FinTech Adoption Across Generations: Financial Fitness in the Information Age

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This version: July 2017

Abstract

This paper analyzes how better access to financial information changes use of consumer credit and affects financial fitness by exploiting the introduction of a smartphone application as a source of exogenous variation in access to information. FinTech adoption improves decision-making, but differs cross-sectionally in the population. Due to adoption of the new app, Millennials and members of Generation X incur fewer financial penalties, whereas Baby Boomers do not benefit from the technology advance. Higher financial fitness results from greater use of credit cards to manage short-term liabilities. While Millennials and Gen Xers enjoy an economic benefit from new technology, Millennials shift more of their spending to discretionary entertainment, whereas members of Generation X remain more austere. Finally, while men tend to adopt new technology and access information at a higher rate, the economic impact of access is higher for women.

JEL classifications: D14, D83, G02.

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We are indebted to Ágúst Schweitz Eriksson and Meniga for providing and helping with the data.

1 Introduction

How access to information affects individual decision-making and welfare is one of the most fundamental issues in economics (e.g., Stigler, 1961). Especially with the advent of the Information Age and the growing use of FinTech by consumers to access knowledge quickly (e.g., Mint, Personal Capital, YNAB), people are presumably better equipped than ever to make good choices. But, measuring the economic impact of this technology is challenging, beyond merely measuring its adoption. Indeed, people of different generations and demographic backgrounds incorporate new technology into their lives at different rates (Anderson, 2015). But, we know very little to date about how this affects outcomes, welfare, and transfers between generations.

Addressing these questions in a robust and careful way is challenging because it is typically impossible to deal with endogeneity, reverse causality, and omitted variables without making some leaps of faith. While it is intuitive that improved access to information may increase welfare, it is also likely that higher welfare and wealth increases either the incentives to acquire information or the ease of accessing it.[1] Additionally, measuring economic welfare typically requires some assumptions regarding what peoples' utility functions are or should be, which may make outcome measurements in an empirical exercise inconclusive.

In this paper, we address these issues by using a unique data set from Iceland. Almost all citizens in the country have access to a common on-line platform that consolidates all of their bank account information in one place. Before 2014, access to this personal information only occurred via the internet on a desktop or laptop computer. On November 14, 2014, a smart phone application was released, which gave users easier and remote access to bank account information. Figure 1 shows the propensity to log in to the personal finance management software before and after the mobile app introduction, documenting

[1] In the United States, as of 2015, high income consumers were much more likely than low income consumers to use the the Internet (97% versus 74%) and own a smartphone (87% versus 52%). See page 6 of Perrin and Duggan (2015) and page 7 of Perrin (2015). Also, according to Smit (2014), this difference is greater in adults greater than 65 years of age. In this age group, 90% of high income elderly people access the Internet, whereas only 39% of low income seniors go on-line.

that consumers indeed increased their information access in response to the availability of new technology. However, it is important to note that the smart-phone application did not offer consumers an easier way to make transactions. As such, any observable change in consumer behavior was only because of improved access to information, not because of more convenient transactions.

{Figure 1 around here}

In the data set, we have time-series information about the frequency and method of access to bank information (desktop vs. smartphone), and we can correlate this with demographic data, economic decisions (e.g., consumption, savings, wealth accumulation), channels through which consumers access credit (credit cards versus debit card overdrafts), and the resultant financial fitness (bank penalties and liquidity). One key economic outcome that we focus on is the tendency for people to pay penalties in the form of late fees, non-sufficient fund fees, and added interest. No matter what an individual's utility function might be (and resultant consumption-investment choice), paying lower bank fees would likely improve welfare for any consumer.

Our empirical strategy is to employ an instrumental variables approach to isolate the causal impact of more information on economic outcomes, assuming that the app introduction is exogenous to individual characteristics. By using the exogenous introduction of the mobile application, we first estimate the change in an individual's propensity to log into their financial accounts. Subsequently, we estimate the relationship between improved information and economic outcomes. We calibrate this effect by generation (Baby Boomers, Generation Xers, Millennials), by gender, and by income level. In our analysis, we also include individual fixed effects to control for all time-invariant omitted factors or individual characteristics that could affect the economic outcomes we measure.

The smartphone application was helpful in improving consumer welfare. Based on just the raw data, Figure 2 shows the total bank penalties paid during our time series. Up until the introduction of the app, financial fees increased. But, once the app was introduced, there was a sharp reversal and the amount of fees paid trended downward. Further, based on our regression results for the entire population, each added login was associated with approximately 242.7 Krona (2.18 USD) lower bank fees per month. This implies that improved access to information led to better financial decisions.

{Figure 2 around here}

We find that the smartphone application was adopted by all generations, but adoption rates differed cross-sectionally. Not surprisingly, increased access to information was highest for Millennials and lowest for Baby Boomers. Two years after the app introduction, 52% of Millennials, 41% of Generation Xers, and 27% of Baby Boomers had accessed their information via the smartphone application. However, Baby Boomers did not benefit from having information through this channel. Each additional login only lowered bank fees by 35.3 Krona (0.32 USD) for Baby Boomers. In contrast, each additional login lowered bank fees by 312.1 Krona (2.81 USD) for Generation Xers and 275.2 Krona (2.48 USD) for Millennials.

Our findings suggest that the observed drop in financial penalties after the app was introduced can be accounted for by changes in how people accessed consumer credit. In the total population, adoption of the technology was associated with roughly a 10.1% growth in credit cards use relative to debit cards in managing short-term liabilities. This effect was highest for Millenials, who increased their use of credit cards by roughly 29.7%. Changing use of credit in this way was a rational response to having better information. Indeed, since credit cards offer a 30-50 day float to avoid paying interest for convenience users, they are superior for consumers who need to carefully manage their expenditures, compared to overdrafts where fees are incurred immediately.

Based on technology adoption, the disposable income of Generation Xers and Millennials increased with technology and better access to information, but this affected spending patterns differently for each generation. Whereas people in Generation X maintained the same balance of discretionary entertainment and necessity purchases, Millennials increased their proportion of discretionary entertainment. This result is intuitive: at this point in their life cycle, it is likely that people in Generation X have more family responsibilities and may even be starting to plan for retirement. It is not surprising that on balance that Millennials would increase discretionary spending on entertainment in response to a small shock of disposable income.

We also find differences in technology adoption with respect to gender. Introduction of the smartphone application had a much higher effect on men than on women. Increased logins were roughly twice as high for men. Based on the raw data, for every age group, men are much more likely to enjoy better access to information than women. However, the financial impact for women was higher per login, perhaps implying that access to better information improved their financial fitness more. Each added login lowered bank fees by 279 Krona (2.51 USD) for women and by 221 Krona (1.99 USD) for men.

Ex ante, we would expect that better access to information improves consumer welfare. Based on an extensive literature studying consumer search for the best alternative (e.g., Lippman and McCall, 1976), anything that lowers search costs should lead to at least weakly better choices.[2] Further, any improvement in the delivery of information that makes important information more salient, should improve consumer decision-making (Hirshleifer and Teoh, 2003; Bertrand and Morse, 2011; Loewenstein et al., 2014). Our study confirms this intuition empirically, but also allows us to calibrate the effect of technology and study cross-sectional differences among consumers.

To date, some industry studies analyzed technology adoption by demographic category. According to PEW Research Center, older Americans are significantly less likely to access the Internet, use social media, or own smartphones (Anderson, 2015; Perrin and Duggan, 2015; Perrin, 2015). However, there appears to be parity with respect to gender: roughly the same proportion of U.S. men and women access the Internet, use social media, or own a smartphone (Anderson, 2015; Perrin and Duggan, 2015; Perrin, 2015).

