic benefits of multichannel shopping, and through the indirect route by getting the customer to buy more frequently. The financial incentive was the provision of price discount coupons. The nature of the financial incentives depended on the message. In the spirit of the direct route, the financial incentives for the multichannel message entailed three coupons, one for each channel.<sup>3</sup> The idea was to provide direct incentive to use multiple channels. For the value proposition message, there were three coupons but no specifications on which channels they were to be used on.<sup>4</sup> This is because the strategy was first to increase purchase frequency.

We designed four test campaigns based on the above description. Each was delivered to its assigned treatment group via a prominent card sent a few days before the catalog mailing plus a reminder attached as an insert when the customer received the catalog. Figure 2

<sup>2</sup> There is no difference between the book-of-the-month price and the price of the same book sold through the firm's channels. Moreover, the average price of the books sold as books of the month is the same as the average price of the books sold through different channels.

<sup>3</sup> Mail order and phone channels were combined under one coupon.

<sup>4</sup> All coupons expired when a new catalog arrived (i.e., after three months, on average).

Figure 2 (Color online) Communications Used in Multichannel Campaigns



shows these cards. Campaign A uses the *multichannel* message and *financial* incentives. We henceforth refer to this as “MF.” Campaign B uses the *multichannel* message but with *no financial* incentive. We refer to this as “MNF.” Campaign C uses the *value proposition* message and a *financial* incentive. We henceforth refer to this as “VPF.” Campaign D uses the *value proposition* message but *no financial* incentive. We henceforth refer to this as “VPNF.”

Whereas our communications are motivated by two elements, message and incentive, company policy as well as our strategy dictated that the communications differ on factors other than these two elements. For example, all financial campaigns contain coupon tags, whereas the nonfinancial campaigns include a spokesperson. Among the two financial campaigns, one used channel-specific coupons, whereas the others used company-wide coupons. Later manipulation checks will show that customers correctly perceived the financial incentives and the messages, but the differences in copy and form of the financial incentive mean this is not a  $2 \times 2$  experiment. Rather, it is a test of four communications versus a control. All five groups received the same base marketing, that is, the catalog, etc., described above. The four treatment groups received *in addition* one of the four test communications. Our analyses will be based on comparing each of the four test communications to the control. See Tucker and Zhang (2010) and Anderson and Simester (2003) for a similar approach.

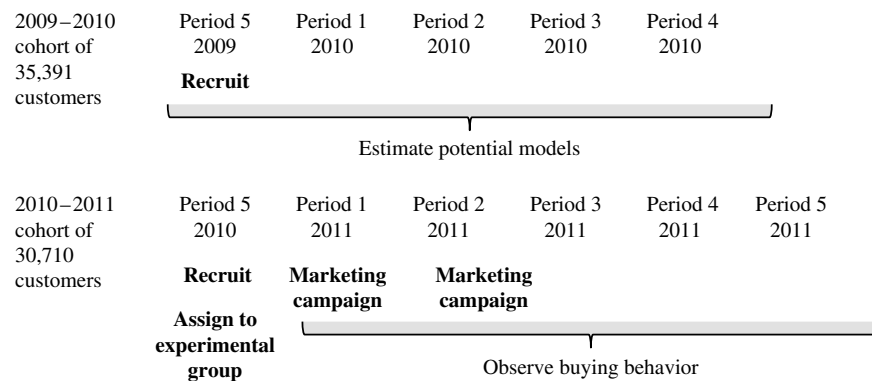
The direct route is a straightforward way to induce multichannel shopping. The indirect route is plausible but requires first that the customer buy more and as a result learn about multichannel behavior. Thus the

value proposition campaigns are more ambitious and we anticipate that the multichannel message campaigns, representing the direct route, will do better.

Promotion literature suggests that monetary incentives are more powerful than nonmonetary incentives (e.g., Chandon et al. 2000). However, the MF campaign *required* customers to engage in multichannel shopping. Customers might see this as an attempt to manipulate them or restrict their freedom. This could precipitate reactance (Fitzsimons and Lehmann 2004, Trampe et al. 2014), rendering the multichannel/financial campaign ineffective. The VPF campaign might induce less reactance but customers could use the coupons for purchases they would have made anyway, producing only modest incrementality and little multichannel shopping. In summary, it appears that the multichannel message should do best because the direct route is a more straightforward strategy for changing behavior. Arguments can be made for or against the financial or nonfinancial versions. We leave it to the field experiment to decide.

### 3.3. Test Implementation and Data

We draw on two cohorts of customers who lived within at least one store’s service area and subscribed with the company after the last catalog mailed in 2009 (Cohort 1) or 2010 (Cohort 2). We refer to the period in which the customer subscribed as the acquisition period; the latter periods are post-acquisition. For Cohort 1 the acquisition period was the fifth and last period of 2009; their behavior was then monitored over the subsequent four periods in 2010. For Cohort 2, the acquisition period was the fifth period of 2010; they were observed over the next five periods until

**Figure 3** Experimental Design-Timeline

January 7, 2012. This means that Cohort 2 was followed for five post-acquisition periods (see Figure 3). Cohort 1 was used to estimate multichannel and profit potential models, which are described subsequently. That is the only way their data are used. Cohort 2 is the experimental cohort, randomly assigned to one of the four test campaigns or to the control group.

On January 7th, 2011, the beginning of period 1 for Cohort 2, customers included in the test conditions received one of the above mentioned cards one to three days before the catalog was mailed to them. A reminder was also prominently displayed in the catalog. Customers in the control group did not receive any communications except the catalog. A second card was sent using the same procedure, i.e., card then catalog, on the 10th of March, the beginning of period 2, to the test group customers. On May 20, July 29, and October 7, respectively, a third, fourth, and

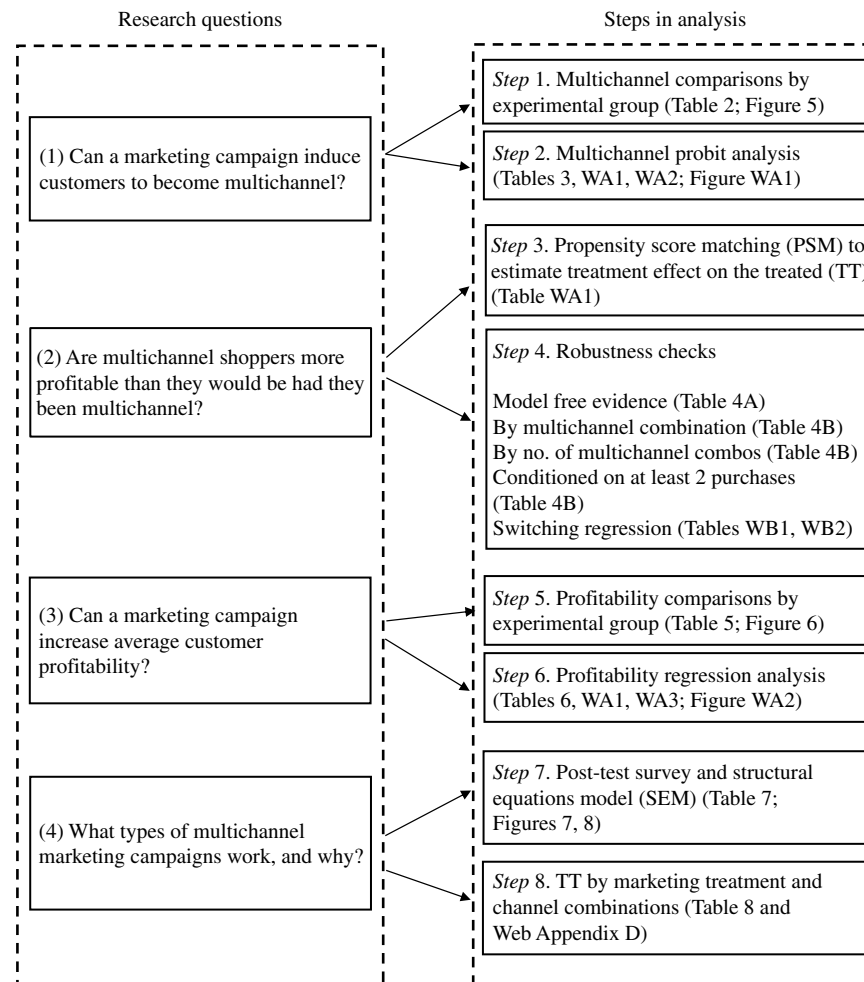
fifth catalog was mailed to all customers in both test and control groups without further communications related to channel use. The firm recorded all customer transactions during these five periods. We have data on which channel was selected by each customer on each purchase occasion, the date of each purchase, and how much was spent.

