"Are multichannel customers really more valuable? An analysis of banking services"

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(*) The name of the authors appear in alphabetical order. Jesus Cambra-Fierro, Iguacel Melero-F. Javier Sese Polo, and are members of the research Generes group (http://generes.unizar.es/en/), and they appreciate the financial support received from the projects ECO2014-54760 (MICINN, FEDER), and S09-PM062 (Gobierno de Aragon and Fondo Social Europeo) as well as from the program "Ayudas a la Investigación en Ciencias Sociales, Fundación Ramón Areces". They want to show their gratitude to the collaborating bank for providing the data for the analyses. The authors want to show their gratitude to Prof. Goldenberg, Prof. Lehmann, and the anonymous reviewer for the guidance, encouragement, comments and suggestions received during the review process.

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Abstract

Conventional wisdom suggests that multichannel customers are more profitable. With a focus on goods, Kushwaha and Shankar (2013) demonstrate that it depends on the type of product purchased. Our study replicates their research by looking at the profit implications of multichannel customers in services (banking). Our research shows that fully multichannel customers (using all channels available) are not the most profitable for service firms. We find that concentrating the interactions through high-margin channels as well as using specific dual-channel combinations produce improvements in profitability.

Key-words: Multichannel customer management; Customer profitability; Banking services; Time series.

1.-Introduction

Whether multichannel customers are really more profitable has become a central research question in marketing (Neslin et al. 2006). The study by Kushwaha and Shankar (2013) (K&S) intends to provide an answer to this question in a product context. They begin with the notion that "across all product categories, multichannel customers have a higher monetary value of purchases than single-channel customers". This thesis is based on three main reasons: a) additional channels provide greater convenience value for customers, increasing their purchase frequency and accelerating purchases across multiple items and categories; b) multichannel providers may offer a wider assortment of products and therefore customers have multiple opportunities to buy and increase their spending; c) customers can combine the benefits that different channels provide to derive a higher value from them and, thus, increase spending. Based on an analysis of single (catalog-only or Internet-only) vs. multichannel preferences and their impact on sales across multiple catalog/online retailers and product categories, K&S conclude that multichannel customers are not always more profitable: multichannel customers are more profitable for hedonic products, while (traditional) single-channel customers have a higher monetary value for low-risk products.

This study replicates K&S's research in a services context (banking). Compared with goods, we expect the nature of services (e.g., intangibility, simultaneity of production and consumption) to influence the way in which customer preferences for channels affect profitability: while an increase in the number of channels used in goods enhances profits by leading customers to purchase more frequently and spend more (Kumar and Venkatesan 2005; Venkatesan, Kumar, and Ravishanker 2007), using multiple channels in services may increase the cost to serve the customer, with negative implications for profitability. We expect the extent to which customers are more or less profitable using various channel combinations in services to depend on the nature of the specific channels used (high vs. low-margin channels) and on whether they promote more vs. less efficient interactions (*substitution effect* vs. *augmentation effect*, Campbell and Frei 2010).

2.-Study

2.1.-Design

The data used in our empirical tests were provided by a European bank that offers financial services (e.g. certificates of deposit, savings accounts, mortgages) to individual customers (B2C) and has a volume of activity of 100,000 million euros, with 3.3 million customers, 6,300 employees and 1,400 offices. We obtained a random sample of 1,000 customers from which we had complete transaction and balance data for multiple services and channels for a period of 24 months (from August 2009 to July 2011). This bank operates on four main channels: point-of-Sales (POS) machines at retail shops and service providers, automatic teller machines (ATM), its own branches (BRANCH) and via internet (ONLINE). We categorized the bank's services into three main groups: ASSETS (savings, interest-bearing checking, investments, etc.), CREDIT (credit card, installment loan, mortgage, line of credit, etc), and SERVICES (debit card, insurance, etc).

The empirical problem we face is distinct from the one faced by K&S, who had access to aggregate measures gathered for multiple products across a large sample of consumers, and relied on cross-sectional analyses, accounting for cross-sectional endogeneity with demographics as instrumental variables. In contrast, we rely on a panel of customers from one bank, which we track over 24 months. Therefore, we are able to account for endogeneity biases due to selection and other effects associated with unobservable heterogeneity more directly, by incorporating fixed effects into our model. Given that we have enough information to account for individual differences, our main preoccupation is with endogenous effects that might affect our results over time.

