Can Marketing Campaigns Induce Multichannel Buying and More Profitable Customers? A Field Experiment

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Abstract

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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 indeed 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 the multichannel/non-financial incentive campaign succeeded in inducing customers to become multichannel because it decreased customer reactance and increased perceived behavioral control.

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

1 Introduction

The ever-expanding multiplicity of channels through which customers can purchase from firms has produced the "multichannel customer", 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 non-multichannel customers (see Neslin and Shankar 2009 for a review). This suggests a "multichannel customer strategy" for the firm: Undertake marketing campaigns that produce more multichannel customers. This should produce higher average revenues and profits per customer, and thereby increase overall firm profits.

The purpose of this paper is 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 where 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. As a result, (3) average profits per customer and hence total profits increase when we induce more multichannel shopping. In addition, it is 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 more newly-acquired customers to become multichannel customers?

2. If so, are multichannel customers more profitable than they would have been had they not been multichannel?
3. As a result, does the marketing campaign that induces more multichannel customers produce higher average profitability per customer and hence higher overall profits?
4. What types of 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, 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 and the campaigns differ in terms of "message" and "incentive". The message is either an explicit invitation for the customer to become multichannel or a general message stating the value proposition of the firm; the incentive is either 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 ROI of this strategy to be 93%. The post-test survey suggests this strategy induces more multichannel shopping because it generates less customer reactance and greater perceived behavioral control (as in Fitzsimons and Lehmann 2004 and 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 non-multichannel 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 regarding the multichannel-profitability link. This leads to our proposed framework. We then present our research design. We next discuss our analysis approach and our results. Then we conduct post-test analyses to diagnose these results. We conclude with a summary and implications for future research.

2 Theory, Evidence, and Framework

2.1 Why Multichannel Customers May Become More Profitable

Blattberg, Kim and Neslin (2008) and Neslin and Shankar (2009) enumerate three reasons why 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 usage as additional service, so the multichannel customer is a happier customer who therefore becomes 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.[1]

[1] We thank the Editor for suggesting this possibility and for encouraging us to explore it.

The positive relationship between multichannel shopping and profitability has received considerable empirical support (Thomas and Sullivan 2005, Kumar and Venkatesan 2005, Venakatesan, Kumar and Ravishanker 2007, Ansari, Mela, and Neslin 2008, Boehm 2008, Campbell and Frei 2010, Xue, Hitt and Chen 2011). Thomas and Sullivan (2005) show that multichannel shoppers generate more revenues, purchase more items in more categories, and purchase more frequently than non-multichannel shoppers. Venkatesan, Kumar, and Ravishanker (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, Mela, and Neslin (2008) attribute the positive relationship to additional marketing and higher responsiveness to marketing.

While 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, Kumar, and Ravishanker (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 multichannel. This theory posits that behavior is determined by consumer perceptions ("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 regarding channel attributes, either through its message or by influencing the customer to use a particular channel. Ansari, Mela, and Neslin (2008) find that email communications route the customer to the Internet to make a purchase. They also find importantly that marketing increases purchase frequency.

The role of marketing in influencing channel choice has been documented in several studies (Thomas and Sullivan 2005, Ansari, Mela, and Neslin 2008, Venkatesan, Kumar, and Ravishanker 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 non-financial communications rather than financial incentives. Gedenk and Neslin (1999) for example found that financial incentives are relatively detrimental to brand loyalty, compared to non-financial 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 Lehman 2004; see Trampe, Konus, and Verhoef (2014) for reactance to a firm's efforts to induce consumers to use the Internet). Reactance theory foretells 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 usage can succeed if it is able to activate positive cognitions regarding multichannel behavior and improve attitudes towards multichannel shopping, despite the risk of reactance. No previous research, however, 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, depicting how marketing communication can induce customers to become multichannel shoppers who in turn are more profitable.

[Insert Figure 1 about Here]

Drawing on the theory of reasoned action, marketing communications can enhance cognitions regarding multichannel shopping and hence improve attitudes toward multichannel behavior. The framework identifies two mechanisms by which this can occur – 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.'s finding that marketing can increase purchase frequency, and then on Venkatesan et al.'s finding that purchase frequency leads to multichannel behavior. The indirect route starts by increasing purchase frequency. The customer then 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/her own about the merits of multichannel shopping.

Once the customer is 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 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 for conducting 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., subscribe) in order 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 he or she is shipped the quarter's featured selection (the "book of the month") and is charged its regular price.[2] 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.

[2] There is no difference between the price of the book of the month 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 not different than the average price of the books sold through different channels.

The firm mails its main catalog five times per year, and its other marketing activities are managed around each mailing – special promotions, price changes, etc. Consequently, customers make purchase decisions in a shopping context created by the current catalog. Importantly, 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 usage prior to the field test. So the communications used in our test were entirely new to these newly acquired customers.

3.2 Marketing Communication 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 making sure the customer is aware of the channel choices available. 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, which entailed assortment, service, and special promotions. The value proposition message urged the customer to buy more, which if the indirect route works, should encourage the customer to buy more frequently and then learn about the benefits of multichannel shopping.

For each message, we either included a financial incentive or not. Financial incentives can work through the direct route by increasing the economic benefits of multichannel shopping, and work 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.[3] 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.[4] This is because the strategy here was first to increase purchase frequency.

We designed four test campaigns based on the above discussion. 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 shows these cards. Campaign A utilizes the *multichannel* message and *financial* incentives. We henceforth refer to this as "MF". Campaign B utilizes the *multichannel* message but with *no financial* incentive. We refer to this as "MNF". Campaign C utilizes the *value proposition* message and a *financial* incentive. We henceforth refer to this as "VPF". Campaign D utilizes the *value proposition* message but *no financial* incentive. We henceforth refer to this as "VPNF".

[Insert Figure 2 about Here]

While 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 non-financial campaigns include a spokesperson. Among the two financial campaigns, one used channel-specific coupons, while 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 2×2 experiment. Rather, it is a test of four communications vs. a control. All five groups received the same "base

[3] Mail-order and phone channels were combined under one coupon.
[4] All coupons expired when a new catalog arrived (i.e., after three months on average).

marketing", that is, the catalog, etc., described above. The four treatment groups *in addition* received 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 inducing multichannel shopping. The indirect route is plausible but requires first that the customer buys more and as a result learns about multichannel behavior. Thus the value proposition campaigns are more ambitious and we anticipate the multichannel message campaigns, representing the direct route, will do better.

Literature on promotions suggests that monetary incentives are more powerful than non-monetary incentives (e.g., Chandon et al. 2001). 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 Lehman 2004, Trampe, Konus, and Verhoef 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 little incrementality and little multichannel shopping. In summary, it appears 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 non-financial 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 entered into a subscription agreement 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 entered into the subscription 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 January 7, 2012. This means Cohort 2 was followed for five post-acquisition periods (see Figure 3). Cohort 1 was used to estimate multichannel and profit potential models, 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.

[Insert Figure 3 about Here]

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 displayed prominently when the catalog was delivered. 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 both in test and control conditions without any further communications related to channel usage. 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 1A shows that 69% made at least one purchase and 57% made at least two. This suggests the potential for multichannel behavior. Indeed, 2,255 out of the 17,528 customers who made two or more purchases became multichannel (12.9%). Out of all 30,710 customers, 7.3% became multichannel. Table 1B shows that the multichannel shoppers were predominantly two-channel users. Importantly, the mean profit for multichannel shoppers is appreciably higher than for single channel customers. This replicates the basic finding in the literature that multichannel shoppers are more profitable.

[Insert Table 1 about Here]

These results show that multichannel shopping exists in our data and that multichannel shoppers are more profitable than non-multichannel 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 propensity score matching (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 treatment effect on the treated (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) - diagnosing the factors that drive success of a multichannel customer strategy.

[Insert Figure 4 about Here]

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.[5] Figure 5 shows the cumulative percentage of customers who become multichannel by test group over the five experimental time periods. The figure suggests that the multichannel/non-financial campaign (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 ($p = 0.052$).

[Insert Figure 5 about Here]

[Insert Table 2 about Here]

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.[6] 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 for a complete list, the estimated probit models, and their performance). Since these same variables are available for Cohort 2, we use the Cohort 1 model to score each Cohort 2 customer, producing a prediction of the likelihood 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.

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[5] We define customer *i* as multichannel if he or she purchased in at least two different channels by the end of the observation window (four periods for Cohort 1 customers; five period for Cohort 2 customers). This definition is consistent with previous work (e.g., Kumar and Venkatesan 2005; Venkatesan, Kumar, and Ravishanker 2007).

[6] Covariates can serve two purposes: (1) decrease standard errors and hence enable more precise estimation of treatment effects, and (2) control for non-random assignment (Liu 2013, pp. 129-130).

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

[Insert Table 3 about Here]

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 Propensity Score Matching (PSM) Analysis

Our task is to calculate the average treatment effect on the treated (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 non-multichannel. TT is defined as (Verbeek 2008, pp. 253-257):

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

where the expectation is over multichannel customers. Equation (1) requires starting at the customer level and therein lies the challenge: $E[Profit_{0i}|Multichannel_i = 1]$ is an unobserved counterfactual. We cannot randomly manipulate multichannel customers to re-set themselves and be non-multichannel.

Multiple approaches can be used to calculate TT. We use propensity score matching (PSM) (Step 3 in Figure 4), in particular the kernel-Gaussian PSM procedure in STATA (Leuven and

Sianesi 2003; Heckman, Ichimura and Todd 1997, p. 630). Appendix A describes the trade-offs between PSM and other methods and provides details on the kernel-Gaussian method we used.

Following equation (1):

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

$$= E[Profit_{1i}|Multichannel_i = 1] - E[Profit_{0i}|Multichannel_i = 1]$$

Using the method in Appendix A, 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 treatment effect on the treated (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).[7]

4.3.2 Robustness Checks of TT Calculation

Step 4 of our analysis is to conduct robustness checks of the TT calculation. The goal is to make sure 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.

[Insert Table 4 about Here]

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 control group for the PSM. We investigate this using model-free evidence as well as different PSM analyses. Table 4A 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 4B, Analysis 2 limits the control group to customers who purchased at least twice. TT is still

[7] Approximate standard error (SE) is calculated following the procedure described by Leuven and Sianesi (2003).

significantly positive, at €15.25. This is lower than our overall estimate of €28.39. But by limiting the control group only to 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 non-multichannel. 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 4B, 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 if the multichannel customer making three purchases were not multichannel, he or she would still make three purchases.