Table 1 describes Cohort 2 behavior during the test period. Table 1(A) shows that 69% made at least one purchase and 57% made at least two. This suggests the potential for multichannel behavior. Indeed, 2,255 of the 17,528 customers who made two or more purchases became multichannel (12.9%). Of all 30,710 customers, 7.3% became multichannel. Table 1(B) shows that the multichannel shoppers were predominantly two-channel users. Significantly, the mean profit for multichannel shoppers is appreciably higher than for single channel customers. This replicates the basic

**Table 1** Descriptive Statistics of Customer Behavior

(A): Multichannel behavior					
Number of purchases	Number of customers	Single channel	Two channels	Three channels	Four channels
0	9,637 (31%)	NA	NA	NA	NA
1	3,545 (12%)	3,545	NA	NA	NA
2	2,240 (7%)	2,182	58	NA	NA
3	2,819 (9%)	2,628	186	5	NA
4	3,998 (13%)	3,519	454	25	NA
5	5,367 (17%)	4,341	942	82	2
>5	3,104 (10%)	2,603	422	78	1
Total	30,710 (100%)	18,818	2,062	190	3
(B): Multichannel behavior and customer profits					
Number of channels	Number of customers	Percentage (%)	Mean profits (€)	Median profits (€)	SD profits (€)
No purchases	9,637	31.4	0	0	0
Single channel	18,818	61.3	28.60	26.91	16.08
Two channels	2,062	6.7	50.03	47.72	17.52
Three channels	190	0.6	58.72	56.16	17.28
Four channels	3	0	43.57	39.90	12.97
Total	30,710	100	21.25	19.13	20.50

Figure 4 Overview of Analysis Approach



Note. WA refers to Web Appendix.

finding in the literature that multichannel shoppers are more profitable.

These results show that multichannel shopping exists in our data and that multichannel shoppers are more profitable than nonmultichannel shoppers. However, these statistics do not identify the role of marketing communications in inducing multichannel shopping, nor do they infer whether multichannel shoppers were more profitable than they would have been if they were not multichannel (i.e., whether  $TT > 0$ ). We investigate these issues next.

## 4. Analysis and Results

### 4.1. Analysis Approach

Figure 4 depicts our analysis approach. We use test versus control and probit analyses to answer Question (1) whether a marketing campaign can induce more customers to become multichannel. We use PSM supplemented by several robustness checks to answer Question (2) whether multichannel customers are more

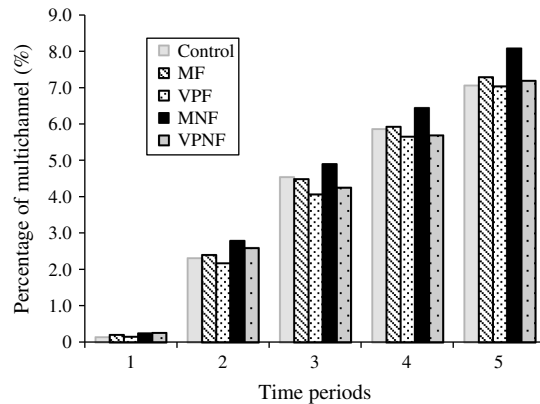
profitable than they would have been had they not been multichannel. This is the TT. We use test versus control and regression analyses to answer Question (3) whether a campaign that induces more multichannel shopping increases average customer profitability. We draw on descriptive statistics and structural equation modeling (SEM) to answer Question (4), i.e., to diagnose the factors that drive success of a multichannel customer strategy.

### 4.2. Question 1: Can a Marketing Campaign Induce Customers to Become Multichannel?

Following Step 1 in Figure 4, we compare test and control groups in terms of the percentage of customers who become multichannel.<sup>5</sup> Figure 5 shows the cumulative percentage of customers who become multichannel

<sup>5</sup> We define customer  $i$  as multichannel if he purchased in at least two different channels by the end of the observation window (four periods for Cohort 1 customers; five periods for Cohort 2 customers). This definition is consistent with previous work (e.g., Kumar and Venkatesan 2005, Venkatesan et al. 2007).



**Figure 5** Cumulative Percentage of Customers Who Became Multichannel in Each Period by Marketing Campaign vs. Control Group

Note. A customer is defined as multichannel if she has bought from more than one purchase channel starting from experimental period 1.

by test group over the five experimental time periods. The figure suggests that the MNF induces more multichannel shopping. Table 2 provides evidence that the MNF campaign increases the percentage of customers who become multichannel by the end of the experimental year ( $p = 0.052$ ).

Proceeding to Step 2, we estimate a probit model where the dependent variable is whether a Cohort 2 customer becomes multichannel. The independent variables are test group assignment plus a multichannel potential covariate.<sup>6</sup> This covariate is constructed by estimating a separate probit model on Cohort 1 where the dependent variable is whether Cohort 1 customers become multichannel, and the independent variables are those we expected would predict whether a customer would become multichannel aside from any experimental treatment. These variables included customer characteristics such as age and gender, channel behavior such as the initial channel used by the customer, and transaction variables such as initial order size (see Web Appendix A (available as supplemental material at <http://dx.doi.org/10.1287/mksc.2015.0923>) for a complete list of the estimated probit models and their performance). Because these same variables are available for Cohort 2, we use the Cohort 1 model to score each Cohort 2 customer. This predicts the likelihood that the customer would become multichannel in the absence of marketing campaigns. This prediction is included as a covariate in the Cohort 2 probit model, along with each customer's test group assignment.

