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ABSTRACT

This paper analyzes how better access to financial information via new technology changes use of consumer credit and affects financial fitness. We exploit the introduction of a smartphone application for personal financial management as a source of exogenous variation. FinTech adoption reduces financial fee payments and penalties, but differs cross-sectionally in the population. After adopting the new technology, Millennials and members of Generation X incur fewer financial fees and penalties, whereas Baby Boomers do not benefit from the technological advance. Millennials and Gen Xers save fees by using their credit cards rather than overdrafts to manage short-term liabilities. Moreover, Millennials shift some 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 larger for women.

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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 (e.g., mint.com, personalcapital.com, YNAB.com), people are presumably better informed and equipped to make good choices. But, beyond merely quantifying the adoption of new technology, measuring its economic impact is challenging. 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 actual outcomes and welfare, and whether any effects vary cross-sectionally in the population.

Sorting this out 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. A substantial fraction of the citizens in the country use a common on-line platform that consolidates all of their bank account information and transaction histories in one place. Before 2014, access to this personal financial information only occurred via the Internet on a desktop or laptop computer. On November 14, 2014, a smartphone 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

[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 older than 65 years. In this age group, 90% of high income elderly people access the Internet, whereas only 39% of low income seniors go on-line.

after the mobile app introduction, documenting 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 and savings), 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 interest on short-term uncollateralized debt. No matter what an individual's utility function might be (and resultant consumption-and-borrowing choices), paying lower bank fees in response to better information (without having access to more convenient transactions) unambiguously improves consumer welfare.

Our empirical strategy is to employ an instrumental variables approach to isolate the causal impact of more information on economic outcomes. We use time as an instrument for logins and exploit the exogenous introduction of the smartphone application. In the first stage, we estimate the change in an individual's propensity to log into their financial accounts, which characterizes how new technology affects access to information. In the second stage, we use the predicted jump in logins at the time of the app introduction to identify the per login effect of the app introduction on financial fee payments and other economic outcomes.[2] Thus, we estimate a causal local average treatment effect (LATE). In our analysis, we include individual fixed effects to control for all time-invariant omitted

[2] An alternative way to think about the identification strategy is that we implement a fuzzy regression discontinuity design where we use time as the assignment variable.

factors or individual characteristics that could affect the economic outcomes we measure. Additionally, we control for concurrent economic conditions (e.g., interest rates, inflation, and unemployment) and rule out any other confounding institutional changes or new regulation that might have taken place when the mobile application was introduced.[3]

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 208.1 Icelandic kronor ($1.73[4]) lower bank fees per month. Given the frequency of individual monthly logins and the magnitude of monthly expenditures during the sample, this represents an economically meaningful change, especially for lower income households.

{Figure 2 around here}

As described above, the LATE effect is estimated from the sample of adopters and the size of the estimated effect therefore varies with the estimation period. Our primary analysis includes all of the data from November 2014 to July 2016 but we can also use shorter periods. When we vary the estimation period from 6 to 18 months, we see that the estimated benefit to adopters in the first 6 months is 457.6 kronor ($3.81) but considering everyone who adopts in the 18 months after the app introduction, arguably a more representative fraction of the population, yields an estimate of 247.0 kronor ($2.06).

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

[3]To our knowledge, the only institutional change that occurred during our evaluation window was on December 14 2014, when a court ruling took place that addressed deceptive merchant fee practices. However, this ruling did not involve consumer financial fees.

[4]Using the exchange rate at the end of July 2016 ($1 = 120 Icelandic kronor)

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 kronor ($0.32) for Baby Boomers. In contrast, each additional login lowered bank fees by 312.1 kronor ($2.81) for Generation Xers and 275.2 kronor ($2.48) for Millennials.

Our findings suggest that the observed drop in financial penalties after the app introduction can be partly 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 card 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 29.6%. Increasing credit card use is a rational response to having better information. Since credit cards offer a 30-50 day float to avoid paying interest for convenience users, compared to overdrafts where interest is incurred immediately, they are superior to consumers for very short-term debt holdings.

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. In contrast, it is not surprising that Millennials would increase discretionary spending on entertainment in response to a small increase in 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 238.1 kronor ($1.98) for women and by 195.2 kronor ($1.63) 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.[5] 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). 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 help consumers to avoid penalties. Fernandes et al. (2014) show that just-in-time access to on-line advice improves financial decision-making. Lusardi et al.

[5]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).

(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.[6] Meniga's 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. This data set has already proved useful for studying the spending responses of individuals to income arrivals and how these effects vary with the financial structure of households (Olafsson and Pagel, 2017). 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

[6] 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 50 million mobile banking users across 20 countries. In the US, comparable software is provided by mint.com, personalcapital.com, or YNAB.com. Relative to these US software providers, Meniga is less focused on advice with respect to spending, saving, or credit cards as well as portfolio performance. In that sense, it offers a cleaner more simple interface as an overview over personal finances. Meniga received substantial amounts of start-up funding but also charges banks a subscription based on how many customers are using its product.

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}

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. All of the users in our 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 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 consider 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 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 identification strategy ameliorates this.

