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Social Media, Customer Service, and Profits: evidence from a large Brazilian retail bank

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Resumo

As inovações digitais como Facebook e Twitter revolucionaram a forma como se dá a comunicação online, e as instituições financeiras também precisaram se adequar ao novo contexto. Esse artigo avalia como o atendimento prestado a clientes via mídias sociais impactam a margem de lucro e a contratação de novos produtos de crédito, seguros, consórcios e investimentos. Utilizando-se os dados de um grande banco de varejo no Brasil, comparamos a rentabilidade de fornecer de serviços de atendimento ao cliente usando a mídia social versus os serviços ao cliente com métodos mais tradicionais (call-centers). O método utilizado leva em consideração as características do cliente que determinam a propensão a usar um canal de comunicação e o seu padrão de consumo de produtos bancários. Os resultados empíricos sugerem que o uso de canal de comunicação com maior teor tecnológico aumenta em média 42 reais o lucro semestral do banco por cliente. A literatura internacional sugere que a intensificação do relacionamento bancário tem impacto sobre a margem de lucro. Nesse artigo demonstra-se que o meio ou canal pelo qual a interação ocorre também pode intensificar o relacionamento banco-cliente. Mais que isso, criando-se uma ferramenta generalizável para a mensuração de rentabilidade para canais de comunicação de instituições financeiras no Brasil.

Palavras-chave: Mídias Sociais; Relacionamento Bancário; Estimador aumentado ponderado pelo inverso do escore de propensão

Abstract

Digital innovations such as Facebook and Twitter have revolutionized the way online communication takes place, and financial institutions have also had to adjust to the new context. This article assesses how customer service via social media impacts the profit margin and the contracting of new credit products, insurance, consortia and investments. Using data from a large retail bank in Brazil, we compared the profitability of providing customer service services using social media versus customer services with more traditional methods (call centers). The method used considers the customer characteristics that determine the propensity to use a communication channel and the client's pattern of consumption of banking products. The empirical results suggest that the use of a communication channel with a higher technological content increases on average 42 reais the semiannual profit of the bank per client. The international literature suggests that the intensification of the banking relationship has an impact on the profit margin. In this article it is shown that the medium or channel used in the interaction can intensify the bank-client relationship. Moreover, a generalizable tool for measuring the profitability for communication channels of financial institutions in Brazil is designed in the article.

Key-words: Social Media; Relationship Banking; Augmented inverse propensity weighted estimator

1. Introduction

A social network is a structure that connects persons (organization, areas) by one or more types of relationships. When computer-mediated technology allows this connection, there is a social media. In this work, we assess the profitability of providing customer services using social media versus the customer services with more traditional methods (e.g. Facebook versus Call Center). The paper uses information from 2014 to 2016 collected in a large retail bank in Brazil (henceforth, LRB). The data set has the bank's semiannual individual profit margin, portfolio of financial products, characteristics of the clients, and records of customer-bank interaction (complaints, questions, and requests) using different types of communication channels.

This article evaluates whether the LRB's profit margin from a client behaves differently after the customer used social media to deal with a bank-related issue. The baseline for comparison is the profit outcome, and the average six-month change in profit, from clients who used a traditional call-center help. We assume that the client's characteristics (or preferences) determine whether he or she will use social media or the telephone to contact their bank. Then a "quasi-experiment" method is applied to compare clients interacting with social media (Facebook and Twitter) to similar clients in traditional media during the same span of time.

One should expect that the quality – efficiency, speed, convenience – of customer services will affect profit outcomes. A bad interaction can result in the client dropping the bank or giving up expensive products, while a good interaction will strengthen the relationship. To the best of our knowledge, this is the first article to evaluate the profitability of a social media service in a developing country's bank. The retail banking sector provides a good case study of the problem. Since the *Real Plan* and subsequent inflation stabilization, the country went through a robust process of financial deepening expanding bank presence and credit. Moreover, in 2002 the

monetary authority led a technological modernization of the sector with the New Brazilian Payments System making financial transactions faster and more reliable.

Data from the Brazilian Statistics and Geography Institute (IBGE) from 2005 to 2011 indicate that the number of persons using the Internet increased by 143.8 percent or 45.8 million users in six years. It is expected that LRB invested in interacting with clients using the Internet, and in 2013 the bank implemented the customer service using social media. There were already other digital media including websites and the bank's mobile app. Meanwhile, traditional channels for placing complaints and questions were kept working and involved mostly call-centers.

All channels serve broadly the same purpose, solving problems related to credit card fees and undue charges, password issues, questions about credit limit and new products. Since the different services were offered simultaneously, it is possible to compare outcomes in terms of profit changes, if we take clients who are expected to render similar profits but differ in terms of the type of bank-customer interaction used. Estimation results suggest that profit changes after social and traditional media interactions are statistically different and higher for social media users.

The paper is divided in five sections. After this introduction, section 2 discusses the related literature and lays out a stylized model of *Relationship Banking* illustrating the role of technology in the interaction between client and bank. Section 3 presents the data. Section 4 discusses the empirical framework and estimation while section 5 has the final remarks.

2 Context and Related Literature

There is a rich literature associating *Relationship Banking* with profits and competition, but there are no guidelines about how the *Relationship* should occur or the best channels to interact

with the customer and strengthen the *Relationship*. While interacting, clients may reveal proprietary information that is not common knowledge in the market. In ownership of this information, banks can decrease adverse-selection and asymmetry of information. We evaluate how the choice of communication channel affects profit margins, by comparing outcomes of clients who contacted their bank using social media or traditional media.

The bank-client interactions that happen through social media are extracted directly from the original platforms (Facebook and Twitter). Clients search for the official LRB's online page and write in the appropriate boxplots their question or complaint. Every interaction is categorized per content and answered by an assistant. Other customer service channels, like the call-centers, have the same categories for content and are stored separately. Traditional media assistants were trained in 2013 to work in the social media environment following Facebook and Twitter guidelines.

The empirical evidence for developed countries suggest that the extent of the client-bank relationship is important to explain outcomes such as default rates, credit card usage, and credit-rating (Agarwal et al 2009) (Mester et al 2004) (Chakravarty et al 1999). Given the asymmetry of information between banks and clients, both sides of the market can potentially benefit from making available information on the value, number, and duration of financial products used by the client. To the best of our knowledge, the impact of *Relationship Banking* has been studied mostly in credit and loans market while the literature did not focus on how banks and clients interact.

2.1 Credit, loans and Relationship Banking

Mester et al (2004) use a sample of 100 Canadian small business-borrowers with information on transaction accounts. The authors test whether accounts receivable and balance help predict loan monitoring and credit risk. Results suggest that checking accounts provides

a relatively transparent information about firm's activity. Moreover, banks use unexpected movements in clients' accounts to assess credit risk.