Table 3 displays the results. Model A shows that, without the multichannel potential covariate, the MNF campaign is significant at  $p = 0.051$ . Model B includes

**Table 2** Multichannel Experimental Group Comparisons: Percentage of Customers Who Become Multichannel by the End of the Observation Period

Experimental group	<i>n</i>	Percent (%)	Z-statistic vs. control group	<i>p</i> -value
MF	6,831	7.3	0.528	0.598
VPF	6,821	7.0	0.060	0.952
MNF	6,810	8.1	1.942	0.052
VPNF	6,829	7.2	0.343	0.731
Control	3,419	7.0	—	—
Total	30,710	7.3	—	—

**Table 3** Multichannel Probit Model of Becoming Multichannel

Variable	Model A			Model B		
	Coeff.	Std. err.	<i>p</i>	Coeff.	Std. err.	<i>p</i>
MF	0.021	0.040	0.597	0.036	0.041	0.379
VPF	0.002	0.040	0.952	0.015	0.041	0.721
MNF	0.077	0.039	0.051	0.085	0.040	0.036
VPNF	0.014	0.040	0.731	0.017	0.041	0.673
Multichannel potential	—	—	—	2.780	0.094	0.000
Constant	−1.477	0.033	0	−1.705	0.035	0
Observations	30,710			30,710		
Log-likelihood	−8,055.281			−7,640.572		

Notes. Likelihood-ratio test of nested vs. full model  $\chi^2(1) = 829.418$ ,  $p = 0$ . Dependent variable:  $Y_i = 1$  if customer  $i$  is multichannel by end of test period; 0 if not.

the covariate, which is highly significant. More important, the MNF variable is now significant at  $p = 0.036$ .

The above analyses suggest that the MNF campaign successfully increased the number of multichannel customers. Interestingly, it is the only campaign to have been successful.

#### 4.3. Question 2: Are Multichannel Customers More Profitable Than They Would Be Had They Not Been Multichannel?

**4.3.1. PSM Analysis.** Our task is to calculate the average TT, i.e., whether multichannel customers on average are more profitable than they would have been if they were not multichannel. Define  $Multichannel_i = 1$  if customer  $i$  becomes multichannel; 0 if customer  $i$  does not become multichannel;  $Profit_{1i}$  = profitability of customer  $i$  if that customer is multichannel;  $Profit_{0i}$  = profitability of customer  $i$  if that customer is nonmultichannel. TT is defined as (Verbeek 2008, pp. 253–257)

$$TT = E[(Profit_{1i} - Profit_{0i}) | Multichannel_i = 1], \quad (1)$$

where the expectation is over multichannel customers. Equation (1) requires starting at the customer level. Therein lies the challenge:  $E[Profit_{0i} | Multichannel_i = 1]$  is an unobserved counterfactual. We cannot randomly

<sup>6</sup> Covariates can serve two purposes, i.e., (1) decrease standard errors and hence enable more precise estimation of treatment effects, and (2) control for nonrandom assignment (Liu 2013, pp. 129–130).

**Table 4** Do Multichannel Customers Become More Profitable? Robustness Checks

(a) Model-free evidence									
	Profit by number of purchases								
	2	3	4	5	6	7	8	9	>9
Single channel mean (€)	20.28	29.18	36.27	37.68	34.14	36.26	38.03	43.20	50.11
<i>n</i>	2,182	2,628	3,519	4,341	1,552	639	235	99	78
Multichannel mean (€)	23.36	37.05	45.14	52.92	59.96	60.37	57.34	67.97	63.34
<i>n</i>	58	191	479	1,026	382	88	20	7	4
Difference (€)	3.08	7.87	8.87	15.23	25.83	24.01	19.31	24.77	13.23
<i>t</i> -stat	2.84	8.59	14.60	26.45	25.95	11.59	3.46	1.50	1.76
<i>p</i> -value	0.006	0.000	0.000	0.000	0.000	0.000	0.003	0.105	0.173
(b) PSM									
	Sample								
Analysis	Control (nonmultichannel)	<i>n</i>	Treatment (multichannel)	<i>n</i>	TT (€)	<i>t</i> -stat			
1	All	28,455	All	2,255	28.39	71.56			
2	≥ 2 purchases	15,273	All	2,255	15.25	38.48			
3	3 purchases	2,628	3 purchases	191	7.01	7.61			
	4 purchases	3,519	4 purchases	479	6.87	11.12			
	5 purchases	4,341	5 purchases	1,026	10.18	16.95			
	6 purchases	1,552	6 purchases	382	19.87	18.58			
	7 purchases	639	7 purchases	88	20.77	8.71			
4	All	28,455	Store/Internet	416	22.18	33.15			
	All	28,455	Store/phone	493	21.88	34.25			
	All	28,455	Internet/phone	531	34.22	41.52			
5	All	28,455	2 channels	2,062	27.64	67.41			
	All	28,455	3 channels	190	39.78	31.51			

manipulate multichannel customers to reset themselves and be nonmultichannel.

Multiple approaches can be used to calculate TT. We use PSM (Step 3 in Figure 4), in particular the kernel-Gaussian PSM procedure in STATA (Leuven and Sianesi 2003; Heckman et al. 1997). The appendix describes the trade-offs between PSM and other methods and provides details on the kernel-Gaussian method.

Following Equation (1):

$$\begin{aligned}
 TT &= E[(Profit_{1i} - Profit_{0i}) | Multichannel_i = 1] \\
 &= E[Profit_{1i} | Multichannel_i = 1] \\
 &\quad - E[Profit_{0i} | Multichannel_i = 1].
 \end{aligned} \quad (2)$$

Using the method in the appendix, we calculate  $E[Profit_{1i} | Multichannel_i = 1] = €50.75$  for our data, and  $E[Profit_{0i} | Multichannel_i = 1] = €22.36$ . From Equation (2), the average TT is therefore  $€50.75 - €22.36 = €28.39$ . Thus we estimate that the average profitability of multichannel customers is €28.39 higher compared to if they were not multichannel. TT is statistically different from zero ( $SE = 0.40$ ,  $p = 0.000$ ).<sup>7</sup>

<sup>7</sup> Approximate standard error (SE) is calculated following the procedure described by Leuven and Sianesi (2003).

**4.3.2. Robustness Checks of TT Calculation.** Step 4 of our analysis is to conduct robustness checks of the TT calculation. We want to ensure that the results consistently show that TT is positive. Table 4 summarizes several robustness checks using PSM. Web Appendix B details a switching regression robustness check. All tests replicate the finding that TT is significantly positive.

One could argue that, by definition, a multichannel customer has more than one purchase, so it is not proper to include zero- or one-purchase customers in the PSM control group. We investigate this using model-free evidence as well as different PSM analyses. Table 4(a) displays the model-free evidence. It shows that multichannel shoppers spend more than single channel shoppers, even when comparing customers who buy the same number of times. Table 4(b), Analysis 2, limits the control group to customers who purchased at least twice. TT is still significantly positive, at €15.25. This is lower than our overall estimate of €28.39. Yet by limiting the control group to only customers who purchased at least twice, we are not allowing for the possibility that multichannel customers would purchase only once or not at all if they were nonmultichannel. The greater-than-two requirement assumes, in fact, that multichannel shoppers would still purchase two or more times if they were not multichannel. That is a conservative assumption. In any case, the TT is still significantly positive.

Table 4(b), Analysis 3, calculates TT using customers who have the same number of purchases. For example, using multichannel customers with exactly three purchases and control customers with exactly three purchases, we still get a positive TT (€7.01). Again, this is conservative because it assumes that if the multichannel customer making three purchases were not multichannel, she would still make three purchases.

We conduct two additional robustness checks. Table 4(b), Analysis 4, calculates TT for specific dual-channel combinations. The results are all significantly positive, with Internet-phone having the highest TT. Table 4(b), Analysis 5, compares TT for two- versus three-channel multichannel customers. Not surprisingly, TT is higher for three-channel multichannel customers. Again, TT is positive, and the results have face validity.

