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A Machine Learning Approach to the Digitalization of Bank Customers: Evidence from Random and Causal Forests

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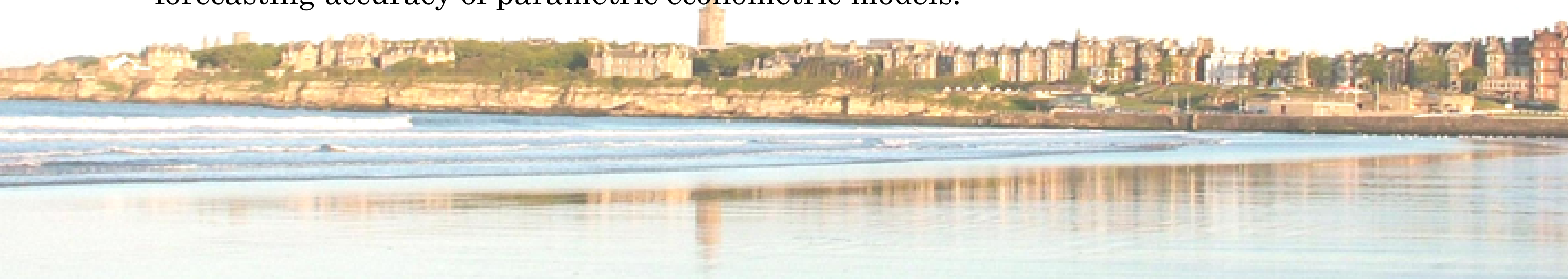

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Abstract

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JEL classification: G21, O33
Key words: Technology adoption, banks, machine learning, random forest, causal forest

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1. Introduction

At the end of 2018, 51.2% of the global population, or 3.9 billion people, used online digital devices.[1] Digitalization is changing the shape of many industries and the way companies and clients interact. This digital revolution has been particularly relevant in the banking industry where the use of digital banking (online and mobile) has become one of the most strategic channels used by bank customers. The Organization for Economic Co-operation and Development (OECD) has identified some of the core properties and crosscutting effects of the digital transformation (OECD, 2017) as the most important business challenge currently underway. Furthermore, the OECD recognizes banking as one of the sectors where such transformation is more relevant in economic, organizational, and social terms.

On the supply side, financial institutions have gradually reacted to these changes. Banks are particularly sensitive to the transformation of information systems, the treatment of personal data, and the emergence of new (fully digital) competitors and delivery channels. Despite incorporating online distribution channels two decades ago, and in spite of the renewed digitalization wave, banks continue to develop more information and systems-oriented business models. Furthermore, information systems in banking are increasingly being developed for customers rather than for organizational users (McKenna, Tuunanen, & Gardner, 2013). This effort is driven by both rival precedence (Hernández-Murillo, Llobet, & Fuentes, 2010) and changes in demand (Campbell & Frei, 2010).

A large number of studies on banking organization and technology have addressed the adoption of the most basic electronic banking services developed over the last few

[1] International Telecommunication Union (ITU) global and regional (Information and Communications Technology (ICT) estimates.

decades including debit and credit cards and more recently online banking (although partially covered). Information systems literature has revealed a variety of mechanisms—motivations, attitudes, behavioral intention, social systems, and associations—involved in technology adoption. These studies have found that perceived security, usefulness, quality, and convenience drive consumer adoption of online services (Casaló, Flavián, & Guinalíu, 2007; Hoehle, Scornavacca, & Huff, 2012; Laukkanen, 2016; Maria Correia Loureiro, Rüdiger Kaufmann, & Rabino, 2014; Yoon & Barker Steege, 2013; Yusuf Dauda & Lee, 2015). However, the relevance of each of these factors depends on the stage of the adoption. This is an important lesson for new digital services given the heterogeneous penetration they have both geographically and demographically (Montazemi & Qahri-Saremi, 2015). This is particularly relevant considering that socio-demographic characteristics—age, gender, income, and location—(Jaruwachirathanakul & Fink, 2005; Kesharwani, 2019; Laukkanen, 2016), cultural characteristics (Tam & Oliveira, 2019), and customer experience (with other products with varying levels of technological sophistication) are strongly related to the demand for online banking services (Szopiński, 2016).

Most prior studies have focused on a single dimension of the digitalization process, the adoption of electronic or mobile banking services. However, there is little evidence of the decision process that leads bank consumers to go digital. Financially speaking, going digital means predominantly or exclusively using online or mobile banking. This transition is not trivial. This paper applies a multidimensional approach to explore the digital transformation of bank customers. By doing so, we aim to examine the process by which consumers become digital bank customers.

Unlike prior studies, our investigation uses machine learning techniques based on random forest models to predict the sequence of adoption of digital financial services using a wide range of indicators from a comprehensive survey specifically designed for this purpose. While conventional econometric models used in other consumer demand studies only identify the determinants, our methodology allows us to examine the digitalization process. Furthermore, instead of being limited to making strong assumptions about the structure of the data, machine learning allows researchers to identify and display complex patterns in a data-driven form (Bishop, 2006). Since traditional information systems factors such as those described in technology acceptance theories may not be sufficient to explain banking digitalization (Bagozzi, 2007; Pousttchi & Dehnert, 2018), the use of algorithms allows us to reveal the patterns of how individuals make their financial digitalization choices. We evaluate the models using cross validation and show that random forests also outperform standard logit and ordered logit models in forecasting accuracy. Finally, we extend random forests using a causal forest algorithm, which is a method that allows for a tractable asymptotic theory and valid statistical inference. In doing so, we provide evidence concerning the causal impact of those features with larger predictive power on the digitalization process.

Our paper offers a twofold contribution to the existing literature on technology adoption in the banking context. First, we explore the sequence of the adoption of digitalization services by bank customers. Unlike previous studies, ours does not limit its scope to analysis of adoption versus non-adoption; it explains how consumers make their decisions and how they become frequent and diversified users of digital financial services. Moreover, we reveal how the adoption process of digital banking services is related to other non-bank digital financial services (e.g., PayPal or Amazon). Second, by employing a machine learning approach, this paper offers a greater statistical accuracy than earlier studies in describing the main determinants of consumers' choices to adopt digital financial services.

Understanding how bank customers go digital could help banks to increase retention of digital users (Campbell & Frei, 2010) and customer loyalty (Xue, Hitt, & Chen, 2011). Furthermore, examining the adoption of alternative digital payment methods (e.g., Amazon Pay, Google Wallet, PayPal, Apple Pay) should increase the understanding of how banks and non-financial providers (BigTech and FinTech) could strategically compete offering payment services.

The empirical analysis relies on extensive data collected from a survey about digital banking and payment services responded by 3,005 consumers between the ages of 18 and 75. The survey includes controlled representative quotas from a sociological standpoint based on age, sex, and location. This dataset allows us to explore financial digitalization in a developed country with deep internet penetration (84.6% of adults are internet users[2]), a highly banked population (97.2% of adults have a bank account[3]), and a growing use of electronic banking among consumers (62% of the sample individuals are e-banking users to some extent, although the degree and scope of the adoption varies substantially across individuals[4]).

By way of preview, the results of our empirical analysis suggest that bank customers need to become familiar with the information content of digital services before they begin to make financial transactions. Going digital begins with information-based services and is then followed by transactional services. Customers check their bank balances, make inquiries, and explore the possibilities of the digital channels before making payments, transferring money, or engaging in other transactional services. As for the scope of digitalization, the perceived safety of digital bank services by consumers becomes a critical filter for consumers' diversified use of digital bank services. However,

[2] ICT Access and Usage by Households and Individuals (2017). OCDE statistics.
[3] G20 Financial Inclusion Indicators. World Bank Data.
[4] The Online Banking Landscape in Europe. GlobalWeb Index (2017Q1).

there appear to be notable exceptions. In the case of mobile banking, for example, even if perceived safety influences consumers' adoption decisions, the speed and ease of use of the device appear to be more decisive. The efficiency of this service contrasts with the adoption process of more traditional and more established bank services such as credit and debit cards, which are used on a regular basis only when they are perceived as safe and relatively costless. Finally, our results also indicate that consumers adopt other non-bank digital financial services (e.g., Amazon or PayPal) only after they have already become frequent and diversified digital bank customers.

The remainder of the paper is organized as follows: Section 2 reviews the related literature; Section 3 describes the dataset and the methodology employed; Section 4 addresses the digitalization dimensions; Section 5 discusses the main empirical results; Section 6 addresses the causal impact using causal forests; Section 7 shows the consistency of the findings over alternative supply-side explanations; Section 8 presents the implications, limitations, and scope for future research; and Section 9 concludes the paper.

2. Related Literature and Theoretical Foundations on Technology Adoption

The main relevant studies related to financial technology adoption in the digital age refer to firm management and information systems. A number of theories aim to explain the evolution of these new technologies and the interaction between the consumer and the firm. Among them, the technology acceptance model (TAM) (Davis, Bagozzi, & Warshaw, 1989) and its latter versions (TAM2 and TAM3) have become popular for explaining how people accept and adopt new technology in the context of banking. The TAM model, which is based on the theory of reasonable action (TRA) (Fishbein & Ajzen, 1975) and the theory of planned behavior (TPB) (Ajzen, 1985, 1991), suggests that technological adoption depends on customers' perception of the utility and ease of use of the technology. Other theories such as the diffusion of innovations (DIT), the task-technology fit (TTF), the unified theory of acceptance and use of technology (UTAUT), and the technology resistance theory (TRT) have complemented the drivers of online adoption. These theories have thereby given prominence to a number of technological components of the service and not just to consumers' perceptions. However, has recently been argued, traditional information systems factors may not be sufficient to explain banking digitalization (Bagozzi, 2007; Pousttchi & Dehnert, 2018). From an empirical standpoint, prior studies on customers' perceptions have identified the main factors that explain the adoption and utilization of online banking. These include security (Casaló et al., 2007; Cheng, Lam, & Yeung, 2006; Hoehle et al., 2012; Vatanasombut, Igbaria, Stylianou, & Rodgers, 2008; Yoon & Barker Steege, 2013), ease of use (Aldás-Manzano, Lassala-Navarré, Ruiz-Mafé, & Sanz-Blas, 2009; Lee, 2009; Maria Correia Loureiro et al., 2014; Yoon & Barker Steege, 2013; Yusuf Dauda & Lee, 2015), convenience (Maria Correia Loureiro et al., 2014; Yoon & Barker Steege, 2013), and cost (Jimmy Huang, Makoju, Newell, & Galliers, 2003; Laukkanen, 2016). Overall, consumers use e-banking services when they perceive them as safe, useful, convenient, and relatively costless.[5] As for the relative importance of these factors, Hoehle et al. (2012) have surveyed the literature and concluded that security is a major determinant of consumers' use of e-banking services. Additionally, many of these studies highlight that a range of socio-demographic characteristics (Jaruwachirathanakul & Fink, 2005; Kesharwani, 2019; Laukkanen, 2016) and cultural characteristics (Tam & Oliveira, 2019) also influence the adoption of online banking services. Specifically, young people who have a higher income and live in areas of high internet penetration (Laukkanen, 2016; Veríssimo, 2016; Xue et al., 2011) are prone to using online services. However, as Montazemi and Qahri-

[5] Hoehle et al (2012) and Dahlberg et al. (2015) have provided detailed coverage of the literature within the last three decades.

Saremi (2015) have highlighted, the importance of these socio-demographic factors depends on the stage of the adoption of online banking services within each market segment or jurisdiction. It is also worth noting that Hitt and Frei (2002) have explored the differences between branch-based and online bank customers. They have suggested that online banking customers are apparently more profitable, primarily due to unobservable characteristics that existed before the adoption of online banking. Moreover, Szopiński (2016) has found that having other banking products such as mortgages and credit cards also has a significant influence on consumers' use of online banking services.

Closely related to online banking, studies on mobile banking adoption have also recently emerged. The empirical and theoretical approaches in these studies are similar to those to online banking (Alalwan, Dwivedi, & Rana, 2017; Baptista & Oliveira, 2015; Lu, Tzeng, Cheng, & Hsu, 2015; Luo, Li, Zhang, & Shim, 2010; Susanto, Chang, & Ha, 2016; Zhou, Lu, & Wang, 2010). The results of these studies suggest that age is the most decisive factor in mobile banking adoption. However, other determinants such as trust in the device, security, and cost have also been reported to strongly influence the adoption of mobile payments (Dahlberg, Guo, & Ondrus, 2015).

The finance and banking literature has also examined online banking but has mainly focused on its impact on bank competition and performance. In line with the studies shown above, Hernández-Murillo et al. (2010) have found that banks' adoption of new technologies such as online banking services is also partially triggered by their competitors' adoption of the technology. Xue et al. (2011) have found that when consumers go digital, they acquire more products from the bank and make more transactions across different channels. Campbell and Frei (2010) have documented a positive relationship between the use of online banking and customer retention. DeYoung, Lang, and Nolle (2007); Hernando and Nieto (2007); and He (2015) have demonstrated that online banking has a positive effect on bank performance, being a complementary channel rather than a substitute for bank branches.

Our paper is linked to the theoretical foundations derived from information systems literature concerning consumers' adoption of digital services. However, since those traditional factors may not be sufficient to explain banking digitalization, we use machine learning algorithms to identify complex and dynamic patterns in the digitalization process.

3. Data and Methodology

3.1 The Survey

The primary data for this study were collected from a consumer survey that was conducted specifically for this research by IMOP during November and December 2016. The survey participants—a population of Spanish consumers between the ages of 18 and 75—were asked about their digital preferences and in particular about those related to banking and payment services. The main structure of the survey followed the Survey of Consumer Payment Choice (SCPC) conducted by the Federal Reserve Bank of Boston. However, our survey incorporated comprehensive information about consumers' digital preferences and not just about payment services. Furthermore, the survey includes information about a set of factors that, based on theoretical foundations for technology acceptance, explains the adoption and use of digital channels (e.g., perceived usefulness, cost, complexity, convenience, and risk).[6] Controlled quotas for a representative sample of the population were established based on age, sex, and location. The survey was conducted via telephone interviews and resulted in a sample size of 3,005 consumers; participation was voluntary. The sample error is estimated to be ±1.8% for a confidence

[6] All the variables extracted from the survey questionnaire are listed in Table A.II of the appendix.

level of 95.5%. Table A.I offers detailed information about the survey and the data collection process.

Spain seems to be a good laboratory for this study because it has overcome the initial implementation phase of electronic banking[7] and ranks third in the world for annual growth in mobile banking adoption.[8] According to official statistics, the penetration of online banking[9] and the general level of financial digitalization[10] in Spanish society are similar to those in other developed economies. Consequently, the main findings—with the necessary caveats—could likely to be extrapolated to other jurisdictions or would at least be useful for informing other research in different countries.

As Table 1 illustrates, the gender breakdown was 49.7% men and 50.3% women. The largest percentage of participants fell into the age bracket of 35–44 years old (22.8%), followed by 45–54 years old (21%). In terms of employment, roughly 60% of participants were employed. The median number of household members was three. The representativeness of the survey data is assured by comparing the sample breakdown with the official statistics.[11]

Consistent with official statistics, 92% of participants were frequent internet users connecting mainly from home, 75% reported having a laptop, 97% reported having a mobile phone (85.3% a smartphone), and 47.2% reported having a tablet.

