The Ostrich in Us: Selective Attention to Financial Accounts, Income, Spending, and Liquidity

Arna Olafsson* and Michaela Pagel†

Copenhagen Business School Columbia GSB, NBER, & CEPR

December 23, 2017

Abstract

A number of theoretical research papers in micro- as well as macroeconomics model and analyze attention but direct empirical evidence remains scarce. This paper investigates the determinants of attention to financial accounts using panel data from a financial management software provider containing daily logins, discretionary spending, income, balances, and credit limits. We argue that our findings cannot be explained by rational theories of inattention, i.e., mechanical information costs and benefits. Instead our findings appear to be more consistent with information- or belief-dependent utility models generating Ostrich effects and anticipatory utility. We find that individuals are considerably more likely to log in because they get paid. Beyond looking at the causal effect of income on attention, we examine how attention depends on individual spending, balances, and credit limits *within* individuals' own histories. We document that attention is decreasing in spending and overdrafts and increasing in cash holdings, savings, and liquidity. Moreover, attention jumps discretely when balances change from negative to positive. Finally, we show that some of our findings can be explained in a recent influential model of belief-dependent utility developed by Kőszegi and Rabin (2009).

*Department of Finance, Copenhagen Business School. ao.fi@cbs.dk

†Division of Economics and Finance, Columbia Business School, NBER, & CEPR. mpagel@columbia.edu

We thank Alex Imas, Ted O'Donoghue, John Driscoll, Nachum Sicherman, Inessa Liskovich, Paul Heidhues, Michael Grubb, Paul Tetlock, Nicola Gennaioli, Botond Koszegi, Daniel Gottlieb, Cary Friedman, Benjamin Keys, Constança Esteves-Sorenson, Silvia Saccardo, Matthew Rabin, David Laibson, Paige Skiba, Devin Pope, Vicki Bogan, Valentin Haddad, Marina Niessner, Andrea Prat, and conference and seminar participants at Cornell, Maryland, 2017 BEAM at Berkeley, Carnegie Mellon, NBER Summer Institute, University of Amsterdam, ECWFC at the WFA, NYU, Columbia, TAU Finance, ESSFM Gerzensee, Zurich, University of Indiana, University of Innsbruck, University of Melbourne, and the National University of Singapore for a range of insightful comments. This project has received funding from Danish Council for Independent Research, under grant agreement no 6165-00020. We are indebted to Ágúst Schweitz Eriksson and Meniga for providing and helping with the data.

1 Introduction

A recent theoretical literature in asset pricing and macroeconomics introduces attention as an explanatory mechanism. Among others, Woodford (2009), Chien et al. (2012), Reis (2006), and Gabaix and Laibson (2002) show that attention matters in the aggregate. Moreover, a number of microeconomic papers model attention such as Caplin and Leahy (2001), Caplin and Leahy (2004), Golman and Loewenstein (2015), Ely et al. (2015), and Van Nieuwerburgh and Veldkamp (2010). Nevertheless, empirical evidence on the determinants of attention lags behind the theoretical advances and remains scarce. To better understand the determinants of paying attention and inform the theoretical literature, this paper constitutes a large-scale empirical study of individual attention to checking, savings, and credit-card accounts.

More specifically, we try to shed light on the following questions: When and under what conditions do individuals pay attention to their financial accounts? Can our empirical findings be explained by "rational" theories of inattention, i.e., mechanical information costs and benefits? To what extent is inattention not "rational" but "selective" and driven by information- or belief-dependent utility? In a nutshell, we argue that inattention is selective rather than rational and that belief-dependent utility generating Ostrich effects and anticipatory utility are first-order important for individual attention to financial accounts. This conclusion is nicely illustrated in Figure 1 showing logins as a function of the checking account balance that may be negative when individuals maintain an overdraft or positive if not. We can see a positive correlation between account balances and logins and a jump when the balance goes from negative to positive. Furthermore, casual observation of the media suggest that the fear of checking bank accounts is a common problem.

Our findings are thus relevant for theories of rational versus selective inattention. Macroeconomic models of rational inattention are likely to generate different aggregate dynamics if inattention were selective (for instance, Andrei and Hasler, 2014; Gabaix, 2016; Paciello and Wiederholt,

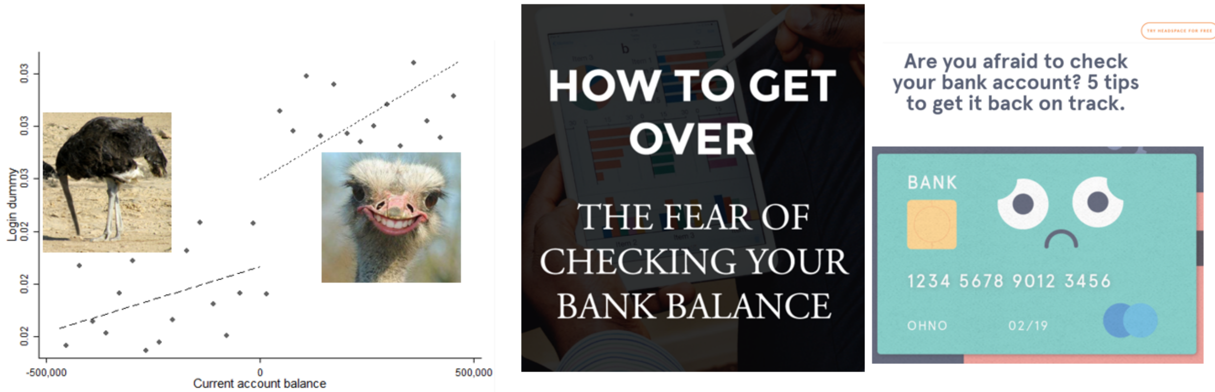

Figure 1: Propensity to log in and checking account balance (raw data)