To test for the impact of channel use on profitability, we estimate the following cross-sectional time-series model:

 $MARGIN_{it} = \mu_{i}^{P} + u_{t}^{P} + \alpha^{C}BAL_{it}^{C} + \alpha^{A}BAL_{it}^{A} + \sum_{k}\beta_{k}CHANNEL_{ikt} + \sum_{k}\gamma_{k}^{C}BAL_{it}^{C} *$ $CHANNEL_{ikt} + \sum_{k}\gamma_{k}^{A}BAL_{it}^{A} * CHANNEL_{ikt} + \sum_{k}\sum_{k'}\beta_{kk'}CHANNEL_{ikt} * CHANNEL_{ik't} + \sum_{k}\sum_{k''}\beta_{kk'k''}CHANNEL_{ikt} * CHANNEL_{ik't} * CHANNEL_{ik't}$ (1)

where,

 $MARGIN_{it}$ = Sum of gross margin for financial and non-financial products plus fees for customer *i* during month *t*

 μ_i^P = fixed profitability (margin) effect for each customer *i*, accounting for endogenous cross-sectional effects.

 μ_t^P = fixed profitability (margin) effect for each month *t*, accounting for seasonal and trend effects.

 BAL_{it}^{C} = balance held by customer *i* on credit services during month *t*

 BAL_{it}^{A} = assets held by customer *i* on deposit and investment services during month *t*. Balances are not relevant for the third category (SERVICES)

 $CHANNEL_{ikt}$ = number of times customer *i* used channel *k* during month *t*, with k=1,4 capturing the use of Point-of-Sales, ATM, Branch and Online channels.

Equation (1) parses out the effect of (single and multiple) channel use on customer profitability, after accounting for individual differences, time trend and volume of funds. While this equation accounts for endogenous effects across customers, it does not take into consideration changes in channel use induced by managers' marketing effort. This marketing effort can be endogenous, as managers usually base their targeting on what they observe in their customer database. Thus, to correct for these endogenous effects, we estimated two additional equations measuring how the customers' channel use is affected by their exposure to marketing communications (Equation A1), and how this marketing effort is affected by the customer information managers observe (Equation A2). We provide details on these two equations and their results in the Appendix I. Appendix II provides information on the correlation matrix and descriptive statistics for the studied variables. Based on this information, we conclude collinearity is not an issue in our empirical application.

We estimated our three-equation model using a 3-stage process. In the first stage, we estimated Equation (A2) as a fixed-effects multi-level Poisson regression, with months nested under individual customers. These estimates were the basis for replacing $MKTG_{it}$ in Equation (A1) with a measure of marketing effort adjusted for the bank managers' targeting decisions. This adjusted marketing effort is combined with other indicators in a multivariate generalized linear model, to adjust the observed use of the four channels (POS, ATM, Branch and Online) by each customer in the 24-month period. In the final stage, we combine the adjusted (for marketing effort) channel use with other factors believed to affect customer profitability, in a fixed-effects

linear model explaining the contribution margin produced by each customer in the 23 months (the first month is lost due to the lagged effect in the marketing-effort model).

2.2.-Results

The results from Equation (1) (the main focus of this study) are shown in Table 1. We also estimated an OLS version of our proposed model. The results appear in Appendix III, and they are largely consistent with the results we obtain. These results indicate that customers with larger ASSET balances tend to be more profitable, as one would expect. On the other hand, customers with larger CREDIT balances tend to be less profitable, which seems unexpected. However, the economic crisis has resulted in a high default rate in the payment of loans, which together with the decreasing interest rates and the lower margins in credit cards can help explain this negative effect. We also included interactions between channel usage and balances in our model. The results show an increase in margin for customers with higher asset balances using POS and with higher credit balances using ATM, and a decrease in margin for customers with large credit balances using the online channel.