Table 2 provides insight into the degree of digitalization by gender, age, and employment situation. Importantly, there seems to be a gap (common to most advanced countries) between the availability of the online services and their (partial or exclusive)

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[7] According to OECD statistics, there are over 22 million e-banking services users in Spain.

[8] Ditrendia Mobile report in Spain and the world (2016).

[9] In 2018, 45% of the population living in the OECD area reported having used online banking in the last three months. In Spain, this same segment of online users accounts for 48.6% of the population

[10] According to the OECD statistics, 86.4% of households have internet access. This percentage is similar to other developed economies: the United Kingdom (93.3%), Canada (93%), France (88.5%), Australia (86.1%), and the United States (77.9%).

[11] Obtained from the Spanish Statistical Office (INE).

use by consumers. In any event, the figures suggest that Spanish consumers have attained a medium-high degree of digitalization and a medium degree of financial digitalization. In general, it seems that adults under the age of 45 (working or studying) are the most digitalized.

3.2 Descriptive Statistics

3.2.1 Degree of Banking Digitalization

On average, each banking client has two bank accounts and operates with more than one entity. It is worth noting that while 79.6% of respondents have an online bank account, only 13% are exclusively online account users. Figure 1 illustrates the degree to which consumers use various financial services. Regarding the type of financial activities conducted online, internet users reported accessing online banking services to check the balances of their accounts (68.7% of respondents), to receive online communications from their bank (51.4%), and to make payments or transfer money (50.9%). In the case of mobile banking, the activities lean even more toward checking and communication rather than transactional services. Debit cards (78.1% of respondents reported using these) seem to dominate over credit cards (50.8%). As for the most common uses, 56% of internet users check the balances of their accounts weekly by either mobile, tablet, or computer, while only 32.4% check their credit card balance weekly. Table 2 also illustrates the degree of financial digitalization by gender, age, and employment situation. Young and employed people exhibit the largest degree of financial digitalization. Furthermore, accounting for all the socio-economic features, the typical profile of a digital banking consumer is an employed woman under 39 years of age who has children, lives in a large residential area of more than 200,000 inhabitants, and has a monthly household income between €3,000 and €5,000.

3.2.2 Consumer Perceptions

According to the results of the survey, 88.8% of respondents considered cash to be safe or very safe, while such a statement was only made by 58.8% of respondents regarding online banking and only 44.2% of respondents regarding mobile banking. As for perceived cost, 63.2% of respondents considered online banking to be a low-cost or costless service, and 58.8% of respondents said the same of mobile banking. While more than 90% considered it to be easy or very easy to withdraw cash at Automatic Teller Machines (ATMs) or pay by debit card, this was only the case for 67.8% and 64.4% of online and mobile banking users, respectively. However, online banking and mobile banking were perceived as high-quality services by 86.2% and 84% of users, respectively.

3.2.3 Non-Banking Services and Social Networks

Importantly, 38% of respondents indicated that they have used at least one non-banking method of payment (Amazon Pay, Google Wallet, PayPal, Apple Pay, etc.). Consumers that reported using non-bank services had on average more than one non-bank account (1.47 accounts per person). Moreover, 20.6% of respondents also reported installing a mobile app in order to make payments. Although 70% of respondents had a Facebook account and 28% had a Twitter account, users preferred email as the main channel to communicate with (30.5%) or make complaints to their bank (17.7%).

3.3 A Machine Learning Approach: Random Forest

Most previous studies have employed discrete choice models to examine consumer preferences regarding payments and other financial services (Dick, 2008; Hernández-Murillo et al., 2010; Honka, Horta, & Vitorino, 2017; Yusuf Dauda & Lee, 2015). These models, derived from utility theory, are based on maximizing consumers' utility. Other studies have used structural equations. These structural equations are useful for imputing relationships between latent variables that affect e-banking adoption (Aldás-

Manzano et al., 2009; Maria Correia Loureiro et al., 2014; Montazemi & Qahri-Saremi, 2015).

However, Pousttchi and Dehnert (2018) have discovered remarkable interdependencies between information systems and related disciplines such as marketing, economics, and sociology, revealing that digitalization is a challenging endeavor. In this sense, machine learning would help reveal the complex patterns driving the digitalization process. Bajari, Nekipelov, Ryan, and Yang (2015) have surveyed a number of methods to be used in demand studies and conclude that random forests are both adequate and effective for this type of study. They have argued that while these methods may be unfamiliar, they are simple and based on robust underlying methods. Today the availability of large datasets where consumers' behavior can be observed as well as the development of computational engineering and big data analysis where algorithmic systems learn automatically motivates the use of machine learning. In addition, among a number of learning algorithms, random forests have been shown to provide the best results (Fernández-Delgado, Cernadas, & Barro, 2014; Varian, 2014).

Since these algorithms are able to identify complex patterns among millions of data points, machine learning exhibits several advantages for our purposes. First, no pre-established or strict assumptions are required regarding the structure of the data. Second, by generating hundreds of random decision trees, it is possible to reveal the most common decision sequences. Therefore, the final outcome improves our understanding of what factors are the most commonly considered in a decision-making process. Additionally, by identifying these characteristics, we are able to build classification trees that illustrate the sequence of consumers' decision-making actions.

Statistically, random forests are an ensemble of tree predictors in which each tree depends on the values of a random vector sampled independently and with the same distribution for all trees within the forest (Breiman, 2001). The algorithm follows these steps:

1. A forest of many trees is grown (1,000 trees in our research). Each tree is grown from an independent bootstrap sample derived from the data.

2. For each node of the tree, *m* variables are independently selected at random out of all *M* possible variables. Then, on the selected *m* variables the algorithm finds the best split.

3. The algorithm grows each tree to the largest extent possible.

4. These steps are iterated over all trees in the ensemble and the average vote of all the trees is reported as the random forest prediction.

The use of random forest regressions in economics is gaining ground. Miguéis, Camanho, and Borges (2017) have used a random forest model to find hidden patterns that may be valuable for decision-making in bank marketing. De Moor, Luitel, Sercu, and Vanpée (2018) have used random forests to identify subjective judgments on sovereign credit ratings. Tanaka, Kinkyo, and Hamori (2016) have employed this algorithm to find patterns that detect banks in danger of failing, while Alessi and Detken (2018) have used random forests to examine the role of credit growth and leverage as a cause of financial crises. Furthermore, such an approach has also been used to estimate consumer preferences for technology products (Chen, Honda, & Yang, 2013) and travel choices (Hagenauer & Helbich, 2017).

The aforementioned studies as well as other related studies (Chen, Luo, Xu, & Wang, 2016; Grushka-Cockayne, Jose, & Lichtendahl, 2016; Jun Huang, Wang, & Kochenberger, 2017; Long, Song, & Cui, 2017; Mercadier & Lardy, 2019) indicate that in a context similar to ours, random forest algorithms provide greater accuracy (compared to other standard approaches).

4. Dimensions of the Digitalization Process

Going digital is a much broader concept than is commonly understood. Digitalization is not a single dimensional technological expansion but a multifaceted phenomenon. While literature about the global digitalization of societies has utilized a multidimensional approach to explore this digitalization (Ali, Hoque, & Alam, 2018; Cruz-Jesus, Oliveira, & Bacao, 2012; Vehovar, Sicherl, Hüsing, & Dolnicar, 2006), previous studies on the financial digitalization of consumers have mainly focused on the adoption of online channels. As the OECD has suggested, it is convenient to apply a multidimensional approach to explore the digital transformation of bank customers. Furthermore, prior findings in the context of online banking—a variety of mechanisms are involved in technology adoption,[12] and the relevance of each one depends on the stage of the adoption (Montazemi & Qahri-Saremi, 2015)—suggest using a multidimensional approach to address issues related to digitalization. Consequently, our study assumes a broad definition of adoption that considers not only the first use of a certain service but also its scope and frequency. Figure 2 plots the main dimensions that we identified from earlier studies: adoption of digital banking, diversification of use, and adoption of bank and non-bank payment instruments (Campbell & Frei, 2010; Montazemi & Qahri-Saremi, 2015; Szopiński, 2016; Xue et al., 2011; Yusuf Dauda & Lee, 2015).

4.1 Adoption of Digital Banking

What drives becoming a digital customer of banking services on a regular basis? Making use of the comprehensive set of variables in our survey on general digitalization and financial digitalization, we classified individuals into three categories: non-users (F), occasional users (N), and frequent users (S). Non-users are defined as those who over the

[12] See for example Hoehle et al. (2012) and Dahlberg, Guo, and Ondrus (2015).

course of the year have not adopted any kind of financial digitalization, including those who are not even digitalized consumers (i.e., they do not use the internet). Respondents who have become digital customers and conduct online banking activities, but not on a monthly basis, were classified as occasional users. Finally, frequent users are those who conducted online financial activities every month over the course of the year. Figure 3 shows that 1,772 out of the 3,005 respondents (58.9%) are frequent users of online financial services, which is consistent with the growth of online banking in Spain officially reported.[13]

4.2 Diversity of Digital Use

While the initial phase of the digital transformation of consumers involves regular online access, going digital is also related to consumers' use of diverse digital services. Going digital therefore means conducting a number of financial activities online and not just a single online activity (e.g., just checking one's account balance). Within this dimension, we acknowledge that there is a transition from beginning to go digital and becoming an "omni-digital" bank customer.

The factors that drive consumers' digital diversification might be different depending on the capabilities of the electronic device used to access the service. Therefore, we differentiate between the diversification of online banking users and mobile banking users. As such, survey respondents were classified according to the variety of tasks they carry out (check account balances, pay bills, make transfers, or receive communications) using each type of terminal used to conduct these activities (computer or mobile). Based on these factors, respondents were then sorted into four categories: no digital users, non-users of digital financial services, incipient users of digital financial services, and diversified users of digital financial services.

[13] European Digital Agenda. http://www.agendadigital.gob.es/digital-agenda/Paginas/digital-agenda-spain.aspx.

Individuals who are outside of the digitalization process (i.e., who have no access to the internet) were classified as no digital users. Individuals who are frequent internet users but do not conduct any financial activity online were classified as non-users of digital financial services. Incipient users are those who perform some but not all online financial activities at least once a month. Finally, those users that carry out all financial activities online at least once a month are classified as diversified users of digital financial services. Figure 3 reveals that most of the respondents are incipient users, which reflects the worth of exploring this dimension. Bank customers also appear to be customers of digital financial services, but they are still far from being considered "omni-digital" users.

4.3 Use of Banks' Payment Instruments

Another dimension that determines the financial digitization process relates to a consumer's method of payment. Although debit and credit cards cannot be considered fully new electronic payment instruments, we also considered them because there has been a technological and safety evolution. There are new, varied, and easy ways (such as contactless technology) to use debit and credit cards.

The sample was then divided into two groups: non-debit (non-credit) card users and debit (credit) card users. As Figure 3 shows, there was a larger use of debit cards in comparison to credit cards.

4.4 Use of Non-Bank Payment Instruments

While banks have traditionally offered non-cash payment instruments, some technology companies, particularly BigTech and FinTech, have begun to offer non-banking alternatives to pay bills or transfer money (Amazon Pay, PayPal, Google Wallet, Apple Pay, etc.). The adoption of these new means of payment provided by non-financial entities has gained ground. Since most of the technological transformation is being led by the irruption of high-tech companies, it is interesting to analyze how consumers adopt these alternative means of payments. Therefore, this paper considers what factors drive consumers to use non-bank payment instruments.

In our research, customers were classified as non-digital users, non-users of non-bank payment instruments, and users of non-bank payment instruments. Consumers who do not use the internet regularly were classified as non-digital users. Consumers of online financial services who do not use non-bank means of payment were classified as non-users of non-bank payment instruments. Finally, users of non-bank payment instruments include consumers that utilize payment methods of non-bank providers. As illustrated in Figure 3, most respondents were non-users of non-bank payment instruments despite being digitalized.

5. Results

In this section we present the random forest regression results of each of the aforementioned dimensions as well as the classification trees that outline the sequential digitalization of bank consumers.

First, we used 1,000 randomly constructed decision trees for each dimension, using the set of variables provided in the survey to obtain the random forest output. We then reported the plots showing the relative statistical importance of each factor in the classification of individuals by their digital profiles. The determinants and characteristics are plotted on the *y*-axis ranked by their absolute level of importance while their relative importance is charted on the *x*-axis. The mean decrease in accuracy reflects the mean loss in accuracy when each specific variable is excluded from the regression algorithm. Therefore, the determinants and characteristics with the greater mean decrease in accuracy are the most relevant for the classification of bank customers. Additionally, the mean decrease in Gini is a measure of how each feature contributes to the homogeneity between the decision trees used in the resulting random forest.

Second, we used the characteristics and determinants with the largest discriminant power for each of the digital dimensions to build a decision tree. A conditional inference tree was estimated. This technique estimated a regression relationship by binary recursive partitioning in a conditional inference framework. The algorithm tested the global null hypothesis of independence between each of the input variables and the response and selected the input variable with the strongest association to the response. The algorithm then implemented a binary split in the selected input variable and recursively repeated this process for the each of the remaining variables. The classification tree inferred the sequencing of customers' decision-making process, which helped to explain how bank customers go digital. This is particularly relevant since those classification trees do not require any linearity assumptions, which is important because many of the digitalization determinants could be nonlinearly related.

5.1 Random Forest Regression Results

5.1.1 Adoption of Digital Banking

The machine learning algorithm revealed that the following bank customers' features stand out as first-order factors that differentiate between non-users (F), occasional users (N), and frequent users (S):

- *Online check balance:* Indicates whether account balances are checked online. Since it is easier, faster, and less costly than physically going to the bank branch, it fosters going digital.
- *Number of online bank accounts*: Indicates the scope of digital banking. Offering online access to bank customers when they open a bank account increases the probability of the customer going digital.

- *Online transfers:* Indicates whether the customer has made an online bank transfer in the last three months. Online bank-to-bank transactions are a driver of transactional financial digitalization.
- *Consciousness*: Is the ratio of the number of bank accounts that the customer believes have online access to the total number of accounts with online access. It indicates the degree to which each customer is aware of the existence of online financial services at his or her disposal since in practical terms all the accounts offer the possibility of online access. Honka, Horta, and Vitorino (2017) have argued that customer awareness is a relevant factor in the use of banking services.

Bank customers' perceptions of security, cost, and ease of use of banking services were found to be secondary factors in going digital. The decision to adopt a digital profile did not seem to be primarily motivated by customers' perceptions. Our results suggest that the relevant factors in going digital are those related to customers becoming accustomed to the online channels by checking their bank account balances or transferring money and being aware that these activities can be conducted online.

As in other industries, consumers tend to go through several stages of adoption: awareness, consideration, and choice. Our results confirm the significance of awareness in the multistage process of going digital.