Finally, we estimated a switching regression that explicitly models unobservables. The result is a rather high TT, €100.28, compared to the PSM approach. Although the estimate is positive and important, it lacks face validity. We therefore view the switching regression as a robustness check, and it suggests  $TT > 0$ . Please see the discussion in Web Appendix B.

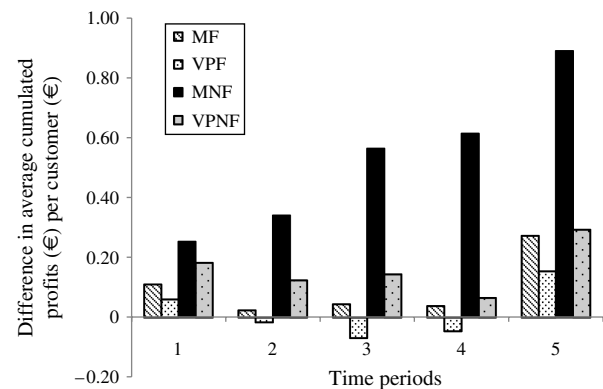
In summary, our finding of a positive TT for multichannel purchasing is robust with respect to: (1) model-free evidence comparing customers with the same number of purchases, (2) PSM analysis conditioned on the number of purchases, (3) PSM analysis conditioned on particular multichannel use combinations, (4) PSM analysis conditioned on the number of channels used by multichannel customers, and (5) a switching regression.

#### 4.4. Question 3: Can a Marketing Campaign Increase Average Customer Profitability?

Our third research question is whether more multichannel shopping increases average profitability per customer and hence overall profits. One might presume that if a campaign induces more multichannel shopping, and if  $TT > 0$ , then by definition average customer profits should increase. However, this need not occur. The campaign may not induce enough multichannel shopping, or TT might be very small, so that in aggregate we cannot detect a significant effect. Therefore the “proof of the pudding” is whether average customer profitability increases due to the marketing campaigns.

We thus undertake Steps 5 and 6 to assess this issue. Because we have concluded so far that MNF is the only campaign to increase multichannel purchasing, and that TT is positive, MNF should be the only campaign that increases average customer profitability. Figure 6 illustrates this, where we see that the MNF customers become increasingly more profitable over time. Following Step 5 in our analysis, Table 5 shows that the MNF group is more profitable on average compared to the control group ( $p = 0.036$ ), and that it is the only group that is more profitable. The ROI for

**Figure 6** Difference in Cumulative Profits per Customer vs. Control Group



**Table 5** Profitability per Customer by the End of the Observation Period

Experimental group	<i>n</i>	Profit <sup>a</sup> (€)	<i>t</i> -statistic vs. control group	<i>p</i>	ROI <sup>b</sup> (%)
MF	6,831	21.17	0.646	0.518	−41
VPF	6,821	21.05	0.364	0.716	−67
MNF	6,810	21.78	2.094	0.036	93
VPNF	6,829	21.19	0.694	0.488	−37
Control	3,419	20.89	—	—	—
Total	30,710	21.25	—	—	—

<sup>a</sup>The company provided the following margins to compute profits: 52.6% for purchases made by mail order or phone, 51.2% for the Internet, 30.8% for the store, and 29.2% for book-of-the-month.

<sup>b</sup>ROI = [(Unit Profit<sub>Marketing Campaign</sub> − Unit Profit<sub>Control</sub>) − Marketing Campaign Cards Cost]/Marketing Campaign Cards Cost.

the MNF campaign is 93%, compared to negative ROIs for the other campaigns.<sup>8</sup>

Step 6 in our analysis incorporates a covariate as we did in measuring whether marketing campaigns induced more multichannel purchasing (see §4.2). Comparable to that analysis, we first estimate a regression model on Cohort 1 customers. The dependent variable is customer profitability; the independents are listed in Web Appendix A, along with specific estimates and performance assessment. We use this model to score Cohort 2 customers, creating a profitability potential score for each customer.

Table 6 presents the regression of customer profitability for Cohort 2. Model A shows the results without the covariate. The MNF variable is significant at  $p = 0.039$ . Model B shows the results with the covariate. The MNF variable is still significant at  $p = 0.050$ .

The above results suggest that in addition to inducing more multichannel shopping, the MNF campaign

<sup>8</sup> ROI includes printing and distribution costs of the promotional cards as the investment. It does not include fixed costs of copy development. To be consistent across communications campaigns, we do not include the costs of price discounts. This would decrease the ROIs of the financial campaigns even more (see Table 5).

**Table 6** Profitability Regression of Profit vs. Treatments and Profit Potential Covariate

Variable	Model A			Model B		
	Coeff.	Std. err.	<i>p</i>	Coeff.	Std. err.	<i>p</i>
<i>MF</i>	0.272	0.429	0.527	0.395	0.405	0.330
<i>VPF</i>	0.154	0.429	0.721	0.327	0.405	0.420
<i>MNF</i>	0.887	0.430	0.039	0.795	0.406	0.050
<i>VPNF</i>	0.292	0.429	0.497	0.298	0.405	0.463
<i>Profit potential</i>	—	—	—	0.726	0.012	0.000
Constant	20.894	0.350	0.000	7.477	0.397	0.000
Observations		30,710			30,710	
<i>R</i> <sup>2</sup>		0.0002			0.1089	

Note. Dependent variable: *Profits<sub>i</sub>* = profits generated by customer *i* by end of test period.

customers on average are more profitable. The net effect of the MNF campaign can be calculated by referring to Tables 2, 5, and 8.

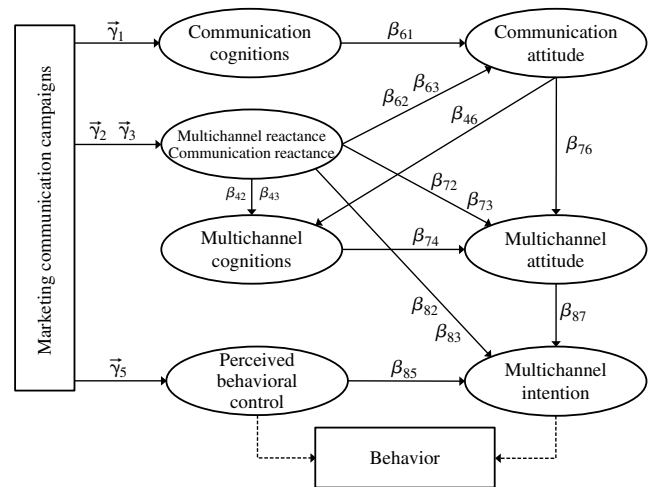
Table 2 shows that MNF increased the fraction of multichannel customers by 0.011 (0.081 for MNF minus 0.070 for the control group). Table 5 shows that MNF increases average customer profit by €0.89 (€21.78 MNF minus €20.89 for the control group). Table 8 shows that the TT estimate for the MNF group is €28.30. One might ask how it can be that TT = €28.30, yet the average profitability per customer increases by only €0.89. The answer is that TT applies to multichannel customers, and the incremental fraction of multichannel customers is 0.011. We can calculate €20.89 (control) + 0.011 (incremental multichannel) × €28.30 (TT) = €21.20. So given our TT estimate, we would predict that average customer profitability in the MNF group would increase to €21.20. This is quite close to the actual average, €21.78. The numbers do not work out perfectly because each calculation term is measured with uncertainty. However, the calculation shows that our estimate of TT is quite consistent with the average customer profitability results shown in Table 5.