We conduct two additional robustness checks. Table 4B, Analysis 4 calculates TT for specific dual-channel combinations. The results are all significantly positive, with Internet-Phone having the highest TT. Table 4B, 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. The estimate is positive and that is important, but lacks face validity. We therefore view the switching regression as a robustness check and indeed it suggests TT > 0. Please see 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 conditioning on the number of purchases, (3) PSM analysis conditioned on particular multichannel usage combinations, (4) PSM analysis conditioning on the number of channels used by multichannel customers, and (5) a switching regression.

4.4 Question 3: Does 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 can't detect a significant effect. Therefore the "proof in the pudding" is whether average customer profitability increases due to the marketing campaigns.

We thus undertake Steps 5 and 6 to assess whether the average profitability per customer increased for due to the campaigns. Since we have concluded so far that MNF is the only campaign to increase multichannel purchasing, and TT is positive, MNF should be the only campaign that increases average customer profitability. Figure 6 shows this graphically, where we see 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 is the only group that is more profitable. The ROI for the MNF campaign is 93%, compared to negative ROIs for the other campaigns.[8]

[Insert Figure 6 about Here]

[Insert Table 5 about Here]

Step 6 in our analysis incorporates a covariate as we did in measuring whether marketing campaigns induced more multichannel purchasing (see Section 4.2). Analogous to that analysis,

[8] 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. Doing so would decrease the ROIs of the financial campaigns even more. See Table 5.

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.

[Insert Table 6 about Here]

The above results suggest that in addition to inducing more multichannel shopping, the MNF campaign 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 tells us that MNF increased the fraction of multichannel customers by 0.011 (0.081 for MNF minus 0.070 for the control group). Table 5 tells us that MNF increases average customer profit by €0.89 (€21.78 MNF minus €20.89 for the control group). Table 8 tells us the estimate of TT for the MNF group is €28.30. One might ask how it can be that TT = €28.30 yet 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 estimate of TT, we would predict that average customer profitability in the MNF group would increase to €21.20. This indeed is quite close to the actual average, €21.78. The numbers don't work out perfectly because each term in the calculation 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 utilize a post-test survey and a structural equations model (SEM) to explore why MNF turned out to be 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 flesh this out in detail, drawing on MacKenzie, Lutz, and Belch's (1986) framework for how communications translate into behavior. We also draw on the theory of consumer reactance (see Section 3.2). Finally, we draw on the theory of planned behavior (Ajzen 1991) to incorporate perceived behavioral control.[9] We include perceived behavioral control because intentions may not translate into behavior if the customer is not confident he or she will be able to perform the behavior (Ajzen1991).

[Insert Figure 7 about Here]

Figure 7 shows that communications create cognitions regarding the communication (Communication Cognitions) and overall attitude toward the communication (Communication Attitude). To the extent these attitudes are favorable the communication is able to influence cognitions toward multichannel shopping (Multichannel Cognitions) and attitude toward multichannel shopping (Multichannel Attitude). Attitude then leads to behavioral intention (Multichannel Intention). We distinguish between reactance to the message of the communication (e.g., limiting the freedom of channel choice (Multichannel Reactance)), and toward the communication itself (e.g., this communication is annoying (Communication

[9] Based on prior work that states the subjective norm component of the TPB is inadequate and rarely predicts intention (Armitage and Conner 2001, p.488), we did not include it in our model to avoid model complexity.

Reactance).[10] Reactance can affect Communication Attitude, Multichannel Cognitions, Multichannel Attitude, and Multichannel Intention (Fitzsimons and Lehmann 2004, p.84). 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 of the firm's customers. The 2,068 respondents were randomly exposed to one of the four communications used in the field test.[11] The questions are detailed in Web Appendix C, where 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 non-financial incentive communications, are lowest on multichannel intentions, while the two financial-incentive communications (MF and VPF) are highest. We surmise 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, p. 184). Therefore, if two consumers have equal intention to become multichannel, the consumer who is more confident he/she can do so is more likely to pursue such behavior. Second, Williams, Fitzsimons and Block (2004, p.549) show that when respondents feel that intention questions are asked for persuasive purposes, responses to

[10] Using these two measures of reactance was strongly suggested by an exploratory factor analysis. Using one aggregate measure does not change our basic results, but the two measures add insight.

[11] The 2.9% response rate is in line with the focal company average response rate for emailed surveys (3%).

these questions do not translate intention into behavior. This is less likely to occur when reactance is lowest i.e. in the MNF condition.

[Insert Figure 8 about Here]

Table 7 shows key parameter estimates for the SEM. The treatment dummies are to be interpreted relative to the omitted category – 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 (γ_{22} = -0.289, p = 0.000). We conjecture this is because the message of MNF clearly communicates the benefits of multichannel shopping but doesn't attempt to force compliance. MNF also mitigates Communication Reactance (γ_{32} = -0.135, p = 0.004) and improves Perceived Behavioral Control (γ_{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.

[Insert Table 7 about Here]

Table 7 includes a counter-intuitive result, namely 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 reasons, "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, and to enhance the customer's belief that he or she could become multichannel if he/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 – marketing, higher customer satisfaction, and higher margin channel usage. We do not have a direct measure of customer satisfaction, but 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. That is, marketing does not explain why multichannel customers become more profitable.

[Insert Table 8 about Here]

Regarding channel usage, we found interestingly that multichannel customers disproportionately use higher margin channels. The lowest margin channel, the store, accounted for 79% of non-multichannel 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 non-multichannel purchases.

To explore further, we computed TT for multichannel customers using two specific channels compared to if they used one specific channel. There are twenty-four possible comparisons (six doubles among the four channels × 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 vs. single channel customers using the Store is €16.32, whereas for Internet/Store vs. Internet, TT equals - €6.30. That is, the Internet/Store customer gains profit vs. being a Store customer, but loses profit vs. being an Internet customer, since Store is a lower margin channel. This suggests a margin effect could be at work. However, the TT for Internet/Phone vs. Internet is €8.52; vs. 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 doesn't explain everything. It is possible that the Internet/Phone customer is more profitable due to higher satisfaction.

In summary, our framework suggests multichannel customers could be more profitable due to self-selection, marketing, using higher margin channels, or higher satisfaction. We can rule out self-selection and marketing. We find that channel margins played a role, since multichannel customers used higher margin channels. This however does not fully explain higher treatment effects, so it is possible that customer satisfaction also 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 this association can be translated into practice by a marketing campaign that produces more multichannel customers, and this 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, 3). The evidence that the individual multichannel customer becomes more profitable than if he or she were not multichannel comes from calculating the treatment effect on the treated (TT), for which we employed propensity score matching (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. We were able to increase multichannel behavior and average customer profitability through a field test. Second is the importance of reactance in the design of communications. This is especially relevant for digital / database marketing, where marketers may interpret targeting as manipulation. A third implication is the importance of field tests. Field tests provide evidence that the relationships found in descriptive analyses are causal.

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

The post-test survey suggests the ability to decrease reactance and enhance perceived behavioral control is important in inducing multichannel shopping. Therefore communications need to strike a delicate balance – they need to 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 he or she is in control, i.e., can become multichannel if he or she wants to. In our research, this was achieved by a communication that clearly communicated 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 simply is to mitigate reactance and convince the customer he or she is in control.

Inducing multichannel shopping is only half the job – multichannel behavior needs to translate to higher profits. In our application, migration to higher margin channels was a prime determinant. This is specific to our study. In fact it is possible that multichannel customers could migrate to lower margin channels, becoming less profitable.[12] The point is that managers pursuing a multichannel strategy should examine their channel margins and consider where the new multichannel customers might migrate (e.g., see Ansari, Mela, and Neslin 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 indeed hedonic (books). It

[12] We thank the Editor for suggesting this discussion.

would be interesting to investigate other categories. Also, it would be useful to investigate contexts where customers are not bound to the firm by a subscription, or buy more frequently.

Second, while 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 just observed customer purchase and we do not know whether the marketing campaigns encouraged customers to *search* across channels. Future work could pursue this avenue and try 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. These customers had never being encouraged to change their channel usage before the field test, so did not have time to form channel preferences with this firm and so were still responsive to marketing (Valentini, Montaguti and Neslin 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 acquiring customers in the first place should be examined.

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

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

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Table 1: Descriptive Statistics of Customer Behavior

Table 1A: Multichannel Behavior

Number of Purchases	Number of Customers	Single Channel	Two Channels	Three Channels	Four Channels
0	9,637 (31%)	n.a.	n.a.	n.a.	n.a.
1	3,545 (12%)	3,545	n.a.	n.a.	n.a.
2	2,240 (7%)	2,182	58	n.a.	n.a.
3	2,819 (9%)	2,628	186	5	n.a.
4	3,998 (13%)	3,519	454	25	n.a.
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

Table 1B: Multichannel Behavior and Customer Profits

Number of Channels	Number of Customers	Percentage	Mean Profits	Median Profits	SD Profits
No purchases	9,637	31.4%	€0.00	€0.00	€0.00
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	0.0%	€43.57	€39.90	€12.97
Total	30,710	100%	€21.25	€19.13	€20.50

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

Experimental Group	n	Percent	Z-statistic vs. control group	p-value
MF	6831	7.3%	0.528	0.598
VPF	6821	7.0%	0.060	0.952
MNF	6810	8.1%	1.942	0.052
VPNF	6829	7.2%	0.343	0.731
Control	3419	7.0%	-	-
Total	30710	7.3%	-	-

Table 3: Multichannel Probit Model of Becoming Multichannel

	Model A			Model B		
Variable	Coef.	Std. Err.	p	Coef.	Std. Err.	p
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	0.000	-1.705	0.035	0.000
Observations	30,710			30,710		
Log likelihood	-8055.281			-7640.572		
Likelihood-ratio test of nested vs. full model $\chi^2(1)=829.418$, p=0.000						
Dependent Variable: Y_i = 1 if customer *i* is multichannel by end of test period; 0 if not.						