5.1.2 Diversity of Digital Use: Online Banking and Mobile Banking

Figures 5 and 6 show the baseline random forest results in terms of the diversification of online and mobile banking services, respectively. We found that the following features have the largest influence on increasing customers' adoption of online banking services:

- *Number of online bank accounts:* In addition to adopting a financial digital profile, bank customers' degree of online diversification depends on how many of their accounts offer digital access.
- *Consciousness:* Is being aware of the possibility of having access to online services, which is essential for customers to diversify their financial activities.
- *Safety of online banking:* Indicates how customers perceive the level of security of online banking.
- *Online banking communication:* Indicates whether customers have used online services or e-mail as their communication method with their bank.

Considering both the adoption and diversification of digital use, we argue that the digitalization process originates from the customers' need to check their bank account balances and transfer money. However, being aware of the possibility of accessing financial services through online banking and the perceived safety of operating online were the main factors in determining whether customers diversified their use of online banking services. Furthermore, the digitalization of the communication channel between customers and banks also fostered the diversification of customers' online activities.

Regarding the diversification of the use of mobile banking, the following factors had the greatest predictive power:

- *Number of online bank accounts*: As is the case with online banking, the degree of mobile banking diversification depends on how many online accounts are available to the customer.
- *Safety mobile banking:* Regards bank customers' perception of the level of security of mobile banking, which is also relevant to them deciding to go broadly digital with mobile banking.

- *Consciousness:* Being aware of the possibility of having access to financial services is again relevant, influencing the diversification of mobile-related services by bank customers.
- *Transferring money via mobile:* Rather than information checking (as was the case with online banking), mobile banking diversification seems to be driven by transactional services.

Overall, the algorithm reveals that online and mobile diversification are driven by common features: consciousness of the possibilities offered by digital banking, the perceived level of security of the channel used, and the number of digital bank accounts available. However, it is worth noting that transferring money was a distinct factor in determining the diversification of mobile banking. One of the firsts steps to becoming "omni-digital" in mobile banking seems to be transferring money. It seems that money transferring via mobile may become the gateway to other digital financial activities. This finding partially explains the importance of the irruption of FinTech companies in the payment sector compared to other financial services (Haddad & Hornuf, 2018; Jagtiani & Lemieux, 2018).

5.1.3 Use of Banks' Payment Instruments: Debit and Credit Cards

Consistent with prior estimations, by employing 1,000 randomly computed forest trees we determined the main factors that influence the use of debit and credit cards, respectively (see Figures 7 and 8):

- *Cost:* Customers' perceived cost affects the usage of both types of cards, although it has a greater impact on the use of debit cards.
- *Safety:* The perceived safety of the transactions conducted with debit and credit cards is relevant in determining their use by customers, although to a slightly greater extent with credit cards.

- *Acceptance:* Merchants' acceptance of debit and credit cards as payment instruments determines their utility, which could explain why bank customers are concerned about ensuring their acceptance before adopting them as regular payment instruments.
- *Convenience:* Customers' perceptions regarding the convenience of using these banking payments (easiness, time savings, etc.) also influence customers' use of them.

Unlike the adoption and penetration of online and mobile banking, the use of debit and credit cards seems to be dominated by bank customers' perceptions of cards' cost, safety, and acceptance.

5.1.4 Use of Non-Bank Payment Instruments

Figure 9 illustrates the most relevant factors in explaining customers' adoption of non-bank payment services.

- *Mobile payment app*: Customers' use of mobile apps to make payments has a large predictive power in determining whether or not customers will use non-bank payment instruments.
- *Frequency and degree of online banking:* The scope and frequency of customers' use of online banking services was also found to explain the use of non-bank payment instruments, suggesting a complementarity between bank and non-bank payment alternatives.
- *Online banking complaint:* Customers' use of online channels to lodge a complaint with the bank also appears to drive their use of non-bank services. In other words, unsatisfied bank customers making online complaints are more prone to adopt non-bank means of payment.

- *Twitter and Facebook user:* Being a user of social media also appears to be related to the use of non-bank payments.

5.2 Accuracy: Random Forest vs. Logit Models

The previous section described the main factors that influence customers' online adoption and diversification. Having established these factors, we used random classification trees to determine the sequence in which these factors operate. However, before estimating these trees, it is important to determine the prediction accuracy of the random forest regressions. Consistent with prior studies (e.g., De Moor et al., 2018), we randomly selected 70% of the data as training data (2,104 observations) and designated the remaining data (901 observations) as test data. Through this process, we aimed to show the out-of-sample fit precision of the random forest technique. The machine learning algorithm was able to accurately predict 88.41% of bank customers' online banking adoption profile, 70.11% of the diversity of digital use of online banking, 70.01% of the diversity of digital use of mobile banking, 85% (74.89%) of debit (credit) card adoption, and 76.14% of non-bank payment instruments adoption.

We also compared the baseline results obtained using a random forest technique with the standard discrete choice models used in most of the previous studies to analyze consumer preferences regarding financial services. We used ordered logit regressions for the adoption decision and the diversification of digitalization usages because they rank consumers according to certain classifications (as shown above). However, the decision between bank or non-bank payment instruments is binary, so it is estimated using a simple conditional logit. The general form of the logit model is as follows:

$$\mathrm{E}(\mathrm{Y} \mid \mathrm{X} = \mathrm{x}) = \Pr(Digital\ dimension = y \mid \mathrm{X}) = \Lambda(\beta_0 + \beta_1 X_{personal\ features} + \beta_2 X_{socio-demographics\ feautures} + e_i) \quad (1)$$

For each digital dimension tested, we included as regressors bank customers' features ($X_{personal\ features}$), which according to prior theoretical and empirical studies are the most relevant factors for going digital. These variables were classified into four different subsets: degree of digitalization, financial profile, perceptions, and social profile. The vector of variable $X_{socio-demographics\ feautures}$ accounts for gender, age, people living at home, and geographical location. The models were estimated considering the sampling weights. Furthermore, the digitalization process may be influenced by customers' choice of bank, because some banks are more digitalized than others. In order to address this issue, errors were clustered on the main bank of each bank customer. The estimation results are reported in Appendix B.

The ordered logit and simple logit models were able to accurately predict 79.27% of bank customers' online banking adoption, 55.01% of diversity of digital use of online banking, 59.57% of diversity of digital use of mobile banking, 84.23% (70.62%) of debit (credit) card adoption, and 73.46% of non-bank payment methods adoption. Table 3 compares the forecasting accuracy obtained using the random forest regressions and the logit models. Random forest models (both in out-of-sample and whole-sample tests) outperformed logit models. The greater predictive power was particularly relevant for the adoption of online banking, the fitting ability of which is close to 90% for both the whole-sample and out-of-sample predictions in the random forest, while the fitting ability for the logit model was 80%. Similarly, the accuracy of the prediction of the diversified use of online (and mobile) banking was 70% with the random forest model approach compared to 55% (and 59%) for the logit models. Consistent with prior studies, the random forest algorithm presented a higher classification accuracy compared to alternative econometric models.

Finally, in order to ensure the stableness in the accuracy of the machine learning results we employed two cross validation methods: the k-fold cross-validation and the repeated K-fold cross-validation.[14] The results reported in Columns 4 and 5 of Table 3 confirm the validity of the models employed.

5.3. Stableness over Subsamples

It was important to ensure that when feeding different data to the algorithm the predicted accuracy was stable. In doing so, we employed different subsamples based on socio-economics characteristics—gender, age, and habitat—to go through the machine learning process in order to show the robustness in terms of accuracy. Young people are those between 18 and 34, while old people are over 55 years old. The rural areas category includes people living in municipalities with less than 10,000 inhabitants while the urban category includes those living in cities with more than 200,000 inhabitants. Figure 10 shows that the accuracy remains stable across the different subsamples that feed the model.

5.4 Classification Trees

In order to obtain a sequence of customers' financial digitalization decisions, we used those variables identified by the random forest as having larger predictive power to build a decision tree for each of the dimensions analyzed. We initially tested whether the decision trees maintained the prediction accuracy of the baseline random forest models. The trees were able to accurately predict approximately 70–85% of individual choices.

5.3.1 Tree: Adoption of Digital Banking

Figure 11 plots the decision tree of customers' adoption of digital banking. Although the range of services available online is wide, the adoption of online banking seems to emerge from customers checking their account balances. It was only after customers checked their account balances that they moved into transferring money online.

[14] The repeated K-fold cross-validation splits the data into k-folds, repeating the process five times.

Bank customers who did not perform either of these activities were classified as occasional or low frequency users (Node 5). Comparing those individuals who only check their account balances (Node 10) with those who only transfer money (Nodes 7 and 8), checking account balances appears to be the more decisive step in becoming a frequent user of online banking services. Furthermore, when customers begin to make transactions and are largely aware of the online possibilities, they become frequent users (Nodes 14 and 15).

In conclusion, an overview of the random models and the classification trees suggests that the main channel by which bank customers become frequent users of online banking services is by their need to check their account balances and, subsequently, transfer money. Consciousness of the availability of online possibilities is also important for the customer to become a frequent digital bank user. Furthermore, the perceived safety of online banking services is not a primary determinant in becoming a frequent user. This finding is relevant since most of the literature has concluded that adoption is mainly driven by consumers' perceptions, including their perception of safety. As we show in the next subsection, safety only becomes influential when customers consider conducting a wide range of transactions online.

5.3.2 Tree: Diversity of Digital Banking Use

Figure 12 illustrates the classification tree for the diversity of digital use in online banking with four main variables. This tree reveals the relevance of the perceived security of online banking in influencing customers' use of online financial services (Branch 2). Customers who did not consider online banking safe were not likely to become diversified users of online services (Nodes 14–21). Together with safety, customers' use of digital channels for information purposes and their awareness of the range of online services were key determinants of the diversification of digital services demanded (Node 11).

However, consciousness did not compensate for the perceived lack of safety. At most, being conscious made customers switch from non-users to incipient users (Nodes 17–21).

Overall, the results suggest that while being a regular online banking user is driven by customers' needs (e.g., checking account balances and transferring money) as well as by having a certain level of consciousness about the online possibilities, becoming a diversified digital user depended largely on the perceived level of safety.

Figure 13 plots the classification tree for the diversity of digital use of mobile banking. The results suggest that the diversity of online and mobile banking use is driven by similar factors. The perceived level of safety of mobile banking is also relevant (Node 7). It is also apparent that one is unlikely to find diversified users who have not transferred money with their phones even if they perceive mobile banking as not safe (Node 5).

5.3.3 Tree: Adoption of Bank Payment Instruments

Figures 14 and 15 plot the classification trees for debit and credit card adoption, respectively. Both trees demonstrate that safety and cost are the main drivers of adoption.

Regarding the adoption of debit cards, customers' perception that debit cards are a convenient payment instrument was a primary determinant of their use. Debit card users can be classified into users who consider debit cards safe, accepted, but not very convenient regardless of their cost (Node 11), and users who consider the method convenient, costless, and safe (Nodes 24 and 26). It can then be argued that a costless perception could compensate for a lack of perceived convenience.

In the case of credit cards, the most influential factor was the perceived safety. Customers who perceived credit cards as unsafe regardless of their cost were less likely to use them (Nodes 14–19). Similar to debit cards, users who perceive credit cards as safe and relatively costless made up the majority of the credit card users (Node 12). The probability of adoption dropped to 12% if the credit cards were considered costly.

5.3.4 Tree: Use of Non-Bank Payment Instruments

The classification tree for the adoption of non-bank payment instruments is shown in Figure 16. This tree reveals that the adoption of non-bank payment methods occurred when customers were frequent and diversified digital banking users. For occasional and incipient online users, the likelihood of using non-bank payment instruments was quite small. However, as the frequency and diversity of use increased, being active on social media and making mobile payments increased the likelihood that customers would use non-bank payment channels. Furthermore, being active on social media and using apps for mobile payments were also relevant factors. However, it is worth noting that frequent online users do not use non-bank payment methods if they are just incipient users (Node 23); it is necessary for customers to undertake several digital financial activities to jump into non-bank payments. Similarly, digital banking users who do not have frequent online access are not regular adopters of non-bank payment methods (Nodes 7, 16, 17, and 28).

6. Causal Inference: Causal Forest

Although machine learning methods have outstanding predictive power, it has been argued that prediction does not imply causation. Machine learning techniques have traditionally been focused on prediction, providing data-driven approaches to building rich models. However, some recent papers have addressed these limitations by developing causal forests (Athey & Imbens, 2016; Athey, Tibshirani, & Wager, 2019; Wager & Athey, 2018). The causal forest algorithm is a forest-based method for treatment effect estimation that allows for a tractable asymptotic theory and valid statistical inference extending Breiman's random forest algorithm. Using causal forests, we were able to make claims on causal impact. Then, we were able to examine the causal effect of those features with the larger predictive power on the digitalization process. In order to be consistent with prior research, we followed the empirical methodology proposed by Athey and Wager (2019).[15] Furthermore, we also took a conservative approach assuming that the level of digitalization of the customers can be arbitrarily correlated within a bank. We then applied cluster-robust analysis tools at the bank level.

Following the multidimensional approach, Figure 16 shows the average treatment effect estimations for those variables identified with the largest predictive power by the random forest. Applying this causal forest algorithm, we found that those features with the largest predictive power also have a large positive effect on the digitalization process. Since the average treatment effects are positive and significantly different from zero, it could be argued that these features drive customers' levels of digitalization. Furthermore, these causal forest estimations also confirm prior findings. The need to check online balances had the largest effect on adopting online banking. Similarly, making money transfers with one's smartphone seems to be relatively more important in order to become a diversified mobile banking customer. Finally, regarding non-bank payment methods, the largest effects on adoption come from being a frequent and diversified digital bank customer.

7. Supply Side Explanations

The variable capturing the bank where the consumer has his/her main account does not rank among those with the largest importance (based on the mean decrease accuracy and mean decrease in Gini). However, this paper aims to confirm that the digitalization process is primarily driven by consumers' characteristics and not by their bank's characteristics. We then re-ran the machine learning algorithm for different samples of consumers aggregated by their main bank characteristics in order to determine

[15] All analyses were carried out using the R package grf (Tibshirani et al., 2018).

whether or not the predictors and decision trees obtained are qualitatively similar to those obtained in the baseline random forests regressions.

First, since bank size (market power) may play a role in digitalizing customers, we re-ran separate regressions for customers of large banks with the largest customer bases in Spain: Santander, BBVA, and CaixaBank. Furthermore, we also conducted a within-bank comparison. This type of analysis helps to ensure that digitalization is not mainly driven by supply-side factors since all the consumers from each subsample would have the same supply level of digitalization. In addition, since the closure of bank branches may force some bank customers to go digital, we also checked whether or not bank closures drive digitalization. In doing so, separate regressions were estimated for those customers whose main bank closed at least one branch in their province. Figure 18 reports the relative importance—measured by mean decrease in accuracy—of those variables with the largest predictive power for the adoption of online banking. The full results for the rest of the dimensions are not reported for the sake of simplicity. Checking balances, transferring money, and being conscious of online banking and the number of one's online accounts are consistently reported as the variables with the largest predictive power across different subsamples. Figure 18 shows that there are not significant differences in the predictive power of the main drivers adoption of online banking. Similarly, no qualitative differences in the relative importance of the predictors and decision trees obtained were found for other dimensions of digitalization.