2013). Our findings are also relevant for the literature on information costs. If individuals are willing to pay to not receive information (which can be inferred from this study in connection with our companion paper Carlin et al., 2017)[1], then information costs are effectively negative rather than positive (for instance, Abel et al., 2013; Alvarez et al., 2012; Huang and Liu, 2007; Van Nieuwerburgh and Veldkamp, 2009, 2010). Beyond rational inattention and information costs, our findings relate to the literature on poverty traps (see Azariadis and Stachurski, 2005, for a survey) as well as the literature on poverty and cognitive function (Mani et al., 2013; Carvalho et al., 2016). Individuals may choose to not pay attention in dire financial standing and make things worse. Finally, our findings are important for policy prescriptions or (field) experimental interventions, i.e., it has to be taken into account that inattention may be highly selective rather than rational.

Standard economic models predict that information is valuable when it helps to make better decisions. Theories of rational inattention posit that individuals trade off mechanical costs and benefits of acquiring and processing information. The costs of attention include information-processing costs as well as time and opportunity costs, while benefits of attention are potential improvements in decision making. There exist countless situations in which information is useful and sought after but there also exist situations in which people seek out apparently useless information or

[1] In Carlin et al. (2017), we find that an exogenous increase in logins causes a reduction in overdrafts saving individuals overdraft fees of approximately $2.50 per log in. Nevertheless, in this paper, we document that individuals do not log in any more, when they hold large overdrafts, relative to their own personal history of overdrafts.

avoid useful information (see Golman et al., 2016, for a survey of the literature).[2] Thus, attention does not appear to only be an input into decision-making for spending and saving. In light of this evidence, a literature on information-dependent and belief-dependent utility emerged positing that information also has a hedonic impact on utility that goes beyond mechanical costs and benefits.[3] We hope to provide new empirical tests for these theories and show that a news-utility model, as developed by Kőszegi and Rabin (2009), can rationalize some of our findings.

The digitization of budgeting processes with financial aggregation apps and the attendance tracking of online behavior allow direct measurement of individual attention in ways that previously were not possible. In this paper, we use online account logins to measure individual attention to financial accounts following three studies that analyze logins to retirement portfolios (Sicherman et al., 2015; Karlsson et al., 2009; Gherzi et al., 2014).[4] We look at the determinants and effects of paying attention to financial accounts using data from a financial aggregation and service app from Iceland—a data source that not only allows individual tracking of attention but also provides high-frequency income and spending data derived from the actual transactions and account

[2]There is a growing literature analyzing when people seek useless information or avoid information, even when it is free and could improve decision making (see, e.g., Loewenstein, 1994; Eliaz and Schotter, 2010; Powdthavee and Riyanto, 2015). Casual observation, as well as considerable theoretical, laboratory, and field research suggests that such behavior is, in fact, common. More specifically, investors are inattentive to their portfolios (Bonaparte and Cooper, 2009; Brunnermeier and Nagel, 2008; Gabaix and Laibson, 2002; Reis, 2006; Woodford, 2009) and may actively avoid looking at their financial portfolios when the stock market is down (Karlsson et al., 2009; Sicherman et al., 2015). Moreover, individuals at risk for health conditions often eschew medical tests (e.g., for serious genetic conditions or STDs) even when the information is costless and should, logically, help them to make better decisions (Ganguly and Tasoff, 2014; Sullivan et al., 2004; Lerman et al., 1996, 1999; Lyter et al., 1987; Oster et al., 2013; Thornton, 2008). Finally, managers often avoid hearing arguments that conflict with their preliminary decisions (see, e.g., Schulz-Hardt et al., 2000), even though such arguments could help them avoid implementing measures that are ill-founded. Finally, the findings by Zimmermann (2014) and Falk and Zimmermann (2014) underscore the importance of attention for belief-dependent utility and support the idea that individuals can actively manage attention in a self-serving way, to increase or decrease anticipatory utility.

[3]Starting with Loewenstein (1987), recent theoretical work has made substantial progress in modeling the notion that beliefs about or the anticipation of future consumption can have direct utility consequences (see, e.g., Caplin and Leahy, 2001, 2004; Brunnermeier and Parker, 2005; Kőszegi and Rabin, 2006; Epstein, 2008; Kőszegi and Rabin, 2009; Dillenberger, 2010; Bénabou, 2012; Strzalecki, 2013; Golman and Loewenstein, 2015; Golman et al., 2016; Ely et al., 2015).

