How customers' offline experience affects the adoption of online banking

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HOW CUSTOMERS' OFFLINE EXPERIENCE AFFECTS THE ADOPTION OF THE ONLINE BANKING

Abstract

Purpose –This paper aims to examine the impact of customers' offline transaction behaviour in the form of loyalty and cross buying on the adoption of self-service technology innovations by non-business customers in the context of online banking.

Design/methodology/approach – This study extends the Diffusion of Innovation Theory, as well as the Technology Acceptance Model adapted to describe and model individual customer observed behaviours in the pre-adoption stage of the adoption process. The Log-logistic parametric survival model is applied using panel data for 1,357 randomly-selected new customers from a bank.

Findings – Remarkable differences arise among customers' behaviours related to periodicity of interactions with the bank and quantity of products involved in the interactions, as well as convenience and risk of the interactions. Our results corroborate that those customers who are more likely to adopt the online banking faster show an offline behavioural pattern more related to higher periodicity of interactions and convenience, rather than a high number of products involved in their interactions, the use of high-risk products or the maintenance a higher average monthly liabilities.

Originality/value – While previous research explaining the process of adoption of the online channel has mainly focused on the analysis of customer's attitudes (i.e., customers' perceptions) and demographics, in this research an additional explanation is proposed using customers' offline transactional behaviours. In addition, there is considerable amount of research about the adoption of new technologies, but there is a scarcity of studies looking specifically at the financial services and banking industry.

Keywords

Online channel, Consumer behaviour, Customer loyalty, Cross-buying, Survival analysis.

1. Introduction

Despite the numerous benefits that online banking offers customers (Ansari *et al*., 2008; Campbell and Frei, 2010), nowadays the adoption of this self-service technology is still limited. In European countries, for example, by 2014 while the largest banks offer online channel, statistics show that online banking penetration is around 44% (Statista, 2014). Limited growth in the diffusion of online banking suggests a need to further explore and examine the drivers for online banking acceptance and adoption (Montazemi and Qahri-Saremi, 2014).

Prior to adopting online banking, customers typically have a history of experience with the physical bank, which can help customers to mitigate the uncertainty related to the use of the online channel (Chiou and Shen, 2012). In this regard, although previous authors suggest that overall customers' transaction volume through the traditional or offline channel is an important motivator of the adoption of the electronic banking (Xue *et al*., 2011), we aim to further deepen in this relationship. In particular, as far as we know, there is no clear evidence in academic literature about how loyalty and cross-buying behaviours through the offline channel affect the adoption of the online banking.

Therefore, this study is an attempt to overcome some of the limitations and drawbacks of previous research about the process of adoption of the online channel, specifically the online banking. In this regard, two major shortcomings can be raised that deserve further investigation. First, empirical studies that analyse behavioural antecedents of adoption of the online channel are limited. Previous research has mainly focused on analysing social and technical dimensions that affect the diffusion of this channel (e.g., Harrison *et al*., 2014). Customer attitudes towards new technologies (Ha and Janda, 2014), usability (Chong *et al*., 2010) or access to this channel (Giordani *et al*., 2014) measured using surveys have been some of the most commonly analysed dimensions within this framework. Despite the fact that survey data are able to consider a wide variety of antecedents of adoption, they have a number of limitations. For example, survey data are typically limited to a single time period (cross-section data), thus they cannot include factors that evolve over time (Xue *et al*., 2011). Additionally, survey data rely on self-reported behaviour (i.e., perceptions) rather than actual observed data, which may introduce measurement error, such as the common-method bias, response consistency and the discrepancy between what customers say and what customers do (Chandon *et al*., 2005). Moreover, survey data are not able to measure a detailed description of exchanges between customers and banks.

A second objection implies that the integration of Internet technology with the customer loyalty and cross-buying behaviours is not widely discussed in the literature (Liang *et al*., 2008), except in case of the analysis of customers' behaviours once they have adopted the online channel (i.e., post-adoption stage). More specifically, while some studies have associated the use of online channel with higher levels of customer retention and cross-buying as consequences of adoption (e.g., Campbell and Frei, 2010; Gensler *et al*., 2012), there is no clear evidence if these higher levels in retention and cross-buying behaviours through offline channel were also antecedents of adoption (i.e., pre-adoption stage). This is where this study offers its main contribution.

In addition, the analysis of the customer behaviours in a multi-media and multi-channel environment, coupled with the necessity to look for better uses of individual-level data to build more powerful customer-level marketing programs, are growing in importance in the marketing field (see "MSI Research Priorities" 2014–2016 (MSI, 2014)). This fact is especially relevant in the financial services and banking industry, because although the interest in the topic of Internet banking adoption has grown during the last years, prior research may not have identified all the issues involved in adoption (Hoehle *et al*., 2012) and it remains as a fertile area for academic research (Hanafizadeh *et al*., 2014).