[2]See also Salop and Stiglitz (1977), Stiglitz (1979), Weitzman (1979), Braverman (1980), MacMinn (1980), Rosenthal (1980), Varian (1980), Braverman and Dixit (1981), Salop and Stiglitz (1982), Kenneth Burdett (1983), Stahl (1989), Jacques Robert (1993), Stahl (1996), Baye et al. (2006), Gabaix and Laibson (2006), Carlin (2009), Wilson (2010), Carlin and Manso (2011), and Glenn Ellison (2012).

Our paper adds to this analysis in that we do not just consider technology adoption and usage. We measure the economic effects that this has on the population.

The academic profession has only hit the tip of the iceberg in characterizing the potential benefits and costs of technology on financial decision-making and consumer welfare. This is a nascent and growing literature. Stango and Zinman (2014) document that individuals respond to surveys about overdrafts by paying greater attention to account balances and incurring less fees. Furthermore, Medina (2016) finds that reminders for timely payment reduce credit card late-fees paid. Karlan et al. (2016) show that text message reminders are helpful for consumers make better choices and avoid penalties. Fernandes et al. (2014) show that just-in-time access to on-line advice improves financial decision-making. Lusardi et al. (2015) show that on-line videos are more effective than standard materials like written disclosures when consumers make choices. Carlin et al. (2016) show that video content is beneficial in helping consumers to both choose better opportunities and avoid falling prey to deceptive advertising in retail financial markets, and are also drivers of social learning in these settings. On the other hand, in some circumstances, it is possible that having more access to information may lead to worse outcomes. As Bernhardt and Cuevas (2016) show, better access to information led to the *Felices y Forrados* consumer financial fiasco in Chile.

The remainder of the paper is organized as follows. In Section 2, we describe the data and offer summary statistics. In Section 3, we explain our identification approach. In Section 4, we report our main results, while Section 5 presents concluding remarks.

2 Data and summary statistics

In this paper, we exploit data from Iceland that are collected by Meniga, a financial aggregation software provider to European banks and financial institutions.[3] Meniga's

[3] Meniga was founded in 2009 and is the European market leader of white-label Personal Finance Management (PFM) and next-generation online banking solutions, reaching over 35 million mobile banking users across 18 countries.

account aggregation platform allows bank customers to manage all their bank accounts and credit cards across multiple banks in one place by consolidating data from various sources (internal and external). Meniga's financial feed reflects consumers' financial lives in familiar social media style. Categorized transactions are mixed in with automated and custom advice, notifications, messages, merchant funded offers, and various insights and interpretations of the users' finances. This data set has already proved useful for studying the spending responses of individuals to income arrivals and how these effects vary with the capital structure of households (Olafsson and Pagel, 2016).

In January 2015, the Icelandic population counted 329,100 individuals – 249,094 of which were older than 18. At the same time, Meniga had 50,573 users, which is about 20 percent of the adult individuals living in Iceland. Because their service is marketed through banks, the sample of Icelandic users is fairly representative. Each day, the application automatically records all the bank and credit card transactions, including descriptions as well as balances, overdraft, and credit limits. Figure 3 displays screenshots of the app's user interface. The first screenshot shows background characteristics that the user provides, the second one shows transactions, and the third one bank account information.

{Figure 3 around here}

All of the active users in this data set are de-identified and we exclude those with missing entries or incomplete data. We study 13,838 active users with complete records from January 2011 until August 2016. Since the app collects demographic information such as age, gender, marital status, and postal code, we can confirm that our sample is reasonably representative of the population of Iceland. According to Panel A of Table 1, this appears to be the case. To perform our analyses, we divide the population into three groups. Baby Boomers were born between 1946-1964 and represent our oldest subjects. People in Generation X were born between 1965-1980. Millennials were born between

1981-2000 and represent our youngest subjects. Panel B of Table 1 gives the numbers of people in each group.

{Table 1 around here}

In the data set, we have a monthly panel of individual logins, financial penalties, credit use, and consumption choices from November 2011-August 2016. The data include information on how many times each individual logs in via the app or via a desktop. The app was introduced on November 14, 2014.

Because we are interested in debt expenses that might be avoided by having better information and allowing consumers to make small and relatively costless changes in their behavior, we focus on three types of penalties: late payment interest, non-sufficient funds fees, and late fees. Additionally, we observe interest expenses for individuals that hold overdrafts.

1 **Late-payment interest:** Credit card companies charge late-payment interest daily from the date a payment is due and payable to the date it is paid in full.

2 **Non-sufficient funds fees:** When there are insufficient funds or the overdraft limit is exceeded in consumer's current account in the event of attempted debit card transactions, the bank charges their account with fees.

3 **Late fees:** Fees assessed for paying bills after their due date.

4 **Interest:** An overdraft occurs when withdrawals from a current account exceed the available balance. This means that the balance is negative and hence that the bank is providing credit to the account holder and interest is charged at the agreed rate. Virtually all current accounts in Iceland offer a pre-agreed overdraft facility, the size of which is based upon affordability and credit history. This overdraft facility can be used at any time without consulting the bank and can be maintained indefinitely (subject to ad hoc reviews). Although an overdraft facility may be authorized,

technically the money is repayable on demand by the bank. In reality this is a rare occurrence as the overdrafts are profitable for the bank and expensive for the customer.

Table 2 displays summary statistics about the penalties incurred and use of various forms of consumer credit used by people in our sample. Comparison is made between consumers who logged in using the app to those who did not, within windows of time around the app introduction that varied from 3 months to 15 months. Total and individual sources of financial penalties were lower for consumers who used the cell phone app. Additionally, consumers who used the app were more likely to use credit cards to cover their expenditures. Of course, Table 2 does not allow us to make causal claims yet, as use of the app and financial performance are endogenous. However, our use of an IV design ameliorates this.

{Table 2 around here}

The income and spending data in the panel is extracted from the PFM system, which has already been categorized by a three tiered approach: system rules as well as user- and community-rules. The system rules are applied in instances where codes from the transactions systems clearly indicate the type of transaction being categorized. For example, when transactions in the Icelandic banking system contain the value "04" in a field named "Text key" the payer has indicated payment of salary. User rules apply if no system rules are in place and when a user repeatedly categorizes transactions with certain text or code attributes to a specific category. In those instances the system will automatically create a rule which is applied to all further such transactions. If neither system rules nor user rules apply, the system can sometimes detect identical categorization rules from multiple users which allows for the generation of a community rule. Multiple additional steps were taken to further categorize transactions based on banking system codes, transaction texts, amounts, and payer profiles. The categorization is very high quality as Iceland is not a particularly large or heterogeneous country. It is also important to note that the PFM system has already detected 1st party transactions such as between two accounts that belong to the same household. These transactions are not included in the sample data set. Payers identity as well as NACE category (The Statistical Classification of Economic Activities in the European Community)[4] are added to each income transfer whenever possible.[5]

The system categorizes the income as described above into 23 different income categories. Regular income categories are: child support, benefits, child benefits, dividends, parental leave benefits, pensions, housing benefits, rental benefits, rental income, salary, student loans, and unemployment benefits. Irregular income categories are: grant, other income, insurance claims, investment transactions, loan write-offs, reimbursements, tax rebates, travel allowances, and lottery winnings. Total household income is defined as the sum of regular and irregular income of spouses.