## 5. Why Did MNF Work?

### 5.1. Inducing Multichannel Shopping

Our fourth objective is to provide insights for interpreting our results. Following Step 7 in Figure 4, we use a post-test survey and an SEM to explore why MNF was successful in inducing multichannel shopping. MNF follows the direct route in Figure 1, which is to induce multichannel shopping by enhancing multichannel cognitions and attitudes. In Figure 7, we detail this, drawing on MacKenzie et al. (1986) framework for how communications translate into behavior. We also draw on the theory of consumer reactance (see §3.2). Finally, we draw on the theory of planned behavior (Ajzen 1991) to

**Figure 7** SEM Model



Note. Parameters correspond to the SEM model; see Table 8.

incorporate perceived behavioral control.<sup>9</sup> We include perceived behavioral control because intentions may not translate into behavior if the customer is not confident that she can perform the behavior (Ajzen 1991).

Figure 7 shows that communications create cognitions about the communication (Communication Cognitions) and overall attitude toward the communication (Communication Attitude). To the extent that these attitudes are favorable, the communication can influence cognitions toward multichannel shopping (Multichannel Cognitions) and attitude toward multichannel shopping (Multichannel Attitude). Attitude leads to behavioral intention (Multichannel Intention). We distinguish between reactance to the communication message (e.g., limiting the freedom of channel choice (Multichannel Reactance)), and toward the communication itself (e.g., this communication is annoying (Communication Reactance)).<sup>10</sup> Reactance can affect Communication Attitude, Multichannel Cognitions, Multichannel Attitude, and Multichannel Intention (Fitzsimons and Lehmann 2004). Perceived behavioral control can affect Multichannel Intention and Behavior (Ajzen 1991).

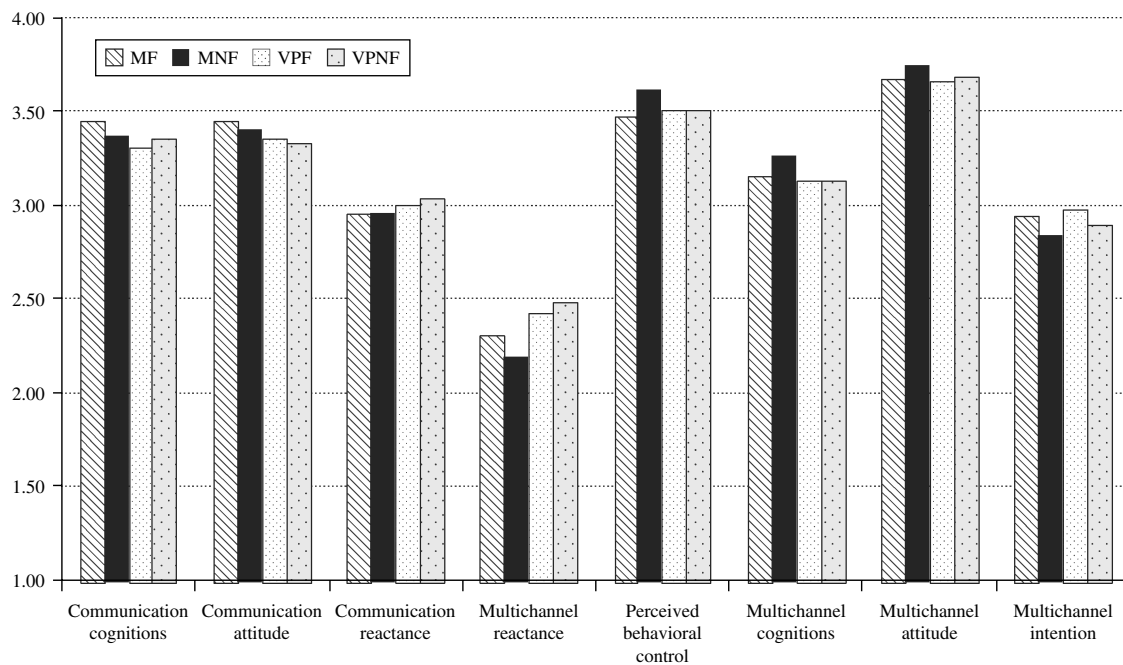
Our survey measured the constructs in Figure 7. It was emailed to 71,500 customers of the firm. The 2,068 respondents were randomly exposed to one of the four communications used in the field test.<sup>11</sup> The questions

<sup>9</sup> Based on prior work that states that the subjective norm component of the theory of planning behavior (TPB) is inadequate and rarely predicts intention (Armitage and Conner 2001), we did not include it in our model to avoid model complexity.

<sup>10</sup> Using these two reactance measures was strongly suggested by an exploratory factor analysis. Utilizing one aggregate measure does not change our basic results, but the two measures add insight.

<sup>11</sup> The 2.9% response rate is in line with the focal company average response rate for emailed surveys (3%).



**Figure 8** Mean Survey Ratings

Note. Variables were measured using a five-point Likert scale ranging from 1 = “strongly disagree” to 5 = “strongly agree.”

are detailed in Web Appendix C; manipulation tests are also provided. These show that the financial aspects of the financial campaigns and the multichannel behavior urged by the multichannel messages were correctly perceived.

Figure 8 displays the means on the constructs for each communication. MNF does well on Multichannel Reactance, Communication Reactance, Multichannel Cognitions, and Multichannel Attitude. However, it does not do as well on Multichannel Intentions. This is inconsistent with what we observe in the field test. Figure 8 shows that MNF and VPNF, the two nonfinancial incentive communications, are lowest on multichannel intentions, whereas the two financial-incentive communications (MF and VPF) are highest. We suppose that this is due to the ability of coupons to boost purchase intentions (e.g., Shimp and Kavas 1984). We believe that the intentions generated by MNF would be more likely to reflect future behavior for two reasons. First, MNF generates higher perceived control, which is a powerful determinant of behavior (Armitage and Conner 2001, Ajzen 1991). Therefore, if two consumers have equal intention to become multichannel, the consumer who is more confident that he can do so is more likely to pursue such behavior. Second, Williams et al. (2004) show that when respondents feel that intention questions are asked for persuasive purposes, responses to these questions do not translate intention into behavior. This is less likely to occur when reactance is lowest, i.e., in the MNF condition.

Table 7 shows key parameter estimates for the SEM. The treatment dummies are to be interpreted relative to the omitted category, i.e., the VPNF treatment. Consistent with Figure 8, MNF does not stand out in terms of Communication Cognitions. However, it does achieve the lowest Multichannel Reactance ( $\gamma_{22} = -0.289$ ,  $p = 0.000$ ). We believe that this is because the MNF message clearly communicates the benefits of multichannel shopping but does not attempt to force compliance. MNF also mitigates Communication Reactance ( $\gamma_{32} = -0.135$ ,  $p = 0.004$ ) and improves Perceived Behavioral Control ( $\gamma_{52} = 0.106$ ,  $p = 0.074$ ). The key results are that MNF did exceptionally well at diminishing Multichannel Reactance, and to some extent improved Perceived Behavioral Control. Table 7 shows the benefits of this. Lower Multichannel Reactance improves Multichannel Cognitions, Communication Attitude, and Multichannel Attitude. Better Multichannel Attitude and better Perceived Control improve Multichannel Intention.