[4]Logging in to financial accounts can be interpreted as paying attention to personal finances. Alternatively, it could be interpreted as a decision to make one's financial standing more salient. Thus, this paper informs a small but growing theoretical literature that is incorporating salience and focus into economic decision-making (e.g., Bordalo et al., 2010; Koszegi and Szeidl, 2013; Bushong et al., 2015).

balances of individuals; overcoming the limitations of accuracy, scope, and frequency that existing data sources of consumption and income have. Gelman et al. (2014) and Baker (2014) were the first to advance the measurement of income and spending with such app data from the US. We use data from Iceland which has four main advantages: 1) It essentially eliminates the remaining limitation of the previously used app data–the absence of cash transactions–since Icelandic consumers use electronic means of payments almost exclusively, 2) the app is marketed through banks thus covering a fairly broad fraction of the population, 3) the spending and income data is pre-categorized and the categorization is very accurate with few uncategorized transactions, 4) the app cannot be used to make transactions and thus serves information purposes only, and 5) all financial accounts are personal.

We first look at the individual propensity to check financial accounts in response to regular income payments that always arrive on a certain day of the month. To alleviate endogeneity concerns, we use indicator variables for the arrival of payments in addition to individual, day-of-week, day-of-month, holiday, and month-year fixed effects to utilize exogenous variation in payment arrival due to weekends and holidays; i.e., the payday is moved if the day of the month happens to be on a weekend or holiday. We find that individuals are 62 percent more likely to log in once and 94.2 percent more likely to log in twice or more on a payday.

To interpret this finding, we argue that a rationally inattentive agent, who does not experience information- or belief-dependent utility, would behave differently. Five rational benchmarks come to mind: 1) individuals log in independently of their transactions because there is either full or no uncertainty associated with them, 2) individuals log in after transactions to verify these post correctly, 3) individuals log in to budget or plan spending, and 4) individuals log in when opportunity costs are low. Hypotheses 1) can be ruled out as we show that income causes logins. Moreover, we can rule out 2) because we find the same responses in magnitudes to salary as well as irregular or exogenous payments for which the transaction verification motive should be more relevant (recall that, for identification purposes we only look at salary payments that come on a certain day throughout the sample period). Additionally, we do not find a larger log in response on paydays with many other transactions. We can rule out 3) because we find that the log in response on paydays is higher when liquidity or cash holdings are high but individuals should care more about budgeting when liquidity or cash holdings are low. Here, it is important to note that we only look at within-individual variation, i.e., we sort individual-date observations of cash, liquidity, and spending into deciles to compare individuals *within their own histories*. Finally, we can rule out 4) because there is no relationship between the payday response and spending, a potential measure of opportunity costs.[5] Finally, when we look at two or more logins, we find an even larger spike on paydays even though all payments post in the mornings. We thus conclude that individuals log in because they enjoy seeing money in their bank accounts, i.e., they experience a form of anticipatory utility.

We also estimate the causal effect of credit card payments using a similar identification strategy. In Iceland, the majority of credit cards impose the 2nd of the month as the automatic credit payment date and individuals use overdrafts to repay credit cards in full rather than revolve credit card debt. Together with individual, day-of-week, day-of-month, holiday, and month-year fixed effects, we can thus utilize exogenous variation in the credit payment date due to weekends and holidays. We also find a positive log in response to credit payment dates. While this log in response is consistent with individuals worrying about their liquidity at first sight, we find that the log in response is increasing rather than decreasing in liquidity, which points towards selective attention and Ostrich effects.

We also examine the direct relationship between logging in and individual spending and financial standing, such as liquidity and cash holdings. Again, we only look at within-individual variation, i.e., we sort each individual into his, her, or their own deciles of spending and financial

[5] To use spending as a measure of opportunity costs is suggested by the negative correlation between logins and spending we document. Olafsson and Pagel (2016) show that individuals spend more on the days they get paid. To shed light on the mechanism by which income affects attention, we control for spending on paydays in additional specifications. However, we find that spending is not the mechanism by which income affects attention.

standing. We thus compare individuals within their own histories. In other words, we construct individual-specific deciles of spending and financial standing based on each individual's own history. Thus, none of the variation reflects cross-sectional differences. Moreover, we control for individual fixed effects and thereby all self selection on observable or unobservable time-invariant characteristics on top of a set of calendar fixed effects. Technically, we can only report correlations. However, given the comprehensiveness of the fixed-effects approach and the absence of selection, the bar for omitted variable and reverse causality bias is high. We document a number of patterns in investor attention and individual financial conditions:

- Attention decreases with individual spending and increases with individual savings.
- Attention increases with individual cash holdings and liquidity.
- Attention decreases with individual overdrafts especially intermediate amounts.
- Attention exhibits a discontinuous jump when the checking account balance changes from negative to positive.