Argawal et al (2009) test whether relationship banking can help banks in assessing attrition and default risk of credit card loans, and their utilization rates. The authors examine 13 measures of relationship related to billing, credit risk scores, combined with demographic and macroeconomic characteristics from a hundred thousand accounts for 24 months. The empirical results show that more intense relationships may be benefited by lower credit risk, lower attrition rates, and increased credit card utilization.

Hauswald et al (2001) develop a theoretical framework to study competition in bank lending. In the model two banks can offer loans to borrowers: the *insider bank* has access to a screening technology, and the *outsider* bank does not have access to same information. Credit analysis depends on the effort the *insider* bank puts into evaluating and gathering information. Both banks compete by simultaneously making interest rate offers and borrowers choose by accepting a loan from the bank quoting the lowest rate. The *insider* bank's strategy has two components: its effort in screening applicant borrowers, and the interest rate offer, which can be conditioned on the results from screening. The *outsider* bank has no informational advantage and can decide on its interest rate offers knowing that the inside bank has screened the client. The authors modeled several dimensions of technological progress and how they impact competition. Technological progress, defined as advances in processing and evaluating information can make markets less competitive, if they widen the informational gap among competitor who invest resources in gathering information and those who do not.

2.2 Two-period model of Relationship Banking

This section presents a two-period stylized model of *Relationship Banking*. The starting point is Freixas and Rochet (2006, p. 99-102) framework to analyze the firm's decision to take

a bank loan. The problem was adapted to illustrating the relationship between a bank offering services and the customer.

The model occurs in two periods. The bank offers a menu of services that can be used by the customer in periods 1 and 2 with probabilities P_1 and P_2 , respectively. If the client uses the services, she must pay the fees R_1 and R_2 . The benefit provided by the service is valued by the customer at Y_1 and Y_2 . There is a sunk cost M to set up the services incurred only in the first period of the relationship. Additionally, the bank has a cost of 1 in the first period, and P_1 if the client stays with the same bank in period 2. The cost of one customer in both periods is $M+1+P_1$. There is an incentive to keep the relationship to dilute the sunk cost.

Assuming no discount in the second period and competition in the sector, the bank will offer the service only if it can get a return of $B > 1$. *Ex-ante* competition ensures that:

$$P_1 R_1 + P_2 R_2 = B(M + 1 + P_1) \quad (1)$$

The bank already holding the customer in the first period is an *insider* with probability P_2 of selling its services in the second period. Assume that the client can change banks after the first period. In this case, the new bank is an *outsider* choosing R_2 to guarantee:

$$P_1 R_2 = B(M + 1) \quad (2)$$

The insider bank can charge the customer in the second period at most:

$$R_2 = B(M + 1)/P_1 \quad (3)$$

Replacing (3) in (1), the fee in the first period is given by:

$$R_1 = B(1 + M(1 - P_2) + (P_1 - P_2))/P_1 \quad (4)$$

Price structure is such that the bank subsidizes services in the first period and obtains monopolistic profit in the second period. Let's assume that the Bank who keeps the relationship in both periods acquires information about the customer, with $P_2 > P_1$. The difference between R_2 and R_1 is increasing in the sunk cost and in the probability of selling services in the second period:

$$R_2 - R_1 = B(MP_2 + (P_2 - P_1))/P_1 \quad (5)$$

In this context, the role of social media technology is to collect and process customer's information generating $P_2 \gg P_1$. Hence, the bank using social media prefers to subsidize more the service in the beginning of the relationship. It also captures more clients because the marginal customer with Y_1 close to R_1 will use the service when R_1 becomes more subsidized by the new technology. In the empirical section of the paper we will test the claim that fees - or profits - increase more after a social media interaction.

3 Data

The information spans from January 2014 to June 2016 and comprises of all clients who interacted using social media or traditional customer service. A random sample with approximately 200.000 observations were extracted separately to serve as a comparison group. In the random sample, less than 5 percent of clients had a registered interaction with customer services and these observations were excluded. The final data are restricted to clients who are between 18 to 45 years-old, since they are the targeted group for social media services.

There are two outcomes of interest. The first variable used in panel data regressions is the six-month profit margin¹. To create this variable, we divide the data into five semesters.

¹ The profit margin is calculated using the total revenue from products consumed by a client minus the average cost of providing these products.

The second variable is the average change in profit margin. The change between two consecutive months is calculated than averaged over the five semesters. The outcome is a sample of costumer services users and comparison clients with their respective characteristics and change in profits.

The variables in Table 1 denoting clients' characteristics include gender, educational attainment, proven income, marital status, number of financial dependents, duration of bank-client relationship in years, and an index of portfolio of products consumed by a person. We expect that the characteristics evaluated are correlated with the choice of customer service interaction preferred by the client and profits. The covariate values are measured in the last month of available data since the bank constantly updates information on clients. The married group is defined as all costumers with a recognized civil or religious union. Remaining cases were classified as single marital status. The college educated group was defined as all clients with tertiary education or more. The secondary education group was defined as all clients with finished high-school. Remaining cases were classified as primary education. Gender was defined by the sex indicated in national ID. The duration of relationship starts when someone registers in a bank branch to become a client, usually to obtain a checking account. The financial dependents are the persons the client is financially responsible, usually the children included the tax return filing. An inspection of the sample shows that persons who interacted using telephone are on average more educated, older and with higher income than the persons who interacted by social media or did not interact during the same period.² When considering as comparison group the clients who used traditional costumer service channel, the social media

² Rigorously, the clients without a registered interaction through costumer services can still contact the bank at the branch offices, but those interactions are not computed by the financial institution or mediated by technology.

users are younger, less educated, and with lower income. Interestingly, the average change in profit for the group of traditional media users is lower than for the other two groups (Table 1).

The portfolio of products (Table 2) consists of each product contracted, counted only once every semester, and indicates the ownership of products in every period. Credit products contracted include loans between the financial institution and its clients, that provides funding for assets as real estate, payday advance, personal loan, credit card, short-term and long-term commercial loans, leasing. The Insurance products include life insurance, general insurance, home and travel insurance. Investment products includes saving accounts, money market accounts, and certificates of deposit. Lastly, the Consortium involves multiple lenders and a single borrower, and the contract is generally reserved for durable goods such as cars. Product ownership and clients' characteristics are related according to a pattern: higher income, education, age and duration of relationship suggest more consumption of the services provided. That is a relevant evidence since the mechanism relating profits and clients' characteristics should work through product consumption.