Spending is categorized into 15 categories and aggregated to generate a monthly panel. The spending categories are groceries, fuel, alcohol (we observe expenditures on alcohol that is not bought at bars and restaurants because a state-owned company, State Alcohol and Tobacco Company, has a monopoly on the sale of alcoholic beverages in Iceland), ready made food, home improvement, transportation, clothing and accessories, sports and activities, pharmacies, media, bookstores, thermal baths, toy stores, insurances, and various subcategories of recreation (.e.g., cinemas, theatres, fishing etc.).

For purposes of empirical analysis, we define two categories of spending. The first contains necessities such as groceries, fuel, and pharmacy. The second includes discretionary entertainment: alcohol, restaurant/takeout, lottery, gambling, gaming, and cinema. Table 3 displays summary statistics about the income and spending categories

[4]This is is the industry standard classification system used in the European Union.

[5]Payers identity can sometimes be hard or impossible to identify because of limited information in transaction data such as generic transaction texts. In specific cases where identifying the payer was not possible, a proxy ID was created to enable the binding of payments from single sources even though the true source ID is not known. In some cases, no attempts could be made to bind transactions by origin via a proxy ID. Some payments without actual payer identity may have a proxy ID but never a NACE category as the real ID of the payer was not known.

for our subjects. All quantities have been converted to US dollars.

{Table 3 around here}

3 Empirical Strategy

Our empirical approach exploits that there is a discontinuity in individual access to the Meniga's financial management software that arises from the introduction of a mobile application on November 14, 2014. The timing of the app introduction is plausibly exogenous to individual characteristics but sorted individuals into different frequencies of logins and is thus a valuable source of identifying variation. We exploit this to estimate a causal effect of access to information on spending as well as financial penalties. The instrumental variable design can be implemented by the following two-equation system:

$$Y_i = \alpha + \beta L_i + \mathbb{1}\left[t \geq c\right] f_l\left(t - c\right) + \mathbb{1}\left[t < c\right] f_r\left(c - t\right) + \epsilon_i, \tag{1}$$

$$L_i = \gamma + \mathbb{1}\left[t \geq c\right]\left(g_l\left(t - c\right) + \lambda\right) + \mathbb{1}\left[t < c\right] g_r\left(c - t\right) + \nu_i, \tag{2}$$

where Y_i is a measure of the economic outcomes (i.e., financial penalties or spending categories) for individual i, c is the time of the app introduction, and f_l, f_r, g_l, and g_r are unknown functional forms that capture the effect of time from the mobile app introduction on economic outcomes. The interpretation of Equation (1) is that it describes the average economic outcomes for individuals under alternative assignments into higher frequency of account logins, controlling for any other relationship between time from the mobile app introduction and economic outcomes. Since logging in more often is not randomly assigned, logins are likely correlated with the error component in a simple ordinary least squares (OLS) regression of economic outcomes on logins. As such, OLS estimates of (1) would not have any causal interpretation. Therefore, we estimate the two-equation system by two-stage least squares (2SLS) using the discontinuity in logins caused by the app introduction as an instrument. In turn, the 2SLS estimate of β gives the causal effect of technology on economic outcomes.

We estimate the system of equations using both polynomial and local linear regressions. The only restriction on the functional forms that capture the effects of time, f_l and f_r (g_l and g_r), is that they must differ at c by λ. We estimate λ as the jump in logins at the mobile app introduction date in the first-stage regression, given by Equation (2). In turn, we estimate β in the second stage. Our empirical design thus uses the discontinuities in the relationship between the mobile app introduction and higher frequency of logins to identify the causal effect of observing financial accounts on economic outcomes, i.e., by distinguishing the nonlinear and discontinuous function, $\mathbb{1}\left[t \geq c\right]$, from the smooth function $f\left(t\right)$.

The key identification assumption that underlies our approach is that $f(\cdot)$ is a continuous function. Intuitively, the continuity assumption requires that differential assignment of logging in more often is the only source of discontinuity in outcomes around the time of the mobile app introduction, c, so that unobservables vary smoothly as a function of time from app introduction and, in particular, do not jump at the time of the introduction. Formally, the conditional mean functions, $E\left[Y_{1i}|t-c\right]$ and $E\left[Y_{0i}|t-c\right]$, are continuous in $(t-c)$ at c, or equivalently $E\left[\epsilon_i|t-c\right]$ are continuous in $(t-c)$ at c. Under this assumption the treatment effect, β, is obtained by estimating the discontinuity in the empirical regression function at the point where the probability of the treatment dummy jumps at the assignment threshold and can be given a causal interpretation.

We can examine whether this quasi-random variation in the cost of accessing information changes individual's economic outcomes by estimating the following reduced form model:

$$Y_i = \tau + \mathbb{1}\left[t \geq c\right]\left(f_l(t-c) + \pi\right) + \mathbb{1}\left[t < c\right] f_r\left(c-t\right) + \xi_i, \tag{3}$$

where π can be interpreted as an 'intention-to-treat" (ITT) effect of the mobile app introduction on economic outcomes. The ratio of the reduced form coefficient π and the first-stage coefficient λ is numerically equivalent to the 2SLS estimate of β, provided that the same bandwidth is used in equations (2) and (3) in the local linear case and the same order of polynomial is used for f and g in the polynomial regression case, since the two-equation system is exactly identified.

In the context of the causal model above, the IV estimate should be interpreted as an average effect of the increased logins for individuals whose log in behavior was influenced by the app introduction. This group may not necessarily be a good representation of the entire population of individuals. Thus, we only estimate a local average treatment effect (LATE) rather than an average treatment effect.

The identification approach relies on a single exogenous event, the app introduction. This event's effects on economic outcomes could be confounded if other events happened or things changed around the same time. To the best of our knowledge, no other event took place around the same time. Nevertheless, we vary the time window and control flexibly for the months around the app introduction to address potential concerns about confounding events around the time of the app introduction.

Normally there is a trade-off between having two periods that are as close in time to each other as possible (obtained by reducing the time window around the reform) and having a longer sample period (by widening the window). In our case this is unlikely to be a problem as it can be argued that individuals who start using the app later are more similar to those that never use it at all than the individuals who start using it immediately after the introduction. However, we feel that it is important to report our findings for several time windows: i.e., we report results using up to six, twelve, and eighteen months before and after its introduction.

We also report our results after including individual fixed effects in all specifications. Individual fixed effects control for all time-invariant observable or unobservable characteristics and thus address all related concerns. Another issue is that individual characteristics for those individuals who adopt the new technology may change around the introduction of the app. Varying the time window helps address concerns regarding individual characteristics changing around the introduction of the app. While we cannot rule out that changes in individual characterestics take place exactly at the introduction of the app and have a confounding impact, such changes do not appear overly plausible given the absence of other confounding events at the same time.

4 Results

4.1 Logins

Based on the raw data plotted in Figure 1, there is an obvious discontinuity in the propensity of individuals to log into their financial accounts around the introduction of the mobile app. This is further described in Table 4, which gives some summary statistics about logins for the age and gender demographic categories. Before the introduction of the application (as of October 2014), men appeared more attentive to their accounts than women. Afterwards, this gap increased once the app became available. Figure 4 shows that for every age group, men were much more likely to access their personal information via the smartphone app right after its introduction. By August 2016, however, approximately the same fraction of men and women had adopted the new technology (43% versus 39%). Figure 5 also characterizes this trend by plotting the cumulative adoption of the smartphone technology through time.

{Table 4, Figure 4, and Figure 5 around here}

People of different generations adopted the new technology at much different rates. According to Table 4, the number of logins for Millennials more than doubled, whereas logins for Baby Boomers increased at a lower rate. In November 2014, even though the app was introduced halfway through the month, the number of app logins accounted for 59.4% of total logins for Millennials (3969/6631), whereas it only accounted for 27.9% of logins for Baby Boomers (855/3061). By August 2016, this gap did not converge. Roughly, 52% of Millennials had used the app, compared to only 27% of Baby Boomers.