{Table 2 around here}

While Table 2 shows the comparison between adopters and non-adopters after the app introduction, Table 3 displays a comparison of financial fees paid as well as overall financial standing before the app introduction. The table shows average income, spending, balances, limits, and financial fees of adopters and non-adopters. The numbers are roughly comparable, though the validity of our identification strategy does not rely on a comparison of adopters and non-adopters. Individuals in Iceland enjoy access to substantial consumer credit and pay considerable financial fees for it. In this sense, Iceland is very similar to the US. As can be seen in Table 3, individuals hold approximately $3,000 in overdrafts conditional on having overdraft debt (in Iceland, individuals typically pay off their credit card in full and use overdrafts to roll-over debt). Nevertheless, they still enjoy substantial liquidity, i.e., further borrowing capacity before they hit their limits, $10,000 on average.

{Table 3 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)[7] are added to each income transfer whenever possible.[8]

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: grants, 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, gaming, gambling etc.).

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

[8]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 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 4 displays summary statistics about the income and spending categories for our subjects. Moreover, we display the spending statistics from the representative consumer survey of Statistics Iceland. All numbers have been converted to US dollars. To the extent that the categories match, we find very similar numbers in our sample as in the representative consumer survey. Thus, our sample appears fairly representative not only in terms of demographics but also income and spending. Furthermore, our sample characteristics are also similar to US data. The average age of our sample is 41 whereas the average age in the US population in 2015 was 38. The percentage of women in our sample is 49% whereas the US representative was 51% in 2015. The mean income in the U.S. population in 2015 dollars per adult member is \$3,266 whereas individual monthly mean income in our sample is \$3,256.[9]

{Table 4 around here}

3 Empirical Strategy

Our empirical approach exploits that there is a discontinuity in individual access to 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:

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

[9]All US numbers stem from the US Census Bureaus American Community Survey (ACS) in 2015.

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

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. The ITT effect captures the effect of the app introduction on the whole population.

In the context of the causal model above, the instrumental variable 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 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, i.e., as outlined above, other variables changed discontinuously and affected adopters differently than non-adopters. To the best of our knowledge, no confounding event took place around the same time. Nevertheless, we perform various robustness checks in Section 4.4 to address potential concerns about confounding events around the app introduction, including varying the time window around the introduction and controling flexibly for the time from it.

Oftentimes in regression discontinuity designs, 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 app introduction) and having a longer sample period (by widening the window). In our case this is not 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 18 months before and after the app introduction.

It is important to note that all our results are robust to 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. A potential issue is that individual characteristics for those individuals who adopt the new technology may change around the introduction of the app. Our robustness checks in Section 4.4 will also address concerns regarding individual characteristics of adopters changing around the introduction of the app.

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 5, which gives some summary statistics about logins for the age and gender demographic categories. Before the introduction of the application (as of November 2014), men appeared more attentive to their accounts than women and 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 5, Figure 4, and Figure 5 around here}

People of different generations adopted the new technology at much different rates. According to Table 5, 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 6 shows that introduction of the app increased the frequency of individual logins on average by 0.76, which is statistically significant. This estimate hardly changes when including individual fixed effects.

{Table 6 around here}

Table 7 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 8 explores this effect by generation, with and without individual fixed effects. All three generations increased their log in intensity after the mobile app was introduced. However, this was stronger for Millennials and members of Generation X than for Baby Boomers.

{Table 7 and Table 8 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 interest payments for consumer debt. Table 9, which summarizes the financial penalties that each generation paid before and after the introduction of the app, suggests that same. All subgroups within the population paid lower financial fees after the introduction of the app.

{Table 9 around here}

This is further characterized empirically in Table 6. Column 3 shows that in the overall population, each extra login was associated with 215.4 kronor reduction in financial fees. 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 10 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 of a potentially more specific part of the population–those who adopt the app early. These early adopters may be more enthusiastic about the new technology, troubled by financial penalties, or prudent generally, which increases the effects of the app introduction. As expected, adopters in the first 6 months benefit by 457.6 kronor ($3.81), and adopters in the 18 months after the app introduction, arguably a more representative fraction of the population, yields an estimate of 247.0 kronor ($2.06).

{Table 10 around here}

Table 7 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 (238 versus 195 kronor). But, the differences across generations is much more striking. According to Table 8, Baby Boomers do not enjoy any economically or statistically significant benefit from the introduction of the app (30.6 kronor, $0.32). In contrast, both members of Generation X and Millennials benefit from lower penalties (291.6 kronor and 199.5 kronor, respectively).

4.3 Credit Use and Expenditures

Beyond knowing that individuals who log in more, reduce their financial fee payments, the exact channel by which individuals save is hard to detect even with comprehensive transaction-level data. A potential channel is individuals' use of credit versus debit cards. After all, overdraft interest is a substantial fraction of financial fees paid, and, 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 11 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 2.0% increase in the fraction of expenditures purchased with a credit card (1.1% when including individual fixed effects).[10] Likewise, using a dummy variable for a login at any time using the app, the fraction of purchases made with a credit card increased by approximately 17.7% (10.1% when including individual fixed effects). This is both statistically and economically significant.