Table 1 - Descriptive statistics of the sample

<i>Variables</i>	<i>Interaction Channel</i>		
	<i>No interaction</i>	<i>Social Media</i>	<i>Telephone</i>
	(1)	(2)	(3)
College education	16%	27%	37%
Primary education or less	26%	6%	8%
Secondary education	58%	67%	55%
Married	21%	14%	29%
Income lower than R\$ 2000	70%	60%	42%
Income R\$ 2001-R\$ 6000	23%	29%	37%
Income R\$ 6001-R\$ 8000	3%	4%	7%
Income R\$ 8001-RS 10000	1%	2%	4%
Income higher than R\$ 10000	3%	4%	9%

Men	52%	62%	55%
Age up to 25	15%	38%	13%
Age 26-35	44%	45%	47%
Age 36-45	41%	18%	40%
Relationship Banking higher than 6 years	68%	69%	75%
Relationship Banking between 3-6 years	26%	25%	20%
Financial Dependent* equals to Zero	70%	78%	61%
Financial Dependent higher than Zero	30%	22%	39%
Average Financial Dependent	0,33	0,25	0,46
Average profit change per semester	2,19	12,14	-12,39

Note: Column (1) has the control group or a random sample from the population of LRB clients. Less than 5 percent of the random sample had a registered complaint and those observations were excluded from the analysis. The social and traditional media groups (Columns (2) and (3), respectively) include clients who placed an interaction (complaint, question, doubt). Sample restricted to clients less than 45 years-old. The income level corresponds to monthly income proved by the client to the bank. Data from 2014-2016, average profit change is calculated between consecutive semesters from Jan/2015 to Jun/2016 measured in Reais. Values correspond to R\$ in July 2016.

Financial dependent: a person who another individual is financially responsible in their tax return, mostly children

Table 2 - Average ownership of products per characteristic

<i>Variables</i>	<i>Type of product</i>			
	<i>Credit</i>	<i>Insurance</i>	<i>Investment</i>	<i>Consortium</i>
	(1)	(2)	(3)	(4)
Relationship Banking < 3 years	1,31	0,11	0,54	0,01
Relationship Banking between 3 - 6 years	1,77	0,16	0,67	0,02
Relationship Banking > 6 years	2,56	0,29	1,38	0,04
Married	2,83	0,37	1,32	0,05
Single	2,15	0,21	1,14	0,03
Income higher than R\$ 10000	4,23	0,68	2,27	0,12
Income R\$ 8001-RS 10000	3,69	0,52	1,71	0,08
Income R\$ 6001-R\$ 8000	3,44	0,46	1,48	0,07
Income R\$ 2001-R\$ 6000	2,73	0,29	1,10	0,04
Income lower than R\$ 2000	1,49	0,11	1,00	0,02
Male	2,44	0,26	1,23	0,05
Female	2,19	0,25	1,14	0,02
Primary education or less	1,41	0,16	1,05	0,02
Secondary education	2,09	0,19	1,00	0,03
College education	3,07	0,39	1,55	0,06
Financial Dependent higher than Zero	2,82	0,37	1,35	0,06
Financial Dependent equals to Zero	2,04	0,18	1,09	0,02

Age up to 25	1,63	0,11	0,85	0,02
Age 26-35	2,27	0,22	1,20	0,04
Age 36-45	2,66	0,35	1,30	0,04

Figures 1 to 3 show the evolution of the profit margin and the number of interactions according to media channel. Social media users are defined as clients who contacted customer services using Facebook or Twitter. Telephone media users contacted the bank using call-centers. The no interaction group comes from a random sample of approximately 200.000 customers who did not use customer services. Profits are flat for clients without bank-interactions. Interestingly, the number of interactions are growing for Social Media users, and decreasing for Telephone users. Figures 4 to 9 below show profit margin for different demographic groups. Overall, profits are higher for groups with the following characteristics: married, more than 6 years of relationship banking, positive number of financial dependents, college educated, male, and with income higher than R\$10000.

Figure 4 shows how educational attainment is related to the profit margin. Higher education usually indicates more income, and a sophisticated portfolio of products being consumed. Figure 5 suggests that the longer the bank-relationship the better the knowledge of clients's needs, and higher profit margin. Figure 6 indicates a positive correlation between the level of income and profits. Figure 7 shows how financial dependents impact positively the profit margin. Marital status also seems to change the pattern of banking consumption and profits. Figure 9 highlights the gap between men and women, indicating lower profit margin for female clients. Figures 10 to 12 show the average profit margin by type of communication channel for the three age groups considered: 18 to 25, 26 to 36, and 36 to 45, respectively. It is interesting to see that the profit margin increases with the client's age, but it is lower among clients in the same age group who did not report any interaction with the bank in the five semesters of data.