Empirical analysis confirms these trends in the first stage regressions for the entire population and for individual demographic groups. Column 1 of Table 5 shows that introduction of the app increased the frequency of individual logins on average by 0.76, which is statistically significant. Table 5 also shows that this estimate is robust to including individual fixed effects.

{Table 5 around here}

Table 6 investigates these effects by gender, with and without individual fixed effects. Column 1 and Column 4 demonstrate that the effect of the app on logins is significant for both groups, but is more than twice as high for men than women. Table 7 explores this effect by generation, with and without individual fixed effects. All three generations increased their login intensity after the mobile app was introduced. However, this was stronger for Millennials and members of Generation X than for Baby Boomers.

{Table 6 and Table 7 around here}

4.2 Financial Fitness

The raw data that is plotted in Figure 2 suggests that access to more information led to less fees and debt interest. This is confirmed in Table 8, which summarizes the financial penalties that each generation paid before and after the introduction of the app. The quantities are negative because they are losses to consumers. The Table shows that the introduction of the app led to lower financial penalties for all subgroups within the population.

{Table 8 around here}

This is further characterized empirically in Table 5. Column 3 shows that in the overall population, each extra login was associated with 242.7 Krona fewer penalties incurred. Not only is this robust to individual fixed effects, but it is also robust to using different time windows around the mobile app introduction. Our primary analysis includes all of the data from November 2014 to July 2016. Table 9 presents the results of our analysis with shorter and symmetric bands of time around the app introduction on November 14, 2014. The statistical and economic significance of our estimates remain mostly unchanged. As would be expected, when we narrow the time window, we identify the effects off of a potentially more specific part of the population–those who adopt the app early. These early adopters are potentially on average more troubled by financial penalties or more prudent generally which increases the effects of the app introduction.

{Table 9 around here}

Table 6 shows that both men and women pay less financial penalties as a result of the mobile app. Women save somewhat more per login than men (279 versus 221 Krona). But, the differences across generations is much more striking. According to Table 7, Baby Boomers do not enjoy any economically or statistically significant benefit from the introduction of the app (35.3 Krona, 0.32 USD). In contrast, both members of Generation X and Millennials benefit from lower penalties (312.10 Krona and 275.2 Krona, respectively).

4.3 Credit Use and Expenditures

Now we consider how introduction of the smartphone app altered peoples' use of credit and their consumption choices. As shown in Table 2, consumers who used the app were more likely to use credit cards to make expenditures. We explore this further in Table 10 where we measure the impact of logins on the fraction of expenditures paid by credit cards. According to the results, for the entire population, each additional login is associated with approximately a 2% increase in the fraction of expenditures purchased wth a credit card[6] (1.1% when including individual fixed effects). Likewise, using a dummy variable for

[6]This growth rate is computed by dividing 0.00927 by the base rate of 0.45.

a login at any time using the app, the fraction of purchases made with a credit card increased by approximately 12.3% (10.1% when including individual fixed effects). This is both statistically and economically significant.

{Tables 10-11 around here}

Table 11 explores these effects by generation. Not surprisingly, the action resides with Millenials while we do not find significant effect for Generation Xers and Baby Boomers. According to the results, when including individual fixed effects, use of the app is associated with a 29.7% increase in the use of credit cards to cover expenditures among millenials.[7] Not only is this economically significant, but it provides a rational explanation for why Millenials had the highest economic gain from the new technology. For consumers with low savings, use of a credit card is superior to overdrawing a bank account with a debit card, in managing short-term liquidity needs. Credit cards typically provide a 30-50 day float until interest is charged, whereas overdraft fees are incurred immediately. Based on our findings, the technology provided consumers more information, allowed them to better manage their use of credit, and protected them from incurring financial penalties.

Gender differences were analyzed in Table 12. The economic magnitudes were similar for each group to the overall sample, varied in whether the estimates approached statistical significance, and were generally not different for men and women. Finally, Table 13 confirms our population estimates with different regression methods.

{Tables 12-13 around here}

Finally, from a consumption standpoint, the change in spending brought about by the mobile application is in Table 14. Millennials decreased their consumption of necessities and increased discretionary entertainment, both of which are statistically significant. In contrast, members of Generation X did not display any statistically significant changes.

[7]This growth rate is computed by dividing 0.00927 by the base rate of 0.29 for millenials.

These results may imply an intuitive behavioral response to a shock to disposable income. Since Millennials have less responsibilities than people in Generation X, it is not surprising that they increase discretionary spending and enjoy life. It is important to note, however, that we are not arguing that Millennials are acting suboptimally. Since we do not know their utility functions per se, we cannot make a definitive judgment.

{Table 14 around here}

5 Concluding Remarks

The introduction of the smartphone app by Meniga eases their consumers' plight to gather information and make good choices in two ways. First, it lowers search costs and makes finding personal information easier. Second, it makes financial information more salient. This latter mechanism is very important for consumers in retail financial markets. According to Loewenstein et al. (2014) [t]here are serious limitations on the amount of information to which people can attend at any point in time and [d]isclosures are so ubiquitous [...] that it would be impossible for people to attend to even a fraction of the disclosures to which they are exposed. Similarly, Hirshleifer and Teoh (2003) note that [l]imited attention is a necessary consequence of the vast amount of information available in the environment, and of limits to information processing power. Given this limited attention span, consumers tend to focus on the most prominent stimuli or salient information. By consolidating each user's financial accounts, Meniga's platform helps to streamline information access and the smartphone application makes that access clearer to consumers that use it.

In this study, we document and quantify the welfare effects that better access to information has on consumers in the market. But, we show that this varies cross-sectionally across generations. Baby Boomers do not enjoy the benefits that younger generations experience, which implies that technology may impose a wealth transfer from the old to the young. Our study implies that welfare may be enhanced by not only granting more access, but also by helping less tech savvy people to keep up. Further, because Millennials appear to exhibit less austerity with their increase in wealth, perhaps pairing the technology with a nudge to consider retirement planning might be beneficial.

As stated before, the analysis in this paper contributes to a small but growing literature on technology and economic outcomes. Given the regime shift we experienced over the last decade associated with on-line education, social learning, and electronic access to information, future study in this area appears warranted.

References

Anderson, M. (2015). Technology device ownership: 2015. Report, PEW Research Center.

Baye, M. R., J. Morgan, and P. Scholten (2006). Information, search, and price dispersion. In T. Hendershott (Ed.), *Handbook on Economics and Information Systems*, pp. 323–371. Elseview Science, Amsterdam.

Bernhardt, D. and C. Cuevas (2016, May). The pied piper of pensioners. Working Paper.

Bertrand, M. and A. Morse (2011). Information disclosure, cognitive biases, and payday borrowing. *The Journal of Finance 66*(6), 1865–1893.

Braverman, A. (1980). Consumer search and alternative market equilibria. *The Review of Economic Studies 47*(3), 487–502.

Braverman, A. and A. Dixit (1981). Consumer search and market equilibria: A note. *Review of Economic Studies 48*(4), 657–658.

Carlin, B. I. (2009). Strategic price complexity in retail financial markets. *Journal of Financial Economics 91*(3), 278 – 287.

Carlin, B. I., L. Jiang, and S. Spiller (2016). Millennial-style learning: Search intensity, decision-making, and information-sharing. *Management Science*.

Carlin, B. I. and G. Manso (2011). Obfuscation, learning, and the evolution of investor sophistication. *Review of Financial Studies 24*(3), 754–785.