{Tables 11-12 around here}

Table 12 explores these effects by generation. Not surprisingly, the action resides with Millenials while we do not find significant effects for Generation Xers and Baby Boomers. According to the results, when including individual fixed effects, use of the app is associated with a 29.6% increase in the use of credit cards to cover expenditures among Millennials.[11] Not only is this economically significant, but it provides a rational

[10] This growth rate is computed by dividing 0.0089 by the base rate of 0.45.
[11] This growth rate is computed by dividing 0.0858 by the base rate of 0.29 for millenials.

explanation for why Millenials had a high 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 millenials more information, allowed them to better manage their use of credit, and protected them from incurring financial penalties. A simple back-of-the-envelope calculation can be used to quantify the impact of using credit cards rather than debit cards on overdraft interest payments. 29.6% of monthly spending, i.e., \$1,315, equals \$389 in additional expenses paid via credit cards rather than debit cards. The monthly interest payment on this amount equals $389(^{0.13}/_{12}) = \$4.21$, as the prevailing overdraft interest rate at the time of the app introduction is approximately 13% (Figure 6).

Gender differences are analyzed in Table 13. The economic magnitudes for men and women are similar to those of the overall sample. Table 14 confirms our population estimates with different regression methods.

{Tables 13-14 around here}

Finally, from a consumption standpoint, the change in spending brought about by the mobile application is in Table 15. Millennials decreased the share of necessities in their consumption basket and increased the share of discretionary entertainment, both of which are statistically significant. In contrast, members of Generation X did not display any statistically significant changes. Moreover, given that standard errors of the coefficients for Generation Xers are very small, we can comfortably say that the app introduction did not affect their spending patterns.

These results may imply an intuitive behavioral response to a small increase in 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 with respect to our spending results. Furthermore, from an economic theory standpoint, it is unclear how the eased access to information about financial accounts would affect spending. It could be that individuals smooth consumption more successfully with more frequent updates about their finances, but that is hard to identify empirically as high-frequency spending patterns do not necessarily translate into consumption.

{Table 15 around here}

4.4 Robustness

The first natural question is whether the identified local treatment effect can be extrapolated to the rest of the population. Adopters could be particularly plagued by financial fees. However, it turns out that the reductions in financial fee payments are not driven by individuals who paid above-average financial fees before the app introduction, as can be seen in Table 3. In fact, all generations pay substantial financial fees on average as can be seen in Table 9. Additionally, Meniga, as a FinTech firm, may cater to Millenials in particular. In this context, it is important to note that the software is marketed to consumers via banks in their online banking portals and the internet penetration is 97% in Iceland. In terms of our sample population, as discussed in Section 2 and shown in Table 1 and 3, our sample is representative of the Icelandic population in terms of demographics, income, and spending. We thus think that our identified effects can be extrapolated. Moreover, our data is uniquely suited in analyzing how financial technology affects different generations.

As mentioned above, the identification approach relies on a single exogenous event, the app introduction. The exact timing of the app introduction appears to be determined solely by inter-organizational considerations of the software provider. Nevertheless, this event's effects on economic outcomes could be confounded if other events happened or things changed around the same time, i.e., as outlined above, other variables changed discontinuously and affected adopters differently than non-adopters. To the best of our knowledge, no confounding event took place around the same time but we now provide additional details and show other macro trends.

Changes in the short-term interest rate around the time of the app introduction, depicted in Figure 6, are a potential concern since this would directly affect interest expenses, which are part of the financial fees we observe. If adopters were disproportionally indebted, then a discontinuous change in the overdraft interest rate would decrease their interest expenses. We indeed see a small decrease around the time of the app introudction but we do not consider this an impediment to our results though for the following reasons. (1) Most straightforwardly, our results are robust to controlling for changes in the central bank policy rate (which determines changes in overdraft interest rates). (2) More generally, our identification approach goes through logins and compares adopters before and after the app introduction to non-adopters. But, adopters do not have systematically larger overdrafts than non-adopters before or after the app introduction as can be seen in Table 2 and Table 3. (3) We observe reductions in overdraft interest as well as late fees and non-sufficient fund fees that are not tied to the interest rate and Figure 7 shows the same trend reversal in late fees in the raw data.

{Figures 7 around here}

In this context it is also important to note that we vary the time window and control flexibly for the months around the app introduction to address potential concerns about confounding events differentially affecting adopters around the time of the app introduction. Moreover, we split the sample in various ways and find robust and sensible results across all sample splits.

Additionally, we use data from the previous two years to look at a placebo treatment effect, i.e., we estimate Equation (2), using a placebo introduction in November 2013 when no actual introduction took place. We do not find any effects for the placebo introduction. The results can be found in Table 16.