Figure 1

Average Profit Margin
by type of media

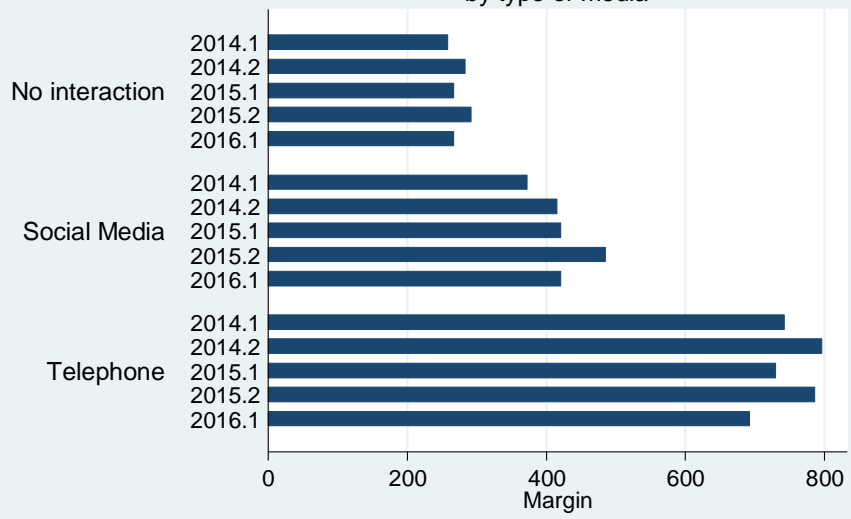


Figure 2

Average Number of Interactions
by type of media

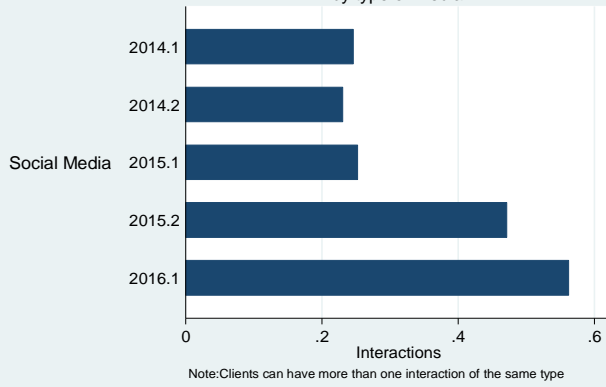


Figure 3

Average Number of Interactions
by type of media

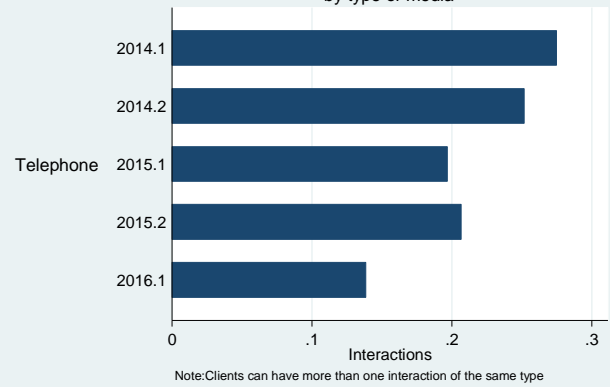


Figure 4

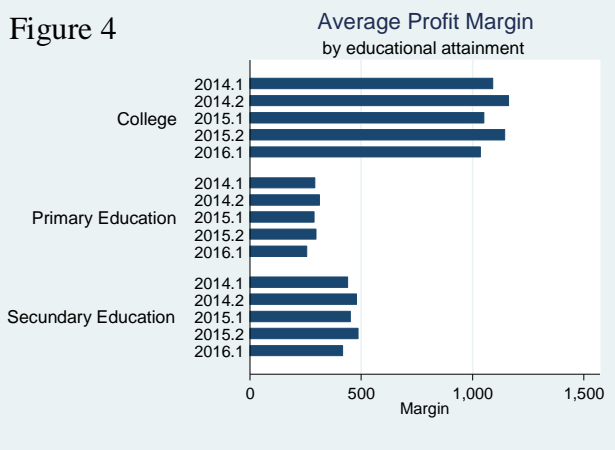


Figure 5

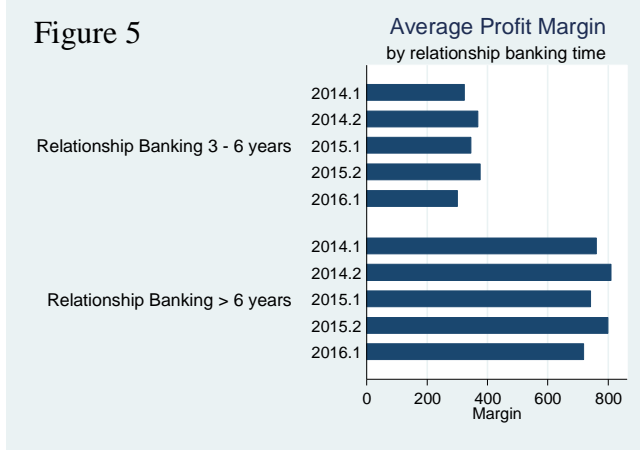


Figure 6

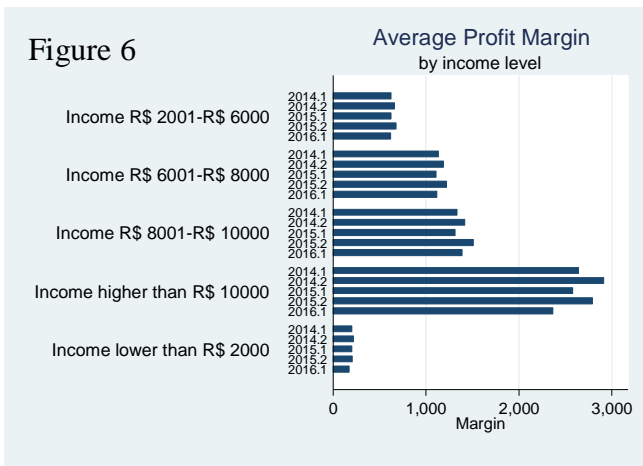


Figure 7

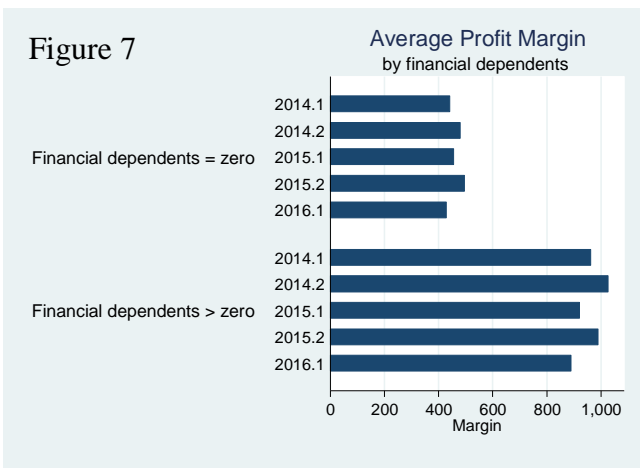


Figure 8