Fernandes, D., J. G. L. Jr., and R. G. Netemeyer (2014). Financial literacy, financial education, and downstream financial behaviors. *Management Science 60*(8), 1861–1883.

Gabaix, X. and D. Laibson (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *The Quarterly Journal of Economics 121*(2), 505–540.

Glenn Ellison, A. W. (2012). A search cost model of obfuscation. *The RAND Journal of Economics 43*(3), 417–441.

Hirshleifer, D. and S. H. Teoh (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics 36*(1-3), 337–386.

Jacques Robert, D. O. S. (1993). Informative price advertising in a sequential search model. *Econometrica 61*(3), 657–686.

Karlan, D., M. McConnell, S. Mullainathan, and J. Zinman (2016). Getting to the top of mind: How reminders increase saving. *Management Science forthcoming*.

Kenneth Burdett, K. L. J. (1983). Equilibrium price dispersion. *Econometrica 51*(4), 955–969.

Lippman, S. A. and J. J. McCall (1976). The economics of job search: A survey. *Economic Inquiry 14*(2), 155–189.

Loewenstein, G., C. R. Sunstein, and R. Golman (2014). Disclosure: Psychology changes everything. *Annual Review of Economics 6*(1), 391–419.

Lusardi, A. M., A. Samek, A. Kapteyn, L. Glinert, A. Hung, and A. Heinberg (2015, 12). Visual tools and narratives: new ways to improve financial literacy*. *Journal of Pension Economics and Finance*, 1–27.

MacMinn, R. D. (1980). Search and market equilibrium. *Journal of Political Economy 88*(2), 308–327.

Medina, P. (2016). Selective attention in consumer finance: Experimental evidence from the credit card market. *Working Paper*.

Olafsson, A. and M. Pagel (2016). The liquid hand-to-mouth: Evidence from a personal finance management software.

Perrin, A. (2015). Social media usage: 2005-2015 - 65networking sites - a nearly tenfold jump in the past decade. Report, PEW Research Center.

Perrin, A. and M. Duggan (2015). Americans' internet access: 2000-2015 - as internet use nears saturation for some groups, a look at patterns of adoption. Report, PEW Research Center.

Rosenthal, R. W. (1980). A model in which an increase in the number of sellers leads to a higher price. *Econometrica 48*(6), 1575–1579.

Salop, S. and J. Stiglitz (1977). Bargains and ripoffs: A model of monopolistically competitive price dispersion. *The Review of Economic Studies 44*(3), 493–510.

Salop, S. and J. Stiglitz (1982). The theory of sales: A simple model of equilibrium price dispersion with identical agents. *The American Economic Review 72*(5), 1121–1130.

Smit, A. (2014). Older adults and technology use: Adoption is increasing, but many seniors remain isolated from digital life. Report, PEW Research Center.

Stahl, D. O. (1989). Oligopolistic pricing with sequential consumer search. *The American Economic Review 79*(4), 700–712.

Stahl, D. O. (1996). Oligopolistic pricing with heterogeneous consumer search. *International Journal of Industrial Organization 14*(2), 243 – 268.

Stango, V. and J. Zinman (2014). Limited and varying consumer attention: Evidence from shocks to the salience of bank overdraft fees. *The Review of Financial Studies 27*(4), 990–1030.

Stigler, G. (1961). The economics of information. *Journal of Political Economy 69*.

Stiglitz, J. (1979). Equilibrium in product markets with imperfect information. *American Economic Review 69*(2), 339–45.

Varian, H. R. (1980). A model of sales. *The American Economic Review 70*(4), 651–659.

Weitzman, M. (1979). Optimal search for the best alternative. *Econometrica 47*(3), 641–54.

Wilson, C. M. (2010). Ordered search and equilibrium obfuscation. *International Journal of Industrial Organization 28*(5), 496 – 506.