The main purpose of this study is to understand what drives customers' adoption of the online channel within the banking context. For this task, our paper extends different literature streams, such as the Diffusion of Innovation Theory (Bass, 2004), as well as the Technology Acceptance Model (Davis, 1989). They are adapted to model individual customer behavioural influences in the process of adoption of innovations and individual adoption decisions rather than aggregate adoption (Peres *et al*., 2010). Therefore, this study proposes a research model to explore the relationships among loyalty and cross-buying behaviours through the offline channel on the adoption of the online banking. More specifically, behavioural loyalty is measured by customers' length of the relationship and actual purchase behaviours according to the Recency, Frequency and Monetary value (RFM) model, and cross-buying behaviour is measured by dynamic cross-buying, level of product ownership, total quantity of products ownership and balance. For this task, we use panel data of a bank that provide individual behavioural measures of 1,357 randomly-selected new customers during 24 months. The results of the Log-Logistic parametric survival model allow us to confirm the influence of customers' loyalty behaviours related to periodicity of interactions, and customers' cross-buying behaviours related to the ownership of some of the frequently used products and average monthly liabilities on the process of adoption of the online banking. The following sections detail the theory bases and derive hypotheses.

2. Literature review and hypotheses development

2.1. Drivers of customers' adoption of the online channel

Several approaches have been used in academic literature to investigate the drivers of customers' adoption of the online channel (Hanafizadeh *et al*., 2014): (i) descriptive, (ii) comparative and (iii) relational. Firstly, descriptive approach does not seek to explain or theorize about the relationship among the factors influencing adoption. More specifically, this approach is mainly focused on identifying channel characteristics, product characteristics and individual customer characteristics as drivers of adoption. On one hand, channel characteristics are related to customers' perceived characteristics of the web as a sale channel, such as perceived risk of online channel (Mansumitrchai and Chiu, 2012), access to this channel (Giordani *et al*., 2014), trust in the web site (Hsu *et al*., 2013) and customer satisfaction with the web site (Ha and Janda, 2014). On the other hand, product characteristics are related to customers' perceived characteristics of products/services. For example, product type in terms of search products, experience products and credence products (Tamimi and Sebastianelli, 2015), product category (Pan *et al*., 2013), whether the products are low-high cost and frequently-infrequently purchased products (Xue *et al*., 2007), and customer perceptions and expectations of service quality factors (Giordani *et al*., 2014). On the other hand, the most relevant characteristics of customers considered as antecedents of adoption of the online channel have been demographics (Giordani *et al.*, 2014), customers' experience in using computers and the Internet (Klaus, 2013), customer innovativeness (Thakur and Srivastava, 2015), and barriers to adoption they face (Mansumitrchai and Chiu, 2012).

Comparative studies investigate adoption by concentrating on comparisons among key variables, for example bank type (i.e., public or private) (Bose and Gupta, 2013) or country type (i.e., developed and developing countries) (Yuen *et al*., 2010). Meanwhile, relational studies seek exclusively to understand how the different factors that affect adoption interact in their influence on adoption using one of the technology adoption theories. Some of the dominant theories from social psychology applied are the Theory of Reasoned Action (TRA) (e.g., Lim, 2015) or the Theory of Planned Behaviour (TPB) (e.g., Liang, 2014). From this perspective, the adoption determinants are based on beliefs, attitudes, subjective norm, and perceptions of behavioural control.

More specific theories to study the adoption of new technologies are also applied within the context of online channel, such as the Diffusion of Innovation Theory (DIT) (e.g., Risselada *et al*., 2014) and the Technology Acceptance Model (TAM) (e.g., Harrison *et al*., 2014). Our paper extends these literature streams. In particular, DIT seeks to understand the spread of innovations throughout their life cycle using factors related to social influence or social contagion. Diffusion of innovations involves a process that consists of two stages, pre-adoption and post-adoption (Rogers, 2003). The present study is related to the pre-adoption stage of the innovation adoption process, which involves the consumer's decision regarding whether to accept or reject the adoption of the innovation (Looney *et al*., 2008). Despite the fact that the first models of innovation diffusion were established by 1960 (Risselada *et al*., 2014), the main modelling developments in this period onwards have been in modifying the existing models by adding greater flexibility in various ways (Peres *et al*., 2010). In particular, increasing the understanding of the diffusion process at the level of the individual (i.e., modelling individual customer influences in the process of adoption), and exploiting developments in hazard and survival models to incorporate marketing mix variables (Mahajan *et al*., 1990). Our study is partially based on these modifications in DIT, because we use objective individual customer characteristics (loyalty, cross-buying and demographics as control variables) and a survival model to study their influence on the pre-adoption stage of adoption of the online channel.

On the other hand, TAM is an adaptation of TRA, which postulates that the individuals' behavioural intention (i.e., adoption) is influenced by his/her attitude towards the concerned behaviour (Hsu *et al*., 2013). The original version of the TAM (Davis, 1989) includes perceived usefulness and perceived ease of use as antecedents of adoption. TAM has been extended within the context of adoption of the online channel including more antecedents, such as trust and government support (Chong *et al*., 2010), web-channel's readiness for adoption and the customer's own readiness to adopt the Internet channel (Harrison *et al*., 2014), personal innovativeness and perceived risk (Thakur and Srivastava, 2014) and bloggers recommendations to purchase online (Hsu *et al*., 2013). Due to most of these studies are based on survey data, we extend this literature stream modelling adoption of online banking using objectively observed individual customer data.