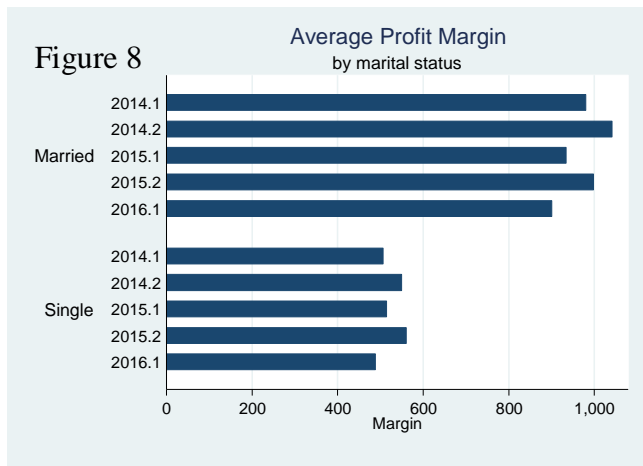


Figure 9

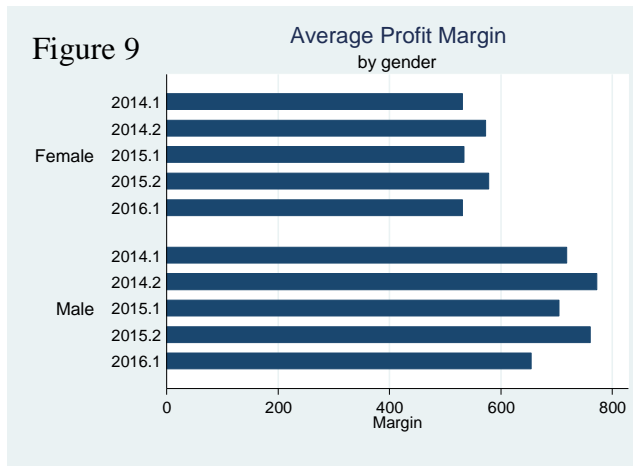


Figure 10

Average Profit Margin
by type of media

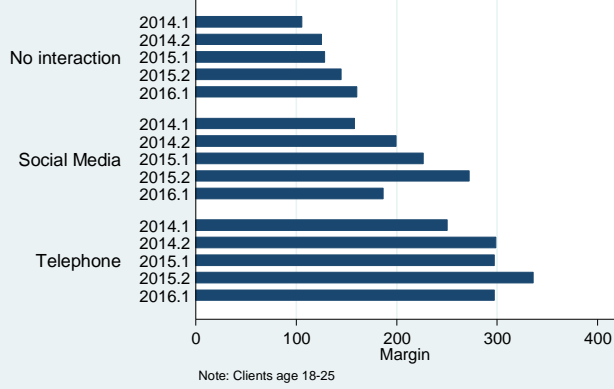


Figure 11

Average Profit Margin
by type of media

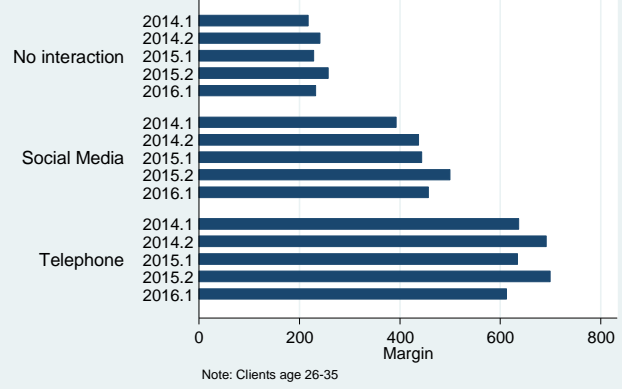
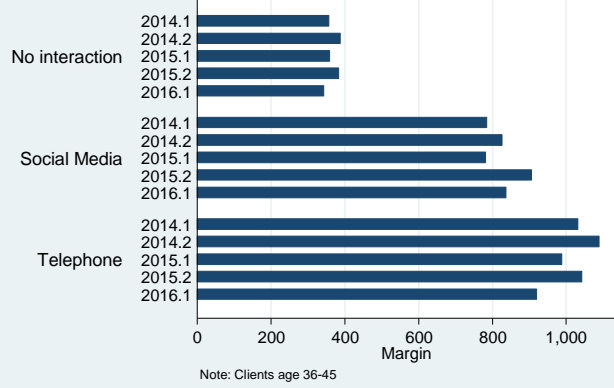


Figure 12

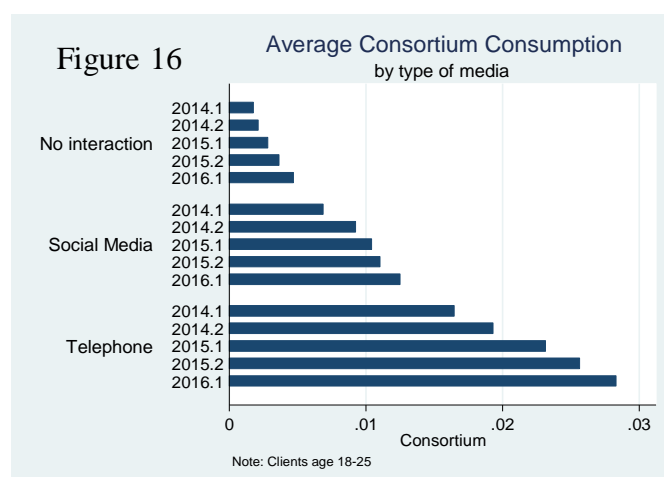
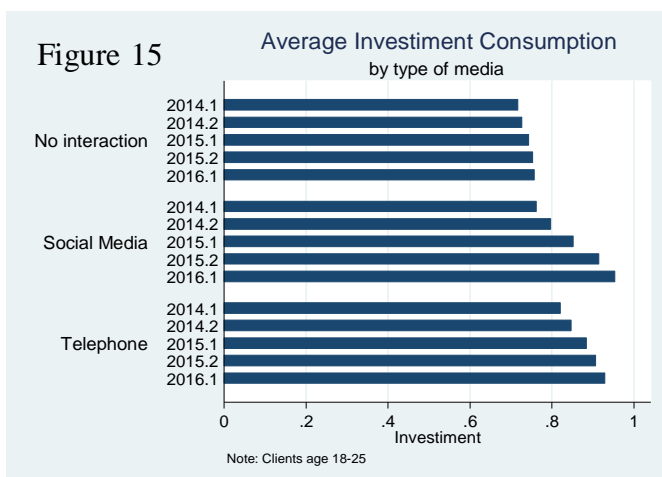
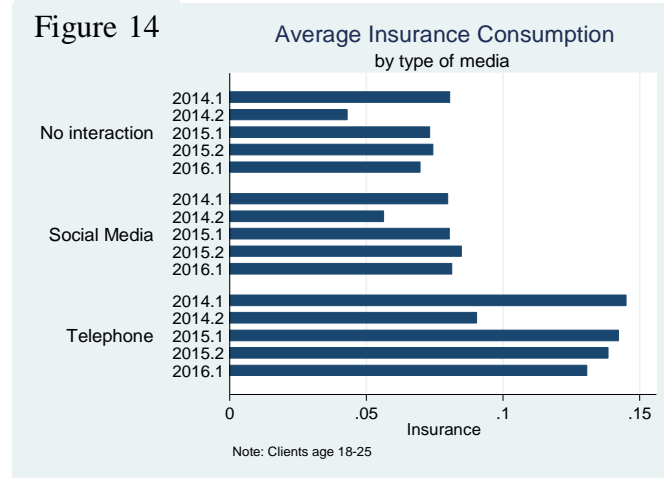
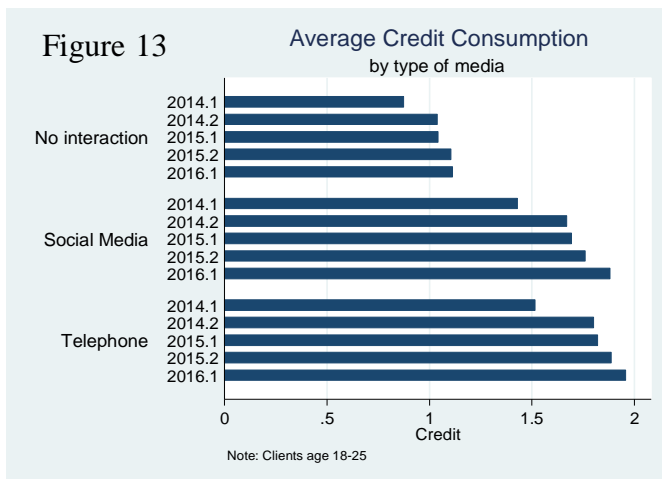
Average Profit Margin
by type of media