TABLE 1 ABOUT HERE

Because K&S only considered two channels, they categorized channel use into single or dual use. In our case, we have four channels, and therefore look into each specific interaction among these four channels. We find that, after adjusting for the endogenous nature of marketing effort and for selection bias, only POS and BRANCH channels have a statistically significant marginal impact on customer profitability. While ATM by itself does not have a statistically-significant effect, using both ATM and BRANCH leads to an increase in profitability. The same positive interaction is observed for POS and BRANCH. On the other hand, we find that using all four channels produces a negative marginal effect on profits. We compute the absolute effect (main plus interactions) of channel usage on margin for all combinations of channels in Table 2. The results indicate that while fully multichannel customers are profitable for the bank, they are outperformed by customers using three-channel combinations (e.g. branch, POS and online), and are almost equally profitable as customers using only two channels (branch and POS), after accounting for estimation errors. Taken together, after controlling for selection and endogeneity biases and accounting for various sources of individual differences, the analyses demonstrate

that, while some single channel use and dual-channel combinations contribute to increase customer profitability, using all channels of the bank produces a decrease in profits.

TABLE 2 ABOUT HERE

3.-Discussion and conclusions

Contrary to conventional wisdom, K&S demonstrate that multichannel customers are not always more profitable. Our analysis of the banking services industry offers additional support to K&S's main thesis. We find that fully multichannel customers are not the most profitable for service firms because using all four channels of the bank leads to a decrease in profits. We also find that concentrating all the interactions through some single channels (branch or POS) as well as using specific dual-channel combinations (branch and ATM; branch and POS) produces improvements in margin, and that the combination of branch, POS and the Internet has the largest total impact on profits. However, in services operations, channel use may change monthly and, thus, the long-term profitability and CLV of customers should account for these variations in channel usage over time.

The results obtained can be explained based on the nature of specific channels used (high vs. low-margin channels) and on whether they promote more vs. less efficient interactions (substitution effect vs. augmentation effect, Campbell and Frei 2010). With regard to the significant effects of single-channel usage on profits, the positive marginal impact of branch banking on customer profitability is due to the fact that customers tend to use this channel for large and important transactions that are often associated with transaction fees (high margin channel). Importantly, this face-to-face channel also helps promote cross-buying and the purchase of higher margin services. Therefore, a larger number of interactions through this channel provides opportunities to develop stronger relationships with high-value customers and improve customer profits. Similarly, using the POS, which provides a higher margin for the bank (because the bank collects a fee from the retailer for each use), significantly contributes to increase the customer profit. About the dual-channel combinations, using the branch and the ATM produces an increase in profit, which is likely due to a *substitution effect* that enables customers to migrate some routine operations from relatively more costly channels (e.g. the branch or POS) to the ATM (Campbell and Frei 2010), thus producing more efficient interactions between the bank and its customers without compromising the quality of the

relationship. Similarly, as expected, combining the branch and the POS leads to increased profits, as these two channels produce margins that are significantly higher than those of the other channels. In contrast, using all channels produces a negative marginal effect on profits. This is probably due to an *augmentation effect*, in which customers usage of multiple channels, some of them highly convenient (e.g. online), leads to an increase in the demand for services (e.g. requests, information), which in turn produces an increase in the cost to serve the customer while not leading to a significant improvement in the relationship. Interestingly, the results show no significant effect of using the online channel on profits either used alone (single-channel) or in combination with one or two more channels. While the online channel is the least costly, prior research shows that, at least in services, the use of this channel may not produce positive effects on performance (Campbell and Frei 2010) as it (i) prevents building close and successful relationships with valuable customers, (ii) is limited in its ability to promote cross-buying of additional, higher-margin, products and services, (iii) makes it easier to switch service providers, and, in a banking context, (iv) facilitates information monitoring and promotes more active account management.

In conclusion, our study replicates K&S in a service setting demonstrating that multichannel customers are not always the most profitable. We extend K&S's findings by noting that while using all channels of the bank reduces customer profits, there are some dual and three-channel combinations that produce improvements in customer profitability. The insights derived from K&S combined with our study findings can contribute to a better understanding of the profitability implications of customer channel usage (Verhoef, Kannan, and Inman 2015).