Table 7 includes a counterintuitive result, i.e., that Multichannel Reactance has a direct positive impact on Multichannel Intention. This supports work suggesting that reactance might not decrease intentions when the message is consistent with individuals’ underlying preferences (Brehm 1966). The respondent could reason, “I don’t like that they are manipulating me to be multichannel, but I intend to do it anyway because I like multichannel shopping.”

In summary, the survey suggests that the ability of MNF to create less reactance to becoming multichannel,

**Table 7** Why Did MNF Work? SEM Path Coefficients Estimates

Path		Parameter	Unstd. coeff.	Robust std. err	<i>p</i>
From	To				
MF <sup>a</sup>	Communication cognitions	$\gamma_{11}$	0.104	0.049	0.032
MNF <sup>a</sup>	Communication cognitions	$\gamma_{12}$	−0.012	0.048	0.802
VPF <sup>a</sup>	Communication cognitions	$\gamma_{13}$	−0.045	0.049	0.352
MF <sup>a</sup>	Multichannel reactance	$\gamma_{21}$	−0.180	0.059	0.002
MNF <sup>a</sup>	Multichannel reactance	$\gamma_{22}$	−0.289	0.060	0.000
VPF <sup>a</sup>	Multichannel reactance	$\gamma_{23}$	−0.056	0.058	0.335
MF <sup>a</sup>	Communication reactance	$\gamma_{31}$	−0.146	0.046	0.002
MNF <sup>a</sup>	Communication reactance	$\gamma_{32}$	−0.135	0.047	0.004
VPF <sup>a</sup>	Communication reactance	$\gamma_{33}$	−0.042	0.047	0.369
MF <sup>a</sup>	Perceived behavioral control	$\gamma_{51}$	−0.039	0.060	0.513
MNF <sup>a</sup>	Perceived behavioral control	$\gamma_{52}$	0.106	0.059	0.074
VPF <sup>a</sup>	Perceived behavioral control	$\gamma_{53}$	−0.019	0.062	0.758
Multichannel reactance	Multichannel cognitions	$\beta_{42}$	−0.211	0.028	0.000
Communication reactance	Multichannel cognitions	$\beta_{43}$	−0.528	0.042	0.000
Communication attitude	Multichannel cognitions	$\beta_{46}$	0.320	0.044	0.000
Multichannel reactance	Communication attitude	$\beta_{62}$	−0.094	0.016	0.000
Communication reactance	Communication attitude	$\beta_{63}$	−0.319	0.026	0.000
Communication cognitions	Communication attitude	$\beta_{61}$	0.733	0.038	0.000
Multichannel reactance	Multichannel attitude	$\beta_{72}$	−0.102	0.032	0.002
Communication reactance	Multichannel attitude	$\beta_{73}$	−0.060	0.047	0.196
Communication attitude	Multichannel attitude	$\beta_{76}$	−0.005	0.044	0.912
Multichannel cognitions	Multichannel attitude	$\beta_{74}$	0.691	0.051	0.000
Multichannel reactance	Multichannel intention	$\beta_{82}$	0.092	0.032	0.004
Communication reactance	Multichannel intention	$\beta_{83}$	−0.259	0.041	0.000
Perceived behavioral control	Multichannel intention	$\beta_{85}$	0.119	0.032	0.000
Multichannel attitude	Multichannel intention	$\beta_{87}$	0.440	0.040	0.000

Notes.  $R^2$  Reactance<sub>Multi</sub> = 2%;  $R^2$  Reactance<sub>Com</sub> = 1%;  $R^2$  Communication Cognitions = 1%;  $R^2$  Perceived Behavioral Control = 1%;  $R^2$  Communication Attitude = 85%;  $R^2$  Multichannel Cognitions = 52%;  $R^2$  Multichannel Attitude = 51%;  $R^2$  Multichannel Intention = 28%. MF, Financial multichannel campaign; MNF, nonfinancial multichannel campaign; VPF, financial value proposition campaign. The parameter estimates of the direct effects of the marketing campaigns on each equation are not reported in the table but are all not significant ( $p > 10\%$ ), with the exception of the path MF → Multichannel Cognitions ( $\gamma_{41} = -0.118$ ,  $p = 0.004$ ).

<sup>a</sup>The nonfinancial value proposition campaign (VPNF) represents the baseline.

and to enhance the customer's belief that she could become multichannel if she wanted to, underlies the success of MNF in inducing more customers to become multichannel. Higher perceived control and less reactance would make it more likely that the intentions created by MNF would translate into behavior. This indeed is what we saw in the field test: MNF was most successful at producing multichannel customers.

## 5.2. Why Are Multichannel Customers More Profitable?

The TT results suggest that multichannel shoppers are more profitable than they would be if they were not multichannel. The question is why. PSM is designed to control for self-selection, so this appears to eliminate self-selection as an explanation. That leaves three explanations according to our framework. These are marketing, higher customer satisfaction, and higher margin channel use. Although we do not have a direct measure of customer satisfaction, we can investigate marketing and channel margin.

The firm treated all customers the same with respect to marketing *except* for the communications used in the field test. If marketing makes multichannel customers more profitable, TT should differ depending on communication received. Table 8 shows TT broken down by experimental group. The mean TT is similar for all five groups, ranging from €27.81 to €28.80. The *F*-test is not significant ( $p = 0.155$ ). This suggests that there was no differential impact due to marketing in translating multichannel purchasing to profitability.

**Table 8** TT by Experimental Group

Group	Mean (€)	Std. dev. (€)	<i>n</i>
MF	28.75	6.87	497
MNF	28.30	6.89	550
VPF	28.80	6.71	479
VPNF	27.81	7.27	490
Control	28.20	7.30	239

Note. Hypothesis test for differences between means:  $F(4, 2,250) = 1.67$ ,  $p = 0.155$ .

That is, marketing does not explain why multichannel customers become more profitable.

As to channel use, we found that multichannel customers disproportionately use higher margin channels. The lowest margin channel, the store, accounted for 79% of nonmultichannel customer purchases, versus 31% of multichannel customer purchases. The higher margin Internet, Mail order, and Phone accounted for 69% of multichannel purchases, compared to 21% of nonmultichannel purchases.

To explore further, we computed TT for multichannel customers using two specific channels compared to whether they used one specific channel. There are 24 possible comparisons (six doubles among the four channels  $\times$  four channels). The results are in Web Appendix D. They suggest that shifting to higher margin channels explains some, but not all, of the increase in profitability of multichannel customers. For example, TT for multichannel customers using Internet/store versus single channel customers using the store is €16.32, whereas for Internet/store versus Internet, TT equals €6.30. That is, the Internet/store customer gains profit versus being a store customer, but loses profit versus being an Internet customer, since the store is a lower margin channel. This suggests that a margin effect could be at work. However, the TT for Internet/phone versus Internet is €8.52; versus phone it is €17.54. So the Internet/phone customer is more profitable than being single channel in either of these channels, even though the margins for the two channels are roughly the same. This suggests that margin does not explain everything. It is possible that the Internet/phone customer is more profitable due to higher satisfaction.

In summary, our framework suggests that multichannel customers could be more profitable due to self-selection, marketing, using higher margin channels or higher satisfaction. We can eliminate self-selection and marketing. We find that channel margins played a role because multichannel customers used higher margin channels. However, this does not fully explain higher treatment effects. Customer satisfaction may also have played a role.