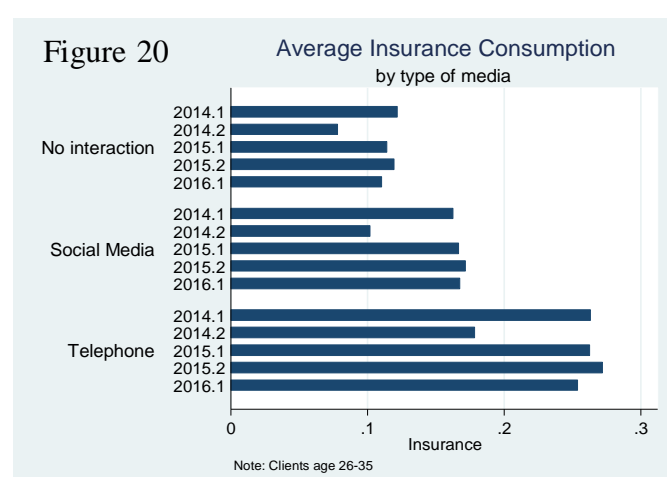
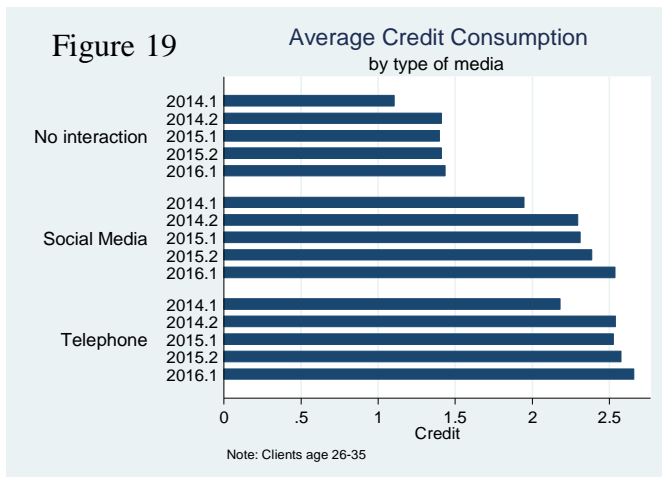
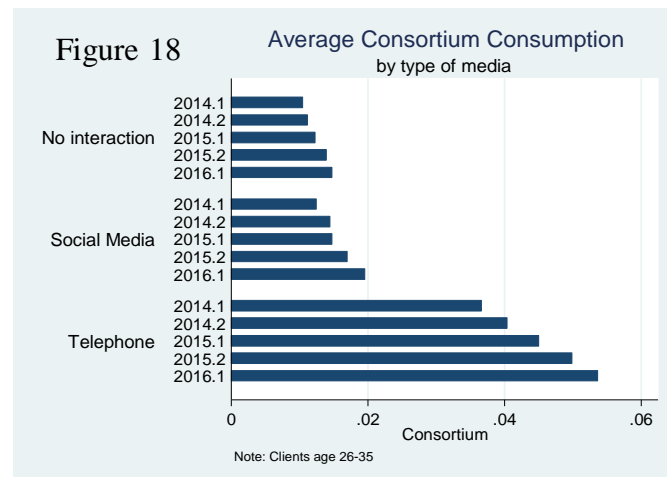
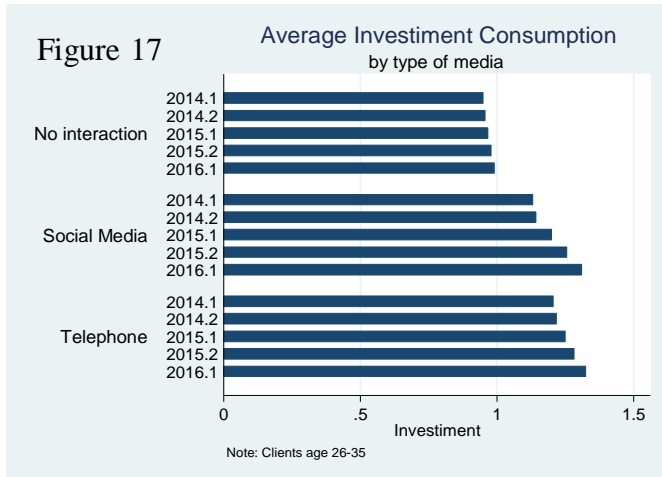
3.1 Progress of products ownership by group of age and channel interaction

Figures 13 to 24 show the evolution of product consumption separated by age group and type of communication channel. There are three main points emerging from the graphs. First, as similarly to the case of average profit margin, the product ownership systematically increases with age. Second, consumption tends to be lower and varies less for the group of clients who did not contact the bank in the five semesters of data considered. Third, product ownership increases over time for clients who contacted the bank using social media or call-centers. The last point is the most important, suggesting that the mechanism connecting profits and client services is the consumption of products while interacting with financial institution.