{Table 16 around here}

One might be concerned that the financial crisis that shook Iceland in 2008 could explain our findings. While the Icelandic financial crisis undoubtedly affected individuals, the country recovered very quickly after the crisis and experienced high GDP growth and low unemployment during our entire sample period. It is therefore hard to imagine how the crisis could jeopardize the internal validity of our findings. One could still argue that because of the financial crisis individuals in Iceland would respond differently to a new technology and therefore we will not necessarily be able to extrapolate our findings. However, even though the crisis went much deeper in Iceland than in other places the effect it had on individuals was not that different because they were protected by its welfare system (Olafsson, 2016) and the economy recovered remarkably fast. Furthermore, Iceland is very similar to many other economies, including the US, when it comes to using consumer debt. As can be seen in Table 3, individuals hold approximately \$3,000 in overdrafts conditional on having overdraft debt (in Iceland, individuals typically pay off their credit card in full and use overdrafts to roll-over debt). Nevertheless, they still enjoy substantial liquidity, i.e., further borrowing capacity before they hit their limits. In comparison, in the US, the average credit card debt for individuals rolling over is approximately \$4,000 in the Survey of Consumer Finances (SCF) data. Furthermore, as discussed in Section 2, our demographic statistics are very similar to US demographics. We thus believe that our results can be generalized to the US and other European countries with relatively large consumer debt holdings, such as the UK, Spain, and Turkey. There is therefore good reason to believe that our findings can be extrapolated to other economies.

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 about financial accounts has on consumers in the market. We document a substantial reduction in financial fee payments in response to accessing information more often. And because individuals sign up for the new technology voluntarily, this effect is unambiguously welfare enhancing. 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. (2016). Household financial distress and initial endowments: Evidence from the 2008 financial crisis. *Health Economics 25*, 43–56. hec.3426.

Olafsson, A. and M. Pagel (2017). 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.