8. Implications, limitations, and scope for future research

Facing digital transformation successfully is among banks' top priorities. Digital banking is likely to soon become the main channel through which customers interact with their banks. Understanding how customers face the digital jump would help banks to retain their current customers and attract more digital users by, for example, improving those functionalities related to information and transaction-based services. Similarly, the results of the study will help banks understand how their customers could potential adopt digital payment methods offered by new competitors such as BigTech and FinTech firms.

Just like any other research work, our study has certain limitations. Despite employing is a representative testing ground for research on banking digitalization, it would be ideal to know the digitalization timing of each bank customer in order to provide further insights into the temporal structure of the digitalization process.

Despite these limitations, we believe that the results of this study are valuable for other researchers and practitioners interested in understanding how people go digital. Overall, our study confirms the need to conduct research that covers the entire digitalization process rather than focusing on a single dimension. In addition, our research finds that the application of machine learning techniques on consumer research provides more accurate results that improve the understanding of complex topics.

9. Conclusion

Modern societies are undergoing a rapid digital transformation. A sizeable part of this change is related to the demand for financial services. The use of electronic devices such as smartphones, laptops, and tablets to conduct many financial activities has risen sharply. While the banking industry is aware of this transformation, adjusting the supply side depends on related changes in demand.

In this paper, we aim to offer a multi-dimensional comprehensive picture of the process by which bank customers become digitalized. While most previous studies have discussed the determinants of certain adoption decisions, we outlined the sequence of steps that customers follow to adopt and become diversified users of digital financial services. We considered various dimensions: the adoption of online banking, the diversification of the use of online services, and the choice of bank versus non-bank payment instruments. Our approach benefitted from the use of machine learning techniques applied to an in-depth consumer survey specifically designed for the purpose of this study. Specifically, we ran random forest models and regression classification trees.

The empirical results suggest that the digitalization process originated from customers' need to gain information about basic aspects of their banking accounts (e.g., checking their account balances), and this facilitates a transition to transactional services (e.g., transferring money). We also found that once the initial adoption had taken place, the diversification of online and mobile services adopted by the customers became larger when they became conscious of the range of possibilities provided by the bank and when they perceived those options as safe. Taken together, these results suggest that while customers' perceptions are important on using digital channels, in banking the adoption is primarily driven by information-based services. Furthermore, we show that the adoption of non-bank payment instruments (e.g., PayPal and Amazon) happens when consumers are already diversified digital bank customers. This suggests a certain degree of complementarity between bank and non-bank digital services.

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Table 1. Sample demographics

	n	%	Official Statistics (%)
Gender			
Male	1493	49.7	48.7
Female	1512	50.3	51.3
Age			
18 - 24 years	282	9.4	10.4
25 - 34 years	498	16.6	14.1
35 - 44 years	686	22.8	19.8
45 - 54 years	631	21.0	18.7
55 - 64 years	500	16.6	14.9
65 - 75 years	408	13.6	14.1
Habitat			
0 - 10000 inhabitants	637	21.2	20.6
10001 - 50000 inhabitants	806	26.8	26.9
50001 - 200000 inhabitants	696	23.2	18.7
> 200000 inhabitants	866	28.8	33.8
Nº People at home			
1 person	644	21.4	19.6
Two people	850	28.3	24.2
Three people	757	25.2	25.2
More than three people	754	25.1	31.0
Employment situation			
Working	1815	60.4	55.2
Pensioner/retired	500	16.6	24.9
Unemployed	338	11.2	9.1
Student	193	6.4	10.9
Unpaid domestic work	159	5.3	
Sample size	3005		

Figure 1. Degree of Financial Digitalization: Financial online activities (% of internet users)

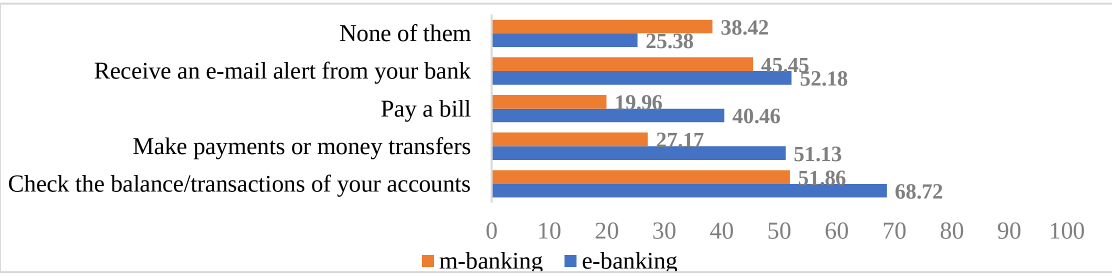


Figure 2. Dimensions of the financial digitalization

Table 2. Sample Matrix (Heatmap) by Dimensions and Socio-Demographics features

	Degree of Digitalization				Degree of Financial Digitalization				Consumers' perceptions						Non-banking services and social networks			
	% Frequent Internet Users	% Mobile Phone	% Laptop	% Tablet	% Online Bank Account	% Exclusive Online Users	% Debit Card	% Credit Card	Low or Very Low Cost: Online Banking	Low or Very Low Cost: Mobile Banking	Safe or Very Safe: Online Banking	Safe or Very Safe: Mobile Banking	Easy or Very Easy: Online Banking	Easy or Very Easy: Mobile Banking	Non-Bank account	Social Network User	Facebook/ Twitter Communication	Facebook /Twitter Complain
Male	93.03	98.00	76.76	46.48	80.44	14.43	78.77	55.12	65.51	61.49	60.35	46.62	67.52	63.43	39.45	64.37	3.33	18.94
Female	89.74	97.00	72.95	47.16	78.31	11.18	78.37	47.09	60.05	56.15	57.61	42.00	66.20	63.76	30.29	66.93	3.75	16.60
18 - 24 years	100	100	91.84	43.62	85.11	5.67	75.18	30.14	76.95	75.53	58.51	45.39	80.85	83.33	50.71	91.13	2.33	21.40
25 - 34 years	100	99.59	83.73	51.41	88.35	21.89	84.14	38.35	79.72	77.91	68.67	57.43	79.12	78.11	50.60	89.36	5.17	19.10
35 - 44 years	98.39	99.71	76.82	56.85	87.32	18.22	82.94	56.71	72.45	70.26	67.64	53.79	74.34	73.62	41.98	76.38	2.86	18.51
45 - 54 years	96.35	97.29	78.76	50.08	82.41	13.15	79.87	49.60	60.22	54.83	61.49	45.01	69.10	63.87	32.96	63.55	2.49	14.71
55- 64 years	86.60	97.87	68.20	39.60	74.00	11.20	75.00	49.08	51.60	43.60	54.80	34.60	57.20	48.40	21.40	46.40	4.74	15.95
> 65 years	61.27	91.88	50.98	30.39	52.94	6.37	69.12	50.00	33.58	29.41	34.07	22.30	37.99	33.58	12.01	27.94	4.39	14.91
Working	97.41	98.90	80.66	52.56	87.05	16.75	83.58	56.25	71.13	67.05	67.82	51.90	74.77	71.40	40.55	72.67	3.94	18.20
Pensioner/retired	70.00	94.11	56.00	35.00	59.60	7.40	72.80	55.00	39.20	33.20	40.60	27.00	42.80	37.20	16.20	34.20	4.68	16.37
Unemployed	92.30	97.39	67.46	38.76	71.89	7.69	67.16	35.50	54.14	50.89	46.75	35.80	60.65	58.58	27.81	68.05	1.74	15.22
Student	100	100	93.78	39.38	87.05	6.74	76.17	25.91	80.83	78.76	60.62	49.74	83.42	85.49	53.37	88.60	2.34	18.71
Unpaid domestic work	77.36	92.98	60.38	44.65	60.38	3.14	66.67	43.40	37.74	37.74	39.62	23.27	45.28	41.51	20.75	51.57	2.44	18.29
Mean	91.38	98.50	74.84	46.82	79.57	12.81	78.57	51.08	62.76	58.80	58.97	44.29	66.86	63.59	34.84	65.66	3.55	17.74

Note: If the box is colored green means the value is above the sample mean
If the box is colored red means the value is below the sample mean

Figure 3. Consumers classification by dimensions (number of surveyed individuals)

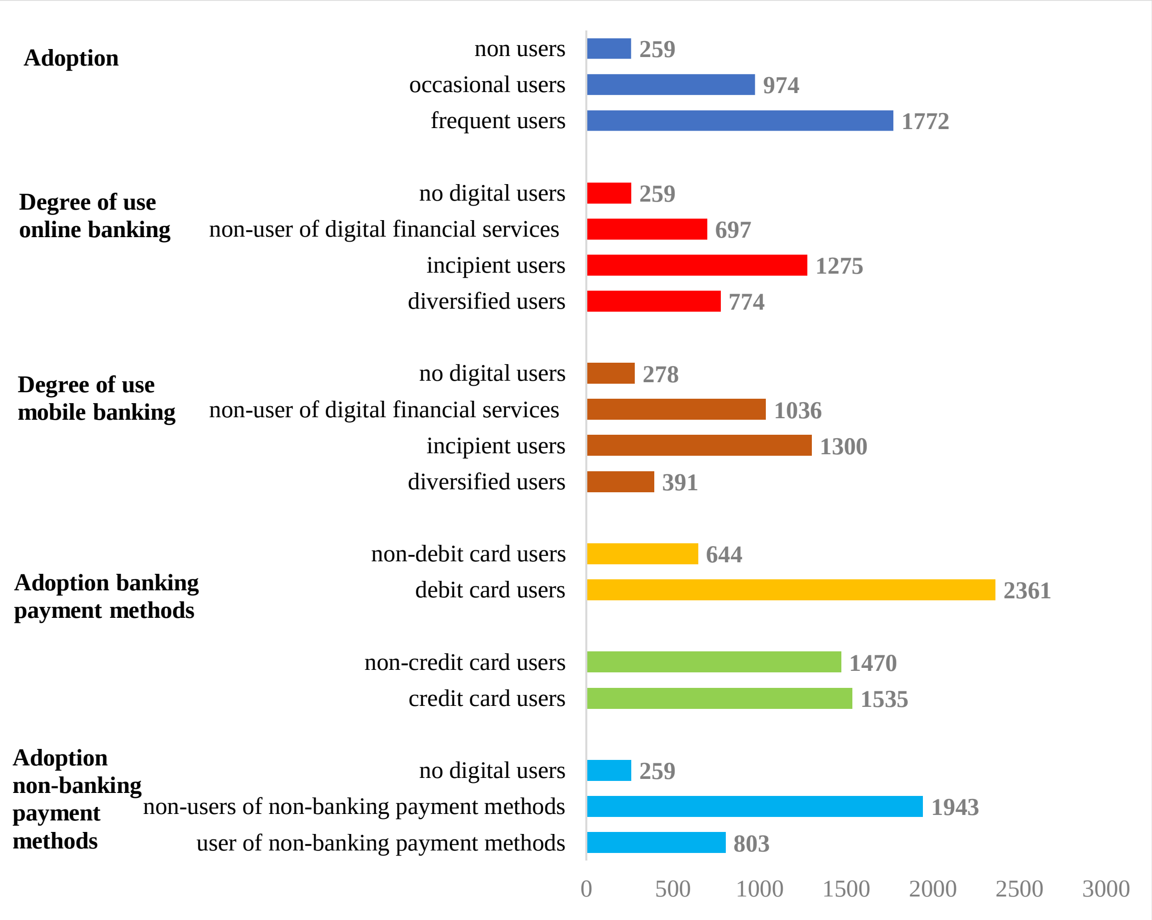


Table 3. Predictive validity of the random forest, logit models and cross-validation

	Out-of-sample fit's precision (70/30% split)	**Whole sample fit's precision**	**Logit fit's precision**	**K-fold cross validation**	**Repeated K-fold cross-validation**
	Accuracy & I.C at 95%	Accuracy & I.C at 95%	Accuracy	Accuracy	Accuracy
Adoption of online banking	88.41% (86.11% - 90.45%)	87.35% (85.62% - 89.08%)	79.27%	86.62%	86.74%
Diversity of digital use: online banking	70.11% (66.97% - 73.12%)	69.15% (67.42% - 70.88%)	55.01%	69.19%	68.94%
Diversity of digital use: mobile banking	70.01% (65.92% - 72.13%)	69.35% (67.62% - 71.08%)	59.57%	68.85%	69.32%
Debit card	85.00% (82.47% - 87.30%)	84.89% (82.77% - 87.01%)	84.23%	75.44%	75.57%
Credit card	74.89% (71.88% - 77.72%)	75.17% (73.29% - 77.05%)	70.62%	84.79%	84.93%
Adoption of Non-bank payment methods	76.14% (73.18% - 78.92%)	76.27% (74.36% - 78.18%)	73.46%	76.17%	76.28%

Figure 4. Variable importance for the random forest model on online banking adoption

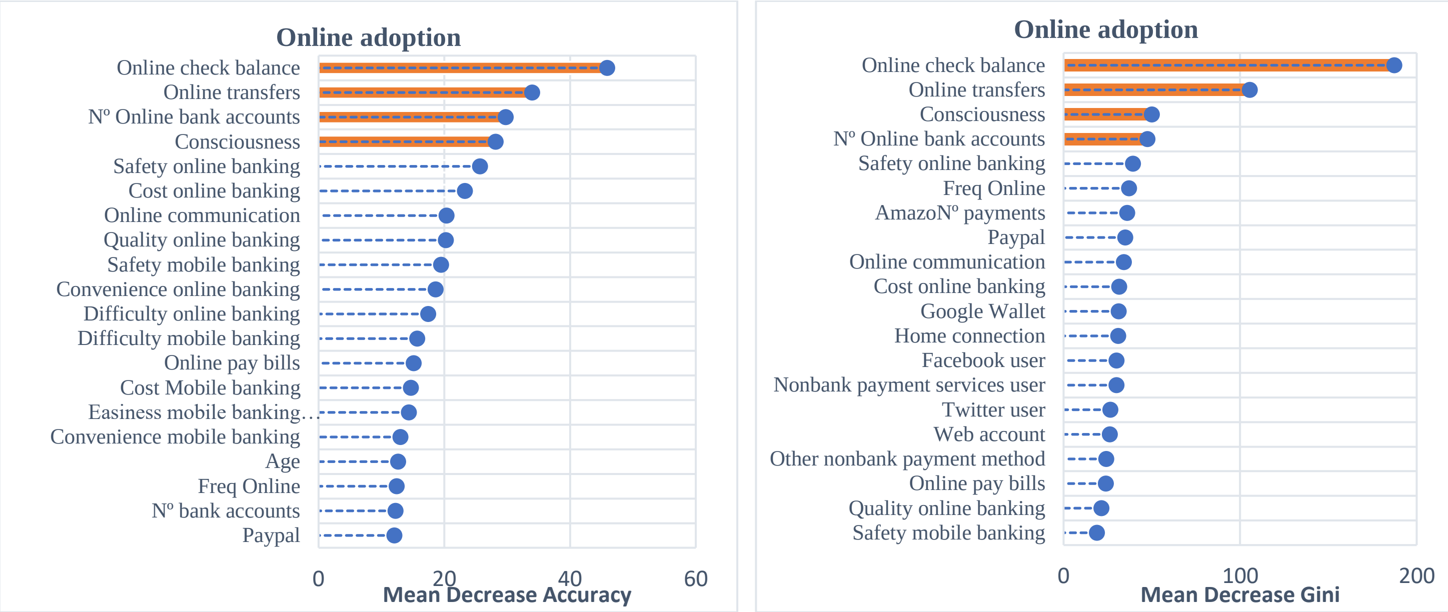


Figure 5. Variable importance for the random forest model on diversification of online banking uses