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

Table 4A: 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
n	2182	2628	3519	4341	1552	639	235	99	78
Multichannel Mean	€23.36	€37.05	€45.14	€52.92	€59.96	€60.37	€57.34	€67.97	€63.34
n	58	191	479	1026	382	88	20	7	4
Difference	€3.08	€7.87	€8.87	€15.23	€25.83	€24.01	€19.31	€24.77	€13.23
t-stat	2.84	8.59	14.60	26.45	25.95	11.59	3.46	1.50	1.76
p-value	0.006	0.000	0.000	0.000	0.000	0.000	0.003	0.105	0.173

Table 4B: Propensity Score Matching (PSM)

Analysis	Sample				TT	t-stat
	Control (Non-Multichannel)	n	Treatment (Multichannel)	n		
1	All	28455	All	2255	€28.39	71.56
2	≥ 2 Purchases	15273	All	2255	€15.25	38.48
3	3 Purchases	2628	3 Purchases	191	€7.01	7.61
	4 Purchases	3519	4 Purchases	479	€6.87	11.12
	5 Purchases	4341	5 Purchases	1026	€10.18	16.95
	6 Purchases	1552	6 Purchases	382	€19.87	18.58
	7 Purchases	639	7 Purchases	88	€20.77	8.71
4	All	28455	Store-Internet	416	€22.18	33.15
	All	28455	Store-Phone	493	€21.88	34.25
	All	28455	Internet-Phone	531	€34.22	41.52
5	All	28455	2 Channels	2062	€27.64	67.41
	All	28455	3 Channels	190	€39.78	31.51

Table 5: Profitibility per Customer by the End of the Observation Period

Experimental Group	n	Profit[a]	t-statistic vs. control group	p	ROI[b]
MF	6831	€21.17	0.646	0.518	-41%
VPF	6821	€21.05	0.364	0.716	-67%
MNF	6810	€21.78	2.094	0.036	93%
VPNF	6829	€21.19	0.694	0.488	-37%
Control	3419	€20.89	-	-	-
Total	30710	€21.25	-	-	-

[a]The company provided the following margins to compute profits: 52.6% for purchases made using mail order or phone, 51.2% for the Internet, 30.8% for the store, and 29.2% for book of the month.
[b]ROI= [(Unit Profit$_{\text{Marketing Campaign}}$- Unit Profit$_{\text{Control}}$) – Marketing Campaign Cards Cost]/Marketing Campaign Cards Cost.

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

	Model A			**Model B**		
Variable	Coef.	Std. Err.	p	Coef.	Std. Err.	p
MF	0.272	0.429	0.527	0.395	0.405	0.330
VPF	0.154	0.429	0.721	0.327	0.405	0.420
MNF	0.887	0.430	0.039	0.795	0.406	0.050
VPNF	0.292	0.429	0.497	0.298	0.405	0.463
Profit Potential	-	-	-	0.726	0.012	0.000
Constant	20.894	0.350	0.000	7.477	0.397	0.000
Observations	30,710			30,710		
R^2	0.0002			0.1089		
Dependent Variable: $Profits_i$ = profits generated by customer *i* by end of test period.						

Table 7: Why did MNF work? SEM Path Coefficients Estimates

Path From	To	Parameter	Unstd. Coef.	Robust Std. Err	p
MF	Communication Cognitions	γ_{11}	0.104	0.049	0.032
MNF	Communication Cognitions	γ_{12}	-0.012	0.048	0.802
VPF	Communication Cognitions	γ_{13}	-0.045	0.049	0.352
MF	Multichannel Reactance	γ_{21}	-0.180	0.059	0.002
MNF	Multichannel Reactance	γ_{22}	-0.289	0.060	0.000
VPF	Multichannel Reactance	γ_{23}	-0.056	0.058	0.335
MF	Communication Reactance	γ_{31}	-0.146	0.046	0.002
MNF	Communication Reactance	γ_{32}	-0.135	0.047	0.004
VPF	Communication Reactance	γ_{33}	-0.042	0.047	0.369
MF	Perceived Behavioral Control	γ_{51}	-0.039	0.060	0.513
MNF	Perceived Behavioral Control	γ_{52}	0.106	0.059	0.074
VPF	Perceived Behavioral Control	γ_{53}	-0.019	0.062	0.758
Multichannel Reactance	Multichannel Cognitions	β_{42}	-0.211	0.028	0.000
Communication Reactance	Multichannel Cognitions	β_{43}	-0.528	0.042	0.000
Communication Attitude	Multichannel Cognitions	β_{46}	0.320	0.044	0.000
Multichannel Reactance	Communication Attitude	β_{62}	-0.094	0.016	0.000
Communication Reactance	Communication Attitude	β_{63}	-0.319	0.026	0.000
Communication Cognitions	Communication Attitude	β_{61}	0.733	0.038	0.000
Multichannel Reactance	Multichannel Attitude	β_{72}	-0.102	0.032	0.002
Communication Reactance	Multichannel Attitude	β_{73}	-0.060	0.047	0.196
Communication Attitude	Multichannel Attitude	β_{76}	-0.005	0.044	0.912
Multichannel Cognitions	Multichannel Attitude	β_{74}	0.691	0.051	0.000
Multichannel Reactance	Multichannel Intention	β_{82}	0.092	0.032	0.004
Communication Reactance	Multichannel Intention	β_{83}	-0.259	0.041	0.000
Perceived Behavioral Control	Multichannel Intention	β_{85}	0.119	0.032	0.000
Multichannel Attitude	Multichannel Intention	β_{87}	0.440	0.040	0.000

R^2Reactance$_{Multi}$=2%; R^2Reactance$_{Com}$=1%; R^2Communication Cognitions=1%; R^2Perceived Behavioral Control=1%; R^2Communication Attitude=85%; R^2Multichannel Cognitions=52%; R^2Multichannel Attitude=51%; R^2Multichannel Intention=28%

Key: MF represents multichannel/financial campaign, MNF represents multichannel/non-financial campaign, and VPF represents value proposition/financial campaign.

[a] value proposition/non-financial campaign (VPNF) represents the baseline

[b] 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 (γ_{41}=-0.118, p=0.004).

Table 8: TT by Experimental Group

Group	Mean	Std. Dev.	n
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: $F(4, 2250) = 1.67$, $p = 0.155$

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

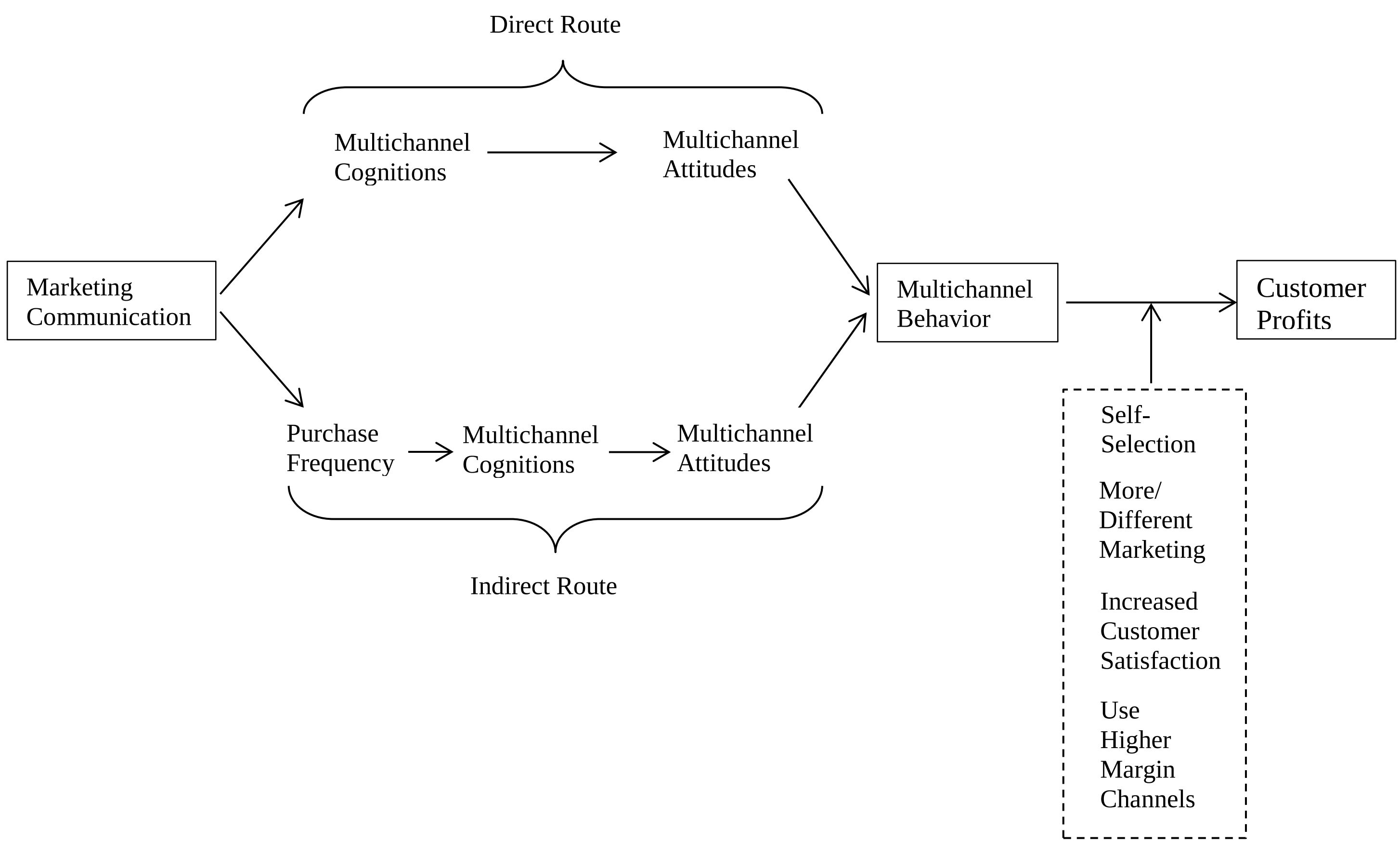


Figure 2: Communications Used in Multichannel Campaigns

A: Financial Multichannel Campaign (MF)

B: Non-Financial Multichannel Campaign (MNF)

C:Financial Value Proposition Campaign (VPF)

D: Non-Financial Value Proposition Campaign (VPNF)