Figures and Tables

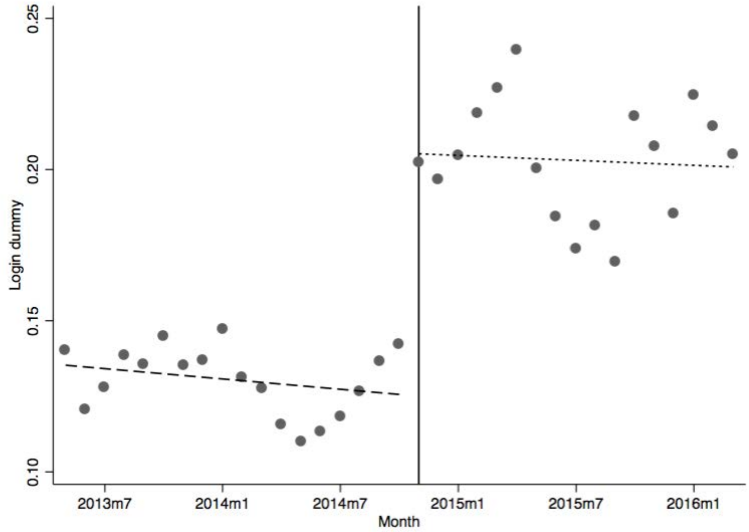

Figure 1: Propensity to log in around the app introduction

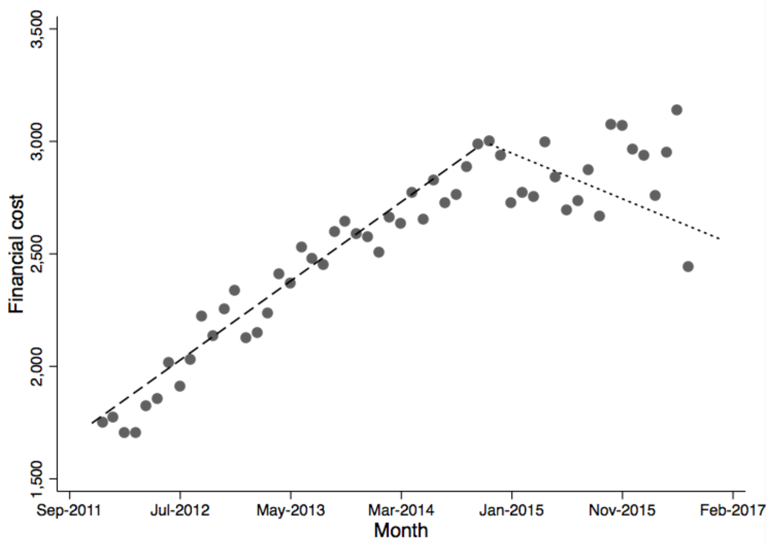

Figure 2: Bank fees and penalty payments around the app introduction

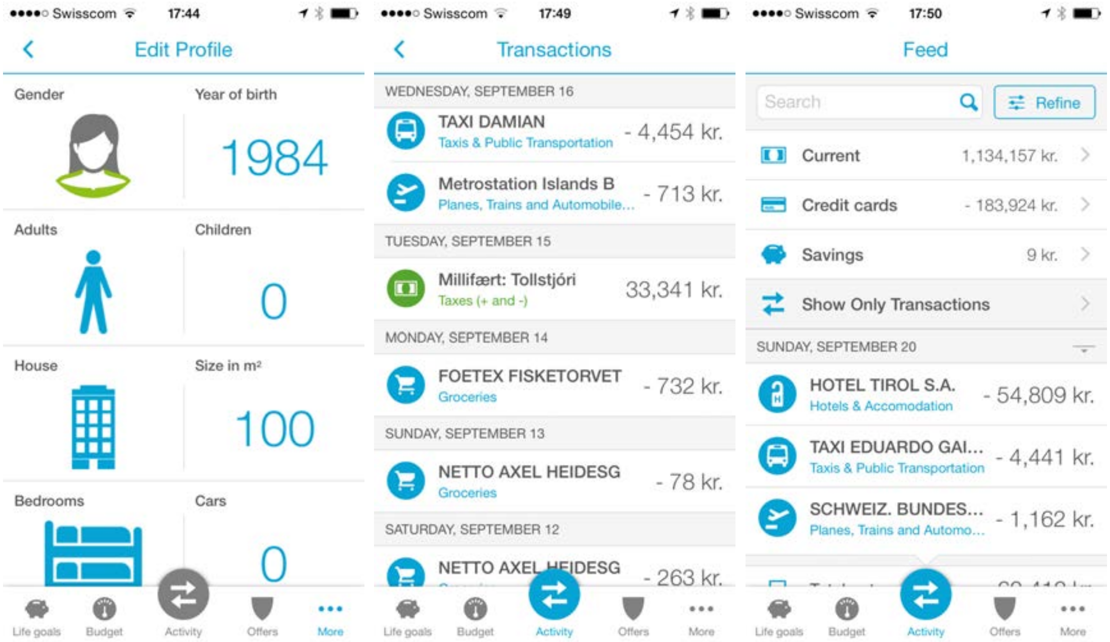

Figure 3: The financial aggregation app: screenshots

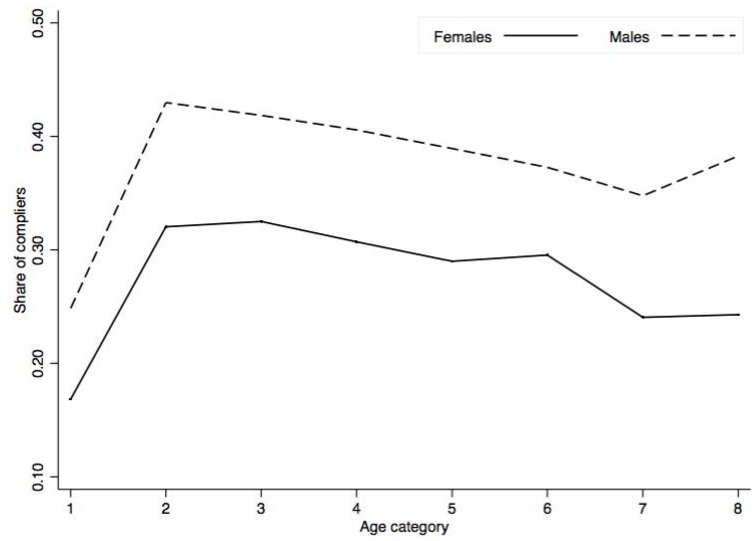

Figure 4: Share of adopters by gender and age group

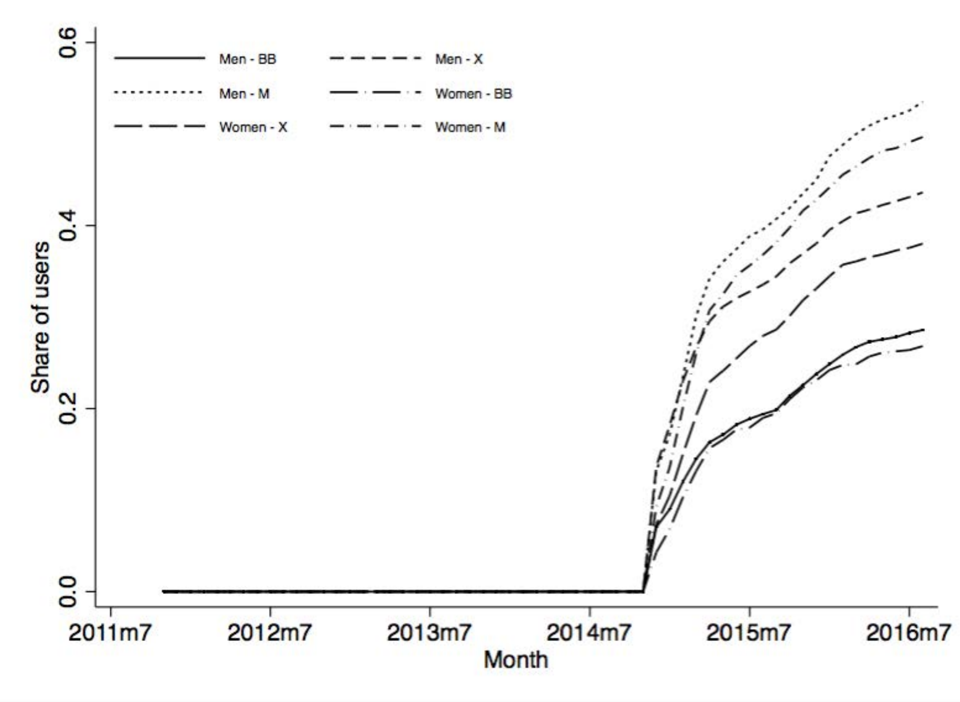

Figure 5: Uptake of adopters around the app introduction

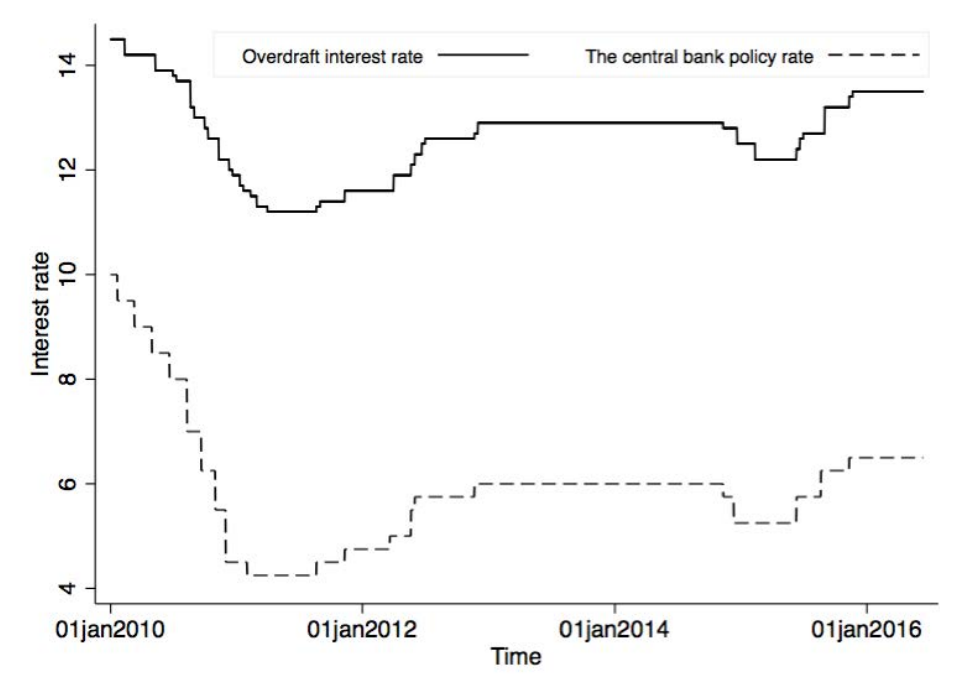