Again, for all of these findings, we consider rational theories of inattention: transaction verification, budgeting, planning, and opportunity costs. However, for each case, we argue that the theory is not consistent with the collection of our empirical findings. Transaction verification is directly ruled out by the negative relationship between attention and spending. In terms of budgeting, consumption smoothing is more beneficial at low income and wealth levels and we would therefore expect the opposite relationship between attention and cash or overdrafts.[6] In terms of planning, it could be that individuals log in when they hold a lot of cash to plan spending. However, this theory is not consistent with us seeing a stronger relationship for savings account balances, that should not be planned for spending, than checking account balances. In terms of opportunity costs, one may argue that individuals do not log in when they are busy spending, which would explain the

[6] We formally show that any risk averse agent finds consumption smoothing more beneficial at low income or wealth levels if her utility function also features prudence in Section 4.

negative correlation between logins and spending. However, such an opportunity costs theory can be rejected because attention increases in cash holdings. After all, if cash holdings are low, then individuals have spent a lot in the past. According to the opportunity costs theory, their opportunity costs should be low in such a situation and they should log in more not less.[7]

Table 1: Empirical findings and possible theoretical explanations

	No/perfect information	Transaction verification	Budgeting	Planning	Opportunity costs	Selective attention
Individuals log in because they get paid	✗	✓	(✗)	✓	(✗)	✓
Individuals log in twice because they get paid	✗	✗	(✗)	✓	(✗)	✓
Income response similar for irregular payments	✗	✗	(✗)	✓	(✗)	✓
Income response increasing in cash and liquidity	✗	✗	✗	✓	(✓)	✓
Income response unrelated to spending	✗	✗	✗	✗	✗	(✓)
Individuals log in because they make a payment	✗	✓	✓	✗	✓	(✓)
Response to payments increasing in cash and liquidity	✗	✗	✗	✓	✓	(✓)
Logins decreasing with spending	✗	✗	✗	✓	✓	✓
Logins increasing with cash and liquidity	✗	✗	✗	✓	✗	✓
Logins more increasing with savings than cash	✗	✗	✗	✗	✓	(✓)
Logins u-shaped in overdrafts	✗	✗	✗	✓	✗	(✓)
Attention jumps when balance turns positive	✗	✗	✗	(✗)	✗	✓

Note: ✗ unlikely to explain, (✗) explain with major modifications, (✓) explain with modifications, ✓consistent with theory

[7] It is important to note that the app does not send push notifications or other messages. Users need to be logged in to see any messages the app sent. Furthermore, our results hold when we only consider the period before the mobile app got introduced.

Table 1 summarizes our empirical findings and the various theories we consider. We indicate whether or not the theories could be easily modified to be consistent with our findings. Overall, we feel that most findings are consistent with anticipatory utility and one specific form of selective attention called the Ostrich effect introduced by Galai and Sade (2006) and Karlsson et al. (2009). Karlsson et al. (2009) propose that attention amplifies the hedonic impact of information, which implies that investors should pay more attention to their finances after good news than after bad news. The authors show that individual investors' attention to personal portfolios increases after positive returns on market indices. In the context of financial accounts, the existing evidence is thus consistent with cash inflows, be it from income payments or wealth shocks, or large cash and liquidity holdings causing individuals to log in to their accounts more often. In contrast, in dire times, when individuals feel they overspent and hold little cash or large overdrafts, they prefer to not pay attention.[8] Two important differences between logging in to retirement accounts, as analyzed by Karlsson et al. (2009), and bank accounts are the following: 1) we know individuals can save money by paying more attention to their accounts (Carlin et al., 2017), while we are not sure whether individual investors have any skill in stock picking or market timing, i.e., logging in may be useless for portfolios but not for bank accounts, and 2) in principle, uncertainty about financial account balances is considerably lower than uncertainty about portfolios.[9] Documenting selective attention in the domain of checking, savings, and credit card accounts is therefore of independent interest.

While our empirical findings point towards Ostrich effects and anticipatory utility as a first-order determinant for checking financial accounts, we also think that the avoidance of fee payments are a determinant of logging in. Individuals in our sample incur substantial fee payments

[8] These empirical results stand in contrast to the idea that individuals pay more attention to their accounts when they have fewer resources and worry about their liquidity. Though, as shown in Olafsson and Pagel (2016), very few individuals are actually hitting their credit limits even right before individual paychecks. Nevertheless, individuals may have personal rules as to how much consumer debt they take. In fact, we see attention being u-shaped in overdrafts and thus some reversal in attention when individuals hold very large overdrafts relative to their own histories.

[9] Gargano and Rossi (2017) show that investors who pay more attention successfully exploit the momentum anomaly in a brokerage account dataset of frequent traders over the time period 2013 to 2014.

that may be avoided if they were to check their accounts more often, as established in Carlin et al. (2017), where the mobile app introduction was found to have decreased financial penalty payments. Furthermore, Stango and Zinman (2014) document that individuals respond to surveys about overdrafts by paying greater attention to account balances and incurring less fees and Medina (2016) finds that reminders for timely payment reduce credit card late-fees paid.

We thus try to reconcile and formalize intuitions consistent with these two key findings for attention, 1) that individuals check their accounts more often if they received income and hold more cash and 2) that individuals worry about incurring fees, in the model by Kőszegi and Rabin (2009). In this model, agents not only derive utility from present consumption but also from changes in expectations or news about present and future consumption. To generate attitudes towards wealth gambles consistent with prospect theory, the model assumes that bad news hurt more than good news please. This assumption implies that expecting to receive news entails a first-order disutility. Thus, the agent is averse to receiving news. However, if the agent is more wealthy, news hurt less on average as the agent fluctuates around a less steep part of her concave utility function. Because the agent trades off the costs of expected news disutility with the benefits of staying fully informed and avoiding fee payments, she checks her accounts more often after income payments or wealth shocks. However, she also checks her accounts more often, if she holds little cash and worries more about fee payments. Thus, the model reconciles the two key empirical findings.