Figure 3: Experimental Design-Timeline

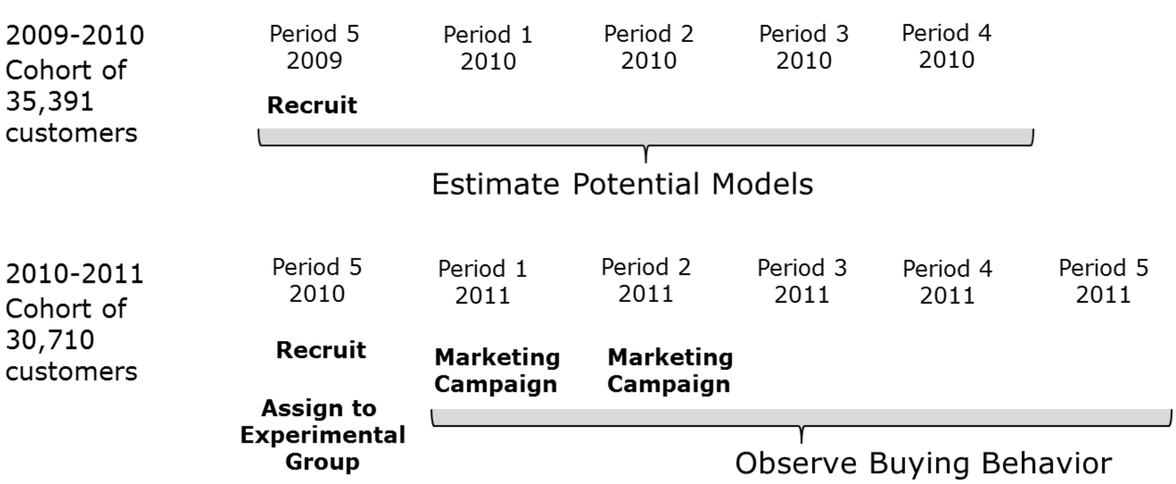


Figure 4: Overview of Analysis Approach

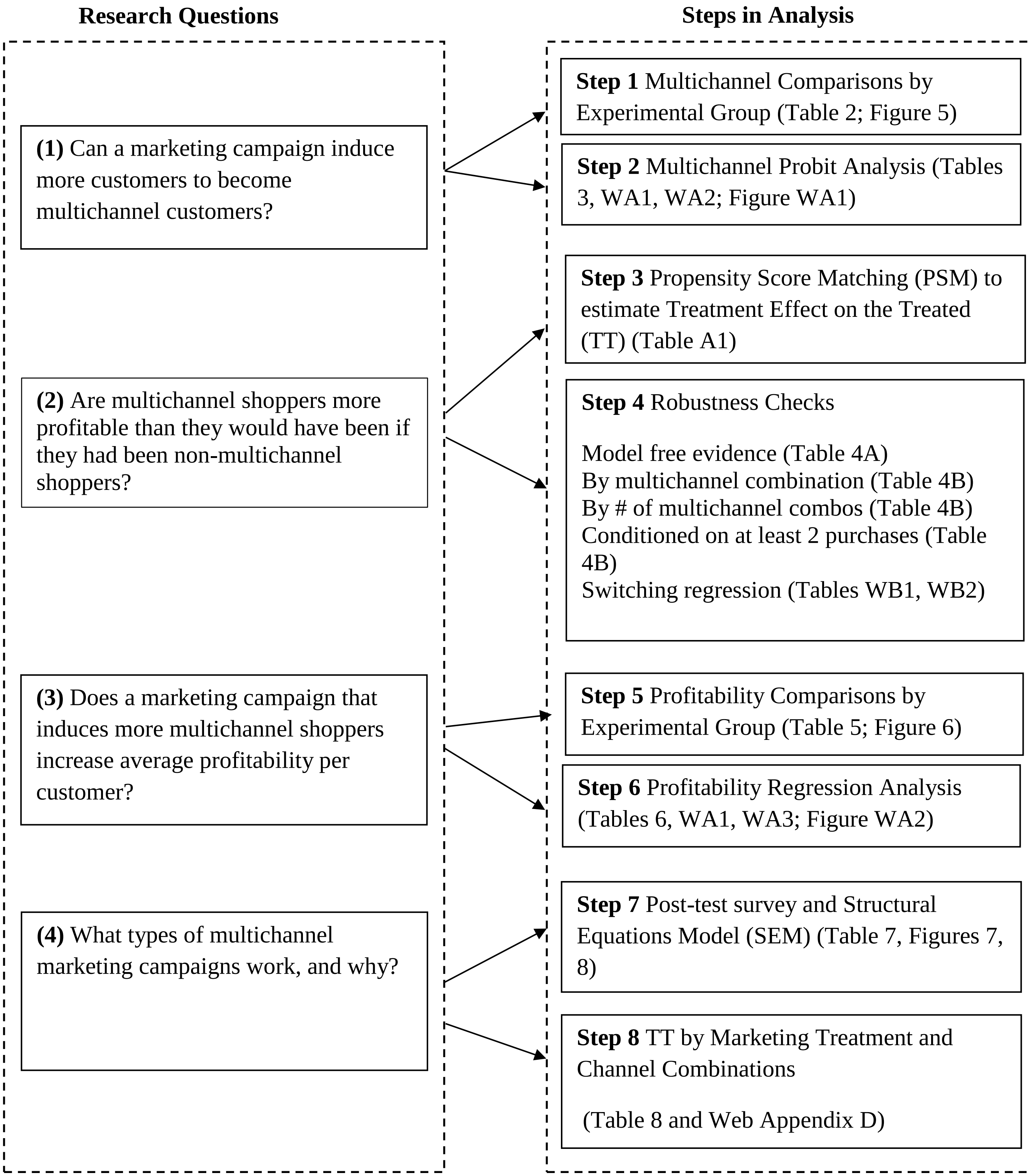
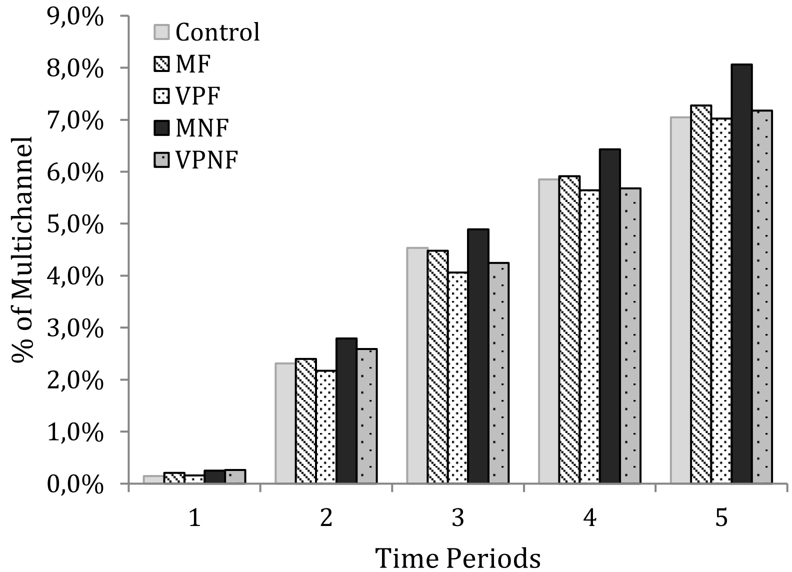


Figure 5: Cumulative Percentage of Customers Who Became Multichannel in Each Period by Marketing Campaign vs. Control Group[a]



[a] A customer is defined as multichannel if he or she has bought from more than one purchase channel starting from the experimental period 1.