Figure 6: Trends of the central bank policy rate and overdraft interest rate through the app introduction

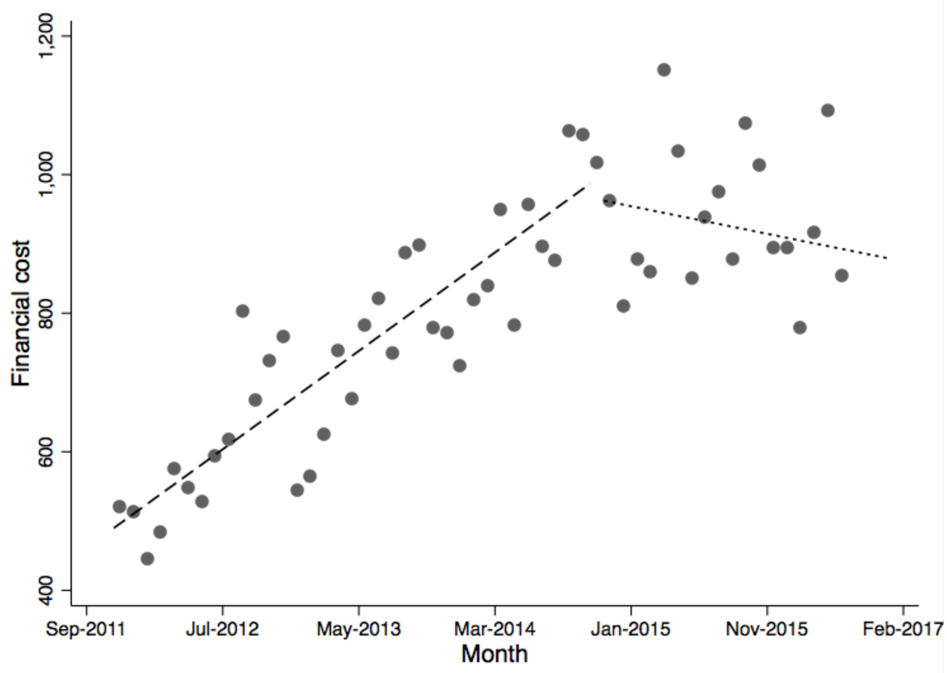

Figure 7: Late fees around the app introduction

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 card expenditure shares for non-adopters and adopters

	3 months			6 months			12 months			15 months		
	no login	login	Δ	no login	login	Δ	no login	login	Δ	no login	login	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: All numbers are in Icelandic kronor. Financial fees and credit card expenditure shares of non-adopters and adopters 3, 6, 12, or 15 months after the app introduction.