The paper is organized as follows: first, we provide a data description and summary statistics in Section 2. Section 3 documents the main analysis. In turn, Section 4 analyzes the theoretical framework for logins while Section 5 concludes.

2 Data and summary statistics

2.1 Data

This paper exploits new data from Iceland generated by Meniga, Europe's leading provider of financial aggregation software for banks and financial institutions. Meniga's PFM solution is checkingly used by more than 40 million individuals in 18 countries. The company allows financial institutions to offer their online customers a platform for connecting all their financial accounts, including bank accounts and credit card accounts, in a single location. Each day, the application automatically records all the bank and credit card transactions including balances and descriptions. We use the entire de-identified population of active users in Iceland and data derived from their records from January 2011 to January 2017 and perform the analysis on normalized and aggregated user-level data for different income and spending categories. In January 2014, the Icelandic population counted 325,671 individuals–254,538 of which were above the age of 16. At the same time, Meniga had 35,855 users–approximately 14 percent of individuals above the age of 16. Because the app is marketed through banks, the sample of Icelandic users is fairly representative. The app collects some demographic information such as age, gender, and marital status. Moreover, we can infer the number of (small) children, employment status, and geographical region. The user population is a substantial fraction of the population and very heterogeneous, including large numbers of users of different ages, education levels, and geographic location.

2.2 Summary statistics

Income, spending, and demographics: Table 2 displays summary statistics of the Icelandic users, including income and spending in US dollars across three log in and income terciles. Moreover, it displays some demographic statistics. Overall, the characteristics of the sample with respect to age, gender, employment, income, and spending figures are remarkably similar to the ones of the representative national household survey conducted by Statistics Iceland as can be seen in Table 3. This information is reassuring because using app data often comes along with a very selected sample of young and tech-savvy folks.[10]

{Table 2 and 3 around here}

In Table 2, it can be seen that those individuals who use the app frequently, as opposed to those who do not, are marginally wealthier, less indebted, and pay less financial fees. However, none of these differences are statistically significant. We thus conclude that not only the overall sample looks representative, but also the sample of individuals causing most of the variation in logins.

Logins: Figure 2 shows the distribution of the daily propensity to log in, i.e., a dummy variable equal to one if the individual logs in that day of the month or week for male and female users. It can be seen that men log in more often than women and all individuals log in more often around the end and beginning of the month and more on workdays than weekends. Figure 3 displays whether or not men and women log in on a particular day when they receive different types of income payments. It can be seen that all individuals log in more often when they get paid but also that there are large differences in the login responses of different payments. Again, men log in more often on average.

{Figure 2 around here}

3 Analyses and results

Here we describe our empirical setting and baseline identification strategy to uncover the effects of receiving a payment and credit card due dates on logins. Moreover, we explore the correlations

[10]For instance, roughly 50 percent of our users are female – a much higher number than the one seen in other papers using data of this kind.

between logins and individual financial standing such as cash holdings, overdrafts, and liquidity as well as individual spending.

3.1 Propensity to check financial accounts in response to income payments

We estimate the payday effects on logins by running the following regression:

$$x_{it} = \sum_{k=-7}^{7} \beta_k I_i(Paid_{t+k}) + \delta_{dow} + \phi_{dom} + \psi_{my} + \xi_h + \eta_i + \epsilon_{it} \quad (1)$$

where x_{it} is an indicator variable of whether individual i logged in to her account on date t, δ_{dow} is a day-of-week fixed effect, ϕ_{dom} is a day-of-month fixed effect, ψ_{my} is a month-by-year fixed effect, ξ_h is a holiday dummy, η_i is an individual fixed effect, and $I_i(Paid_{t+k})$ is an indicator that is equal to 1 if individual i receives a payment at time $t + k$ and that is equal to 0 otherwise. The β_k coefficients thus measure the fraction by which income arrival increases the probability of logging in on the days surrounding the receipt of a payment. We use indicator variables for income payments to alleviate potential endogeneity concerns at the income level. The day-of-week dummies capture within-week patterns for logins. The day-of-month dummies capture within-month patterns for logins. We restrict the income payments to regular payments that occur on a certain day of the month. When paydays fall on a weekend or a holiday they are moved to the last working day before or the next one. Weekends and holidays therefore generate an exogenous source of variation in the pay date.[11] Standard errors are clustered at the individual level.

Figure 4 displays the payday response for the two weeks and four weeks around paydays of regular salary payments. As can be seen, the log in coefficient is five times larger on the days individuals get paid relative to the days surrounding payment receipt. In terms of magnitudes relative to the average logins, individuals are 62 percent more likely to log in on the day they get

[11] Theoretically, we need individual-by-day-of-month fixed effects to single out this exogenous variation or everyone has to be paid on the same day of the month. In practice, 85 percent of individuals get paid within a few days in the end or beginng of the month and we can also restrict the sample to individuals who get paid on the same day. For instance, the figures are virtually unchanged when we only consider individuals who get paid on the first of the month.

paid.