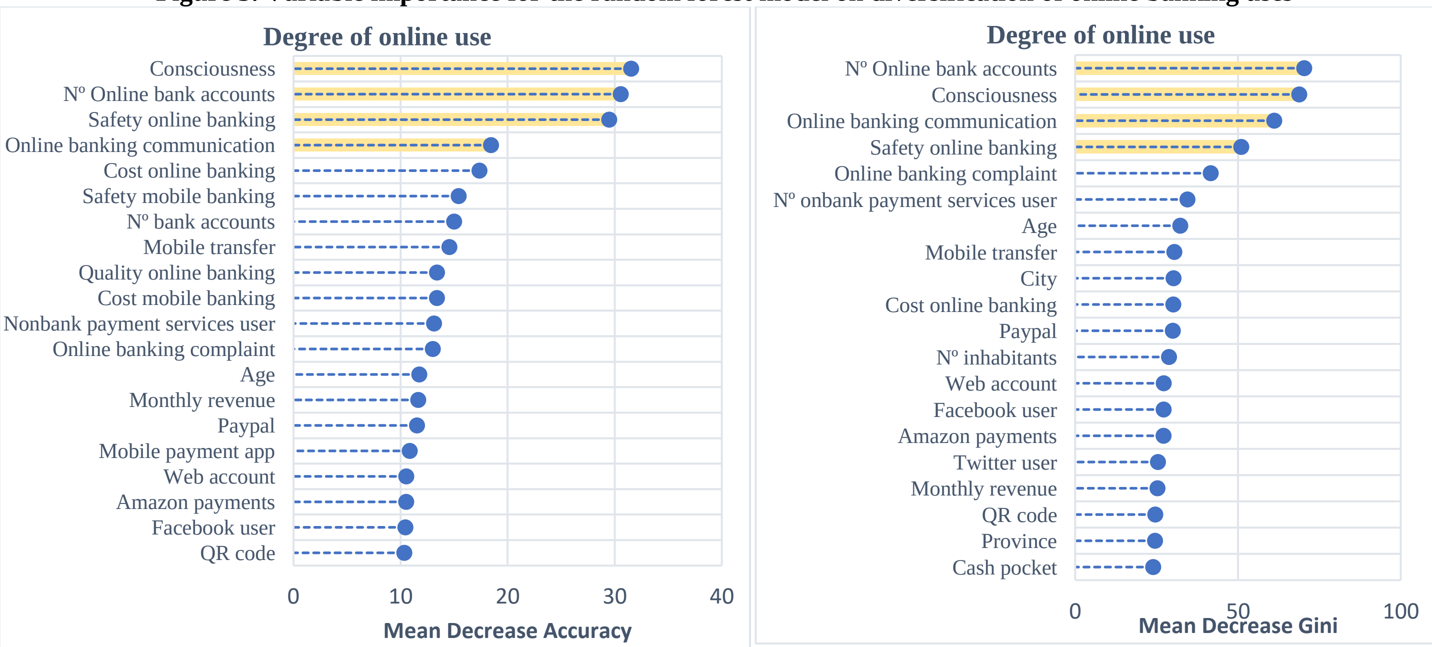


Figure 6. Variable importance for the random forest model on diversification of mobile banking uses

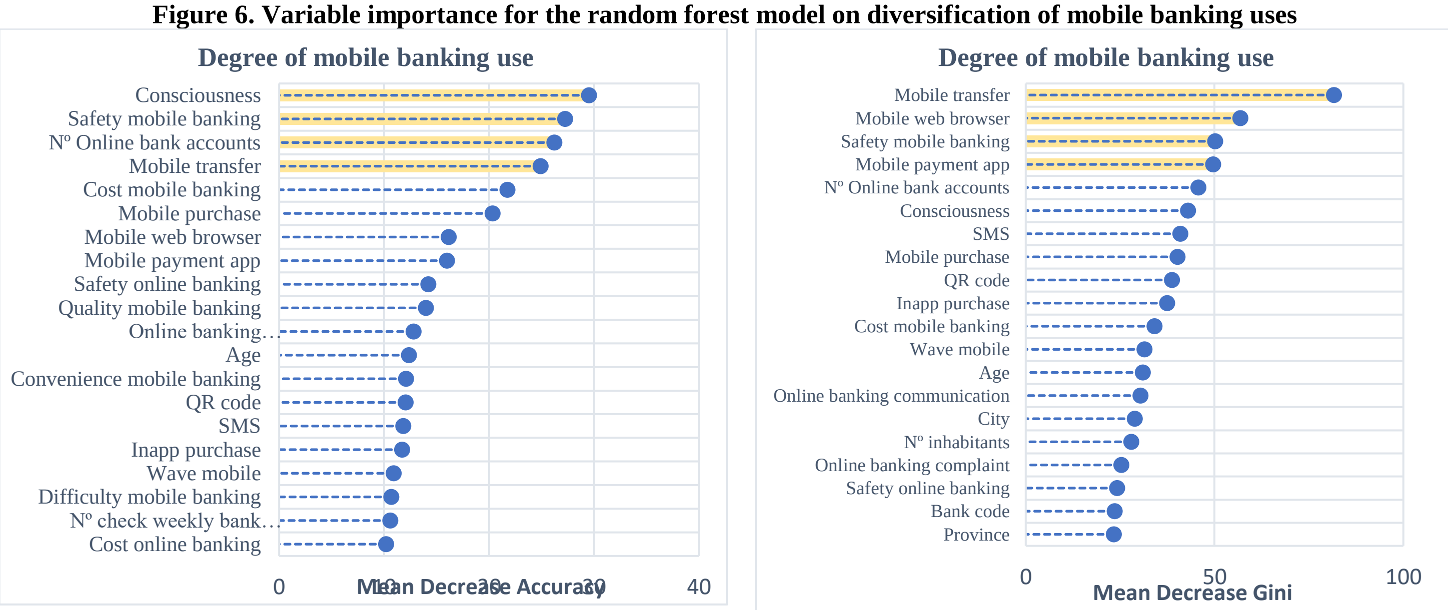


Figure 7. Variable importance for the random forest model on debit card adoption

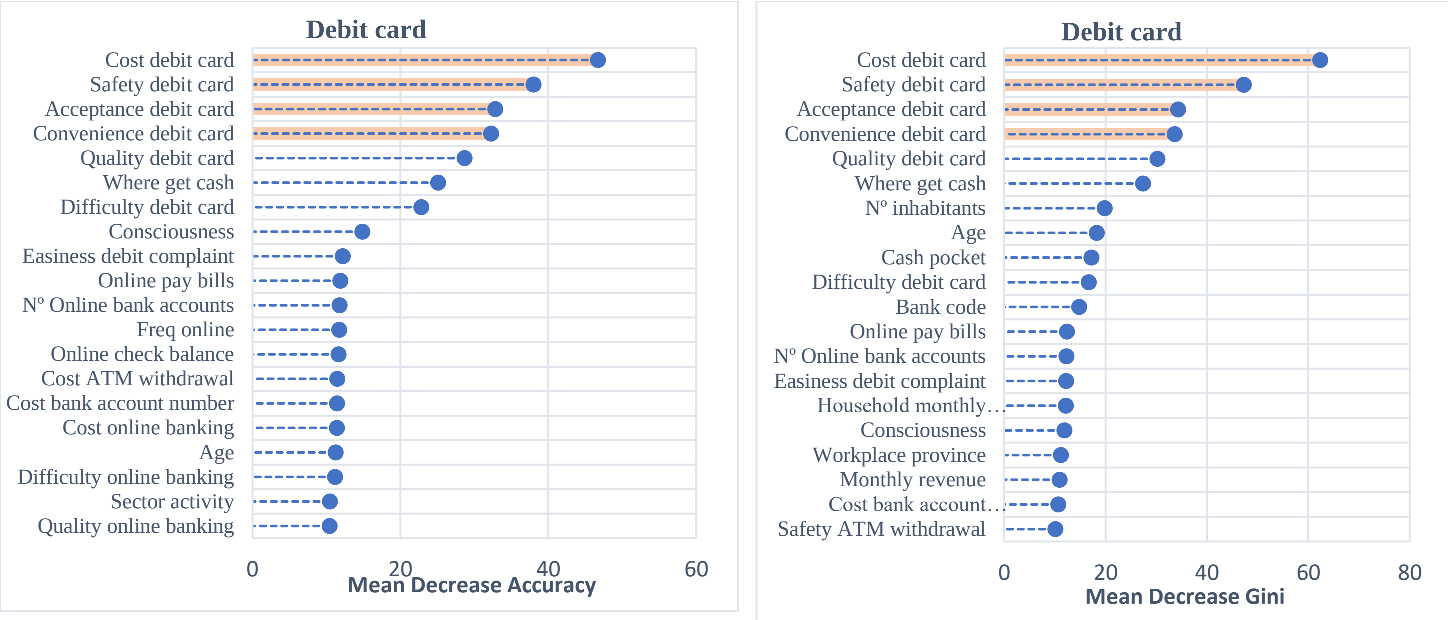


Figure 8. Variable importance for the random forest model on credit card adoption

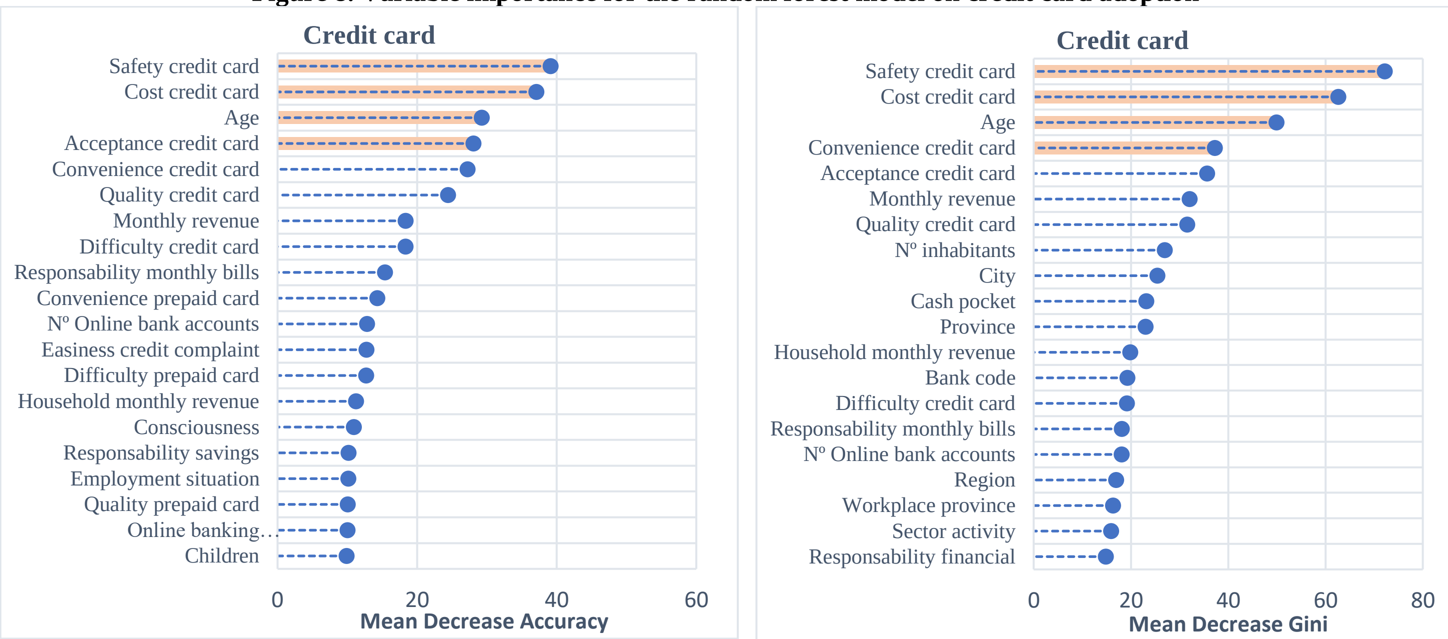


Figure 9. Variable importance for the random forest model on adoption of non-bank payment methods