2.2. Offline experience as driver of adoption of the online banking: loyalty and cross-buying

While for decades managerial experience and customer management literature have treated customer loyalty and retention as the most relevant transactional behaviours (Verhoef *et al*., 2010), most previous academic studies have ignored the importance of customers' cross-buying behaviour (Reinartz *et al*., 2008). However, this behaviour is meaningful for its relationship with customer's loyalty, because those customers who are more attached to the business (i.e., expressed as greater customer retention) are also engaged in more buying from various categories (i.e., through cross-buying behaviour) (Reinartz *et al*., 2008). Indeed, cross buying can be used as a strategy for reducing customer churn and improve profitability. The rationale behind this strategy implies that those customers who acquire additional products or services from a vendor increase the number of touch points between them, leading to a higher switching cost to the customer (Kamakura *et al*., 2003), allowing the firm to learn more about the customers' preferences (Li *et al*., 2005), and minimising relationship costs (Leverin and Liljander, 2006). Certainly, while customer loyalty can be viewed as a measure of relationship continuation and is concerned with minimising customer defection, cross-buying can be considered in terms of relationship development (Liu and Wu, 2007). Therefore, both related behaviours are included in the proposed model (see Figure 1)

In an online environment (i.e., in the post adoption stage of the adoption process), both loyalty and cross-buying behaviours have been suggested as clear consequences of the use of the online channel (e.g., Shankar *et al*., 2003; Xue *et al*., 2011). However, their role as motivators (i.e., antecedents) of the adoption of this channel needs to be clarified. In this regard, some previous authors suggest that total customers' transaction volume through the traditional or offline channel is an important motivator of the online channel adoption (Xue *et al*., 2011), but the role of more specific measures (i.e., reflecting offline behavioural loyalty and cross-buying) still have to be confirmed. The analysis of both behaviours is essential to better understand what helps customers to mitigate the uncertainty related with the adoption of the online channel (Chiou and Shen, 2012). Indeed, customers' offline experiences in terms of loyalty and cross-buying (i.e., transactional behaviours) provide critical consumption messages about customers' purchase patterns to retailers (Liao *et al*., 2014). Therefore, the use of this data can support companies to uncover customers' behavioural inclinations, which will help them to improve their Internet competitive level by meeting more adequately customers' needs (Kumar *et al*., 2013).

[Insert **Figure 1**. Research model]

2.2.1. Customer behavioural loyalty

Previous research about customer loyalty has been divided into three different perspectives: (i) the attitudinal approach, (ii) the behavioural approach and (iii) the composite approach (Jacoby and Chestnut, 1978). In practice, attitudinal loyalty is less used as behavioural loyalty (Bandyopadhyay and Martell, 2007), mainly because behavioural loyalty is more objectively observed than the attitudinal one. Therefore, we have included behavioural loyalty in the proposed model, defined as a composite measure based on customers' behaviours related to the length of the relationship between customers and company and customers' purchase recency, cancellation recency and monetary value at a retailer (RFM score) (Kumar *et al*., 2006).

Length of the relationship between customers and company

Trust is a key factor in the establishment of long-term relationships between providers and their customers (Hsu *et al*., 2014). It has been suggested that customers, who trust in traditional brick-and-mortar retailer, will have a similar level of confidence in shopping for products at the online channel (Hahn and Kim, 2009). In this regard, when customers feel save and confident in a company as a result of long relationships, perceived obstacles to the adoption of the online channel can be minimised (Winch and Joyce, 2006). Moreover, when a customer decide to adopt a new self-service technology (e.g., the online channel), he or she assumes the implicit costs associated with the use of this new channel, such as those created by learning how to use a new technology, as well as the costs of establishing a relationship with the company through a new channel (Ackermann and von Wangenheim, 2014). Therefore, if the customer does not take enough time operating with the company, the customer would not probably assume risks and indirect costs of adopting the online channel. Thus, we propose:

H1: A higher length of the relationship is associated with a faster adoption of the online channel.

Recency, frequency and monetary value (RFM)

RFM model comprises three types of information concerning customers' buying behaviour. In particular: (1) recency, or time interval between purchases/cancellations (Donkers *et al*., 2007), (2) frequency or the number of purchases conducted during a specific period (Reinartz *et al*., 2008), and (3) monetary value or the amount of money spent during a specific period (Kumar and Shah, 2009). Customers, who have bought more recently, those who buy frequently, and those who tend to spend more are likely to contribute with higher economic values to a retailer and are recognized as being loyal (Cheng and Chen, 2009). Since lower purchase recency usually implies higher frequency of acquisitions by definition, in order to achieve a parsimonious model, this study considers purchase recency, cancellation recency and monetary value to represent customers' behavioural loyalty (Liao *et al*., 2014).