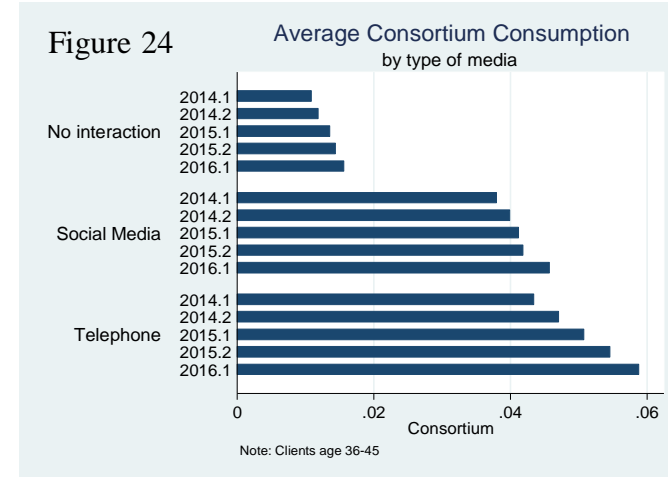
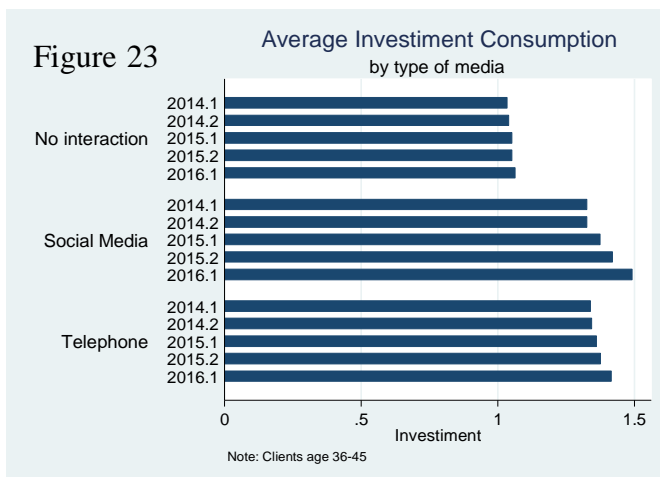
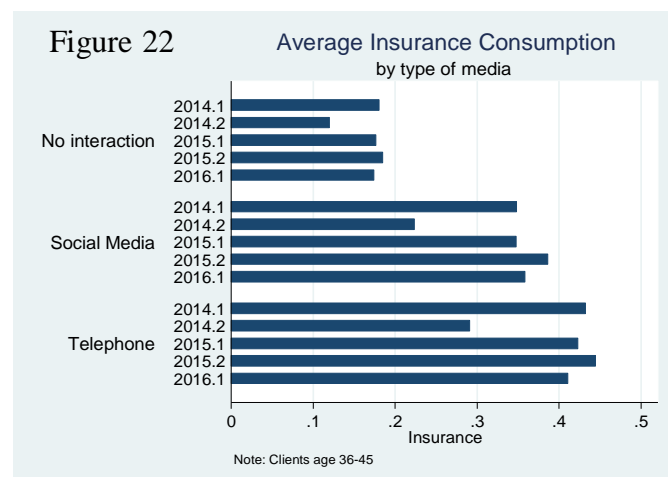
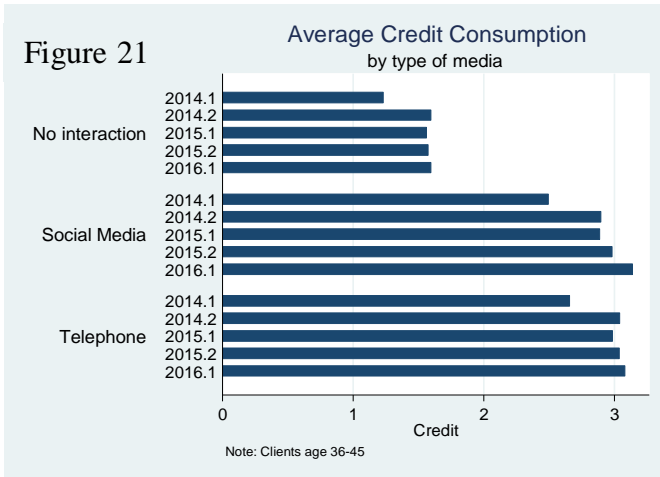
3.1.1 Progress of products ownership up to 25 years old



3.1.2 Progress of products ownership between 26 - 36 years old



3.1.3 Progress of products ownership between 36 - 45 years old



4 Empirical Model and Results

This section presents the methods used to analyze the data. There are two main empirical exercises. In the first one, the information is organized as a balanced panel data set combining 5 semesters and all clients. The dependent variable is the individual i profit margin in period t equal to PM_{it} . The independent variables are time dummies for semesters μ_t , a dummy equal to one if the client contacted the bank in period t using social media DS_{it} , and a dummy equal to one if the client contacted the bank in period t using telephone DT_{it} . There is an additive error in the model with two components: an individual specific effect a_i that is time constant and correlated with characteristics that potentially affect the margin and the choice of communication channel, and a random component ϵ_{it} that is time variant with mean zero and uncorrelated with other covariates. The following equation is estimated with fixed effects:

$$PM_{it} = \mu_t + \delta_T DT_{it} + \delta_S DS_{it} + a_i + \epsilon_{it} \quad (5)$$

The coefficients of interest relate the dummies for client-bank interaction and the profit margin.

The second empirical exercise relies on the widely used Rubin Causal Model (RCM) (see IMBENS, 2014, and STUART and RUBIN, 2007). Consider a random sample of size N , with $i=1, 2, \dots, N$, from an infinite size population. For each unit i there is a triplet of potential outcomes of interest $Y_i(0)$, $Y_i(1)$ and $Y_i(2)$, that occur in case unit i participates in the control, the client-bank interaction with low-technology, and the client-bank interaction with high technology, respectively. Each unit also has a vector of covariates represented by X_i . Let's denote $W_i=1$ if unit i received active treatment of low technology or telephone, $W_i=2$ if the treatment was social media, and zero otherwise. From the triplet of potential outcomes, we can only observe $Y_i(0)$ if $W_i=0$, $Y_i(1)$ if $W_i=1$, and $Y_i(2)$ if $W_i=2$. The other combinations are not available and consist of counterfactuals.

We want to estimate the average treatment effect $\tau_T = E[Y_i(w) - Y_i(0)]$, with $T=1,2$. To estimate τ we rely on a regression function \mathcal{M} with $w \in \{0,1,2\}$ defined by:

$$\mathcal{M}_w(x) = E[(Y_i(w)|X_i = x)] \quad (6)$$

The Ordinary Least Square (OLS) estimator gives a prediction of the regression model. There were two underlying hypotheses to apply the method. The first one is the conditional independence:

$$(Y_i(0), Y_i(1), Y_i(2)) \perp\!\!\!\perp W_i/X_i$$

And the second one is the overlap or common support:

$$0 < Pr(W_i = T|X_i = x) < 1$$

The hypotheses constitute *strong ignorability* in the RCM. It is straightforward from equation (6) that if the regression model is well specified and the conditional expectation is linear, the average outcomes are good substitute for data moments if the distribution of the covariates is similar across treated and control units. Moreover, the RCM may constitute an improvement on equation (5) since it has a more direct causal interpretation of the effect of bank-client interaction on the outcome of interest.

Consider now the propensity score $e(x)$ – the conditional probability of receiving the treatment.

$$e(x) = Pr(W_i = T|X_i = x) \quad (7)$$

The propensity score is usually not known and estimated with a multinomial logit model in the case of multiple levels of treatment. The literature offers several double-robust estimators based on the propensity score and the regression model in equation (6). The augmented inverse propensity weighted estimator is chosen since it is robust to misspecification in either the propensity score or the regression equation (Glynn and Quinn, 2010).