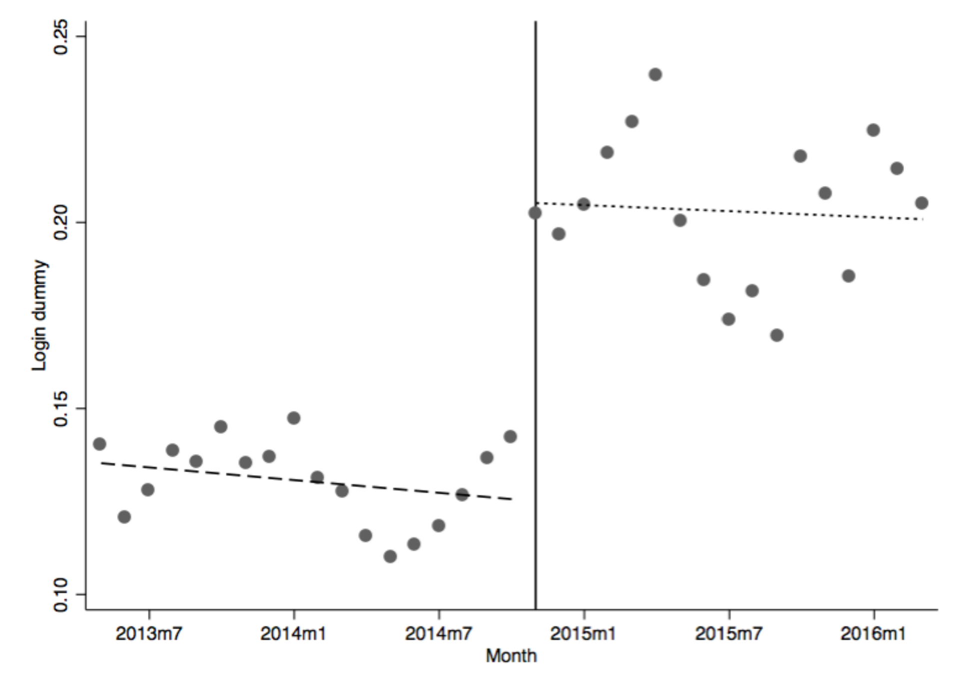

Figure 1: Propensity to log in around the APP introduction

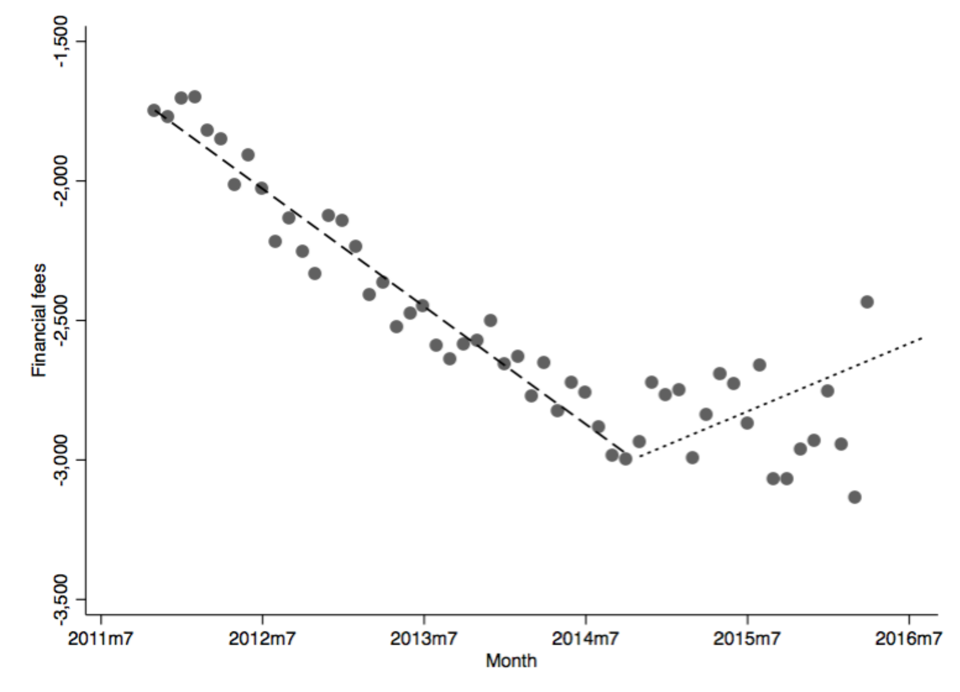

Figure 2: Bank fees and penalty payments around the APP introduction

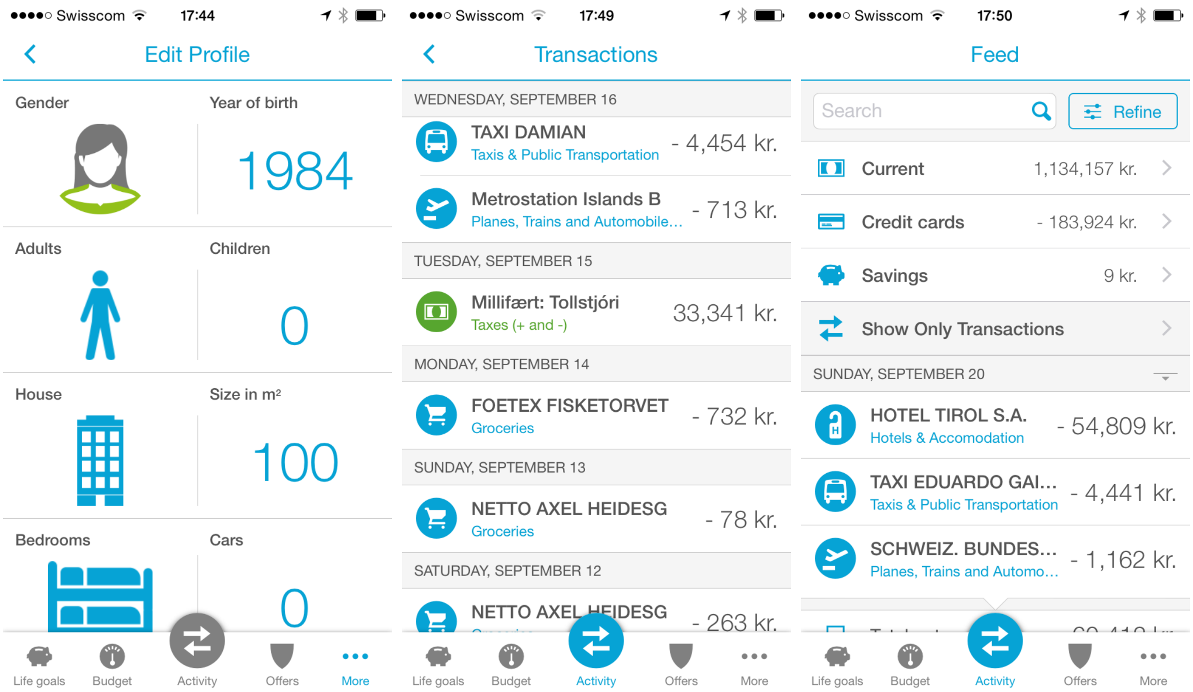

Figure 3: The financial aggregation app: screenshots

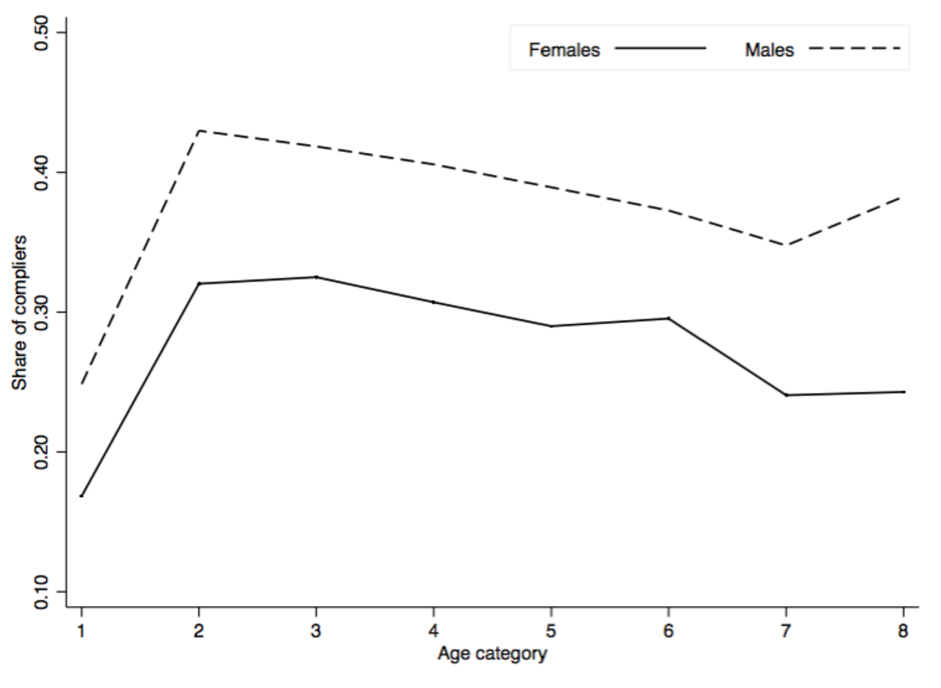

Figure 4: The figure shows the share of compliers by gender and age group. Compliers are defined as those who log in more often in the three months after the mobile app introduction than they did in the three month before the mobile app introduction.

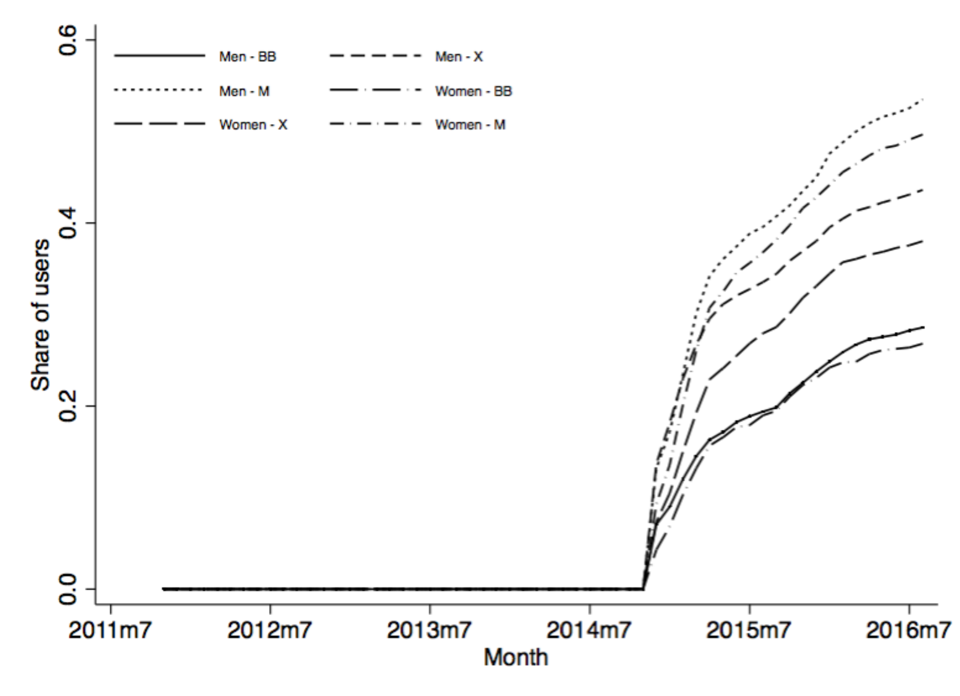

Figure 5: Uptake

Table 1: Demographic Statistics

Panel A	Mean	Standard Deviation	Statistics Iceland
Age	40.6	11.5	37.2
Female	0.49	0.50	0.48
Unemployed	0.08	0.27	0.06
Parent	0.23	0.42	0.33
Pensioner	0.15	0.36	0.12