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

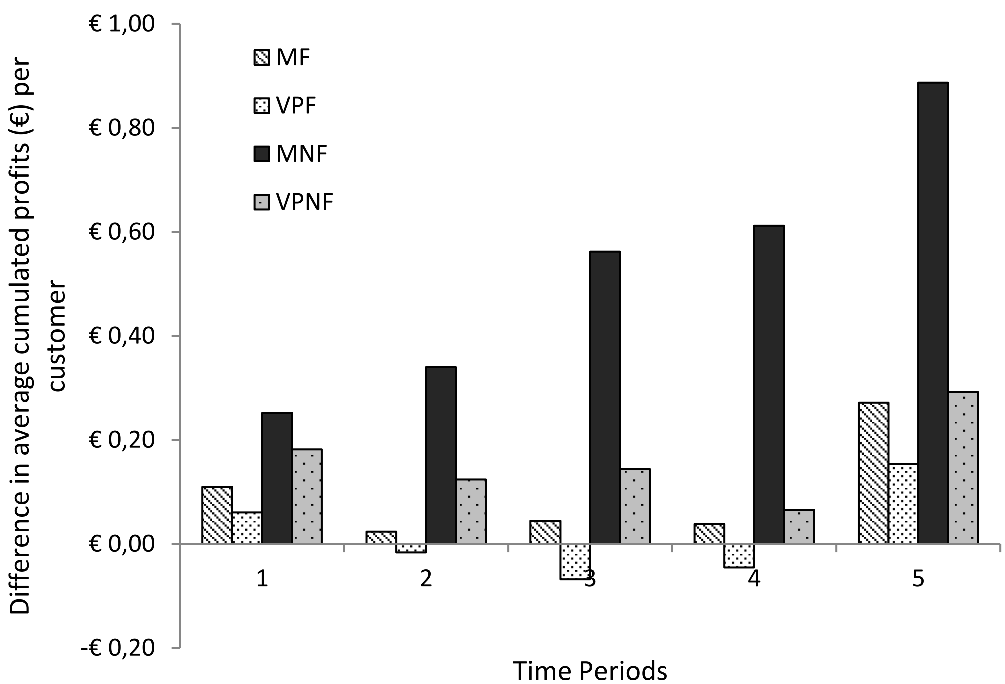
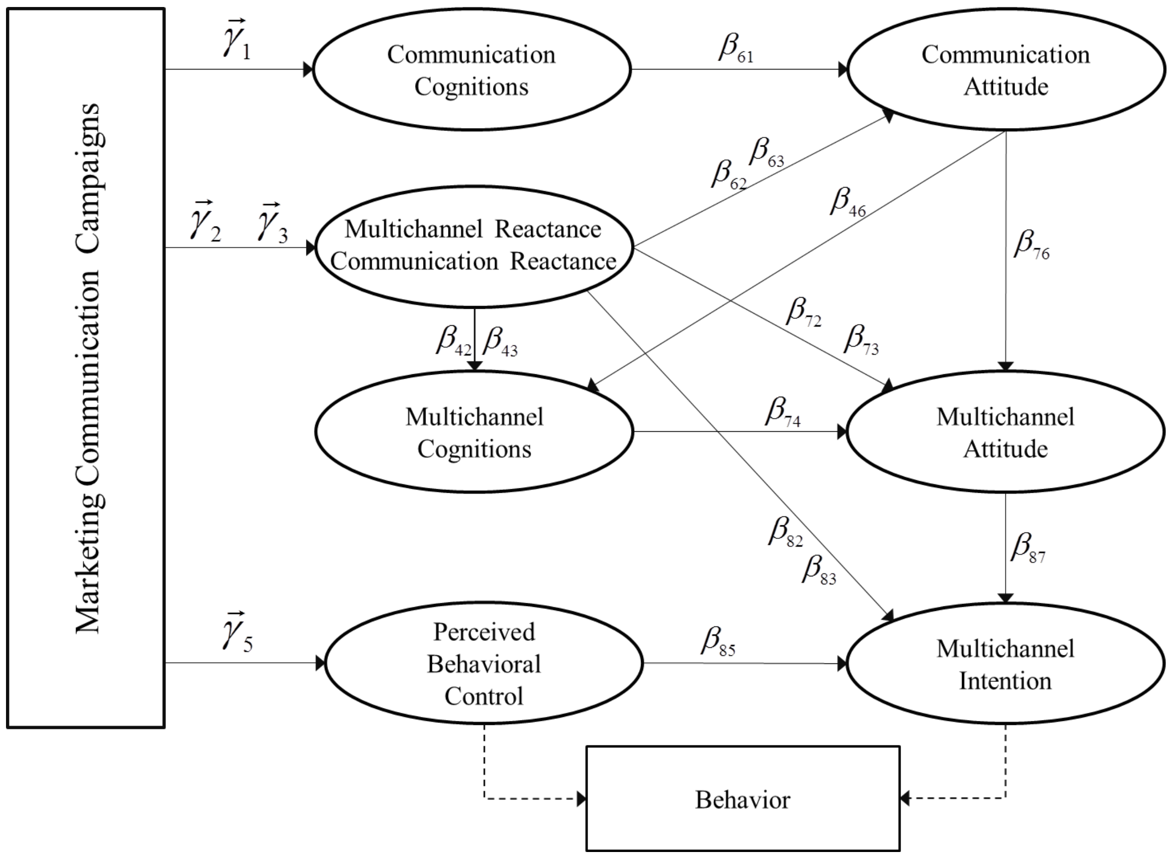
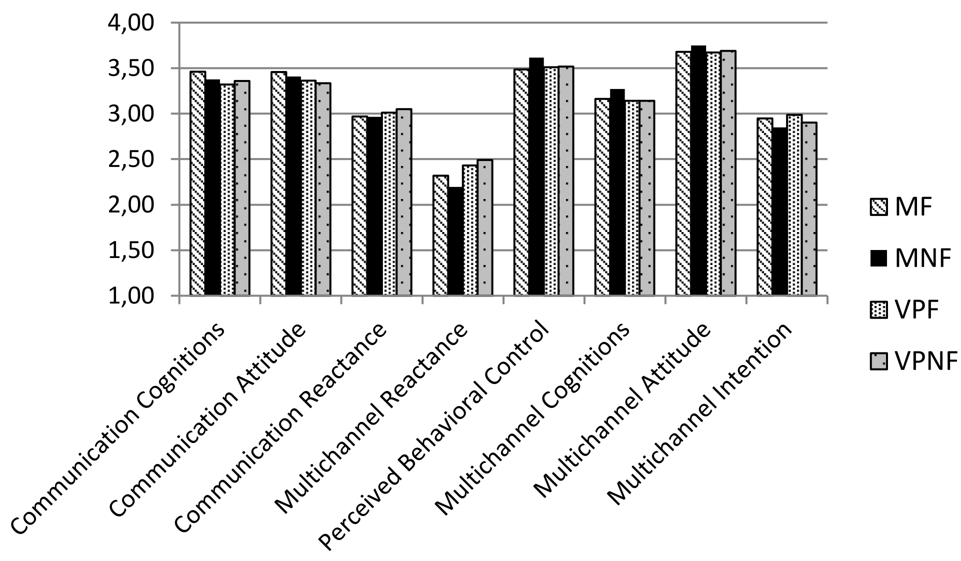


Figure 7: SEM Model[a]



[a] Parameters correspond to the SEM model; See Table 8.

Figure 8: Mean Survey Ratings[a]



[a] Variables were measured using 5-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree."

Appendix

Propensity Score Matching Method

Two approaches to calculate TT are matching procedures and switching regressions. Matching procedures create for each multichannel customer a "matched" composite of non-multichannel customers to serve as a control for that customer. The average profitability of these matched composites provides an estimate of $E[Profit_{0i}|Multichannel_i = 1]$. The matching is based on observed variables that are expected to influence both profits and multichannel behavior. This is so that differences in profits between multichannel customers and non-multichannel 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, and switching regressions work better when instrumental variables are available that correlate with treatment but not with the dependent variable (Wooldridge 2002, p.622-624). Perhaps for these reasons matching, particularly propensity score matching (PSM) (Rosenbaum and Rubin 1983, 1985), is gaining acceptance in marketing (Mithas, Krishan, and Fornell 2005, Boehm 2008, Bronnenberg, Dubé and Mela 2010, Gensler, Leeflang and Skiera 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, Ichimura and Todd 1997, p. 630 for additional references).[13]

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 the likelihood or "propensity" of becoming multichannel.

PSM begins by estimating this propensity. We employed a probit model for that purpose:[14]

$$(A1) \quad Prob(Multichannel_i = 1) \quad = Prob(\alpha + X_i\beta + \varepsilon_i \geq 0),$$

[13] Our results are robust using different kernel functions and different PSM matching approaches (e.g., single nearest-neighbor, Mahanolobis distance, and hybrid matching as proposed by Gensler, Leeflang, and Skiera (2012). The results from these methods were statistically equivalent.

[14] 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.

where α is a constant, X_i is a vector of observed variables, β is the sensitivity to these characteristics, ε_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 A1 displays the X variables we used.

[Insert Table A1 about Here]

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

$$\text{(A2)}\quad w_{ij} = \frac{K\left(\frac{p_i - p_j}{h}\right)}{\sum_{j=1}^{m}\left(\frac{p_i - p_j}{h}\right)}$$

where i (=1 to n) indexes multichannel customers and j (=1 to m) indexes non-multichannel customers. There are thus $n \times m$ weights. $K()$ is a Gaussian kernel function, 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. For this kernel function, h is the standard deviation of a normal distribution. [15] Since the kernel function is monotonically decreasing in $|p_i - p_j|$, higher weights are given to non-multichannel customers with propensity scores closer to customer i. For each multichannel customer, the weights sum to one over the non-multichannel customers. The estimate of $Profit_{0i}$ is therefore $\sum_{j=1}^{m} w_{ij} Profit_{0j}$, and the estimate of $E[Profit_{0i}|Multichannel_i = 1]$ is $\sum_{i=1}^{n}\left(\sum_{j=1}^{m} w_{ij} Profit_{0j}\right)/n$ (Heckman, Ichimura, and Todd 1998, p. 261-262).

Table A1 compares means of the X variables for multichannel customers (A), non-multichannel customers (B), and the matched composites of non-multichannel customers (D). Recall that PSM uses the weights derived from equation (3) to create for each customer i, a composite of non-multichannel customers to serve as a control for that customer. Since we have 2,255 multichannel customers, we have a corresponding set of 2,255 composites created by weighting the 28,455 non-multichannel customers. For example, $\sum_{j=1}^{m} w_{ij} Age_j$ is the composite age of non-multichannel customers for customer i, and $\sum_{i=1}^{n}\left(\sum_{j=1}^{m} w_{ij} Age_j\right)/n$ 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 non-multichannel 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 non-multichannel customers before matching. Column E reports t-tests that show there are no significant mean differences between multichannel customers and the composites of non-multichannel customers. This suggests the weighting produces composites of non-multichannel customers who are equivalent

[15] 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 non-treated samples for each considered covariate). Following Nichols 2007, p. 529), we conduct a sensitivity analysis for our choice of bandwidth. The estimate of TT using the selected bandwidth (i.e. 0.01) equals 28.39, the estimate of TT using twice the selected bandwidth (i.e. 0.02) equals 28.74, finally the estimate of TT using half the selected bandwidth (i.e. 0.005) equals 28.27.

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 $\sum_{i=1}^{n}\left(\sum_{j=1}^{m} w_{ij} Profit_{0j}\right)/n$, which equals €22.36 for our data. The average treatment effect on the treated (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).[16]

[16] Approximate standard error (SE) is calculated following the procedure described by Leuven and Sianesi (2003).