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	With Endogeneity Corrections				
Predictors	Beta	Significance			
Balances					
BAL ^A _{it}	0.116	0.000			
BAL ^C _{it}	-0.029	0.000			
Channel Use					
POS	0.048	0.000			
ATM	-0.010	0.129			
BRANCH	0.040	0.000			
ONLINE	0.000	0.987			
ATM*BRANCH	0.017	0.003			
ATM*ONLINE	-0.002	0.718			
POS*ATM	-0.002	0.706			
BRANCH*ONLINE	0.000	0.949			
POS*BRANCH	0.018	0.006			
POS*ONLINE	0.009	0.113			
ATM*BRANCH*ONLINE	-0.002	0.548			
POS*ATM*BRANCH	0.000	0.997			
POS*ATM*ONLINE	-0.001	0.735			
POS*BRANCH*ONLINE	-0.003	0.570			
POS*ATM*BRANCH*ONLINE	-0.005	0.005			
Interaction: Balance * Channel Use					
BAL ^A _{it} *POS	0.015	0.008			
BAL ^A _{it} *ATM	-0.005	0.387			
BAL ^A _{it} *BRANCH	-0.009	0.120			
BAL ^A _{it} *ONLINE	-0.003	0.561			
BAL ^C _{it} *POS	0.002	0.742			
BAL ^C _{it} *ATM	0.021	0.011			
BAL ^C _{it} *BRANCH	0.003	0.745			
BAL ^C _{it} *ONLINE	-0.017	0.032			
Adjusted R ²	0.183				

 $Table \ 1-Estimates \ for \ the \ final \ Fixed-effects \ Regression \ model \ for \ Contribution \ Margin$

Table 2 – Total impact of every channel combination on profitability

Channel use	Total Effect	Std. Error			
Single-channel use		l			
POS	0.048	0.007			
ATM	-0.010	0.007			
BRANCH	0.040	0.007			
ONLINE	0.000	0.007			
Dual-channel use					
ATM*BRANCH	0.046	0.0115			
ATM*ONLINE	-0.013	0.0110			
POS*ATM	0.035	0.0110			
BRANCH*ONLINE	0.040	0.0115			
POS*BRANCH	0.105	0.0115			
POS*ONLINE	0.057	0.0115			
Three-channel use					
ATM*BRANCH*ONLINE	0.043	0.0156			
POS*ATM*BRANCH	0.110	0.0156			
POS*ATM*ONLINE	0.041	0.0152			
POS*BRANCH*ONLINE	0.112	0.0159			
Four-channel use					
POS*ATM*BRANCH*ONLINE	0.106	0.0212			

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APPENDIX I: Details on the econometric model

Here we explain in detail Equations A1 and A2 (and their estimation results), which help account for potential endogeneity biases.

As noted previously, Equation A1 measures how the customers' channel use can be affected by their exposure to marketing communications from the bank:

$$CHANNEL_{ikt} = \mu_{ik}^{C} + \varphi_{k}DEMO_{i} + \delta^{A}ACCNT_{it}^{A} + \delta^{C}ACCNT_{it}^{C} + \delta^{S}ACCNT_{it}^{S} + \omega_{k}MKTG_{it}$$
(A1)

where,

 $CHANNEL_{ikt}$ = number of times customer *i* used channel *k* during month *t*, with k=1,4 capturing the use of Point-of-Sales, ATM, Branch and Online channels.

 μ_{ik}^{C} = fixed effect for each customer *i*, and channel *k* accounting for endogenous cross-sectional effects in channel use.

 $DEMO_i$ = vector containing the demographic profile of customer *i*, accounting for customer-level effects beyond the fixed effect, such as demographic targeting implemented by management.

 $ACCNT_{it}^{A}$ = number of asset (e.g., checking, savings, investment) accounts held by customer *i* during month *t*

 $ACCNT_{it}^{C}$ = number of credit accounts (e.g., loans, credit card, mortgage) held by customer *i* during month *t*

 $ACCNT_{it}^{S}$ = number of service accounts (insurance, debit card) held by customer *i* during month *t* $MKTG_{it}$ = marketing effort targeted towards customer *ii* during month *t*, to account for the possibility that channel use by customer *i* may vary over time in response to marketing communications. While Equation (A1) above helps to account for customers' response to marketing communications, we must consider that managers make an effort to target their marketing efforts to specific customers, based on what they observe in their customer database. In other words, this marketing effort is also endogenous. Therefore, we attempt to capture the managers' targeted outbound customer contacts to what managers observe and may use to focus their efforts in the next month. We do this via the following equation:

$$MKTG_{it} = \mu_i^M + \theta^C BAL_{it-1}^C + \theta^A BAL_{it-1}^A + \gamma COST_{it-1} + \tau TENURE_{it-1}$$
(A2)

where,

 $MKTG_{it}$ = marketing effort, measured as the number of contacts initiated by the bank, targeted towards customer *i* during month *t*

 μ_i^M = fixed marketing effect for each customer *i*, accounting for endogenous cross-sectional effects.