The ubiquity that Internet provides customers is an ideal environment for anytime, anywhere shopping, especially for those who frequently purchase online (Grewal *et al*., 2003). Online channel offers customers convenience (Wu and Wu, 2015), which implies time savings, as well as 24-hours access to services. For banking customers, online channel also offers an effective management of personal finances (Lee *et al*., 2003), which implies giving customers more information and control over the service process (Ding *et al*., 2007). Therefore, if a customer has a low recency in product acquisitions, the customer can exploit the benefits provided by the online channel, which time and location are irrelevant. Thus, we propose:

H2a: A lower purchase recency is associated with a faster adoption of the online channel.

Anonymity through the Internet has been one of the most important motivators for use it, as the Internet allows people to play a role that in the real life is difficult to fulfil (Christopherson, 2007). Similarly, online channel offers customers anonymity, which implies to avoid face-to-face interactions when customers perform any kind of transaction with the company (Parsons, 2002). Although in general customers prefer human interaction when they transact or exchange with the company (Lee *et al*., 2003), especially with banks (Jaruwachirathanakul and Fink, 2005), customers with financial needs of medium and high complexity do not regard a lack of face-to-face interaction for simple products as an inhibitor to using the online banking (Durkin *et al*., 2008). In this regard, in certain unkind situations (e.g., when customers switch products), they can prefer to avoid unpleasant face-to-face interactions, because customers feel unrestricted while using Internet banking (Liao and Cheung, 2001). Indeed, online banking can make products cancellations easier for customers, avoiding numerous explanations to the bank personnel about their own decisions. Therefore, if a customer has a lower recency in product cancellations, he/she can exploit the benefits of anonymity provided by the online channel. Thus, we propose:

H2b: A lower cancellation recency is associated with a faster adoption of the online channel.

Monetary value of customers is related to the amount of money spent during a specific period (Kumar and Shah, 2009). Customers who spend more in the same company are more likely to contribute with higher economic values (Cheng and Chen, 2009). In the banking industry, monetary value of customers is derived, for example, from the average money in all of the customer's deposits during each season (Khajvand and Tarokh, 2011), product margins (Donkers *et al*., 2007), interest payments and commission fees (Haenlein *et al*., 2007). Consequently, customer interactions usually generate monetary value of customers to the bank (Campbell and Frei, 2010). From a customer perspective, self-service technologies, such as online banking, decrease the marginal cost of service interaction through increased convenience, accessibility and improved service efficiency by offering shorter waiting times than those ones suffered by customers at bank branches (Wu and Wu, 2015).

Therefore, if a customer has a high monetary value, he/she can benefit from a marginal cost reduction provided by the online channel. Thus, we propose:

H3: A higher monetary value of a customer is associated with a faster adoption of the online channel.

2.2.2. Cross-buying

In order to get a richer perspective about cross-buying, some authors also suggest using a wide behavioural perspective (Reinartz *et al*., 2008). Within this view, several behaviours are usually included, such as dynamic cross-buying (Verhoef *et al*., 2001), behaviours related to level of product ownership (relationship 'width' indicator) and behaviours related to intensity of product ownership or balance (relationship 'dispersion' indicator) (Reinartz *et al*., 2008).

Dynamic cross-buying

Whereas cross-selling is a firm-side action employed to broaden customer relationships, its counterpart on the demand side, cross-buying, refers to a customer's propensity to make cross-category purchases (Reinartz and Venkatesan, 2008). In this research, dynamic cross-buying reflects the attractiveness for customers of the focal supplier through the difference in the number of products or services acquired and cancelled between *t* and *(t-1)* (Verhoef *et al*., 2001). Cancellations are also included because in line with Bolton and Lemon (1999), we assume that increasing the number of services and decreasing the number of services is the same decision process. As a result, a positive dynamic cross-buying is related to a customer who acquires more quantity of products. Therefore, the previously mentioned ubiquity of Internet (Grewal *et al*., 2003), convenience (Wu and Wu, 2015) and more information and control over the service process (Ding *et al*., 2007), may be motivators to adopt online channel by those customers with a higher positive dynamic cross-buying. Thus, we propose:

H4a: A higher positive dynamic cross-buying is associated with a faster adoption of the online channel.

On the other hand, a negative dynamic cross-buying is related to a customer who cancels more quantity of products. In this case, the previously mentioned anonymity and the avoidance of face-to-face interactions allowed by online banking (Parsons, 2002), may be motivators to adopt it by those customers with a higher negative dynamic cross-buying. Thus, we propose:

H4b: A higher negative dynamic cross-buying is associated with a faster adoption of the online channel.