{Figure 4 around here}

To interpret this finding, we have to think about how a rationally inattentive agent, who does not experience information- or belief-dependent utility, would behave. As outlined in the introduction, five possibilities come to mind: 1) individuals log in unrelated to their transactions because there is either full or no uncertainty associated with transactions, 2) individuals log in to verify all transactions post correctly, 3) individuals log in for budgeting and planning purposes, and 4) individuals log in when opportunity costs are low.

Hypotheses 1) can be ruled out as we see that income causes logins. Moreover, we can rule out 2) for the following three reasons. First, is important for identification that we only use payments that come on a certain day of the month to make sure that weekends and holidays generate an exogenous source of variation in the pay date. Moreover, by using only payments that come at a certain day of the month throughout the sample period, we can rule out transaction verification as a motive for logging in as there should be no news associated with their arrival. Second, we find almost the same responses in magnitudes to irregular as well as exogenous payments for which the transaction verification motive should be more relevant. Figure 5 shows responses to irregular income payments, such as insurance claims, dividends, or grants. Here, we find a marginally larger spike in the attention response in addition to a bit of a run-up before the payment. This additional margin may capture a transaction-verification motive, which we thus not consider first-order important. Alternatively, we can use plausibly exogenous income payments, such as lotteries and tax rebates, and also document a marginal propensity to log in of similar magnitude. Third, the spike in attention caused by the paycheck seems to be unaffected by other transactions, such as spending, as can be seen in Figure 6.

{Figure 5 and 6 around here}

Additionally, we can rule out 3), the budgeting motive, because we find that the log in response on paydays is higher when liquidity or cash holdings are high (rather than low when individuals should care more about budgeting). We argue that individuals should care more about budgeting and pay more attention because any agent with a prudent utility function can benefit more from consumption smoothing at low wealth levels (see Section 4). To analyze the effect of cash and liquidity on attention to financial accounts on paydays we run the following regression:

$$x_{it} = \sum_{d=0}^{10} \beta_d I_i(Paid_t) * Liq_i(d_t) + \delta_{dow} + \phi_{dom} + \psi_{my} + \xi_h + \eta_i + \epsilon_{it} \qquad (2)$$

where the variables x_{it}, δ_{dow}, ϕ_{dom}, ψ_{my}, ξ_h, η_i, and $I_i(Paid_t)$ are specified as above and $Liq_i(d_t)$ is an indicator for each liquidity decile (relative to individuals' own average liquidity). The β_d coefficients thus measure the fraction by which income arrival increases the probability of logging in for each liquidity decile. The same approach can be used to look at the effect of cash holdings on attention to financial accounts. Figure 7 displays the relationship between logging in on paydays relative to other days for different levels of individual cash and liquidity holdings. We can see that individuals are more likely to log in on paydays especially when their cash holdings and liquidity are relatively large. Here, one can nicely see the heterogeneity: individuals are around 30 percent more likely to log in relative to the baseline probability to log in of around 3 percent for low cash holdings and around 200 percent more likely to log in for high cash holdings.

{Figure 7 around here}

Moreover, when we sort according to spending rather than liquidity, we find no relationship, as can be seen in Figure 6. Spending can be seen as a measure of opportunity costs and thus addresses Hypothesis 4). As we show below, individuals tend to log in less when they spend a lot relative to their own history of spending. Thus, spending may be a measure of opportunity costs. However, there is no relationship between spending and the log in response on paydays. As an alternative to conchecking spending one can consider cash holdings as a measure of opportunity costs as they reflect past spending (when past spending was high then cash holdings are low and thus opportunity costs are low). Here, the positive relationship we observe in Figure 7 goes against the opportunity costs story. Moreover, it is evidence against hypthesis 3), the planning motive. If spending is high on a payday, there is less need to plan and individuals should log in less. However, we do not find a relationship between spending on paydays and the attention response.

We know from Olafsson and Pagel (2016) that spending responds to income arrival. To single out the effect of income, we control for spending in additional specifications. While controlling for spending constitutes a bad controls problem, it is still informative about the mechanism if the coefficients are not affected. We find that controlling for spending does not change our coefficients and we thus conclude that spending is not the mechanism underlying how income affects attention.

Finally, we find an even larger spike for second or more logins. In terms of magnitudes relative to the average logins, individuals are 62 percent more likely to log in once and 94.2 percent more likely to log in twice or more on a payday. It is important to note that the second log in is unlikely to be explained by individuals not being able to verify the payment upon the first log in because the vast majority of income payments are posted in the early morning. Overall, we thus conclude that individuals log in because they enjoy seeing money in their bank accounts, i.e., they experience a form of anticipatory utility.

We find a unique spike on paydays whereas an anticipatory utility story would suggest that logins are higher in the days after the payday too. In the above regression, this motive is captured by the day-of-month fixed effects as we will show now. Figure 6 shows logins as a function of days since the regular payment controlling for individual, day-of-week, day-of-month, month-by-year, and holiday fixed effects. Here, we can see a clear payday cycle that is not captured by the day-of-month fixed effects or the calendar cycle. It can be seen that individuals log in most often on paydays for regular payments and logins steadily decline after. These findings support the idea that anticipatory utility plays a role for deciding whether or not to pay attention.