## 6. Conclusions

This research sheds light on the relationship between multichannel shopping and profitability. Previous work provides important evidence of a positive association. We show that this association can be translated into practice by a marketing campaign that produces more multichannel customers, which translates to higher average customer profitability.

There are three steps to our argument: (1) Marketing induces more customers to become multichannel; (2) Multichannel customers are more profitable than

if they were not multichannel; and (3) Marketing, therefore, increases average customer profitability. The evidence that marketing can produce more multichannel customers comes from test versus control analyses (Tables 2 and 3). The evidence that the individual multichannel customer becomes more profitable than if he were not multichannel comes from calculating the TT, for which we used PSM. We found  $TT > 0$ , reinforced by several robustness checks. The evidence that the net result is higher average customer profitability comes from test versus control analyses (Tables 5 and 6).

Our research has important implications for researchers. First, we validate the link between multichannel behavior and profitability. Using a field test, we increased multichannel behavior and average customer profitability. Second is the importance of reactance to the communications design. This is especially relevant for digital/database marketing, wherein marketers may interpret targeting as manipulation. A third implication is the importance of field tests; they provide evidence that the relationships found in descriptive analyses are causal.

Our field test also offers implications for managers. First and foremost, the multichannel customer strategy is viable. Firms can devise marketing campaigns changing customers into multichannel shoppers, thus making them more profitable. Second, not all communications and incentives are equally effective. In our application, we find nonprice oriented communication that emphasizes the benefits of multichannel shopping is most effective.

The post-test survey suggests that the ability to decrease reactance and enhance perceived behavioral control is important in inducing multichannel shopping. Therefore communications must strike a delicate balance. They must present a clear argument for the customer to become multichannel, but cannot be construed as overly manipulative. At the same time, the communication needs to provide the customer with confidence that she is in control, i.e., can become multichannel if she wants to. In our research, this was achieved by a communication that clearly showed the benefits of multichannel shopping, but did not overtly try to manipulate customers through a financial incentive. This does not rule out the possibility that incentives, if used correctly, could induce multichannel shopping. Our guidance is simply to mitigate reactance and convince the customer that he is in control.

Inducing multichannel shopping is only half the job. Multichannel behavior must also translate to higher profits. In our application, migration to higher margin channels was a prime determinant. This is specific to our study. In fact, multichannel customers may migrate to lower margin channels and become less profitable.<sup>12</sup>

<sup>12</sup> We thank the editor for suggesting this discussion.

The point is that managers pursuing a multichannel strategy should examine their channel margins and consider where new multichannel customers might migrate (e.g., see Ansari et al. 2008).

## 7. Limitations and Future Research

First, we use data from a single company and a single product category. Kushwaha and Shankar (2013) find that hedonic categories are most likely to foster a positive relationship between multichannel and profits. The category we investigated was hedonic (books). It would be interesting to investigate other categories. Also, it would be useful to investigate contexts wherein customers are not bound to the firm by a subscription, or where they buy more frequently.

Second, whereas the best campaign is profitable, the percentage of customers who became multichannel is relatively low (8.1%). This might be related to the low number of purchase occasions in this industry, which limit a customer's opportunity to use multiple channels.

Third, we only observed customer purchase. We do not know whether the marketing campaigns encouraged customers to *search* across channels. Future work could pursue this avenue to assess whether marketing campaigns boost channel search and make customers more satisfied with the shopping experience.

Fourth, our marketing campaigns targeted recently acquired customers who had never been encouraged to change their channel use before the field test. Because they had no time to form channel preferences with this firm, they were still responsive to marketing (Valentini et al. 2011). It would be useful to investigate the impact of a multichannel marketing strategy on current customers. In addition, the role of multiple channels in initially acquiring customers should be examined.

Last, our results may have been influenced by the specifics of communication, i.e., the visual impression and the copy itself. Our post-test survey suggests that manipulations worked in that MF and MNF were correctly seen as communicating multichannel, and MF and VPMF were seen as communicating financial messages (see Web Appendix C). This is reassuring. However, we cannot rule out that the results would change with different execution.

In summary, this research builds on the knowledge base in this critical area by demonstrating the effectiveness of multichannel campaigns, offering guidance on campaign design, and demonstrating the potential for targeting.

## Supplemental Material

Supplemental material to this paper is available at <http://dx.doi.org/10.1287/mksc.2015.0923>.

## Acknowledgments

The authors are grateful for the grant provided by the Marketing Science Institute (MSI) and the Wharton Interactive Media Initiative (WIMI) to support this research, and for feedback provided by participants in the joint WIMI-MSI Multichannel Conference. The authors thank Amit Bhattacharjee and Robert Rooderkerk for valuable suggestions on an earlier draft of this paper. The authors also thank the editor-in-chief, associate editor, and two anonymous reviewers for their constructive and insightful comments. Finally, the authors thank the anonymous firm that provided the data.

## Appendix. PSM Method

Two approaches to calculate TT are matching procedures and switching regressions. Matching procedures create for each multichannel customer a matched composite of nonmultichannel customers to serve as a control for that customer. The average profitability of these matched composites provides an estimate of  $E[Profit_{0i} | Multichannel_i = 1]$ . Matching is based on observed variables that are expected to influence both profits and multichannel behavior. Thus differences in profits between multichannel customers and nonmultichannel composites are due to multichannel behavior and not to other factors that may have determined multichannel behavior. This, in turn, hinges on the “ignorability of treatment” assumption, which requires that conditioned on the observed factors, *unobserved* factors that influence multichannel behavior are uncorrelated with profits (Wooldridge 2002, pp. 607–608; Rosenbaum 1984).

Switching regressions parametrically model the impact of unobservables on multichannel behavior and profits. However, results tend to be sensitive to these parametric assumptions. Switching regressions work better when instrumental variables are available that correlate with treatment but not with the dependent variable (Wooldridge 2002, pp. 622–624). Perhaps for these reasons, matching, particularly PSM (Rosenbaum and Rubin 1983, 1985), is gaining acceptance in marketing (Mithas et al. 2005, Boehm 2008, Bronnenberg et al. 2010, Gensler et al. 2012, Garnefeld et al. 2013). We use PSM to estimate TT. In particular, we use the kernel-Gaussian PSM procedure in STATA described next (see also Leuven and Sianesi 2003 and Heckman et al. 1997 for additional references).<sup>13</sup>

From Equation (1), we need estimates of  $E[Profit_{1i} | Multichannel_i = 1]$  and  $E[Profit_{0i} | Multichannel_i = 1]$ . The average observed profit of multichannel customers, i.e.,  $\sum_{i=1}^n Profit_{1i}/n$ , where  $n$  is the number of multichannel customers, provides an estimate of  $E[Profit_{1i} | Multichannel_i = 1]$ . Kernel-Gaussian PSM computes weights that create the matched composites, then averages over the composites to estimate  $E[Profit_{0i} | Multichannel_i = 1]$ . The weights are based on how similar each non-multichannel customer  $j$  is to each multichannel customer  $i$  in terms of the likelihood or “propensity” of becoming multichannel.

<sup>13</sup> Our results are robust using different kernel functions and different PSM matching approaches (e.g., single nearest-neighbor, Mahalanobis distance, and hybrid matching as proposed by Gensler et al. 2012). The results from these methods were statistically equivalent.