Level of product ownership

In the context of grocery retailers, some products categories tend to be more related to specific channels than others (Inman *et al*., 2004). In the special case of banking industry, frequency of use and perceived product risk represent important product characteristics for matching products to channels (San Martín-Gutiérrez *et al*., 2010). On one hand, frequently used products (such as 'foundation services', see Table 1) are more likely to benefit more from the use of online channel (Xue *et al*., 2007), because of the accessibility and convenience that the online channel offers to the customer. But on the other hand, for high-risk products (such as 'risk management and cash reserves',' growth to offset inflation', 'risky, task protection assets' and 'current income-post retirement', see Table 1), the adoption of online channel may also provide continuous access to detailed product information, which may result in increased information monitoring and more active product management (Campbell and Frei, 2010). Therefore, although for certain industries some products categories tend to be more related to specific channels than others, there is an a priori reasoning which suggests a different explanation in the banking context. Thus, we propose:

H5a: The ownership of a greater number of frequently used products is associated with a faster adoption of the online channel.

H5b: The ownership of a greater number of high-risk products is associated with a faster adoption of the online channel.

In sum, those customers, who owned more products or services from the same financial services provider, will have a high demand for interactions with the provider (Kumar *et al*., 2008). Consequently, customers with a high demand of interactions with the provider have more to gain from adopting online banking (i.e., convenience, time saving, access 24-hours, more information and control over their services). Thus, we propose:

H5c: The ownership of a greater number of products is associated with a faster adoption of the online channel.

Balance or average monthly assets and liabilities

Intensity of product ownership or balance reflects the level of spending dispersion across product or service categories (Reinartz *et al*., 2008). In addition, balance is also used to define conditions under which the customer is considered as active (versus inactive) in a banking context (Haenlein *et al*., 2007). In particular, (condition 1) all customers owning either a home financing product, a credit, a loan or an insurance product (assets) are defined as being active due to the regular revenue streams (interest payments, insurance fees) resulting from any of these products; and (condition 2) all customers owning transaction accounts, custody accounts and savings deposits (liabilities) are defined as active customers when these accounts showed a positive balance of at least 100 euros and/or at least one transaction had been carried out during the last three months (for transaction accounts) or twelve months (for custody accounts and savings deposits). So apparently, both average monthly assets and average monthly liabilities offer information on the level of customers' activity with the bank (Haenlein *et al*., 2007). Therefore, if a customer has high average monthly assets, he/she can benefit from the previously mentioned increased convenience, accessibility and shorter waiting times offered by online banking (Wu and Wu, 2015). Thus, we propose:

H6a: A higher average monthly asset is associated with a faster adoption of the online channel.

H6b: A higher average monthly liabilities is associated with a faster adoption of the online channel.

3. Research methodology

3.1. Data collection

For the empirical analysis, we use panel data collected by a large Spanish bank, which operates at the national level. This bank has an extensive physical branch network, as well as an online banking offering the same product assortment. The observed time period begins in December 2010 and ends in November 2012. A complete analysis of missing data was carried out. Missing data were presented in the variables: income (with 1,974 missing observations or 6.06% over the total number of observations), average monthly assets (with 50 missing observations or 0.15% over the total number of observations) and average monthly liabilities (with 50 missing observations or 0.15% over the total number of observations). Missing data have been imputed by multiple imputation method, because it has several desirable features. In particular, multiple imputation introduces an appropriate random error into the process that makes it possible to get approximately unbiased estimates of all parameters. Additionally, the repeated imputation allows getting good estimates of the standard errors. Moreover, multiple imputation can be used with any kind of data and any kind of analysis without specialised software (Little and Rubin, 1989). Once the data pre-processing and the imputation of missing data are carried out, the database contains 24 months of behavioural data for 1,357 new customers located in Spain (who began their relationship with the bank at the beginning of the observation period) with 32,568 datasets.

3.2. Variables measurement

Time event: adoption of the online banking

The variable adoption of the online banking is measured using a dummy variable for each customer *i* and each time period *t*. In particular, this variable takes the value 1 if the customer *i* adopts online channel in the month *t* and 0 otherwise (Campbell and Frei, 2010).

Explanatory variables

As loyalty behaviours we include length of the relationship, purchase recency, cancellation recency and monetary value of customers. Length of the relationship (L_i) measures the time between the entry of the individual *i* as a customer of the company and his/her defection or the end of the observation period (Glady *et al*., 2009). A continuous variable is used to measure length of the relationship in months (Reinartz and Kumar, 2003 p.88). For recency, we include two continuous and time-varying variables, (1) purchase recency (PR_{it}), which measures the number of periods (in months) since the last purchase across all product categories, and (2) cancellation recency (CR_{it}), which measures the number of periods (months) since the last cancellation across all product categories. Donkers *et al*. (2007) operationalised these two variables as binary variables, but we have adapted the pure definition of recency (Pfeifer and Caraway, 2000) to purchase recency, as the difference between the last purchase and the (period of) time of analysis, and cancellation recency, as the difference between the last cancellation and the (period of) time of analysis. Finally, monetary value (M_{it}) is measured using a standardised continuous time-varying variable (Kumar and Shah, 2009). Monetary value indicates the difference between interest and fees charged to the customer minus the bank cost paid or the bank incomes earned (because of the bank invests the money of customers funds and other products) at the Interbank Lending Market (a market in which banks extend loans to one another for a specified term using the interbank or overnight rate; low transaction volume in this market was a major contributing factor to the financial crisis of 2007).