Panel B	Years	Sample Count
Baby Boomer	1946-1964	2,974
Generation X	1965-1980	6,239
Millennial	1981-2000	4,328

Table 2: Financial fees and credit ratio for those who log in and not around the app intro

	3 months			6 months			12 months			15 months		
	no login	log in	Δ	no login	log in	Δ	no login	log in	Δ	no login	log in	Δ
Total financial fees	2,994	2,406	-588	2,954	2,348	-606	2,875	2,354	-520	2,849	2,405	-444
Credit card interest	33	21	-12	34	19	-15	32	18	-14	33	20	-13
NSF fees	23	20	-3	22	18	-4	22	16	-6	24	17	-7
Late fees	1,012	708	-303	1,012	692	-320	964	681	-283	940	700	-241
Overdraft interest	1,927	1,657	-270	1,887	1,618	-269	1,856	1,639	-218	1,852	1,669	-183
Credit card expenditure share	0.452	0.559	0.11	0.453	0.553	0.10	0.455	0.559	0.10	0.456	0.56	0.10

Notes:

Table 3: Income and Consumption Statistics

	Mean	Standard Deviation	Statistics Iceland
Monthly total income	3256.1	3530.5	4316
Monthly regular income	3038.2	3184.3	3227
Monthly salary	2703.5	2992.5	2456
Monthly irregular income	217.82	1414.8	1089
Monthly spending:			
Total	1315.1	1224.3	
Groceries	468.29	389.29	490
Fuel	235.88	258.77	(359)
Alcohol	61.75	121.43	85
Ready Made Food	170.19	172.64	(252)
Home Improvement	150.16	464.94	(229)
Transportations	58.33	700.06	66
Clothing and Accessories	86.62	181.27	96
Sports and Activities	44.29	148.41	(36)
Pharmacies	39.62	62.08	42

Note: All numbers are in US dollars. Parentheses indicate that data categories do not match perfectly.

Table 4: Login Statistics

	Logins Oct 2014	Logins Nov 2014	App Logins Nov 2014	% Pop log in Nov 2014	Freq App Use Aug 2016
Total	12,120	21,245	11,477	20%	41%
Men	7,131	13,901	7,510	24%	43%
Women	4,989	7,344	3,967	17%	39%
Baby Boomers	2,346	3,061	855	18%	27%
Generation Xers	6,435	11,064	6,621	21%	41%
Millennials	3,020	6,631	3,939	20%	52%

Note:

Table 5: The Impact of logins on financial fees

	(1) First Stage	(2) ITT	(3) IV
Total Logins	0.7581***	183.9***	242.7***
	(0.0713)	(45.05)	(74.80)
$I(Logins_{it} > 0)$	0.0835***	183.9***	2,204.2***
	(0.0028)	(45.05)	(573.43)
#Obs.	725,936	725,936	725,936
Including individual fixed effects			
Total Logins	0.7473***	155.5***	208.1***
	(0.0398)	(57.60)	(77.87)
$I(Logins_{it} > 0)$	0.0817***	155.5***	1,904.8***
	(0.0023)	(57.60)	(707.61)
#Obs.	789,051	789,051	789,051
#Individuals	13,843	13,843	13,843

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the assignment threshold for logging in to financial accounts. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 6: The Impact of logins on financial fees by gender

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage	ITT	IV	First Stage	ITT	IV
Total Logins	1.0308***	227.6***	220.8***	0.4691***	130.9**	278.98***
	(0.1074)	(72.59)	(79.36)	(0.0899)	(55.16)	(150.36)
$I(Logins_{it} > 0)$	0.0967***	227.6***	2,352.7***	0.0690***	130.9**	1,895.5***
	(0.0041)	(72.60)	(771.45)	(0.0037)	(55.16)	(817.19)
#Obs.	380,444	380,444	380,444	355,621	355,621	355,62
Including individual fixed effects						
Total Logins	1.0238***	199.9**	195.2**	0.4574***	108.9	238.1
	(0.0556)	(87.23)	(85.88)	(0.0571)	(74.57)	(165.67)
$I(Logins_{it} > 0)$	0.0958***	199.9**	2,086.8***	0.0669***	108.9	1,672.9
	(0.0034)	(87.23)	(913.88)	(0.0032)	(74.57)	(1,117.38)
#Obs.	404,130	404,130	404,130	384,636	384,636	384,636
#Individuals	7,090	7,090	7,090	6,748	6,748	6,748

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the assignment threshold for logging in to financial accounts.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 7: The Impact of logins on financial fees of by different generations

	(1) First Stage	(2) ITT	(3) IV	(4) First Stage	(5) ITT	(6) IV
Baby Boomers:						
Total Logins	0.3191*** (0.0555)	11.3 (143.2)	35.3 (446.3)	0.2992*** (0.0474)	11.9 (184.36)	30.59 (616.22)
$I(Logins_{it} > 0)$	0.0630*** (0.0069)	11.3 (143.2)	178.6 (2,257.8)	0.0611 (0.0049)	11.9 (184.36)	193.78 (3015.97)
#Obs.	165,656	165,656	165,656	172,492	172,492	172,492
#Individuals				2,974	2,974	2,974
Generation X:						
Total Logins	0.8223*** (0.1433)	310.4*** (65.29)	312.10*** (92.90)	0.8565*** (0.0653)	249.7*** (81.23)	291.6*** (97.43)
$I(Logins_{it} > 0)$	0.0867*** (0.0041)	268.6*** (57.23)	3,098.6*** (721.6)	0.0855 (0.0035)	249.7*** (81.23)	2,920.7*** (958.24)
#Obs.	338,386	338,386	338,386	355,623	355,623	355,623
#Individuals				6,239	6,239	6,239
Millenials:						
Total Logins	0.9450*** (0.1326)	185.0*** (56.59)	275.2*** (77.40)	0.9112*** (0.0786)	181.8*** (61.41)	199.5*** (69.57)
$I(Logins_{it} > 0)$	0.0957*** (0.0050)	185.0*** (56.59)	1,953.7*** (613.27)	0.0914*** (0.0041)	181.8*** (61.41)	1,988.6*** (677.3)
#Obs.	224,328	224,328	224,328	246,696	246,696	246,696
#Individuals				4,328	4,328	4,328

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the assignment threshold for logging in to financial accounts. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 8: Financial penalties around the App Introduction

	October 2014	December 2014
Baby Boomers		
Men	-4,144	-3,734
Women	-2,907	-2,756
Generation X		
Men	-3,764	-3,602
Women	-3,228	-3,032
Millenials		
Men	-2,294	-1,608
Women	-1,685	-1,579

Note:

Table 9: The effects of the number of monthly logins on financial fitness

	Local Linear Method			Global Polynomial Method		
	(1)	(2)	(3)	(4)	(5)	(6)
Total logins	179.5***	262.6***	457.6***	323.1***	440.1***	529.6***
	(61.4)	(64.3)	(166.4)	(87.9)	(155.9)	(386.1)
Bandwidth	18	12	6	20	20	20
Polynomial order:				Second	Third	Fourth
Number of observations.	534,957	336,950	482,251	534,957	534,957	534,957