Table 3: Financial fees and standing for non-adopters and adopters

	Non-adopters	Adopters
Age	42.7	37.8
Female	0.50	0.46
Total income	427,273	435,280
Regular income	410,983	378,339
Irregular income	16,290	56,942
Total expenditure	154,313	143,792
Current account balance	200,589	173,755
Savings account balance	362,314	428,971
Cash	562,903	602,725
Liquidity	1,069,726	1,116,901
Overdraft	163,728	135,635
Credit card balance	166,483	158,021
Overdraft limit	276,510	248,352
Credit card limit	441,387	471,450
Credit utlization	0.43	0.42
Total financial fees	2,575	2,072
Overdraft interest	1,715	1,349

Notes: All numbers are in Icelandic kronor. Financial fees and standing of adopters and non-adopters before the app introduction.

Table 4: Income and consumption statistics

	Mean	Standard Deviation	Statistics Iceland
Monthly total income	3,256	3,531	4,316
Monthly regular income	3,038	3,184	3,227
Monthly salary	2,704	2,993	2,456
Monthly irregular income	218	1,415	1,089
Monthly spending:			
Total	1,315	1,224	
Groceries	468	389	490
Fuel	236	259	(359)
Alcohol	62	121	85
Ready Made Food	170	1723	(252)
Home Improvement	150	465	(229)
Transportations	58	700	66
Clothing and Accessories	87	181	96
Sports and Activities	44	148	(36)
Pharmacies	40	62	42

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

Table 5: Login statistics

	Logins Oct 2014	Logins Nov 2014	app Logins Nov 2014	% Pop logins 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: Logins before and after the app introduction.

Table 6: The impact of logins on financial fees

	(1) First Stage	(2) ITT	(3) IV
Total Logins	0.7515***	-161.9***	-215.4***
	(0.0706)	(51.9)	(71.9)
$I(Logins_{it} > 0)$	0.0821***	-161.9***	-1,970.4***
	(0.0027)	(51.9)	(635.1)
#Obs.	771,552	771,552	771,552
Including individual fixed effects			
Total Logins	0.7473***	-155.5***	-208.1***
	(0.0398)	(57.6)	(77.9)
$I(Logins_{it} > 0)$	0.0817***	-155.5***	-1,904.8***
	(0.0023)	(57.6)	(707.6)
#Obs.	789,051	789,051	789,051
#Individuals	13,843	13,843	13,843

Notes: Standard errors are clustered at the individual level and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the mobile app introduction. *** 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 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***	0.4618***	-130.9**	-267.6*
	(0.1076)	(81.7)	(82.3)	(0.0886)	(64.4)	(150.36)
$I(Logins_{it} > 0)$	0.0967***	-227.6***	-2,352.7***	0.0690***	-130.9**	-1,895.5***
	(0.0041)	(81.7)	(849.9)	(0.0037)	(64.4)	(936.5)
#Obs.	380,444	380,444	380,444	361,436	361,436	361,436
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 individual level and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the mobile app introduction. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 8: The impact of logins on financial fees of by different generations

	Without individual fixed effects			Including individual fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage	ITT	IV	First Stage	ITT	IV
Baby Boomers:						
Total Logins	0.3106***	12.1	39.1	0.2992***	-11.9	-30.6
	(0.0552)	(144.1)	(464.1)	(0.0474)	(184.3)	(616.2)
$I(Logins_{it} > 0)$	0.0624***	12.1	194.8	0.0611	-11.9	-193.8
	(0.0054)	(144.1)	(2,310.6)	(0.0049)	(184.4)	(3,016.0)
#Obs.	172,492	172,492	172,492	172,492	172,492	172,492
#Individuals				2,974	2,974	2,974
Generation X:						
Total Logins	0.8571***	-249.8***	-291.5***	0.8565***	-249.7***	-291.6***
	(0.1207)	(80.8)	(102.7)	(0.0653)	(81.2)	(97.4)
$I(Logins_{it} > 0)$	0.0856***	-249.8***	-2,918.1***	0.0855	-249.7***	-2,920.7***
	(0.0041)	(80.8)	(955.2)	(0.0035)	(81.2)	(958.2)
#Obs.	355,623	355,623	355,623	355,623	355,623	355,623
#Individuals				6,239	6,239	6,239
Millenials:						
Total Logins	0.9319***	-162.3***	-174.2***	0.9112***	-181.8***	-199.5***
	(0.1310)	(54.2)	(63.0)	(0.0786)	(61.41)	(69.57)
$I(Logins_{it} > 0)$	0.0930***	-162.3***	-1,744.4***	0.0914***	-181.8***	-1,988.6***
	(0.0049)	(54.2)	(586.7)	(0.0041)	(61.41)	(677.3)
#Obs.	246,696	246,696	246,696	246,696	246,696	246,696
#Individuals				4,328	4,328	4,328

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

Table 9: 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: All numbers are in Icelandic kronor.