Cross-buying is measured using four different behaviours: dynamic cross-buying, level of product ownership, total quantity of products ownership and balance. Dynamic cross-buying (DCB_{it}) measures the difference in the total number of products acquired and cancelled across all product categories from the focal supplier between the period *t* and *(t-1)* (Verhoef *et al*., 2001). Dynamic cross-buying completes the information provided by purchase recency and cancellation recency measures, because none of the two quantify the real number of products that are purchased or cancelled. For level of product ownership, we include 9 continuous time-varying variables for ownership of each product type at period *t* by each customer *i*, which are represented by FS_1_{it}, FS_2_{it}, FS_3_{it}, FS_4_{it}, $RMCR\_5_{it}$, $RMCR\_6_{it}$, $GTOI\_9_{it}$, $GTOI\_11_{it}$, $CIPR\_17_{it}$ (Bolton and Lemon, 1999; Venkatesan *et al*., 2007 p. 585). We have used the classification of banking products proposed by Kamakura *et al*. (1991) in order to reflect the portfolio of the company products available in the database (see Table 1). In order to reflect the latent nature of this predictor variable without losing the detailed information provided by their respective items (i.e., individual products), we have calculated an additional predictor variable (Q_TOT_{it}) by summing up all or sub-sets of their indicators. In particular, Q_TOT_{it} measures the total quantity of products used by customer *i* at period *t* (Venkatesan and Kumar, 2004) across all product categories. This approach is in line with the basic philosophy behind this type of measurement (see Jarvis *et al*. (2003) for more details). Balance is measured using two additional standardised continuous time-varying variables: (1) average monthly assets (AMA_{it}) (measured in euros), and (2) average monthly liabilities (AML_{it}) (measured in euros). The first one (AMA_{it}) measures balances on short and long-term credit accounts, loans and debt on current accounts (assets) (Haenlein *et al*., 2007; Prinzie and Van den Poel, 2006). The second one (AML_{it}) measures balances on saving and investment products, credits on current account and monthly insurance fees (liabilities) (Haenlein *et al*., 2007; Prinzie and Van den Poel, 2006). Although these two variables are continuous dimensions, they are registered in the database at discrete moments in time, for example, at the end of the month for bank accounts and on a yearly basis for insurance products.

[Insert **Table 1**. Classification of banking products]

As previous research has paid great attention to demographic indicators in order to identify factor leading to the adoption of technological services (Giordani *et al*., 2014), we have included this type of information as control variables in our model. For age, we used a continuous variable measured at the end of the observation period. For gender, we used a binary variable that takes the value 1 for men and the value 2 for women, measured at the beginning of the relationship between the customer and the bank. Finally, for income, we used a standardised continuous variable, which indicates the average annual salary received by each customer. Table 2 shows descriptive statistics of all variables included in the model.

[Insert **Table 2**. Descriptive statistics]

3.3. Research model

We use survival analysis methods to test our hypothesis about online channel adoption. This methodology relates the explanatory variables (including individual and time varying measures) to the time when the customer adopts the online channel. More specifically, each individual in the database exits for survival analysis until the event adoption of online channel occurs or the individual leaves the bank. For the purpose of analysis of customers' transactional behaviours affecting the adoption of the online banking, the model explicitly uses a log logistic form of a parametric survival model. We have selected parametric models since they are more statistically efficient in analysing the influence of some covariates evolving over the time interval (i.e., time-varying variables) than non-parametric or semi-parametric survival analysis models (Cleves *et al*., 2010). Following the product and innovation diffusion literature (Tellis *et al*., 2003), we fit our proposed model using a log-logistic distribution accelerated failure-time (AFT) model, as follows:

$$
\begin{aligned}
&Ln(online\ channel\ adoption)\\
&\quad = L\beta_1 + PR\beta_2 + CR\beta_3 + M\beta_4 + DCS\beta_5 + FS\_1\beta_6 + FS\_2\beta_7 + FS\_3\beta_8 + FS\_4\beta_9\\
&\quad + RMCR\_5\beta_{10}\\
&\quad + RMCR\_6\beta_{11} + GTOI\_9\beta_{12} + GTOI\_11\beta_{13} + CIPR\_17\beta_{14} + Q\_TOT\beta_{15} + AMA\beta_{16}\\
&\quad + AML\beta_{17} + AGE\beta_{18} + GENDER\beta_{19} + INCOME\beta_{20} + \varepsilon_i
\end{aligned}
$$

AFT model relates the explanatory variables to the time when the customer adopts the online channel. In the AFT model, the natural logarithm of the survival time, log *t*, is expressed as a linear function of the covariates, as follows:

$$logt_i = x_j\beta + \varepsilon_j$$

Where x_j is a vector of covariates, β is a vector of regression coefficients and ε_j is the error term with density $f()$. The distributional form of the error term determines the regression model (using models such as the exponential, Weibull, Log-normal, Log-logistic and generalized gamma). The outcome of this approach is an event time. The effect of the AFT model implies to change the time scale by a factor of $\exp(-x_j\beta)$. If this factor is less or greater than 1, failure time is either decelerated (implying a decrease in the expected waiting time for failure) or accelerated (implying an increase in the expected waiting time for failure), respectively.