Table A1: Propensity Score Matching (PSM) – Comparisons of Mean Customer Descriptors (X's)

Variable	Variable Description	A: Multichannel Customers	B: Non-Multichannel Customers	C: t-stat A vs.B	D: Matched Composite Non-Multichannel	E: t-stat A vs. D
Age	Age in years	39.65	38.50	3.22	39.61	0.09
Female	Fraction of female	0.75	0.72	3.93	0.76	0.00
Street Agents	Fraction of customers acquired by on-the-street agents	0.39	0.48	-8.67	0.39	-0.32
North	Fraction of customers living in the north of the country	0.71	0.51	18.13	0.69	1.21
Early Email	Fraction of customers who provided their email address during the acquisition quarter	0.59	0.52	6.37	0.59	0.16
Nov Acquisition	Fraction of customers acquired in November	0.26	0.29	-3.14	0.27	-0.31
Dec Acquisition	Fraction of customers acquired in December	0.0004	0.0001	1.09	0.0003	0.24
Big City	Fraction of customers living in a big city (more than 500 thousand inhabitants)	0.09	0.15	-7.67	0.09	-0.52
Average City	Fraction of customers living in an average city (100 – 499 thousand inhabitants)	0.04	0.07	-5.49	0.04	-0.36
Franchisee	Fraction of 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
Initial Returns	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
Initial Price Cut	Average amount (€) of price discounts used by the customer in the acquisition period	€0.33	€0.24	1.47	€0.34	-0.13
Initial Store Promo	Fraction of 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
Initial Revenues	Average € spent during the acquisition quarter by the customer	€11.60	€7.41	11.46	€11.53	0.12
Initial Purchase	Fraction of 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 non-multichannel customers.
Column D is computed across all 2,255 multichannel customers using the weighted matched composite X values for each multichannel customer *i* (equation (3)). E.g., let Age_j = the age of non-multichannel customer j. Then Weighted $Age_i = \sum_{i=1}^{m} w_{ij} Age_j$, and the average of these weighted ages is 39.61

WEB APPENDIX

WEB APPENDIX A
Multichannel and Profitability Covariate Analysis

The multichannel potential probit is estimated on Cohort 1 customers as follows. We first calculate several predictor variables available during the acquisition period. These are listed in Table WA1 and include customer characteristics (e.g., age, gender), transaction variables such as returns and purchase levels, and channel variables representing the channel used by the customer during the acquisition period. It is important that these variables are all computed during the acquisition period, because we can then apply the estimated model to Cohort 2 customers without having to look at their behavior during the test period, which is the behavior we want to predict. Table WA2 shows the estimated Cohort 1 probit and Figure WA1 shows a lift chart to establish its predictive validity. Figure WA1 shows excellent lift for example in that actual multichannel behavior declines monotonically by decile, and the top decile is approximately five times more likely to be multichannel than average. Hence we are confident we can score Cohort 2 customers using this model and use the resulting score as a covariate to help predict whether they become multichannel in the experimental period.

Table WA1: Independent Variables Used in the Multichannel and Profit Potential Models

Class	Variable	Description
Customer Charcteristics	Age	Age of the customer
	Female	Dummy variable that takes value 1 if the customer is a female and 0 otherwise
	North	Dummy variable that takes value 1 if the customer lives in the north of the country, and 0 otherwise
	Big City	Dummy variable that takes value 1 if the customer lives in a big city (more than 500 thousand inhabitants), and 0 otherwise
	Average City	Dummy variable that takes value 1 if the customer lives in an average city (499 – 100 thousand inhabitants), and 0 otherwise
	Early Email	Dummy variable that takes value 1 if the customer provided her email address during the acquisition quarter, and 0 otherwise
	Franchisee	Dummy variable that takes value 1 if the store closest to the customer place of residence is run by a franchisee, and 0 if the closest store is run directly by the firm.
	Street Agent	Dummy variable that takes value 1 if the customer was acquired through an on-the-street agent, and 0 otherwise
	Nov Acquisition	Dummy variable that takes value 1 if the customer was acquired in November, and 0 otherwise
	Dec Acquisition	Dummy variable that takes value 1 if the customer was acquired in December, and 0 otherwise
Channel Behavior	Initial Mail Order	Dummy variable that takes value 1 if the customer purchased through the mail order during the acquisition time unit and 0 otherwise
	Initial Web	Dummy variable that takes value 1 if the customer purchased through the Internet during the acquisition time unit and 0 otherwise
	Initial Store	Dummy variable that takes value 1 if the customer purchased through the store during the acquisition time unit and 0 otherwise
	Initial Phone	Dummy variable that takes value 1 if the customer purchased through the phone during the acquisition time unit and 0 otherwise
Transaction Variables	Initial Store Promo	Dummy variable that takes value 1 if in the closest store was running special store promotions, and 0 otherwise
	Initial Returns	Total value (€) of products returned to the firm by the customer *i* in the acquisition period.
	Initial Price Cut	Total value (€) of price discounts used by the customer *i* in the acquisition period
	Initial Revenues	Total amount (€) spent during the acquisition quarter

Table WA2: Estimates for Probit Model Predicting the Probability of Becoming a Multichannel Shopper – Multichannel Potential Model

Variable	Coef.	Std.Err.	p
Age	0.004	0.001	0.000
Female	0.103	0.025	0.000
Street Agent	-0.165	0.024	0.000
North	0.226	0.031	0.000
Early Email	0.230	0.027	0.000
Nov Acquisition	0.200	0.029	0.000
Dec Acquisition	0.273	0.037	0.000
Big City	-0.079	0.041	0.056
Average City	-0.118	0.045	0.009
Franchisee	-0.044	0.023	0.057
Initial Mail Order	1.651	0.077	0.000
Initial Web	1.500	0.074	0.000
Initial Store	0.296	0.047	0.000
Initial Phone	1.143	0.061	0.000
Initial Store Promo	-0.117	0.044	0.008
Initial Returns	-0.004	0.003	0.185
Initial Price Cut	-0.007	0.003	0.011
Initial Revenues	0.000	0.001	0.950
Constant	-2.146	0.053	0.000

Dependent Variable: $Multichannel_i$
Number of obs = 35,391
LR $\chi^2(18)$ = 1892.0, p=0.000, PseudoR^2=0.114

Table WA3: Estimates for Regression Model Predicting Customer Profitability – Profitability Potential Model

Variable	Coef.	Std.Err.	p
Age	0.160	0.005	0.000
Female	1.375	0.170	0.000
Street Agent	2.742	0.167	0.000
North	2.442	0.213	0.000
Early Email	2.615	0.185	0.000
Nov Acquisition	1.496	0.202	0.000
Dec Acquisition	1.907	0.245	0.000
Big City	0.083	0.270	0.757
Average City	-0.028	0.284	0.922
Franchisee	0.353	0.167	0.034
Initial Mail Order	23.080	0.834	0.000
Initial Web	21.140	0.777	0.000
Initial Store	0.445	0.341	0.191
Initial Phone	16.770	0.580	0.000
Initial Store Promo	-3.015	0.360	0.000
Initial Returns	-0.415	0.034	0.000
Initial Price Cut	-0.129	0.017	0.000
Initial Revenues	0.501	0.010	0.000
Constant	3.905	0.347	0.000

Dependent Variable: $Profit_i$
Number of obs = 35,391
R^2 = 0.275

Figure WA1: Lift Chart Performance of Multichannel Potential Model Estimated on Cohort 1

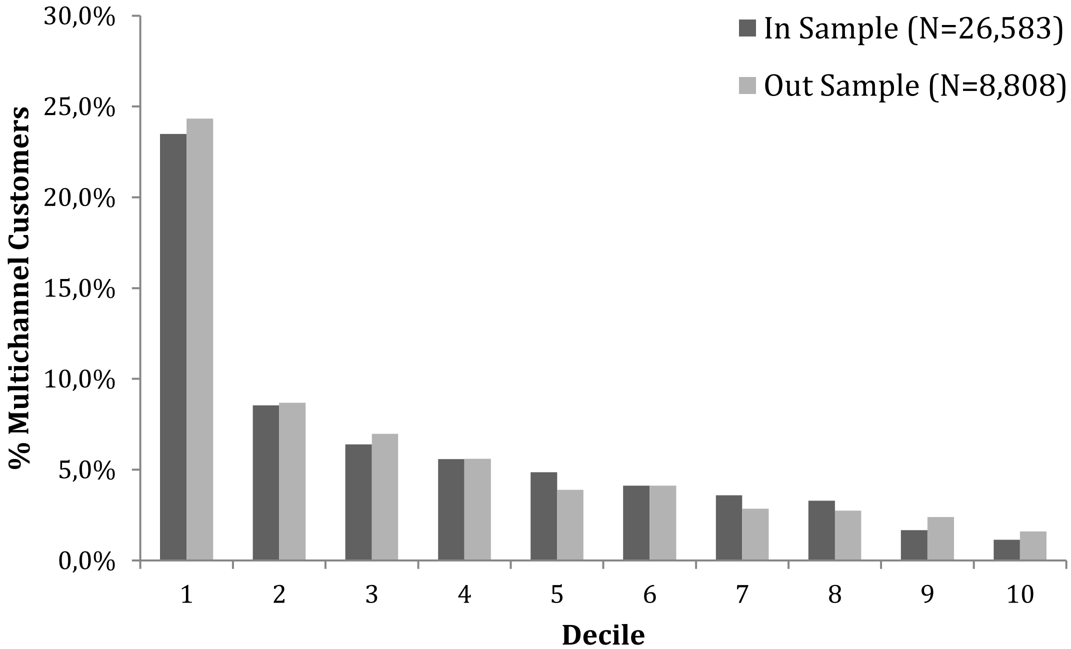
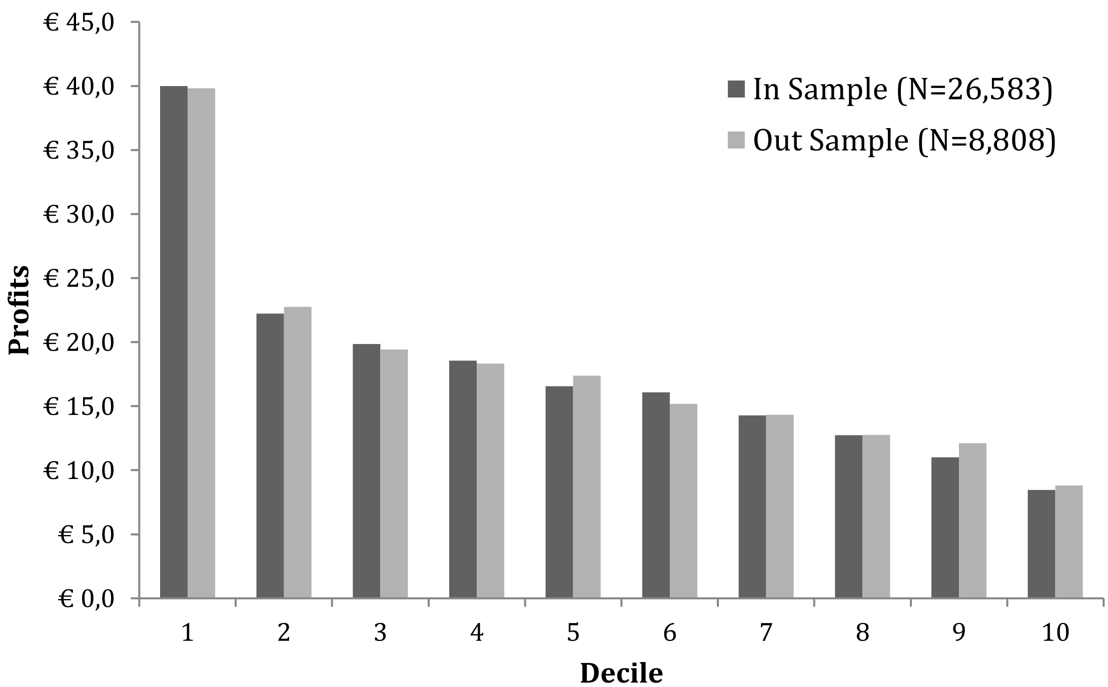