**Table A.1** PSM—Comparisons of Mean Customer Descriptors ( $X$ 's)

Variable	Variable description	A: Multichannel customers	B: Nonmultichannel customers	C: $t$ -stat A vs. B	D: Matched composite Nonmultichannel	E: $t$ -stat A vs. D
<i>Age</i>	Age in years	39.65	38.50	3.22	39.61	0.09
<i>Female</i>	Dummy indicating female	0.75	0.72	3.93	0.76	0.00
<i>Street Agents</i>	Dummy indicating customers acquired by on-the-street agents	0.39	0.48	−8.67	0.39	−0.32
<i>North</i>	Dummy indicating customers living in the north of the country	0.71	0.51	18.13	0.69	1.21
<i>Early Email</i>	Dummy indicating customers who provided their email address during the acquisition quarter	0.59	0.52	6.37	0.59	0.16
<i>Nov Acquisition</i>	Dummy indicating customers acquired in November	0.26	0.29	−3.14	0.27	−0.31
<i>Dec Acquisition</i>	Dummy indicating customers acquired in December	0.0004	0.0001	1.09	0.0003	0.24
<i>Big City</i>	Dummy indicating customers living in a big city (more than 500,000 inhabitants)	0.09	0.15	−7.67	0.09	−0.52
<i>Average City</i>	Dummy indicating customers living in an average city (100,000–499,000 inhabitants)	0.04	0.07	−5.49	0.04	−0.36
<i>Franchisee</i>	Dummy indicating customers for whom the store closest to their place of residence is run by a franchisee	0.51	0.55	−4.35	0.51	−0.21
<i>Initial Returns</i>	Average amount (€) of products returned to the firm by the customer in the acquisition period	0.12	0.15	−3.68	0.12	0.18
<i>Initial Price Cut</i>	Average amount (€) of price discounts used by the customer in the acquisition period	€0.33	€0.24	1.47	€0.34	−0.13
<i>Initial Store Promo</i>	Dummy indicating customers for whom the closest store was running special store promotions during the acquisition period	€1.72	€1.68	0.43	€1.70	0.20
<i>Initial Revenues</i>	Average € spent during the acquisition quarter by the customer	€11.60	€7.41	11.46	€11.53	0.12
<i>Initial Purchase</i>	Dummy indicating customers making at least one purchase during the acquisition period	0.43	0.27	16.61	0.43	0.26

Notes. Column A is computed across all 2,255 multichannel customers. Column B is computed across all 28,455 nonmultichannel customers. Column D is computed across all 2,255 multichannel customers using the weighted matched composite  $X$  values for each multichannel customer  $i$  (Equation (4)). For example, let  $Age_j$  = the age of non-multichannel customer  $j$ . Then  $\text{Weighted Age}_i = \sum_{j=1}^m w_{ij} \text{Age}_j$ , and the average of these weighted ages is 39.61.

PSM begins by estimating this propensity. We used a probit model for that purpose<sup>14</sup>

$$\text{Prob}(\text{Multichannel}_i = 1) = \text{Prob}(\alpha + X_i\beta + \varepsilon_i \geq 0), \quad (3)$$

where  $\alpha$  is a constant,  $X_i$  is a vector of observed variables,  $\beta$  is the sensitivity to these characteristics, and  $\varepsilon_i$  is the error term distributed as a standard normal. The  $X$ 's are those that would be expected to influence multichannel behavior as well as profits. For example, customer age might fit this requirement. Table A.1 displays the  $X$  variables we used.

We use the following kernel function to create the weights that define the matched composites:

$$w_{ij} = \frac{K((p_i - p_j)/h)}{\sum_{j=1}^m K((p_i - p_j)/h)}, \quad (4)$$

where  $i$  ( $= 1$  to  $n$ ) indexes multichannel customers and  $j$  ( $= 1$  to  $m$ ) indexes nonmultichannel customers. There are thus  $n \times m$  weights. The Gaussian kernel function is indicated by  $K()$ ,  $p$  is the propensity score of each customer, and  $h$  is a bandwidth parameter. The Gaussian kernel (also known as the normal kernel) is the standard normal density function.

<sup>14</sup> There are alternative propensity models. For example, others have used binomial logit. We found our results were virtually identical between logit and probit. See Zhao (2008) for further studies of alternative propensity models.

For this kernel function,  $h$  is the standard deviation of a normal distribution.<sup>15</sup> Because the kernel function is monotonically decreasing in  $|p_i - p_j|$ , higher weights are given to nonmultichannel customers with propensity scores closer to customer  $i$ . For each multichannel customer, the weights sum to one over the nonmultichannel customers. The estimate of  $\text{Profit}_{0i}$  is therefore  $\sum_{j=1}^m w_{ij} \text{Profit}_{0j}$ , and the estimate of  $E[\text{Profit}_{0i} | \text{Multichannel}_i = 1]$  is  $\sum_{i=1}^n (\sum_{j=1}^m w_{ij} \text{Profit}_{0j})/n$  (Heckman et al. 1998).

Table A.1 compares means of the  $X$  variables for multichannel customers (A), nonmultichannel customers (B), and the matched composites of nonmultichannel customers (D). Recall that PSM uses the weights derived from Equation (4) to create for each customer  $i$ , a composite of nonmultichannel customers to serve as a control for that customer. Because we have 2,255 multichannel customers, we have a corresponding set of 2,255 composites created by weighting the 28,455

<sup>15</sup> We used a normal function for the kernel with a fixed bandwidth equal to 0.01. This choice was mainly based on the quality of match. More specifically, we selected the approach that minimized the absolute bias, i.e., the difference of the sample means in the treated and nontreated samples for each considered covariate. Following Nichols (2007, p. 529), we conduct a sensitivity analysis for our choice of bandwidth. The TT estimate using the selected bandwidth (i.e., 0.01) equals 28.39. The TT estimate using twice the selected bandwidth (i.e., 0.02) equals 28.74. Finally, the TT estimate using half the selected bandwidth (i.e., 0.005) equals 28.27.

nonmultichannel customers. For example,  $\sum_{j=1}^m w_{ij} Age_j$  is the composite age of nonmultichannel customers for customer  $i$ , and  $\sum_{i=1}^n (\sum_{j=1}^m w_{ij} Age_j)/n$  is the mean of these composites, the 39.61 shown in column D. If the propensity matching is successful, the means for A and D should be equal, since the composites of nonmultichannel customers are supposed to serve as controls for multichannel customers. Column C reports  $t$ -tests that show there are significant mean differences between multichannel and nonmultichannel customers before matching. Column E reports  $t$ -tests that show there are no significant mean differences between multichannel customers and the composites of nonmultichannel customers. This suggests the weighting produces composites of nonmultichannel customers who are equivalent on average to multichannel customers, and hence these weights can be used to calculate counterfactual profits.

As discussed in the text, the estimate of  $E[Profit_{1i} | Multichannel_i = 1]$  is  $\sum_{i=1}^n Profit_{1i}/n$ , which equals €50.75 for our data. The estimate of  $E[Profit_{0i} | Multichannel_i = 1]$  is  $\sum_{i=1}^n (\sum_{j=1}^m w_{ij} Profit_{0j})/n$ , which equals €22.36 for our data. The average TT is therefore €50.75 – €22.36 = €28.39. We therefore estimate that the average profitability of multichannel customers is €28.39 higher when they are multichannel compared to when they are not multichannel. TT is statistically different from zero (SE = 0.40,  $p = 0.000$ ).<sup>16</sup>

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<sup>16</sup> Approximate SE is calculated following the procedure described by Leuven and Sianesi (2003).