3.4. Results

The model parameters are estimated by maximum-likelihood with a robust variance estimator in STATA software v.12. In particular, we use commands STSET, to define the failure indicator and treat right censoring, and STREG, to run the log-logistic AFT model. Results with the log-logistic AFT model are reported in Table 3. More specifically, the column 1 reports the regular regression coefficients (*log-time* β_i) in the log-time format. The column 2 reports the more easily interpreted time ratio coefficients (applying the transformation e^{β_i}). A negative log-time coefficient or a time-ratio coefficient less than 1 implies faster adoption. The overall model fit is assessed via the likelihood ratio χ^2 statistic, which compares the likelihood of the models with and without the variables. As Table 3 indicates, the model is significant with $\chi^2(20)$ = 1,759.86 (p < 0,05). As a robustness check, we also fit the AFT model under different distribution assumptions (exponential, lognormal, Weibull) with similar results (not shown). We have compared the results of these models using the Bayesian Information Criteria (BIC) (Schwarz, 1978) and Akaike Information Criteria (AIC) (Akaike, 1974). The model with the lower value of BIC and AIC is the log-logistic, being the one preferred and selected.

[Insert **Table 3**. Log-logistic AFT model results]

The results show that the probability of adoption of the online banking is not affected by the length of the relationship between the customer and the company (β = -0.007, p > 0.05). H1 is therefore not supported. On the contrary, purchase recency (β = 0.296, p < 0.05) and cancellation recency (β = 0.141, p < 0.05) have a significant impact on adoption of the online banking. Particularly, both drivers make slower the process of adoption of this channel, corroborating H2a and H2b. In this case, both purchase recency and cancellation recency quantify the number of time periods between purchases and cancellations made by customers, which essentially implies considering periodicity of both processes. The results also show that the probability of adoption of the online banking is not affected by customers' monetary value (β = 0.038, p > 0.05). H3 is therefore not supported, demonstrating that monetary value is not always linked with a high level of customers' interactions. Concerning the first cross-buying behaviour considered, the results show that the probability of adoption of the online banking is not affected by customers' dynamic cross-buying (β = -0.022, p > 0.05). Therefore, H4a and H4b are not supported. Dynamic cross-buying quantifies the total number of products acquired and cancelled between periods *t* and *(t-1)*, which essentially implies considering quantity of products involved in both processes. The results also show that the level of ownership of some frequently used products has a significant impact on the adoption of the online banking, partially supporting H5a. In particular, 'home loan and account' (FS_1) (β = -0.228, p < 0.05) and 'debit card and credit card' (FS_2) (β = -0.521, p < 0.05). However, the results show that the probability of adoption of the online banking is not affected by customers' level of high-risk products ownership. H5b is therefore not supported. Consequently, the variable total quantity of products owned does not exert a significant effect over the adoption of the online channel (β = -0.071, p > 0.05). H5c is therefore not supported, giving more evidence about the importance periodicity of interactions in the process of adoption of the online banking. On one hand, the probability of adoption of the online banking is not affected by the average monthly assets (β = -0.045, p > 0.05) and H6a is not supported. On the contrary, average monthly liabilities (β = 0.108, p < 0.05) have a significant impact on the process of adoption of the online banking making slower the process of adoption of this channel, supporting H6b but with opposite effect than expected, and providing evidences redefining the predictable customer offline behavioural inclinations in adopting the online banking. Finally, with regard to the control variables (i.e., age, gender and income), the results indicate that younger customers tend to adopt online banking faster (β = 0.003, p < 0.1) but conversely, customers with a lower income tend to adopt online banking slower (β = -0.094, p < 0.05). However, no significant gender difference in adoption of the online banking is found (β = 0.065, p > 0.05).

4. Implications for research

The findings of this study provide several important theoretical implications regarding adoption of the online banking. The main results obtained show that in terms of loyalty, customers with lower levels in purchase recency and cancellation recency are more likely to adopt online banking faster. Therefore, the ubiquity (Grewal *et al*., 2003) and anonymity (Parsons, 2002) provided by the Internet offer customers an ideal environment to acquire and switch products, respectively. The results also show that the length of the relationship between the customer and the company does not affect the probability of adoption of the online banking. In this regard, despite the fact that in some industries customers are reluctant to use online channel and they need time to feel safe and confident operating with the company in order to adopt it (Hahn and Kim, 2009), for banking customers the time spend with the company seems not to be a significant motivator for its adoption. In addition, the results show that the probability of adoption of the online banking is not affected by customers' monetary value. More specifically, if a customer has a high monetary value but this is not combined with movements of money in terms of acquisitions and cancellations of products, the adoption of the online banking does not seem to have much sense for the customer.