Figure WA2: Lift Chart Performance of Profitability Potential Model Estimated on Cohort 1



WEB APPENDIX B
Switching Regression Analysis of Whether Multichannel Customers Become More Profitable

Switching regressions consist of a selection model (in our case, did the customer become multichannel) and then two regression equations – one for the profitability of multichannel customers; the other for the profitability of non-multichannel customers. The probit selection model is defined as:

$$(WB1) \quad r_i^* = x_i'\beta$$
$$= \iota + \delta MPOT_i + \kappa_1 MF_i + \kappa_2 VPF_i + \kappa_3 MNF_i + \kappa_4 VPNF_i + \nu_i$$

Where:

$$r_i = \begin{cases} 1 & if \quad r_i^* > 0 \\ 0 & if \quad r_i^* \le 0 \end{cases}$$

And

r_i	=	Dummy variable that takes value 1 if customer *i* shops using at least two different channels during the experimental observation period (a year), and 0 otherwise.
$MPOT_i$	=	*Multichannel Potential*, the probability that customer *i* becomes multichannel in the absence of marketing efforts. This is customer *i*'s score on the probit model described in Table WA2, and Figure WA1 in Web Appendix A .
MF_i	=	Dummy variable that takes value 1 if customer *i* was randomly assigned to the multichannel/financial experimental group, and 0 otherwise.[17]
VPF_i	=	Dummy variable that takes value 1 if customer *i* was randomly assigned to the value proposition/financial experimental group, and 0 otherwise.
MNF_i	=	Dummy variable that takes value 1 if customer *i* was randomly assigned to the multichannel/non-financial experimental group, and 0 otherwise.
$VPNF_i$	=	Dummy variable that takes value 1 if customer *i* was randomly assigned to the value proposition/non-financial experimental group, and 0 otherwise.
x'_i	=	Vector of {$MPOT_i$, MF_i, VPF_i, MNF_i, $VPNF_i$} for each customer.
β	=	Vector of {$\iota, \delta, \kappa_1, \kappa_2, \kappa_3, \kappa_4$}, i.e., the coefficients for the probit model.

[17] The control group (i.e. no campaign) represents the base case.

Equations (WB2) and (WB3) are the switching regression equations used to model profits:

$$(WB2) \qquad y_{0i} = \alpha_0 + \sum_{l=1}^{L} \beta_{0l} O_{li} + \varepsilon_{0i} \qquad if \quad r_i = 0$$

$$(WB3) \qquad y_{1i} = \alpha_1 + \sum_{l=1}^{L} \beta_{1l} O_{li} + \varepsilon_{1i} \qquad if \quad r_i = 1$$

Where:

y_i = Cumulative profit (€) that customer *i* generated during the experimental period. The variable y_{0i} corresponds to profits cumulated by a single channel customer, and y_{1i} corresponds to profits cumulated by a multichannel customer.

O_{li} = A set of *L* observable customer-level variables like age, gender, etc. available at the time the customer is acquired (variables described in Table WA1). We replaced the Channel Behavior variables in Table WA1 by a new dummy variable, "Initial Purchase", indicating whether the customer made an initial purchase in the acquisition period.[18]

The error terms of equations (WB2) and (WB3) are assumed normal with variances σ_0^2 and σ_1^2 and covariances σ_{02} and σ_{12} with ν_i (the error term of the probit model equation 1). These covariances reflect unobserved factors that affect both becoming multichannel (equation WB1) and profits depending on whether or not the customer becomes multichannel (equations 2 and 3).

Following Verbeek (2008, pp. 255-257), we compute the treatment effect on the treated (TT) for customer *i* as follows:

$$(WB4) \quad \begin{aligned} TT_i &= E[y_{1i} - y_{0i} \mid \mathrm{O_{li}},\ \mathrm{r_i} = 1] = (\hat{\alpha}_1 - \hat{\alpha}_0) + \sum_{l=1}^{L} O_{ji}\left(\hat{\beta}_{1l} - \hat{\beta}_{0l}\right) + E\{\varepsilon_{1t} - \varepsilon_{0t} \mid O_{li}, r_i = 1\} \\ &= (\hat{\alpha}_1 - \hat{\alpha}_0) + \sum_{l=1}^{L} O_{ji}\left(\hat{\beta}_{1l} - \hat{\beta}_{0l}\right) + (\hat{\sigma}_{12} - \hat{\sigma}_{02}) \frac{\phi(x_i'\hat{\beta})}{\Phi(x_i'\hat{\beta}))} \end{aligned}$$

where ϕ and Φ respectively are the distribution and cumulative distribution functions of the standard normal distribution, and the " ^ " signifies estimated parameters.

Equation (WB4) has an important interpretation. The first term ($(\hat{\alpha}_1 - \hat{\alpha}_0)$) is the "baseline" treatment effect (see equations WB2 and WB3), i.e., that portion of TT that is

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[18] Our motivation for doing this is twofold: (1) The C_i variables indicate whether the customer purchased in a particular channel during the acquisition period. They therefore contain two aspects – purchase and channel choice. The channel choice aspect indicates a tendency for multichannel behavior. The purchase aspect indicates potential for profits. We therefore created Initial Purchase to capture the purchase aspect for the profit equation. (2) As noted by Verbeek (2008, p. 256), the switching regression system is identified parametrically so technically one could include the exact same variables in the selection and regression equations. However, Verbeek recommends that some variables be excluded from the regression equations to aid identification. Excluding the C_i variables but creating the Initial Purchase dummy accomplishes this.

common to all customers. The next term ($\sum_{l=1}^{L} O_{ji}\left(\hat{\beta}_{1l} - \hat{\beta}_{0l}\right)$) represents the impact of factors we can observe. This equals zero for example if all observed factors influence multichannel and non-multichannel profitability the same. The third term, ($(\hat{\sigma}_{12} - \hat{\sigma}_{02})\frac{\phi(x_i'\hat{\beta})}{\Phi(x_i'\hat{\beta})}$) represents the impact of multichannel on customer *i* due to factors we cannot explicitly observe, i.e., self-selection. This equals zero when the unobserved factors are uncorrelated with the profit equations ($\hat{\sigma}_{02} = \hat{\sigma}_{12} = 0$), or if they are correlated but the correlation is exactly the same with both multichannel and non-multichannel profitability ($\hat{\sigma}_{02} = \hat{\sigma}_{12}$). The term $\frac{\phi(x_i'\hat{\beta})}{\Phi(x_i'\hat{\beta})}$ is the inverse Mills ratio and is a decreasing function of $x_i'\hat{\beta}$. This means that if observed variables do not have a strong impact on becoming multichannel (from equation (1), lower $x_i'\hat{\beta}$ means less likely to become multichannel), the unobserved contribution to TT is greater.

In short, the expression for TT allows us to calculate the impact of multichannel purchasing on profits while controlling for observed and unobserved factors. In fact, we can decompose the impact of multichannel purchasing on each customer in terms of a baseline + observable factors pertaining to that customer + unobservable factors pertaining to that customer. We calculate equation (B4) and each of its components for each customer so we can not only measure TT but decompose it into baseline, observed, and unobserved effects. To the extent that the unobserved component has an impact, the switching regression is demonstrating its value by including an important cause of multichannel customer profitability.

We estimate equations (WB1), (WB2), and (WB3) in *STATA* using the two-stage approach (Maddala 1983, p. 121 and p. 223-225). We first estimate the probit model (equation WB1) using maximum likelihood. This provides us with estimates of the inverse Mills ratio. We then run separate regressions for equations (WB2) and (WB3) including the single channel customers in equation (B2), and the multichannel customers in equation (WB3). This produces consistent estimates of all the parameters in equations (WB1), (WB2), and (WB3) (Maddala 1983, p. 121, and p.223-225).

Switching regression results

Table WA2 in Web Appendix A shows the estimation results for the probit selection model (equation WB1), since it is exactly the same model we used earlier for the covariate analysis. Table WB1 shows the estimates of the regression equations (WB2) and (WB3). These estimates provide the means to calculate TT for the customers who became multichannel. The estimates themselves therefore are not of direct interest. However, Table WB1 shows that multichannel shopping has a positive baseline impact as $\hat{\alpha}_1$ (68.920, p = 0.000) is greater than $\hat{\alpha}_0$ (0.261, p = 0.493) (see equation B4). Also, note the covariances between the error terms of the multichannel and profit models are significant ($\hat{\sigma}_{12}$ = -9.781, p =0.000, $\hat{\sigma}_{02}$ = -36.500, p =0.000). This might suggest that factors we do not observe influence both multichannel behavior and customer profits (Verbeek 2008). Since $\hat{\sigma}_{12} > \hat{\sigma}_{02}$, these unobserved factors contribute positively to TT, so in principle not considering them could under-estimates TT.

Table WB2 displays TT averaged across customers and its decomposition into the baseline impact, the observable component, and the unobserved component (equation WB4). We also estimate the precision (standard error) of these statistics using 250 bootstrap samples. Table WB2 shows that on average, the customer who becomes multichannel generates an additional profit of €100.28 compared to if that customer had not become multichannel. The baseline contribution to TT is € 68.66, the mean contribution of observables is - €16.43, and the mean contribution from unobservables is €48.06. The estimate of TT is positive and that is important, but lacked face validity. In particular, the model inferred that the counterfactual profit level for the average customer was negative 50, i.e., a loss of 50 Euros. While it is possible the multichannel customer would become unprofitable if that customer were single channel, - €50 was out of the range of our data and hence not credible. We believe the problem was the fit of the probit selection model wasn't very good (pseudo $R^2 = 0.052$). As a result, the switching regression assumed there were a lot of unobserved factors influencing multichannel behavior. Note as stated above, the mean contribution from unobservables is €48.06. Therefore, as discussed in the text, we decided to use these result as a robustness check (indeed these results suggest TT > 0), and use propensity score matching as our main approach to estimate TT.