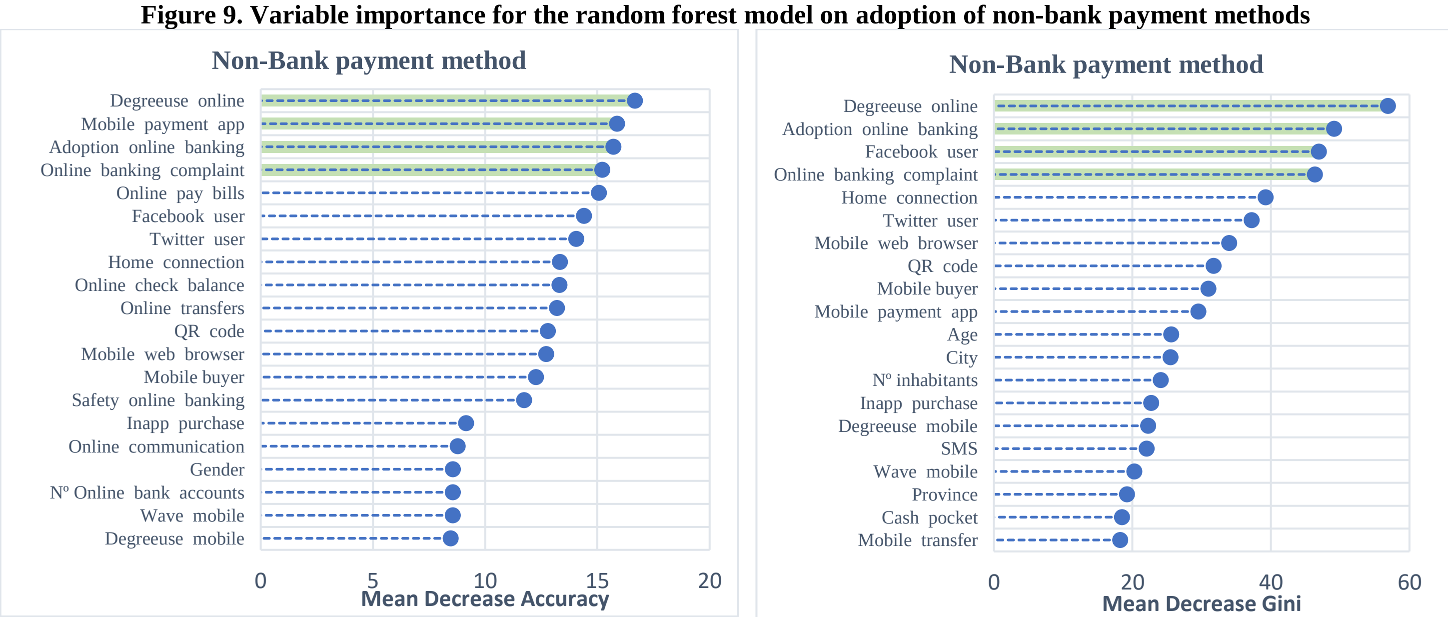


Figure 10. Stableness over Subsamples

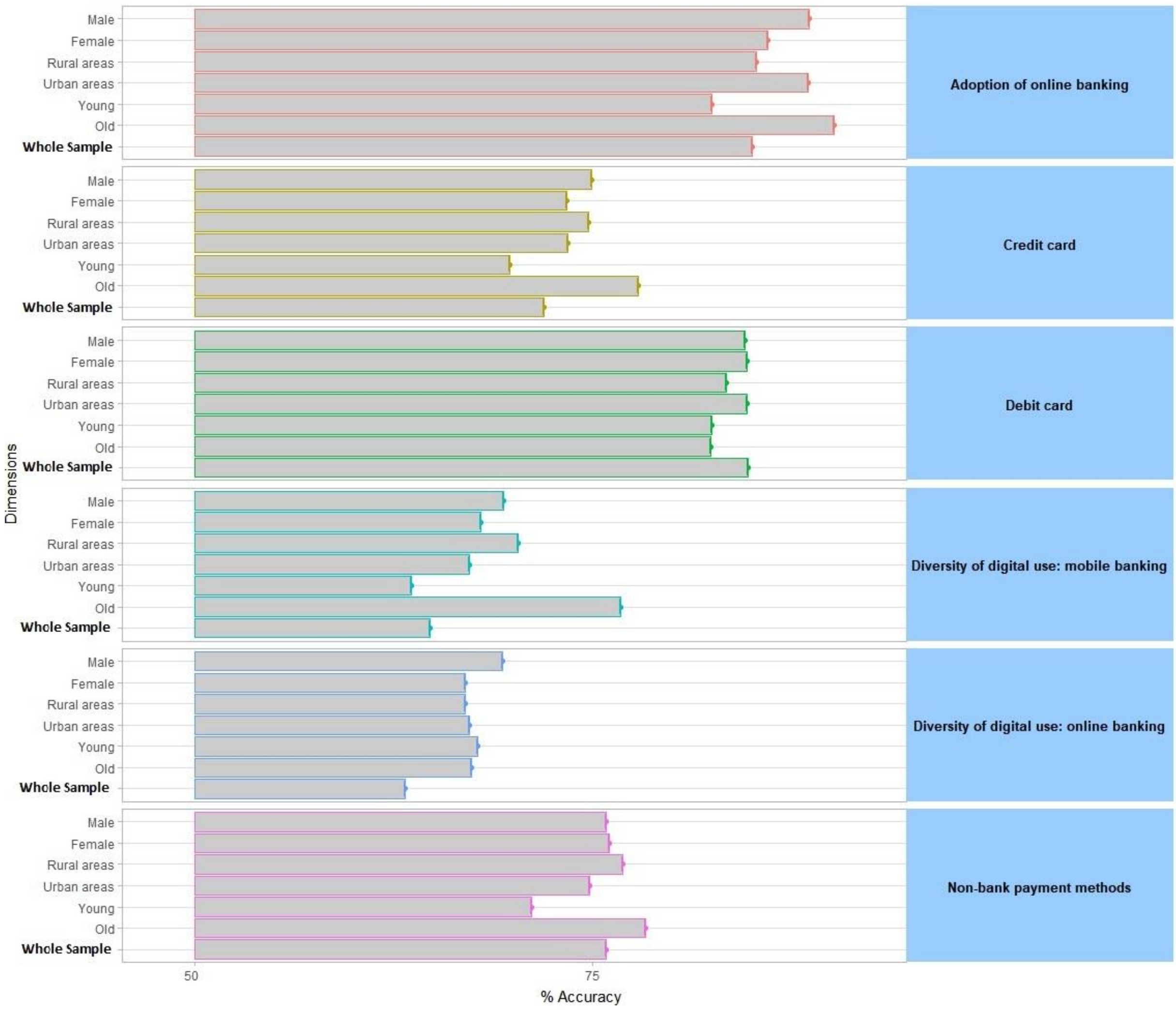


Figure 11. Tree: Adoption of digital banking

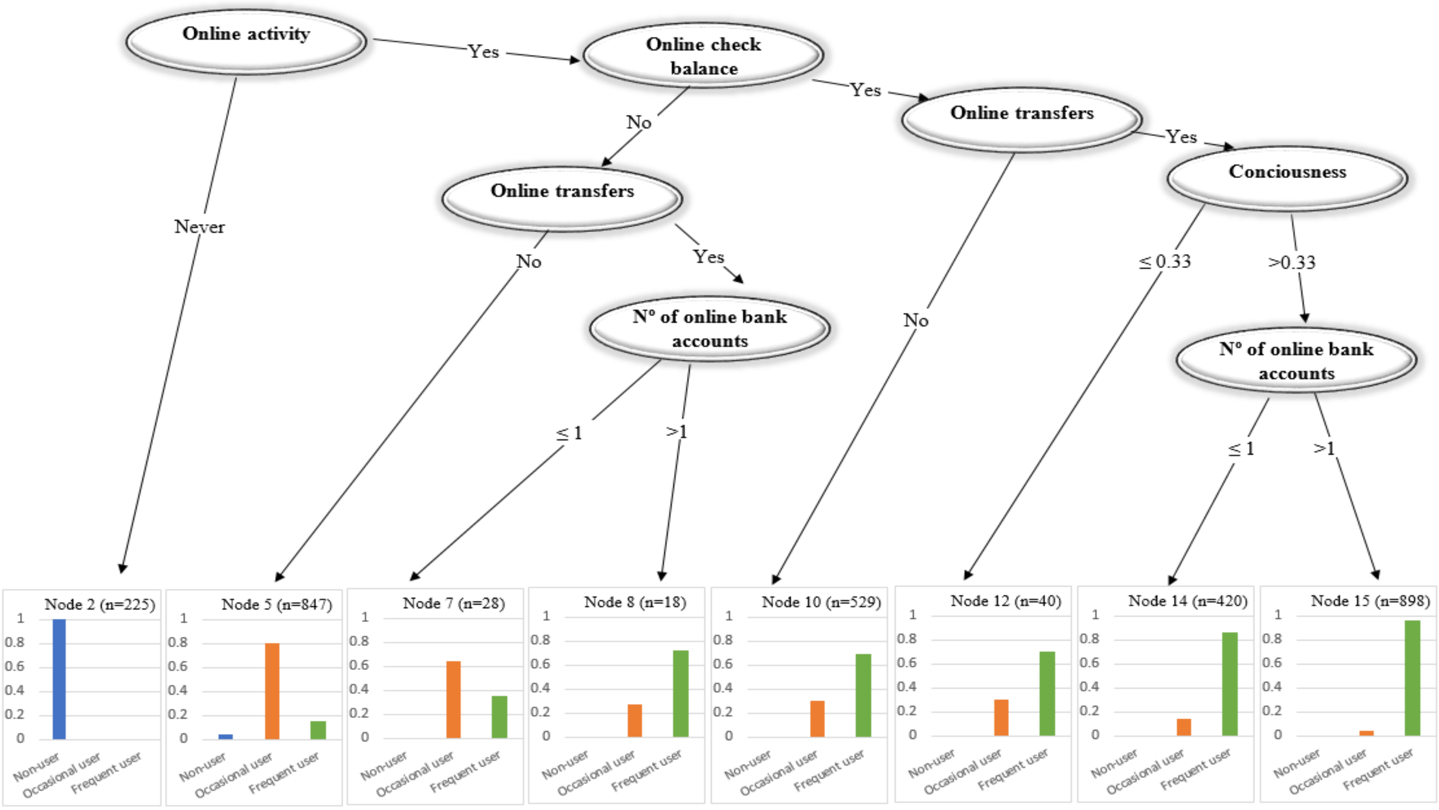


Figure 12. Tree: Diversity of digital use - online banking

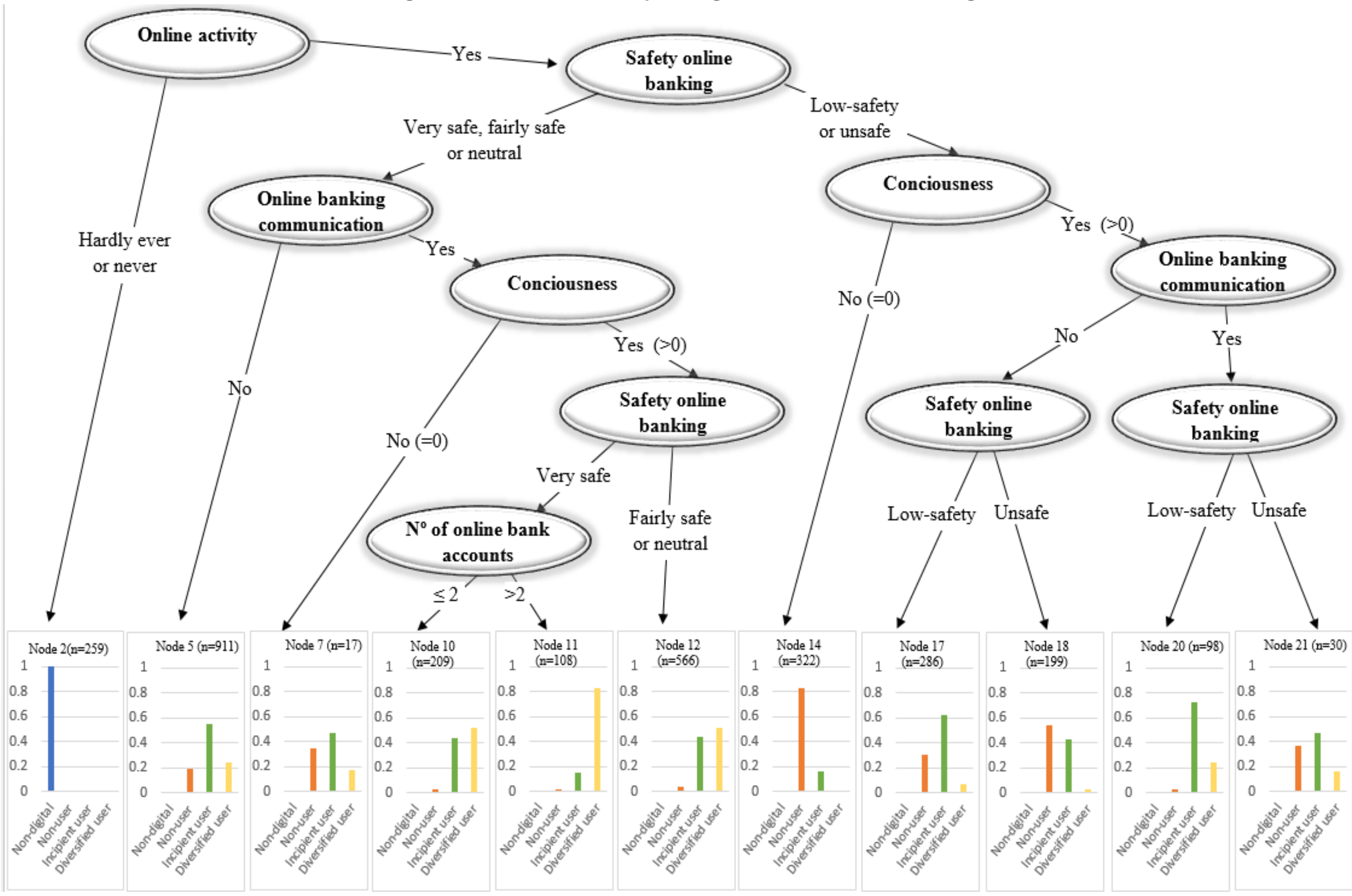


Figure 13. Tree: Diversity of digital use - mobile banking

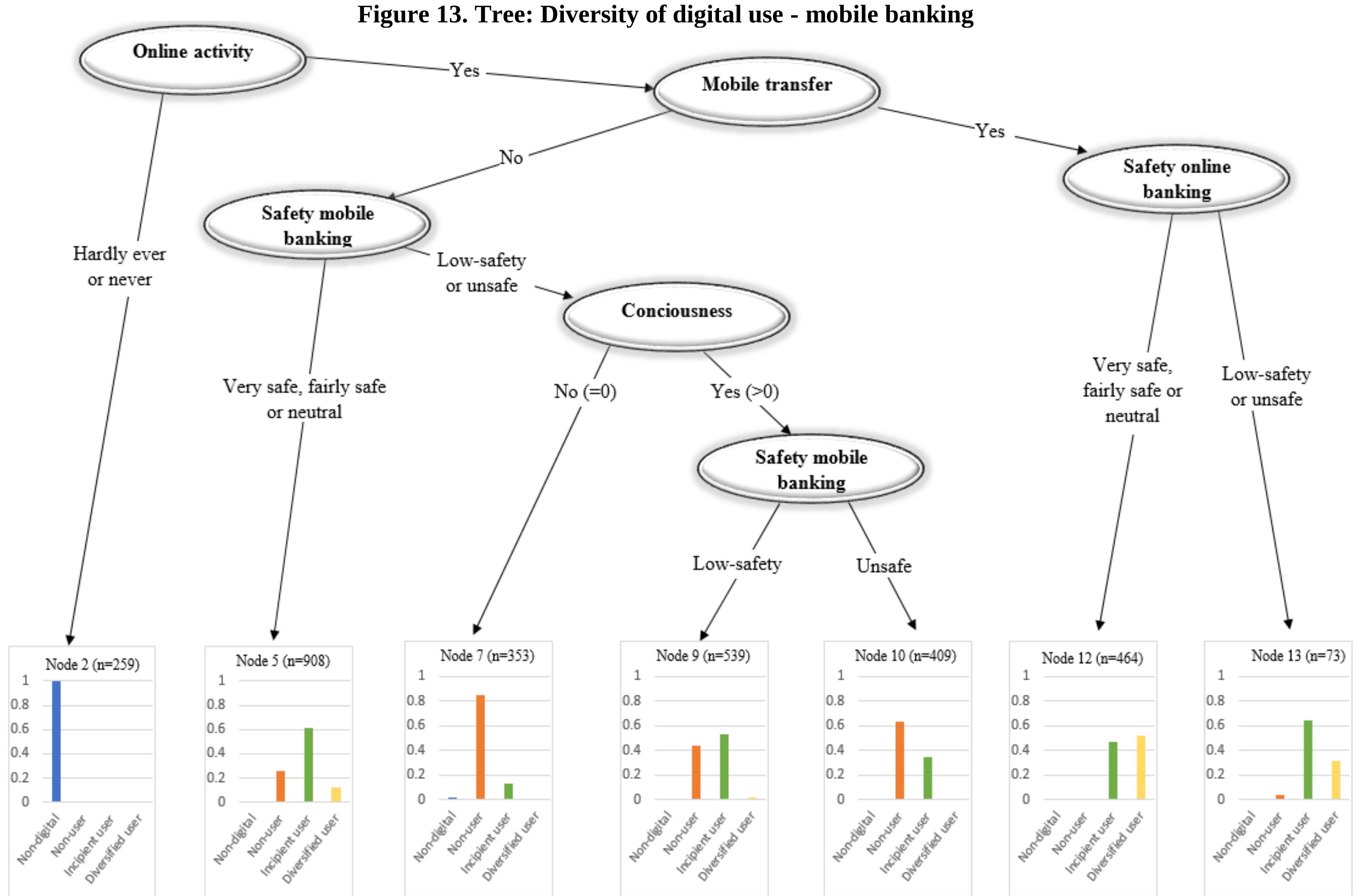


Figure 14. Tree: Debit card use

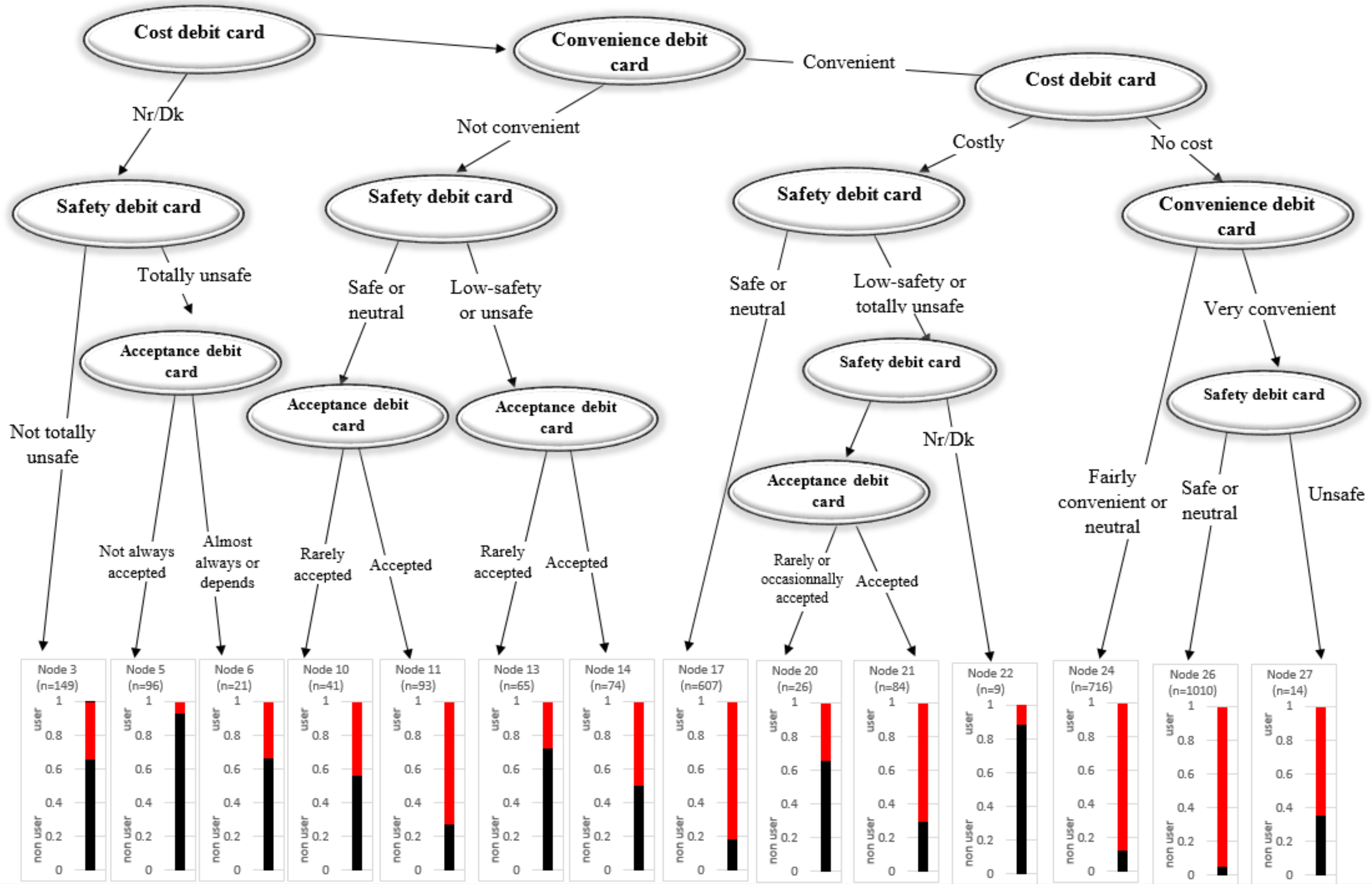


Figure 15. Tree: Credit card use

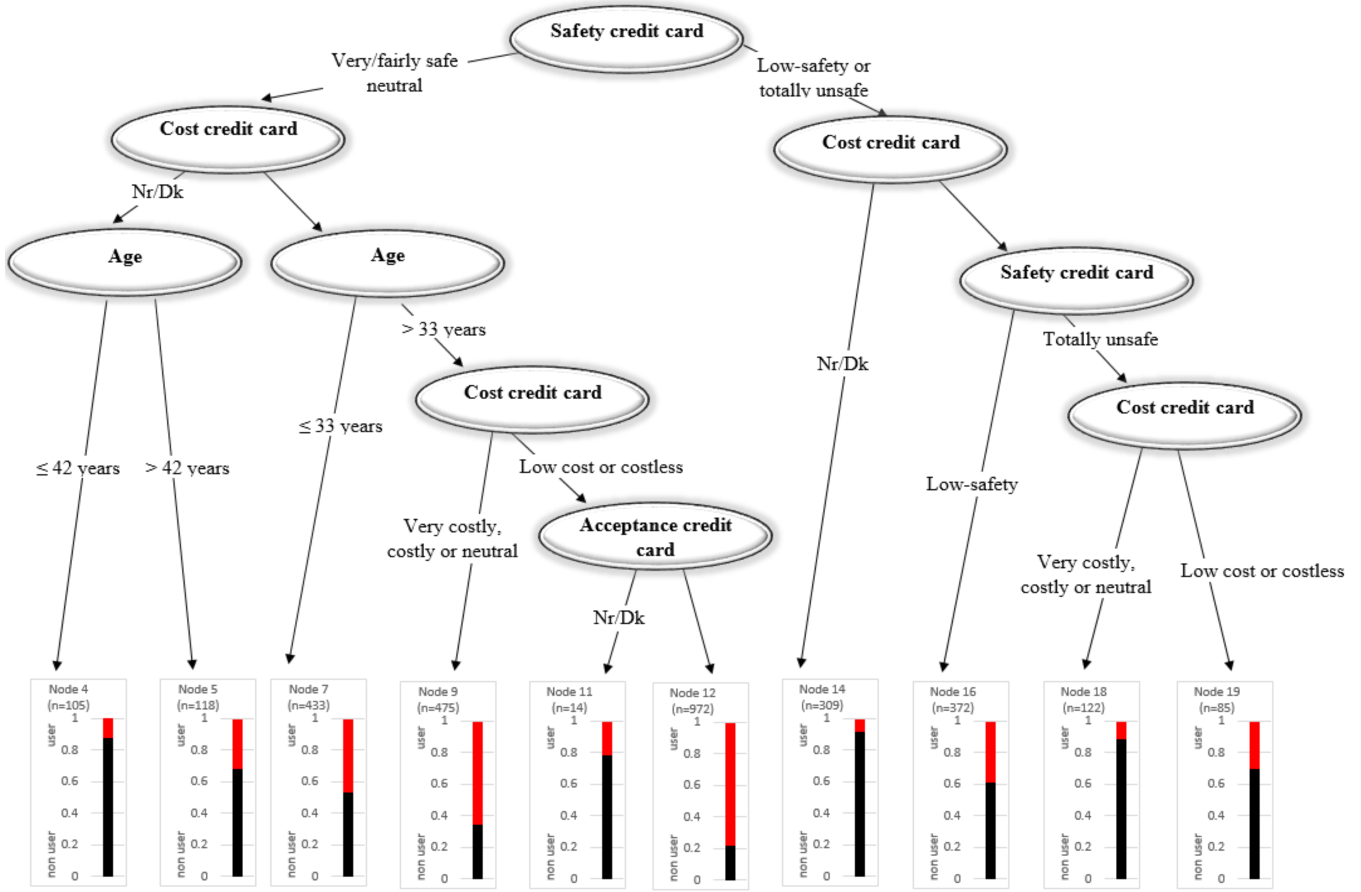


Figure 16. Tree: Use of non-bank payment instruments

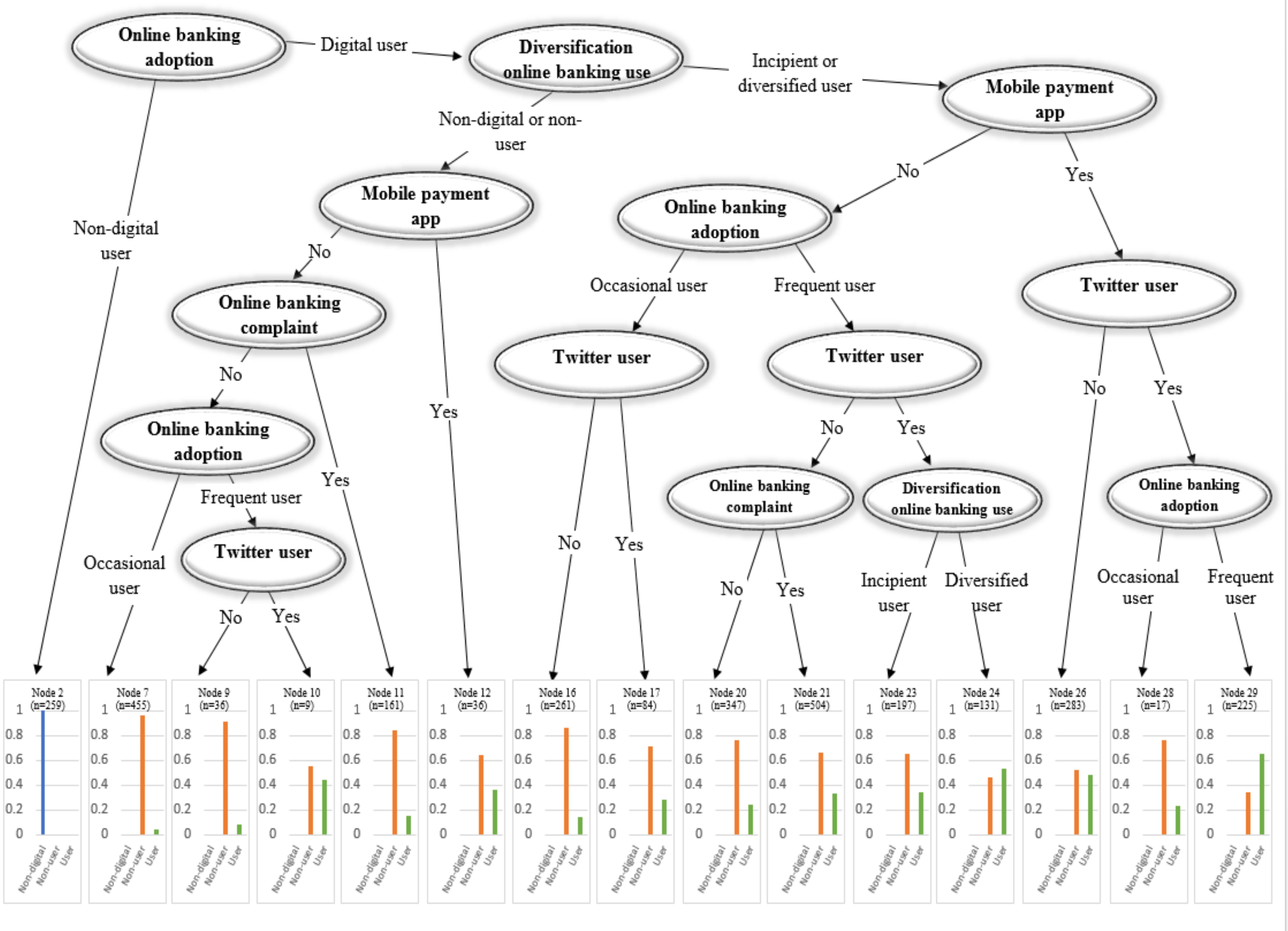


Figure 17. Average Treatment Effects using Causal Forests

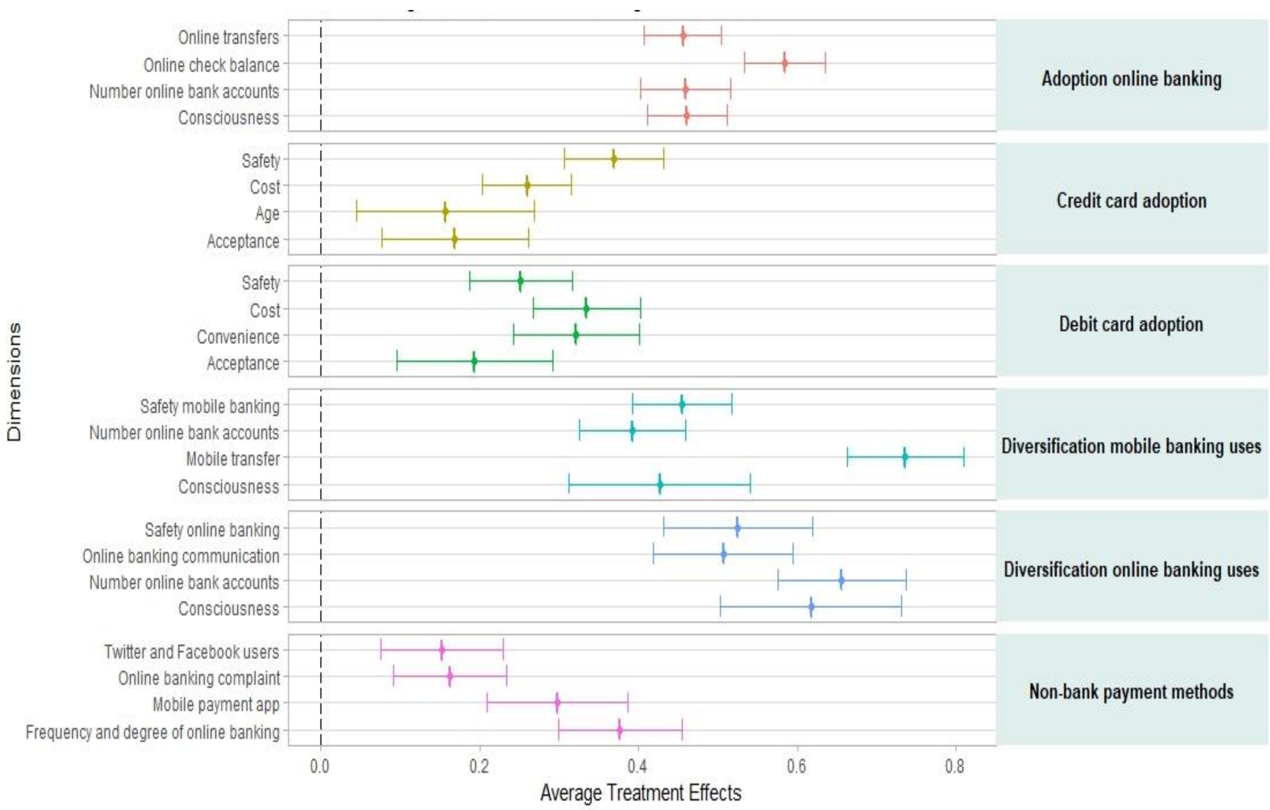
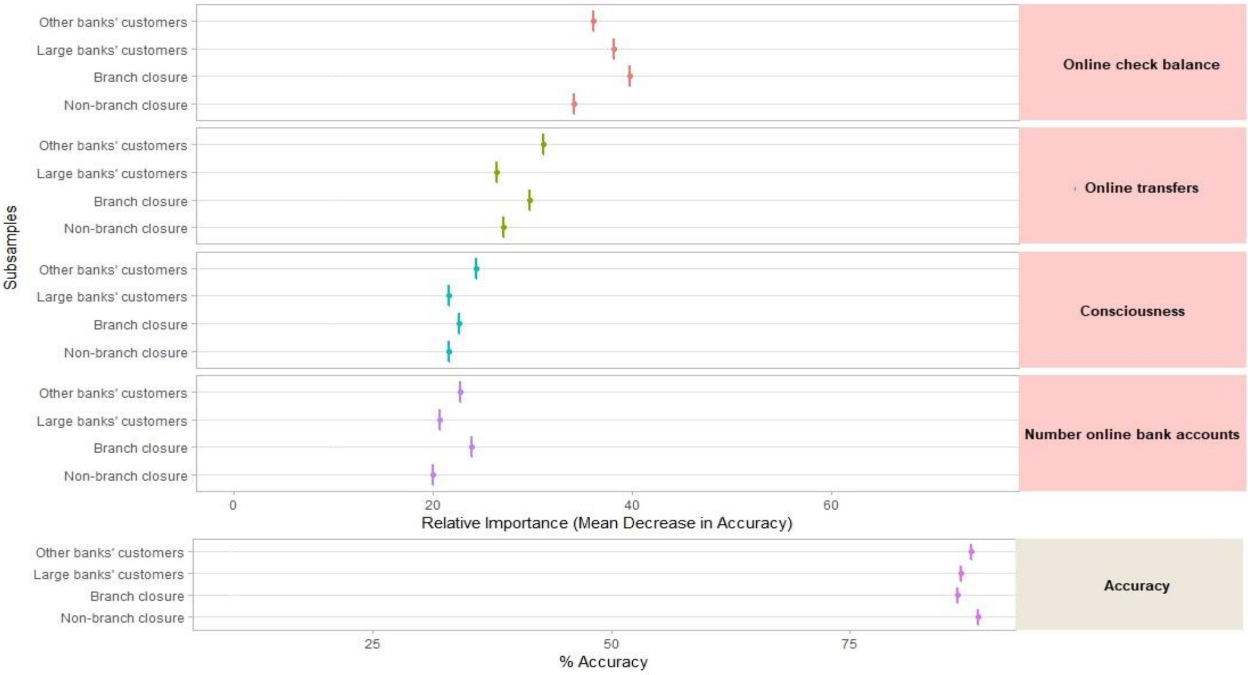


Figure 18. Subsample Analysis of Supply-Side Explanations



APPENDIX

Appendix A.I. Sample Design and Data Collection Process

Sample design	Landline: • Phase 1: the municipality. Stratified randomized selection using the size of the municipality and the region. • Phase 2: household. Randomized selection using the Irismedia directory recoded and debugged by IMOP. • Phase 3: individual. Selection employing sex and age quotas. The application selects the household member who is relatively less represented in the sample at the time of the call and establishes a postponement if the chosen person is not at home at that moment. Mobile phone: Simple random selection using the mobile phone database generated by IMOP from the data provided by each mobile operator. This database was tested before beginning the survey in order to detect inactive lines.
Technique	All the telephone interviews are conducted through the CATI system using a computer.
% mobile phone interviews	40.4%
% landline (fixed phone) interviews	59.6%
Questionnaire duration (on average)	21.5 minutes
Denial rate	14.7% of the people who took the telephone call declined to answer the questionnaire.
Not completion	0.9% of the people who began answering the questionnaire decided to end the survey before its completion.

Appendix A.II. List of Survey Questionnaire Variables

Socio-demographic characteristics	Age
	Gender
	Province
	City
	Nº inhabitants
	Household size
	Children
	Employed worker
	Employment situation
	Sector activity
	Unemployment period
	Full-time job
	Permanent job contract
	Monthly revenue
	Household employees
	Household monthly revenue
	Workplace province

Digital media	Landline or mobile phone
	Tablet
	Computer or laptop
	Nº computers
	Nº household laptops
	Exclusive computer
	Home connection
	Workplace connection
Financial status	Nº bank accounts
	Nº banks
	Savings bank account
	Current bank account
	Nº Online bank accounts
	Nº Online only bank accounts
	Consciousness
	Bank code
	Credit card holder
	Debit card holder

Financial activities	Online check balance
	Online communication
	Online pay bills
	Online transfers
	Nº online uses
	Mobile check balance
	Mobile communication
	Mobile pay bills
	Mobile transfers
	Nº mobile uses
	Mobile transfer
	Mobile payment app
	Mobile web browser
	Mobile purchase
	In-app purchase
	QR code
	SMS
	Wave mobile
	Online banking communication
	Online banking complaint
	Phone complaint
Social profile	Facebook user
	Twitter user
	Twitter FB bank comm
	Twitter FB bank complaint
Non-bank alternatives	Nonbank payment services user
	Google Wallet
	Amazon payments
	Paypal
	Web account
	Other non-bank payment method
Are you responsible for?	Responsibility financial