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the assignment threshold for logging in to financial accounts. Columns 1-3 provide estimates using local linear regressions. Columns 4-6 present estimates using global polynomials using a 2^{nd}, 3^{rd}, and a 4^{th} order polynomial function of time from the mobile app introduction. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 10: The Impact of logins on the share of expenditures paid by credit cards

	(1) First Stage	(2) ITT	(3) IV
Total Logins	0.50590***	0.00469***	0.00927**
	(0.02717)	(0.00210)	(0.00406)
$I(Logins_{it} > 0)$	0.08498***	0.00469***	0.05520***
	(0.00306)	(0.00210)	(0.02421)
#Obs.	734,577	734,577	734,577
Including individual fixed effects			
Total Logins	0.75335***	0.00382**	0.00507**
	(0.04110)	(0.00167)	(0.00222)
$I(Logins_{it} > 0)$	0.08424***	0.00382**	0.04535***
	(0.00012)	(0.00167)	(0.01977)
#Obs.	769,268	769,268	769,268
#Individuals	13,411	13,411	13,411

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in the share of expenses paid by credit cards as a result of the assignment threshold for logging in to financial accounts. Regressions without individual fixed effects include month, year, generation and gender fixed effects. All regressions control for total expenditure. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 11: The Impact of logins on the share of expenditure paid by credit card by different generations

	(1) First Stage	(2) ITT	(3) IV	(4) First Stage	(5) ITT	(6) IV
Baby Boomers:						
Total Logins	0.33814***	0.00526*	0 .01555	0.29608***	0.00342	0.01156
	(0.08266)	(0.00314)	(0.00993)	(0.04888)	(0.00315)	(0.01081)
$I(Logins_{it} > 0)$	0.07095***	0.00526*	0.07409*	0.06573***	0.00342	0.05205
	(0.00675)	(0.00314)	(0.04458)	(0.00486)	(0.00315)	(0.04805)
#Obs.	152,512	152,512	152,512	181,082	181,082	181,082
#Individuals				3,059	3,059	3,059
Generation X:						
Total Logins	0.94407***	0.00218	0.00231	0.88437***	0.00384	0.00043
	(0.09087)	(0.00315)	(0.00328)	(0.05708)	(0.00244)	(0.00277)
$I(Logins_{it} > 0)$	0.08838***	0.00218	0.02472	0.08609***	0.00384	0.00446
	(0.00490)	(0.00315)	(0.03511)	(0.00357)	(0.00244)	(0.02843)
#Obs.	311,466	311,466	311,466	362,101	362,101	362,101
#Individuals				6,215	6,215	6,215
Millenials:						
Total Logins	0.95875***	0.01445***	0.01507***	0.92940***	0.00817***	0.00879**
	(0.15138)	(0.00343)	(0.00499)	(0.10560)	(0.00339)	(0.00377)
$I(Logins_{it} > 0)$	0.10259***	0.01445***	0.14081***	0.09519	0.00817***	0.08583**
	(0.00613)	(0.00343)	(0.03738)	(0.00470)	(0.00339)	(0.03563)
#Obs.	170,929	170,929	170,929	206,607	206,607	206,607
#Individuals				3,805	3,805	3,805

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the assignment threshold for logging in to financial accounts. Columns 1-3 provide estimates without individual fixed effects. Columns 4-6 present estimates using gusing individual fixed effects. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 12: The Impact of logins on the share of expenses paid by credit by gender

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage	ITT	IV	First Stage	ITT	IV
Total Logins	0.52255***	0.00394	0.00721	0.93502***	0.00444*	0.00475*
	(0.05976)	(0.00313)	(0.00594)	(0.09275)	(0.00234)	(0.00258)
$I(Logins_{it} > 0)$	0.07199***	0.00394	0.05479	0.09693***	0.00444*	0.04577*
	(0.00408)	(0.00313)	(0.04330)	(0.00446)	(0.00234)	(0.02404)
#Obs.	360,330	360,330	360,330	386,815	386,815	386,815
Including individual fixed effects						
Total Logins	0.52519***	0.00308	0.00587	0.97044***	0.00452*	0.00466
	(0.04854)	(0.00236)	(0.00452)	(0.06556)	(0.00235)	(0.00244)
$I(Logins_{it} > 0)$	0.07124***	0.00308	0.04324***	0.09660***	0.00452*	0.04682*
	(0.00338)	(0.00236)	(0.03312)	(0.00349)	(0.00235)	(0.02432)
#Obs.	374,992	374,992	374,992	394,276	394,276	394,276
#Individuals	6,535	6,535	6,535	6,876	6,876	6,876

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the assignment threshold for logging in to financial accounts.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 13: The effects of the number of monthly logins on the share of expenditure paid by credit cards

	Local Linear Method			Global Polynomial Method		
	(1)	(2)	(3)	(4)	(5)	(6)
Total logins	0.01389***	0.01307***	0.00864***	0.00880***	0.01850***	0.00625*
	(0.00276)	(0.00274)	(0.00303)	(0.00276)	(0.00414)	(0.00356)
Bandwidth	18	12	6	26	26	26
Polynomial order:				Second	Third	Fourth
Number of observations.	475,844	325,359	170,857	662,464	662,464	662,464

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the assignment threshold for logging in to financial accounts. Columns 1-3 provide estimates using local linear regressions. Columns 4-6 present estimates using global polynomials using a 2^{nd}, 3^{rd}, and a 4^{th} order polynomial function of time from the mobile app introduction.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 14: The Impact of logins on consumption

	Discretionary Entertainment			Necessities		
	Baby Boomers	Generation X	Millenials	Baby Boomers	Generation X	Millenials
Linear controls:						
Total Logins	-0.0080	-0.0062	0.0152***	-0.0247	-0.0058	-0.0074***
	(0.0635)	(0.0066)	(0.0049)	(0.0444)	(0.0046)	(0.0027)
Second order polynomial:						
Total Logins	0.05954	0.0019	0.0180***	-0.0721	-0.0058	-0.0051
	(0.1907)	(0.0088)	(0.0059)	(0.1356)	(0.0063)	(0.0032)
#Obs.	159,244	328,596	211,574	159,244	328,596	211,574
Using a 12 month window around the mobile app introduction:						
Total Logins	0.0220	0.0092	0.0252***	0.0139	-0.0011	-0.0087**
	(0.0280)	(0.0092)	(0.0095)	(0.0200)	(0.0077)	(0.0041)
#Obs.	73,602	153,685	105,175	73,602	153,685	105,175
Individual FE	✓	✓	✓	✓	✓	✓
#Individuals	2,974	6,236	4,326	2,974	6,236	4,326

Notes: Standard errors are clustered at the individuals level and are within parentheses. Discretionary entertainment includes expenditures on alcohol, ready made food, lotteries, gambling, gaming, and cinema tickets. We define necessities as spending in grocery stores, gas stations, and pharmacies. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 15: Placebo Test - The Impact of logins on financial fees

	(1) First Stage	(2) ITT	(3) IV
Total Logins	0.113***	-49.0	-435.3
	(0.019)	(100.1)	(888.1)
#Obs.	498,348	498,348	498,348
Including individual fixed effects			
Total Logins	0.099***	-57.9	-582.7
	(0.019)	(88.34)	(896.5)
#Obs.	498,348	498,348	498,348
#Individuals	13,843	13,843	13,843

Notes: Standard errors are clustered at the postal code of residence and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the placebo app introduction in November 2012. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.