On the other hand, the main results obtained in terms of cross-buying show that the level of ownership of some frequently used products, such as 'home loan and account' and 'debit card and credit card', has a significant impact on the adoption of the online banking. These frequently used products are more likely to benefit from the use of the online channel (Xue *et al*., 2007), because of the accessibility and convenience that the online channel offers to customers. However, the aggregated measure average monthly assets, which collects balance accounting information regarding different asset products, does not seem to be a significant motivator of the adoption of the online channel, indirectly corroborating that not all the asset products are linked with a high level of customers' interactions.

Moreover, the results show that the probability of adoption of the online banking is not affected by customers' level of high-risk products ownership. As their name suggests, high-risk products are inherently riskier products that can generate doubts and uncertainty to customers who can perceive online banking as an insecure way to interact with the bank. Indeed, we have demonstrated that customers with higher average monthly liabilities are more likely to acquire online banking slower than other customers, suggesting that perceived risk of transact online is higher for those customers who have higher balance in liabilities. More specifically, when customers have to decide whether to use online banking, the risk associated with possible losses from the online banking interactions is greater than in traditional environments (Yang *et al*., 2015). As a consequence, the least frequently performed online financial transactions are related to saving and investment products (liabilities) (Aldás-Manzano *et al*., 2009). Therefore, a possible explanation of our results is given by the fact that if a customer has lower (greater) average monthly liabilities, he/she can perceive less (more) risk associated with transact online, encouraging (discouraging) the process of adoption of this channel.

In line with these results, we have coped with a double dichotomy related to the customer offline behavioural inclinations in adopting the online banking, that is, quantity of products involved in the interactions versus periodicity of the interactions, and convenience versus risk of the interactions. From these two dichotomies, our results corroborate that those customers who are more likely to adopt the online banking faster show an offline behavioural pattern more related to higher periodicity of interactions (reflected in lower purchase recency and cancellation recency) and convenience (reflected in a high level of ownership of some frequently used products), rather than a high number of products involved in their interactions, the use of high-risk products or the maintenance a higher average monthly liabilities.

5. Implications for practice

The findings of this study provide several important practical implications regarding adoption of the online channel, especially the online banking. Due to the limited growth of the diffusion of the online banking, the additional explanation provided by this research using customers' observed behaviours can enrich the existing knowledge about this process, especially because many banks still "trial and error" their electronic banking applications (Hoehle *et al*., 2012). In this sense, the proposed additional explanation can help companies to uncover customers' behavioural inclinations in order to improve their online strategy by identifying those customers more likely to adopt the Internet as a channel for transactions. Indeed, financial service providers perform annually important investments in demographic data from outside vendors (Campbell and Frei, 2004), because usually they mainly use customer demographics in order to study their customers (e.g., to segment their customer base and offer product promotions) (Xue *et al*., 2011). Thus, this paper aims to analyse a wider customers' perspective identifying potential mechanisms through which banks can increase their online banking penetration using their database of customers. More specifically, the management implications emerging from this research are related to the understanding of customers' offline transactional behaviours that are more likely to influence the process of adoption of the online channel. Knowing these drivers, companies, and particularly banks, are able to make a diagnostic about the opportunity (or not) of implementing and/or improving their online strategy.

6. Conclusions, limitations and future research

This study contributes to a more thorough understanding of the relationship between customers' offline experience and the adoption of the online channel in the banking context. In particular, the contributions of this study to research on online banking are twofold. First, in contrast to previous research focused on exploring the determinants of the adoption of the online banking using attitudes and perceptions, the current study is focused on analyse behavioural antecedents related to customers' offline experience with the bank, that is, loyalty and cross-buying behaviours. Second, due to the lack of studies integrating Internet technology with the customer loyalty and cross-buying behaviours, especially in the pre-adoption stage of the adoption of the online channel process, this integration is the main contribution of this study.

This study suffers from several limitations that suggest avenues for further research. First, our data is limited to a single bank, so we cannot observe changes in behaviour or differences across institutions. Second, the empirical setting for this study is limited to restricted information regarding products, customers and the period of time for the analysis. Future research should consider customers' data from different banks, a longer time period and further data about products and customers. We also propose to include an additional perspective about customer engagement including non-transactional behaviour (Verhoef *et al*., 2010) as antecedents of adoption of the online banking (e.g., word-of-mouth, customer-to-customer interactions). It is obvious that for firms the transactional side of the relationship is fairly important, as it usually creates immediate cash flows for the firm. However, ignoring non-transactional behaviour can lead to loss of opportunities (Verhoef *et al*., 2010). Useful extensions of this work would be to analyse cross-channel adoption and whether customers perform less/more transactions across other channels (e.g., ATMs, mobile commerce), different cultures, and contexts (e.g., different countries, customer segments and business models). The omni-channel retailing perspective (i.e., how shoppers are influenced and move through channels in their search and buying process) (Verhoef *et al*., 2015), as well as the online-offline channel integration (i.e, the analysis of channel synergies and channel cannibalization process) (Herhausen *et al*., 2015), can be used to implement these proposed extensions.

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