	Responsibility monthly bills
	Responsibility savings
	Responsibility shopping

Have you been?	Victim fraud
Do you know?	Know interest rate
	Know prepaid card
Cash	Cash home
	Cash pocket
	Annual cash payments
Where do you get cash?	ATM cash
	Bank branch cash
	Family cash
	Cashback cash
	Never cash
	Nº where cash
	Times withdrawal
How often do you . . . ?:	Freq bank branch check
	Freq check bank account
	Freq check credit
	Freq check prepaid
	Freq online
	Freq online check
	Freq phone complaint
	Freq use online
	Freq withdrawal
How many times do you . . . ?	Nº bank branch check
	Nº check credit weekly
	Nº check monthly bank account
	Nº check monthly credit
	Nº check prepaid
	Nº check prepaid weekly
	Nº check weekly bank account
	Nº check weekly credit
	Bank branch check
	Check monthly prepaid
	Check weekly prepaid

Bank customers' perceptions	Acceptance	Bank account number, cash, credit card, debit card, prepaid card
	Convenience	Bank account number, cash, credit card, debit card, mobile banking, online banking, prepaid card
	Cost	ATM withdrawal, bank account number, credit card, debit card, mobile banking, online banking, prepaid card
	Difficulty	Bank account number, credit card, debit card, mobile banking, online banking, prepaid card
	Easiness	Bank account number, credit card, debit card, mobile banking, online banking, prepaid card
	Quality	ATM withdrawal, bank account number, cash, credit card, debit card, mobile banking, online banking, prepaid card
	Safety	ATM withdrawal, bank account number, cash, credit card, debit card, mobile banking, online banking, prepaid card
	Risk pay	App, email, online, personally, SMS
	Value	Confidentiality, easiness, protection losses, speed deduction, speed payment, speed registration

Appendix B.

Table B.I. Ordered logit estimation results for the determinants of online banking adoption

Dependent variable: Adoption of online banking		
Online check balance	2.059***	(0.183)
Online pay bills	0.188	(0.175)
Online communication	0.699***	(0.162)
Online transfers	1.113***	(0.154)
Consciousness	-0.0406	(0.0387)
Nº Online bank accounts	0.0152	(0.0153)
Safety online banking	0.212***	(0.0459)
Cost online banking	0.0351	(0.0787)
Quality online banking	0.176***	(0.0325)
Difficulty online banking	-0.104*	(0.0614)
Convenience online banking	0.0587	(0.0663)
Nº check weekly bank account	0.256***	(0.0406)
Social network user	1.120***	(0.0854)
Gender: Woman	-0.355***	(0.0924)
Nº inhabitants	1.08e-07	(7.45e-08)
Household monthly revenue	0.0621**	(0.0317)
Age	-0.243***	(0.0331)
Household size	0.0133	(0.623)
Constant cut1	-0.611**	(0.268)
Constant cut2	3.395***	(0.329)
Observations	3,005	
Pseudo R^2	0.4598	
Errors	Clustered at the bank-level	
Log Likelihood	-1537.1433	
Note: *** p<0.01, ** p<0.05, * p<0.1		

Table B.II. Ordered logit estimation results for the determinants of the diversification of online and mobile banking uses

Diversification of online banking uses			**Diversification of mobile banking uses**		
Consciousness	-0.0109	(0.0442)	Consciousness	-0.0241	(0.0470)
Nº Online bank accounts	0.00848	(0.0104)	Nº Online bank accounts	0.0204*	(0.0104)
Online communication	1.420***	(0.0858)	Online transfers	1.852***	(0.109)
Nº check weekly bank acc.	0.177***	(0.0334)	Mobile purchase	1.093***	(0.108)
Safety online banking	0.454***	(0.0471)	Safety m-banking	0.343***	(0.0401)
Cost online banking	0.0386	(0.0364)	Cost m-banking	0.0189	(0.0452)
Quality online banking	0.163***	(0.0252)	Quality m-banking	0.131***	(0.0252)