3.2 Propensity to check financial accounts in response to automatic credit card bill payments on due dates

We can use the same identification strategy to assess the response in attention to regular credit card bill payments. In Iceland, a number of credit cards mandate that individuals set up an automatic payment on the 2nd of the month. Moreover, credit card due dates vary in the same way as paydays because of weekends and holidays, generating an exogenous source of variation in bill payments. Figure 8 displays the log-in response for the two weeks around the credit card due date. The first graph excludes day-of-month fixed effects while the second graph includes them. As can be seen, individuals are more likely to log in on the days they have to pay their credit card bill, although the magnitude is only half of the one from regular or incoming payments. Moreover, the initial spike in the graph excluding day-of-month fixed effects is probably due to other events in the beginning of the month that are captured by the day-of-month fixed effects as it disappears in the second graph. We thus conclude that incoming or large outgoing payments cause spikes in attention but incoming payments three times more so than outgoing ones.

{Figure 8 around here}

While the spike in attention on credit card due dates appears to be consistent with individuals worrying about liquidity constraints at first sight, we also find that the increase in attention on credit card due dates is increasing in liquidity, which is again consistent with an Ostrich-effect intuition. This pattern can be seen in Figure 9.

{Figure 9 around here}

Moreover, in Figure 9, we display the endogenous response to credit card payments. Here, we use a dummy for days after which credit card balances reduce by at least 50 percent. One can nicely see that making payments increase logins as one would expect. Additionally, this figure reassures us that logins via the app are positively, rather than negatively, correlated with logins to bank accounts (for instance, to pay the credit card bill as the app does not have a transaction functionality). This partly alleviates the concern that individuals simply log in by other means when we see less logins to the app.

3.3 Attention, spending, balances, and liquidity

Figure 10 displays the estimates of a logit model for the probability of logging in when individuals spend relatively more or less and when they have more or less savings. We first calculate how much one individual spends (saves) compared to how much she spends (saves) on average and then split that individual's spending (savings) in 11 groups. The first group is zero spending (savings) and the remaining groups split spending (savings) up in deciles 1 to 10. Each point is therefore comparing the individual's propensity to log in to the log-in rate when he spends (saves) nothing. While we technically report correlations, in practice, the set of fixed effects imposes a high bar for selection, omitted variable bias, and reverse causality. All selection on (un)observables is controlled for and we only compare individuals within their own histories. Moreover, the calendar fixed effects should control for all recurring planning motives. Finally, we know from our companion paper (Carlin et al., 2017) that logins do not cause substantial changes in spending patterns. More formally, we run the following regression:

$$logit(x_{it}) = \sum_{d=0}^{11} \beta_d S_i(d_t) + \psi_{my} + \delta_{dow} + \xi_h + \eta_i + \epsilon_{it} \tag{3}$$

where x_{it}, ψ_{my}, δ_{dow}, ξ_h, and η_i are specified as above. Thus, we control for individual, month-by-year, day-of-week, and holiday fixed effects. $S_i(d_t)$ is an indicator that is equal to 1 if individual i is in spending (savings) decile d on date t as explained above.

We find that individuals are generally less likely to log in when they spend relatively more. In contrast, individuals are more likely to log in when they have low or high levels of savings relative to some intermediate range. The coefficient interpretation of this logit regression is not obvious. Spending increases the odds of logging in but little spending less so than a lot of spending. The log of the baseline probability to log in (that is in the ballpark of two percent) is -1.5, thus a variation in the coefficient of 0.3 for spending or saving increases the odds by approximately 20 percent.

{Figure 10 around here}

An opportunity costs explanation for paying attention would suggest that individuals log in less when they are busy spending. To rule out this explanation, one can look at past spending that is summarized in cash holdings and overdrafts. When individuals' past spending was relatively high, their cash holdings are relatively low, and thus their opportunity costs are low. As documented next, however, we find a negative relationship between logging in and cash holdings as well as overdrafts suggesting that opportunity costs are not a key determinant of when individuals log in.[12]

Figure 11 displays the propensity to log in by deciles of individual cash (savings plus positive checking account balances). In the same way as before, each individual's cash holdings are split into 11 groups, group 0 is when the individual holds zero cash and groups 1 to 10 are deciles of the her value of cash. Again, we control for individual, month-by-year, day-of-week, and holiday fixed effects and thus impose a high bar in terms of selection, omitted variables, and reverse causality. We can see that cash holdings are positively related to logging in, i.e., individuals log in more often when they have more cash.

{Figure 11 around here}

The way that low cash holdings and large overdrafts imply high past spending, large cash holdings imply future spending. Thus, the question is whether individuals use the app to rationally plan

[12] In principle, low cash today implies either high past spending or low past income. To make sure, we pick up the variation in past spending, we can control for the monthly cycle using week-of-month fixed effects in the following regressions.

future spending. While planning to spend in the future is very hard to distinguish from anticipatory utility, we can address this theory by noting that the positive relationship is more pronounced for savings than checking account balances. Given that a savings account is not dedicated to spending, as the debit card always subtracts from the checking account, we thus conclude that planning future spending is not the main determinant of logging in to financial accounts when cash holdings are large.