 BAL_{it-1}^{C} = balance held by customer *i* on credit services during month *t*-1

 BAL_{it-1}^{A} = assets held by customer *i* on deposit and investment services during month *t*-1

 $COST_{it-1} = Cost of servicing customer i during period t-1$

 $TENURE_{it-1}$ = Customer *i*'s tenure in months up to period *t-1*.

As noted, we estimated the three-equation model using a 3-stage process. In the first stage, we estimated Equation (A2), as a fixed-effects multi-level Poisson regression, with months nested under individual customers. We used a Poisson regression because of the limited number of contacts observed each month for each customer. These estimates are shown in Table A.1 (estimates of the 999 customer fixed effects are not reported, due to space limitations). These estimates indicate that the bank is more likely to contact recently-acquired customers who are less costly to serve. The bank is also more likely to contact customers who hold large balance in ASSET accounts.

TABLE A.1 ABOUT HERE

In Equation (A1), marketing effort adjusted for the bank managers' targeting decisions (Equation A2) is combined with other indicators in a multivariate generalized linear model. The estimates (reflecting the relative contribution of each predictor) from this stage are reported in Table A.2.

TABLE A.2 ABOUT HERE

Table A.2 indicates that, beyond the customer-level fixed effects (utilized to correct for selection biases), the only demographic characteristics that affects channel use is age; older customers are heavier users of POS, ATM and BRANCH. Direct Marketing communications has a statistically significant impact only on the use of BRANCH and ONLINE banking. This suggests that the bank's managers are effective in inducing some customers (probably the most valuable ones) towards branch banking and others to online banking. Moreover, the relative contribution of marketing effort in explaining use of these two channels is reasonably high, when compared to the other predictors.

Predictor	Estimate	Std. Error	Significance
COST _{it-1}	-7.43E-04	3.41E-04	0.000
TENURE _{it-1}	-1.56E-04	4.36E-05	0.000
BAL ^A it-1	1.27E-06	4.32E-07	0.000
BAL ^C it-1	-1.28E-06	1.18E-06	0.537

Table A.1 – Estimates for the Poisson Regression model for Marketing Effort

LL=-15230; AIC=32469; BIC=40544

]	POS	А	TM	BRA	ANCH	ON	LINE
Predictor	Beta	Significance	Beta	Significance	Beta	Significance	Beta	Significance
Age (years)	0.001	0.026	0.001	0.021	0.001	0.007	0.000	0.109
Male (dummy)	-0.001	0.949	-0.001	0.947	-0.001	0.939	0.000	0.964
Education (years)	0.001	0.428	0.001	0.411	0.001	0.340	0.000	0.569
Urban (dummy)	-0.001	0.930	-0.001	0.928	-0.001	0.916	0.000	0.950
Married (dummy)	-0.009	0.415	-0.011	0.398	-0.015	0.327	-0.005	0.558
Low income	-0.001	0.929	-0.001	0.927	-0.002	0.915	-0.001	0.949
Medium-low income	-0.002	0.888	-0.003	0.884	-0.004	0.865	-0.001	0.919
Medium-high income	-0.003	0.868	-0.003	0.863	-0.005	0.842	-0.001	0.905
High income	-0.001	0.977	-0.001	0.976	-0.001	0.972	0.000	0.983
ACCNT ^S _{it} (adjusted)	0.129	0.000	0.108	0.000	-0.027	0.045	0.059	0.000
ACCNT ^C _{it} (adjusted)	0.042	0.000	-0.014	0.158	-0.026	0.026	0.011	0.083
ACCNT ^A _{it} (adjusted)	0.017	0.010	0.027	0.000	0.039	0.000	0.011	0.011
MKTG _{it} (adjusted)	0.000	0.941	0.008	0.161	0.050	0.000	0.021	0.000
Adjusted R ²	0).009	0.	.005	0	.004	0.	006