Table WB1: Estimates for Switching Regression Profits Equations Cohort 2

	Multichannel (equation WB2)			Single Channel (equation WB3)		
Variable	Coef.	Std. Err.	p	Coef.	Std. Err.	p
Age (β_{11}, β_{01})	0.078	0.024	0.001	0.146	0.007	0.000
Female (β_{12}, β_{02})	-0.262	0.842	0.755	1.046	0.230	0.000
Street Agent (β_{13}, β_{03})	0.592	0.777	0.446	4.776	0.217	0.000
North (β_{14}, β_{04})	0.283	1.009	0.779	2.309	0.257	0.000
Early Email (β_{15}, β_{05})	-0.624	0.815	0.444	1.468	0.226	0.000
Nov Acquisition (β_{16}, β_{06})	-1.150	0.887	0.195	1.837	0.235	0.000
Dec Acquisition (β_{17}, β_{07})	-3.081	17.090	0.857	-1.708	8.668	0.844
Big City (β_{18}, β_{08})	-1.205	1.514	0.426	0.193	0.346	0.578
Average City (β_{19}, β_{09})	-1.128	2.030	0.579	-0.013	0.457	0.978
Franchisee (β_{110}, β_{010})	-2.670	0.758	0.000	-0.795	0.223	0.000
Initial Store Promo (β_{111}, β_{011})	-6.203	1.358	0.000	-2.492	0.406	0.000
Initial Returns (β_{112}, β_{012})	0.313	0.117	0.007	-0.440	0.040	0.000
Initial Price Cut (β_{113}, β_{013})	0.078	0.102	0.447	-0.184	0.024	0.000
Initial Revenues (β_{114}, β_{014})	0.065	0.032	0.043	0.034	0.010	0.001
Initial Purchase (β_{115}, β_{015})	-4.584	1.254	0.000	12.080	0.406	0.000
Covariance between the error terms (σ_{12}, σ_{02})	-9.781	1.464	0.000	-36.500	1.577	0.000
Constant (α_1, α_0)	68.920	3.634	0.000	0.261	0.493	0.596
Dependent Variable: $Profit_i$	Sample (Multichannel=1) Observations:= 2,255 F(16, 2238) = 11.85, p=0.000			Sample (Multichannel=0) Observations:= 28,455 F(16, 28438) = 320.34, p=0.000		

Table WB2: Switching Regression

Components[a]	Mean Profit Impact[b]	Bootstrap Std. Err.[c]	Mean Proportion[d]	Bootstrap Std. Err.[c]
Baseline	€68.66	€0.81	51.0%	0.83%
Observables	-€16.43	€0.18	13.5%	0.44%
Unobservables	€48.06	€2.84	35.5%	1.24%
Average TT	**€100.28**	**€3.66**	**100.0%**	

[a] Computation performed for each of the 2,255 customers who became multichannel, then aggregated to calculate mean TT and mean proportion of total.

[b] Computation utilizes approach described by Verbeek (2008, p. 255):

Baseline= $\alpha_1 - \alpha_0$

Observables= $\sum_{l=1}^{L} O_{li}\left(\beta_{1l} - \beta_{0l}\right)$

Unobservables= $E\{\varepsilon_{1i} - \varepsilon_{0i} \mid O_{li}, r_i = 1\}$

[c] Bootstrap based on 250 samples drawn with replacement. For each sample, we re-estimated the switching regression and calculated the customer-level and mean statistics.

[d] To calculate this proportion, for each customer we divided the absolute value of each component by the sum of the absolute values for all three components. We then aggregated to calculate the mean.

WEB APPENDIX C
Post-Test Survey

Table WC1: Measurement Scales for Post-Test SEM Analysis

Variable	**Cronbach's Alpha**	**Items**
Communication Cognitions	0.77	This communication catches my attention This communication is pleasant to look at The message of this communication is clear This communication is convincing
Communication Attitude	0.88	This is an effective communication I like this communication This communication reflects well on the company This communication tries to fool me This communication is interesting My overall reaction to this communication is favorable
Communication Reactance (Scale adapted by Hong and Faedda 1996)	0.92	This communication gave me a negative feeling I feel like acting against the wishes of Book-R-Us This communication made me feel annoyed This communication made me feel angry This communication made me feel irritated
Multichannel Reactance (Scale adapted by Hong and Faedda 1996)	0.82	I feel that my freedom to choose a channel to make my purchases is threatened I feel that I am forced to use a channel I don't want to use to buy from Book-R-Us in the future I believe I can choose between multiple channels to buy from Book-R-Us I feel that I am free to choose between using my current channel and the other available channels to buy from this Book-R-Us I feel that this communication forces me into a specific behavior
Perceived Behavioral Control	na	I could easily become a multichannel shopper at Book-R-Us if I wanted to
Multichannel Cognitions	0.84	Multichannel shopping ensures I'll buy the right thing Multichannel shopping makes my life easier Multichannel shopping makes shopping more fun Multichannel purchasing guarantees the personal assistance I am looking for
Multichannel Attitude	0.85	I like the idea of being a multichannel shopper Buying through a variety of channels is the smart thing to do My overall feeling about multichannel shopping is favorable
Multichannel Intention	0.87	I expect to do more multichannel shopping in the future I intend to try a different channel the next time I buy It is possible that I'll do more multichannel shopping in the future

All items were measured using a 5-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree."

Manipulation Checks

There are three types of communications attributes: (1) those for which there should be no differences among communications, (2) those for which there should be differences because they relate to our manipulations, and (3) those for which there may or may not be differences due to the innate nature of the communication itself.

An example of a type 1 attribute is "imagery" of the communication. Regarding imagery, we asked respondents to rate the communications on the following (agree/disagree format; monadic testing): "This communication uses nice images, colors, and it is pleasant to look at." The means and F-test for differences are as follows:

Mean Scores: This communication uses nice images, colors, and it is pleasant to look at.				
MF	**MNF**	**VF**	**VNF**	**p-value**
3.27	3.29	3.20	3.26	0.376

This shows that any differences in consumer response were not due to the attractiveness of the communication *per se*:

As a manipulation check to make sure the right messages were communicated, we asked the following two questions, and show in bold the numbers we wanted to be higher.

Item	**MF**	**MNF**	**VF**	**VNF**	**p-value**
This communication provides a clear financial incentive.	**3.75**	2.80	**3.59**	3.42	0.000
This communication is trying to get me to buy from multiple channels.	**3.80**	**3.89**	3.47	3.38	0.000

As desired, customers clearly perceived that MF and VF provided a financial incentive. They also were able to discern that MF and MNF were more about multichannel behavior compared to VF and VNF.

The above comparisons show that the communications were correctly perceived and that there was no inherent advantage to one communication in terms of imagery.

As noted above, there are some attributes of communications that may be innately different. For example, we included communications attributes pertaining to attention, clarity and convincingness. The mean results are below and show some differences:

Item	**MF**	**MNF**	**VF**	**VNF**	**p-value**
This communication catches my attention.	3.69	3.27	3.43	3.34	0.000
The message of this communication is clear.	3.74	3.73	3.47	3.56	0.000
This communication is convincing.	3.32	3.25	3.18	3.27	0.078

The financial communications (MF and VF) were more likely to capture attention. This may be due to the particular presentation of the coupons, but we were constrained by company policy on how to present coupons, and in fact it makes sense that a financial incentive will be more likely to capture attention.

The communications involving multichannel (MF and MNF) were perceived to be clearer than those that involved value proposition (VF and VNF). This may have to do with particulars of copy, or to the innate ease of communicating something more specific (multichannel) vs. more general (the value proposition of the company).

There is little difference in the convincingness of the communications. The p-value is marginal and the magnitudes of the differences are not very strong.

In summary, there are three types of communications attributes: (1) those for which there should be no differences among communications, (2) those for which there should be differences because they involve attributes we manipulated, and (3) those for which there may or not be differences due to the innate nature of the communication. We find for the first type (imagery/pleasantness) indeed there are no differences. On the second type (financial and multichannel message) there are differences we intended. On the third type (attention, clarity, convincingness) there are some differences but it isn't clear whether these are due to copy execution or the innate nature of what was being communicated.

Web Appendix D
TT Calculations for Specific Channel Combinations

Sample				TT	t-stat
Control (Non-Multichannel)	n	Treatment (Multichannel)	n		
Only Internet	972	Internet - Phone	531	€8.52	7.62
Only Phone	2,563	Internet - Phone	531	€17.54	17.47
Only Store	9,891	Internet - Phone	531	€30.82	36.06
Only Mail Order	701	Internet - Phone	531	€9.64	5.92
Only Internet	972	Store-Internet	416	-€6.30	-4.62
Only Phone	2,563	Store-Internet	416	€4.99	3.37
Only Store	9,891	Store-Internet	416	€16.32	24.41
Only Mail Order	701	Store-Internet	416	-€4.44	-2.06
Only Internet	972	Store-Phone	493	-€4.93	-3.47
Only Phone	2,563	Store-Phone	493	€3.99	3.62
Only Store	9,891	Store-Phone	493	€14.23	22.09
Only Mail Order	701	Store-Phone	493	-€5.64	-3.48
Only Internet	972	Store- Mail Order	155	-€2.38	-1.12
Only Phone	2,563	Store- Mail Order	155	€5.71	4.01
Only Store	9,891	Store- Mail Order	155	€17.96	17.01
Only Mail Order	701	Store- Mail Order	155	-€3.83	-2.11
Only Internet	972	Internet- Mail Order	82	€12.31	5.67
Only Phone	2,563	Internet- Mail Order	82	€23.34	11.06
Only Store	9,891	Internet- Mail Order	82	€34.14	16.82
Only Mail Order	701	Internet- Mail Order	82	€13.64	5.84
Only Internet	972	Phone- Mail Order	385	€7.23	2.46
Only Phone	2,563	Phone- Mail Order	385	€18.00	18.47
Only Store	9,891	Phone- Mail Order	385	€29.02	30.44
Only Mail Order	701	Phone- Mail Order	385	€8.00	5.71