Difficulty online banking	-0.111***	(0.0397)	Difficulty m-banking	-0.0709*	(0.0412)
Convenience online banking	-0.0168	(0.0238)	Convenience m-banking	-0.0280	(0.0458)
Non-bank payment user	0.631***	(0.106)	Nº check weekly bank acc.	0.176***	(0.0360)
Social network user	0.982***	(0.143)	Non-bank payment user	0.409***	(0.123)
Gender: Woman	-0.408***	(0.0656)	Social network user	1.038***	(0.0945)
Nº inhabitants	3.06e-08	(8.02e-08)	Gender: Woman	-0.178*	(0.108)
Household monthly revenue	0.130***	(0.0195)	Nº inhabitants	1.85e-07***	(5.75e-08)
Age	-0.0795***	(0.0220)	Household monthly revenue	0.0383	(0.0248)
Household size	0.0699	(0.0471)	Age	-0.161***	(0.0354)
Constant cut1	0.262	(0.263)	Household size	0.0595	(0.0469)
Constant cut2	2.667***	(0.252)	Constant cut1	-0.248	(0.302)
Constant cut3	5.605***	(0.306)	Constant cut2	2.297***	(0.318)
			Constant cut3	6.033***	(0.383)
Observations	3,005			3,005	
Pseudo R^2	0.2738			0.294	
Errors	Clustered at the bank-level			Clustered at the bank-level	
Log Likelihood	-2838.2248			-2704.581	
Note: *** p<0.01, ** p<0.05, * p<0.1					

Table B.III. Logit estimation results for the determinants of the debit and credit card adoption

Dependent variable:	Debit card adoption		Credit card adoption	
Safety debit card	0.389***	(0.0466)	0.453***	(0.0335)
Cost debit card	-0.0431	(0.0375)	0.0718	(0.0480)
Quality debit card	0.265***	(0.0592)	0.144***	(0.0489)
Difficulty debit card	-0.115	(0.0784)	-0.117**	(0.0512)
Convenience debit card	-0.163**	(0.0667)	-0.106***	(0.0378)
Acceptance debit card	0.310***	(0.0484)	0.187***	(0.0350)
Easiness debit card complaint	0.0189	(0.0594)	0.0739*	(0.0410)
Bank branch cash	-1.202***	(0.195)	-0.855***	(0.118)
Cashback cash	-2.791**	(1.185)	-0.571	(1.059)
Salary cash	-0.841	(0.891)	0.336	(0.623)
Family cash	-1.163***	(0.422)	0.309	(0.465)
Never cash	1.525	(1.843)	-	-
Credit card	-0.0818	(0.159)	-0.0391	(0.172)
Mobile phone	-0.112	(0.386)	0.761*	(0.404)
Non-bank payment user	0.440**	(0.176)	0.214	(0.137)
Social network user	0.281**	(0.139)	0.284***	(0.0920)
Gender: Woman	0.0542	(0.0912)	-0.272***	(0.0816)
Nº inhabitants	2.30e-07***	(7.17e-08)	-2.62e-08	(8.18e-08)
Household monthly revenue	0.0445*	(0.0245)	0.0895***	(0.0144)
Age	0.0684	(0.0485)	0.356***	(0.0444)
Household size	0.00971	(0.0699)	-0.0368	(0.0406)
Constant	-2.160***	(0.662)	-4.987***	(0.467)
Observations	3,005		3,005	
Pseudo R	0.2834		0.203	
Errors	Clustered at the bank-level		Clustered at the bank-level	
Log Likelihood	-1169.3937		-1650.7946	
Note: *** p<0.01, ** p<0.05, * p<0.1				

Table B.IV. Logit estimation results for the determinants of non-bank payment adoption

Dependent variable: Adoption of Non-bank payment instruments		
Adoption online banking	2.333***	(0.197)
Diversification online banking uses	0.948***	(0.128)
Mobile payment app	0.391***	(0.0864)
Online check balance	-0.786***	(0.137)
Twitter user	0.271**	(0.125)
Facebook user	0.782***	(0.108)
Credit Card	0.0786	(0.159)
Debit Card	0.167	(0.120)
QR code	0.346**	(0.142)
SMS	0.0344	(0.0828)
Wave mobile	-0.204	(0.152)
Online communication	-0.0329	(0.0927)
Mobile Phone	0.804**	(0.333)
Gender: Woman	-0.261***	(0.0785)
Nº inhabitants	-7.92e-08*	(4.20e-08)
Household monthly revenue	0.0573**	(0.0244)
Age	-0.213***	(0.0338)
Household size	0.0886**	(0.0432)
Constant cut1	4.659***	(0.456)
Constant cut2	11.39***	(0.517)
Observations	3,005	
Pseudo R	0.4291	
Errors	Clustered at the bank-level	
Log Likelihood	-1513.3098	
Note: *** p<0.01, ** p<0.05, * p<0.1		

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