Table A.2 – Estimates for the fixed-effects Generalized Linear Model for Channel Use

Desviation Med-high Income Med-low Income Services Assets High Income Income _Credit urban_rural Tenure(-1) Marketing Assets(-1) Credit(-1) education BRANCH Standard ONLINE Cost(-1) Married Margin Assets Means Credit POS ATM ACT ACT ACT Male Ň age Var Margin 67.27 131.78 0.05 0.05 -0.02 -0.01 0.02 0.02 0.05 0.04 0.04 -0.17 0.02 0.06 0.06 -0.01 0.00 0.00 0.00 0.00 0.00 1.00 0.07 0.00 0.00 0.00 71793.3 95982.79 Assets 0.07 1.00 -0.01 0.06 0.06 0.08 0.05 0.02 $0.38 \quad 0.08 \quad 0.03 \quad 0.10 \quad 0.04 \quad 0.02 \quad 0.31 \quad 0.01 \quad 0.00 \quad$ 0.00 52635.47 Credit 20898.8 0.05 -0.01 1.00 0.02 -0.08 -0.11 -0.07 -0.02 0.06 0.29 0.07 -0.26 0.00 0.04 0.41 POS 1.98 5.29 0.06 0.02 1.00 0.30 0.13 0.14 -0.01 0.04 0.03 0.01 0.18 0.00 0.05 ATM 2.12 4.46 -0.02 0.06 -0.08 0.30 1.00 0.17 0.11 0.01 0.05 0.01 0.01 0.20 0.06 0.00 0.03 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 BRANCH 3.66 7.51 -0.01 0.08 -0.11 0.13 0.17 1.00 0.13 0.06 $0.02 \ -0.01 \ -0.02 \ 0.22 \ -0.01 \ -0.01 \ 0.03 \ 0.02 \ 0.00 \ 0.0$ 0.00 ONLINE 5.5 22.83 0.02 0.05 -0.07 0.14 0.11 0.13 1.00 0.05 $0.04 \quad 0.01 \quad 0.01 \quad 0.13 \quad 0.06 \quad 0.02 \quad 0.02 \quad 0.01 \quad 0.00 \quad$ 0.00 Marketing 0.35 0.69 0.02 0.02 -0.02 -0.01 0.01 0.06 0.05 1.00 0.02 0.00 -0.02 -0.02 0.01 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 Assets(-1) -32.39 21755.55 0.05 0.38 0.06 0.04 0.05 0.02 0.04 0.02 1.00 0.29 0.09 0.08 0.00 0.04 0.26 0.00 Credit(-1) 17.37 10559.01 0.04 0.08 0.29 0.03 0.01 -0.01 0.01 0.00 0.29 1.00 0.05 -0.03 0.00 Cost(-1) -0.55 27.32 0.04 0.03 0.07 0.01 0.01 -0.02 0.01 -0.02 0.09 0.05 1.00 0.00 0.00 0.07 0.05 0.01 -0.01 -0.01 -0.01 0.00 -0.01 -0.01 0.00 0.00 Tenure(-1) -4.71 316.67 -0.17 0.10 -0.26 0.18 0.20 0.22 0.13 -0.02 0.08 -0.03 0.00 1.00 -0.02 -0.08 -0.01 0.04 -0.01 0.00 0.00 0.00 -0.01 0.00 0.00 0.00 ACT_Services 0.89 0.82 0.02 0.04 0.04 0.08 0.06 -0.01 0.06 0.01 $0.00 \quad 0.04 \quad 0.00 \quad -0.02 \quad 1.00 \quad 0.05 \quad 0.05 \quad 0.00 \quad$ 0.00 ACT Credit 3.64 3.06 0.06 0.02 0.41 0.04 0.00 -0.01 0.02 0.01 0.04 0.23 0.07 -0.08 0.00 ACT Assets 0.77 0.98 0.03 0.03 0.02 0.00 0.26 0.07 0.05 -0.01 0.06 0.31 0.05 0.02 0.05 0.05 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 age 51.48 14.06 -0.01 0.01 -0.01 0.01 0.01 0.02 0.01 0.00 0.01 0.00 0.01 0.04 0.00 0.00 0.00 1.00 0.03 -0.38 0.08 0.40 0.00 0.03 0.02 0.00 Male 0.59 0.492 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 -0.01 -0.01 0.00 0.00 0.00 0.03 1.00 0.01 -0.03 0.02 0.06 0.00 -0.06 0.03 education 10.81 5.546 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 -0.01 0.00 0.00 0.00 0.00 -0.38 0.01 1.00 -0.11 -0.16 -0.02 0.05 0.05 0.09 1.22 urban_rural 0.65 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 -0.01 -0.01 0.00 0.00 0.00 0.00 0.08 -0.03 -0.11 1.00 0.04 -0.04 0.00 -0.03 -0.01 Married 0.71 0.45 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.00 0.00 0.00 0.00 0.00 0.40 0.02 -0.16 0.04 1.00 0.00 0.02 -0.03 0.11 0.42 Low Income 0.49 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 -0.01 -0.01 0.00 0.00 0.00 0.00 0.06 -0.02 -0.04 0.00 1.00 -0.30 -0.28 -0.24 Med-low Income 0.11 0.31 0.00 0.00 0.00 0.00 0.00 0.00 -0.01 0.00 0.00 0.00 0.00 0.03 0.00 0.05 0.00 0.02 -0.30 1.00 -0.12 -0.10 0.00 0.00 0.00 0.00 Med-high Income 0.1 0.29 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.02 -0.06 0.05 -0.03 -0.03 -0.28 -0.12 1.00 -0.09 High Income 0.07 0.26 $0.00 \quad 0.00 \quad 0.00 \quad 0.00 \quad 0.00 \quad 0.00 \quad 0.00 \quad 0.00$ 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.03 0.09 -0.01 0.11 -0.24 -0.10 -0.09 1.00