Table 10: 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	-247.0***	-312.8***	-457.3***	-370.0***	-440.1***	-469.8
	(72.2)	(72.6)	(160.0)	(94.9)	(155.9)	(350.1)
Bandwidth	18	12	6	20	20	20
Polynomial order:				Second	Third	Fourth
Number of observations.	487.296	338,400	162,432	541,440	541,440	541,440

Notes: Standard errors are clustered at the individual level and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the mobile app introduction. 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 11: The impact of logins on the share of expenditures paid by credit cards

	(1) First Stage	(2) ITT	(3) IV
Total Logins	0.7739***	0.0068***	0.0089***
	(0.0652)	(0.0018)	(0.0024)
$I(Logins_{it} > 0)$	0.0859***	0.0068***	0.0797***
	(0.0027)	(0.0018)	(0.0209)
#Obs.	769,268	769,268	769,268
Including individual fixed effects			
Total Logins	0.7534***	0.0038**	0.0051**
	(0.0411)	(0.0017)	(0.0022)
$I(Logins_{it} > 0)$	0.0842***	0.0038**	0.0454**
	(0.0001)	(0.0017)	(0.0198)
#Obs.	769,268	769,268	769,268
#Individuals	13,411	13,411	13,411

Notes: Standard errors are clustered at the individual level 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 mobile app introduction. Regressions without individual fixed effects include month, year, generation and gender fixed effects. All specifications control for total expenditure.
*** 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 expenditure paid by credit card by different generations

	Without individual fixed effects			Including individual fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage	ITT	IV	First Stage	ITT	IV
Baby Boomers:						
Total Logins	0.2985***	0.0030	0 .0099	0.2961***	0.0034	0.0116
	(0.0549)	(0.0033)	(0.0110)	(0.0489)	(0.0032)	(0.0108)
$I(Logins_{it} > 0)$	0.0665***	0.0030	0.0444	0.0657***	0.0034	0.0521
	(0.0054)	(0.0033)	(0.0490)	(0.0049)	(0.0032)	(0.0481)
#Obs.	181,082	181,082	181,082	181,082	181,082	181,082
#Individuals				3,059	3,059	3,059
Generation X:						
Total Logins	0.8945***	0.0010	0.0011	0.8844***	0.0038	0.0004
	(0.0879)	(0.0026)	(0.0029)	(0.0571)	(0.0024)	(0.0028)
$I(Logins_{it} > 0)$	0.0873***	0.0010	0.0111	0.0861***	0.0038	0.0045
	(0.0041)	(0.0026)	(0.0299)	(0.0036)	(0.0024)	(0.0284)
#Obs.	362,101	362,101	362,101	362,101	362,101	362,101
#Individuals				6,215	6,215	6,215
Millenials:						
Total Logins	0.9876***	0.0150***	0.0152***	0.9294***	0.0082***	0.0088**
	(0.1732)	(0.0036)	(0.0046)	(0.1056)	(0.0034)	(0.0038)
$I(Logins_{it} > 0)$	0.0985***	0.0150***	0.1526***	0.0952	0.0082***	0.0858**
	(0.0054)	(0.0036)	(0.0376)	(0.0047)	(0.0034)	(0.0356)
#Obs.	206,607	206,607	206,607	206,607	206,607	206,607
#Individuals				3,805	3,805	3,805

Notes: Standard errors are clustered at the individual level 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 mobile app introduction. Regressions without individual fixed effects include month, year, and gender fixed effects. All specifications control for total expenditure. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 13: 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	1.0007***	0.0054**	0.0054**	0.5293***	0.0046*	0.0083*
	(0.1033)	(0.0025)	(0.0026)	(0.0590)	(0.0023)	(0.0048)
$I(Logins_{it} > 0)$	0.0979***	0.0054**	0.0550**	0.0730***	0.0046*	0.0630*
	(0.0044)	(0.0025)	(0.0255)	(0.0040)	(0.0023)	(0.0345)
$\#Obs.$	394,276	394,276	394,276	374,974	374,974	374,974
Including individual fixed effects						
Total Logins	0.9704***	0.0045*	0.0047*	0.5252***	0.0031	0.0058
	(0.0656)	(0.0023)	(0.0024)	(0.0485)	(0.0024)	(0.0045)
$I(Logins_{it} > 0)$	0.0966***	0.0045*	0.0468***	0.0712***	0.0031	0.0432
	(0.0035)	(0.0023)	(0.0243)	(0.0034)	(0.0024)	(0.0331)
$\#Obs.$	394,276	394,276	394,276	374,974	374,974	374,974
$\#Individuals$	6,876	6,876	6,876	6,535	6,535	6,535

Notes: Standard errors are clustered at the individual level and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the mobile app introduction. Regressions without individual fixed effects include month, year, and generation fixed effects. All specifications control for total expenditure.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 14: 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	0.0137***	0.0126***	0.0088***	0.0077***	0.0191***	0.0052
	(0.0023)	(0.0022)	(0.0028)	(0.0022)	(0.0037)	(0.0036)
Bandwidth	18	12	6	26	26	26
Polynomial order:				Second	Third	Fourth
Number of observations.	479,075	327,481	171,851	672,559	672,559	672,559

Notes: Standard errors are clustered at the individual level and are within parentheses. Each entry is separate regression and presents the estimated discontinuity in financial fees as a result of the mobile app introduction. 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 15: 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
Individual FE	✓	✓	✓	✓	✓	✓
#Individuals	2,974	6,236	4,326	2,974	6,236	4,326

Notes: Standard errors are clustered at the individual 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 16: 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.