4.1 Specification

The groups of clients being compared are denoted according to the type of communication channel used to interact with the bank: social media or telephone. The outcome of interest Y_i is profit margin in the case of equation (5) and the average six-month change in profit margin in the case of equation (6). The covariates X_i determining the propensity score in equation (7), and the regression in equation (6) are the dummy variables for income brackets, gender, marital status, duration of client-bank relationship, and financial dependents. The empirical exercises emulate a “quasi-experiment” where treated and non-treated clients with similar scores are only different randomly.

4.2 Results

Estimation results for equations (5) and (6) are presented in tables 3 and 4, respectively. Table 3 uses the panel data in the regression of profit margin on dummies indicating client-bank interaction. Column (1) indicates a positive and statistically significant correlation between social media and telephone interaction with profit margin. An interaction in social media (or call-center) is related to an increase of R\$ 63,7 (or R\$ 43,6) in the profit margin. Column (2) includes lagged values of the dummies as covariates to assess if there is a persistent effect of the interaction. The relationship between social media and profit margin is still positive and statistically significant.

Table 4 shows the average treatment effect of bank-client interactions with different technological levels using the RCM framework and the augment inverse propensity weighted estimator. The results are separated in three panels by age group since previous data inspection suggested distinct consumption patterns and social media usage according to clients' age. The dependent variable is the average six-month change in profit margin. The table shows the average treatment effect comparing groups two-by-two along with the population outcome mean of the baseline comparison group. Statistically significant results are highlighted in bold.

There are two comparisons worthy of attention: telephone versus no interaction in the 26-35 age group, and social media versus telephone in the 36-45 age group. The average treatment effect estimated is negative and amounts to approximately R\$15 in the comparison between telephone users versus clients with no bank-interaction. The comparison of changes in profit margin between clients from the two communication channels (high and low technological content) indicates a positive average treatment effect. That effect amounts to R\$42 favoring social media usage for the clients in the 36-45 age group. It should come as no surprise that the 36-45 age group carried the results since these clients can afford and consume more bank related products. More interestingly, the estimated effect of the interaction is only positive when the clients use Facebook or Twitter.

As a robustness check, equation (5) is estimated again using panel data with the number of products consumed by the client at each semester as the dependent variable. The estimation is a test of mechanism through which the bank-client interaction can affect the profit margin: variation in portfolio consumption. Overall the results show a positive and statistically significant relationship between the dummies for social media and telephone interaction and the consumption of bank products, especially in the case of credit and investment instruments.

Table 3 - Regression of profit margin on dummies for bank-client interaction: panel data

<i>Variable</i>	<i>Dependent variable: Profit Margin</i>	
	<i>(1)</i>	<i>(2)</i>
	<i>Coefficient</i>	<i>Coefficient</i>
Social media	62.796***	61.156***
Telephone	43.623***	35.390***
Social media (t-1)		-10.998
Telephone (t-1)		-37.043***
<i>N</i>	1395345	1395344

Note: Statistical significance denoted by * p<0.10, ** p<0.05, *** p<0.01. Column (1): Results from estimation of coefficient of interest in equation (5) using fixed effects Column (2): same as column (1) but includes lagged values of dummies denoting interaction

Table 4 - Average Treatment Effects obtained with Augmented Inverse Propensity Weighted Estimator

	<i>Groups</i>	<i>Coef</i>	<i>Std. Error</i>	<i>z</i>	
Age 18- 25 Years	Panel A: Average Treatment Effect				
	(Telephone vs Control)	-11,97	9,12	-1,31	
	(Social Media vs Control)	-9,37	15,58	-0,60	
	(Social Media vs Telephone)	2,60	13,68	0,19	
	<i>Population outcome mean</i>				
	Control	22,34	8,33	2,68	
	Telephone	10,37	3,71	2,79	
	<i>Number of observations</i>	40726			
	Age 26-35 Years	Panel B: Average Treatment Effect			
		(Telephone vs Control)	-15,49	8,25	-1,88
(Social Media vs Control)		-7,55	22,58	-0,33	
(Social Media vs Telephone)		7,94	21,36	0,37	
<i>Population outcome mean</i>					
Control		9,33	7,79	1,20	
Telephone		-6,16	2,73	-2,26	
<i>Number of observations</i>		128677	2,73	-2,26	
Age 36-45 Years		Panel C: Average Treatment Effect			
		(Telephone vs Control)	-13,90	18,63	-0,75
	(Social Media vs Control)	28,26	29,00	0,97	
	(Social Media vs Telephone)	42,15	24,75	1,70	
	<i>Population outcome mean</i>				
	Control	-12,02	16,96	-0,71	
	Telephone	-25,92	7,70	-3,37	
	<i>Number of observations</i>	109666			

Note: Regression outcome model from equation (6) uses dummy for income, gender, marital status, duration of relationship and dependents. Same covariates used in multinomial logit from equation (7). Dependent variable is the average six-month change in profit margin.

Table 5 -Regression of product consumption on dummies for bank-client interaction: panel data

<i>Dependent variable: product consumption</i>				
	(1)	(2)	(3)	(4)
Variable	Credit	Credit	Consortium	Consortium
Social media	0.048***	0.044***	-0.002***	-0.003***
Telephone	0.037***	0.041***	0.002***	0.003***
Social media (t-1)		-0.004		-0.001
Telephone (t-1)		0.046***		0.003***
N	1395345	1395344	1395345	1395344
	(5)	(6)	(7)	(8)
Variable	Insurance	Insurance	Investment	Investment
Social media	0.003	0.006	0.047***	0.049***
Telephone	0.009***	0.008***	0.008***	0.011***
Social media (t-1)		0.021***		0.027***
Telephone (t-1)		-0.011***		0.016***
N	1395345	1395344	1395345	1395344

Note: Statistical significance denoted by * p<0.10, ** p<0.05, *** p<0.01. Column (1): Results from estimation of coefficient of interest in equation (5) using fixed effects and dependent variable equal to product consumption in the semester

5 Final Remarks

Entering the age of social media, business might have to rely more on technology-mediated interactions with clients. This paper studies the case of a large retail bank in Brazil that started using Facebook and Twitter to attend costumers along with the traditional call-centers. The data consist of profit margin, product consumption, and client's characteristics spanning 5 semesters since 2014. The empirical exercises evaluate whether the type of communication channel (high versus low technological content) can influence the client's consumption of banking products and profit margins. Results suggest that the banking relationship is strengthen after a high technology interaction, and interactions are correlated with increased profits and consumption.

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