APPENDIX II: Descriptive statistics and correlation matrix

APPENDIX III: OLS estimation

Table A.3 – Estimates for the OLS model

	Without Corrections				
Predictors	Beta	Significance			
Balances					
BAL ^A it	0.000	0.004			
BAL ^C _{it}	0.000	0.634			
Channel Use	L				
POS	0.022	0.031			
ATM	-0.002	0.832			
BRANCH	0.028	0.004			
ONLINE	-0.018	0.162			
ATM*BRANCH	-0.001	0.878			
ATM*ONLINE	-0.009	0.224			
POS*ATM	-0.003	0.408			
BRANCH*ONLINE	-0.003	0.639			
POS*BRANCH	-0.001	0.677			
POS*ONLINE	-0.004	0.567			
ATM*BRANCH*ONLINE	-0.002	0.319			
POS*ATM*BRANCH	-0.000	0.842			
POS*ATM*ONLINE	0.006	0.002			
POS*BRANCH*ONLINE	0.0004	0.852			
POS*ATM*BRANCH*ONLINE	0.001 0.029				
Interaction: Balance * Channel Use					
BAL ^A _{it} *POS	0.000	0.275			
BAL ^A it*ATM	0.000	0.125			
BAL ^A _{it} *BRANCH	0.000	0.000			
BAL ^A it*ONLINE	0.000	0.193			
BAL ^C _{it} *POS	0.000	0.000			
BAL ^C _{it} *ATM	0.000	0.127			
BAL ^C _{it} *BRANCH	0.000	0.759			
BAL ^C _{it} *ONLINE	0.000	0.000			
Adjusted R ²	0.	168			

Channel use	Total Effect	Std. Error			
Single-channel use					
POS	0.022	0.010			
ATM	-0.002	0.010			
BRANCH	0.028	0.009			
ONLINE	-0.018	0.013			
Dual-channel use					
ATM*BRANCH	0.025	0.015			
ATM*ONLINE	-0.029	0.018			
POS*ATM	0.017	0.015			
BRANCH*ONLINE	0.007	0.017			
POS*BRANCH	0.049	0.014			
POS*ONLINE	0.000	0.018			
Three-channel use					
ATM*BRANCH*ONLINE	-0.007	0.022			
POS*ATM*BRANCH	0.015	0.018			
POS*ATM*ONLINE	-0.008	0.022			
POS*BRANCH*ONLINE	0.024	0.021			
Four-channel use					
POS*ATM*BRANCH*ONLINE	0.014	0.026			

Table A.4 – Total impact of every channel combination on profitability based on OLS results