Figure 12 displays the propensity to log in by deciles of overdraft debt. We split each individual's overdraft debt into 11 groups, group 0 belongs to zero holdings of debt and groups 1 to 10 are deciles of the value of debt. Again, we control for month-by-year, day-of-week, and holiday fixed effects. Here, it can be seen that holding debt is always negatively correlated with logging in. More specifically, the coefficient on overdrafts is always negative implying that individuals log in more when they carry more overdrafts. While overdrafts always reduces logins, the effect is U-shaped within negative overdrafts, i.e., having little or a lot of overdraft reduces logins less relative to having some intermediate amount. Because logins are always reduced by overdrafts and holding a relatively small amount of overdrafts still reduces logins less than having a relatively large amount of overdrafts, we again conclude that selective attention is more consistent with our findings than budgeting or liquidity constraints.

{Figure 12 around here}

A potential explanation for the above finding could be the following: individuals cannot perform transactions using the app. Therefore, when they have large overdrafts and want to transfer money, they log in using their bank account rather than the app. Note that, however, when the individual holds overdrafts, the checking account balance is negative (as is the credit card balance), thus, the individual would have to transfer money from a savings account or an unlinked account. To address that explanation, we can only look at individuals who have zero or low savings levels or control for the change in overdrafts the following day. We find that the documented negative

U-shape is very robust across sample splits and specifications. For instance, Figure 12 shows that the propensity to log in by deciles of overdraft debt are virtually unchanged whether or not we control for savings account balances.

Moreover, Figure 13 displays the propensity to log in by deciles of the checking account balance. We can see that the propensity to log in jumps discretely when the checking account balance changes from negative to positive. It is important to note that the figure only includes individuals that hold both a positive and a negative checking account balance during our sample period. Therefore, the discontinuous jump at zero is not caused cross-sectionally by one group being on the left side of zero and another group being on the right side. Instead the jump suggests that as soon as individuals do no longer have a negative checking account balance or overdraft they are more likely to look up their financial accounts. Individuals prefer to see a black checking account balance as opposed to a red one. This figure also shows a negative correlation between overdrafts and logins and a positive correlation between cash holdings and logins in the raw data, which again bolsters the robustness of our findings.

Furthermore, Figure 13 illustrates the jump in a regression controlling for individual and calendar fixed effects as well as for the receipt of payments, overdraft limits, and savings account balances. More specifically, the figure displays the regression coefficients for each decile of individual overdraft relative to individual's own history of overdrafts and the positive checking account balance relative to individual's own history of positive checking account balances. We can clearly see a discontinuous larger increase at zero relative to all other linear differences in the regression coefficients. Table 4 illustrates in great detail how the regression coefficients change with the addition of controls as well as documents standard errors to assure that all the regression coefficients are statistically significantly different from each other.

{Figure 13 and Table 4 around here}

We can also quantify the jump as a regression coefficient of a positive balance on logins in a linear probability model controlling for individual fixed effects, day-of-week, month-by-year, and holiday fixed effects as well as income payments. We obtain an 8.1% relative increase of the baseline probability to log in.

It is important to note here that the app does not send reminders or notifications. Users only see notifications after they log in to the app. Individuals do not see their credit card bills in the app and are not able to receive push notifications due to unpaid bills. The app's only notifications appear after users have logged into the app. More specifically, next to irregular transactions, there appear messages. Moreover, if the balance of an account is very low, there appears a message. Finally, there appears a message next to income transactions saying "you got paid." The app does not send push notifications, however, users need to be logged in already to see these messages.

Overall, we conclude from this analysis that our causal results for selective attention with respect to income hold much more generally. Individuals do not pay attention when they spend a lot or have low cash holdings. On the other hand, it seems sensible to assume that individuals worry to some extent about financial fee payments. After all, in an accompanying paper, Carlin et al. (2017) document that the mobile app introduction of this personal finance software decreased financial penalty payments. Furthermore, Stango and Zinman (2014) document that individuals respond to surveys about overdrafts by paying greater attention to account balances and incurring less fees and Medina (2016) finds that reminders for timely payment reduce credit card late-fees paid.

4 Theoretical framework

We now outline a model of belief-dependent utility that was derived by Kőszegi and Rabin (2009) and assumed in a life-cycle model with inattention to brokerage accounts by Pagel (2014). This model formalizes our intuitions for our key empirical results: individuals dislike paying attention to their accounts especially when cash holdings are low but they also worry about fee payments.

Moreover, we formally show that a rationally inattentive agent, subject to exogenous attention costs, would pay more attention if wealth and income is low.

The agent experiences news utility as modeled in Kőszegi and Rabin (2009) and given by $\nu(u(c) - u(\tilde{c}))$ with $c \sim F_c(\tilde{c})$, which may be positive or negative depending on the realizations of her income and bill payments: $\tilde{Y} - \tilde{B} \sim F_{YB} = N(\mu, \sigma^2)$ with the realization denoted by $\tilde{y} - \tilde{b}$ and $\tilde{S} = \frac{\tilde{Y} - \tilde{B} - \mu}{\sigma} \sim F = N(0, 1)$ with the realization denoted by $\tilde{s}$. Kőszegi and Rabin (2009) generalize prospect-theory preferences via the function $\nu(\cdot)$ that is given by $\nu(x) = \eta x$ for $x > 0$ and $\nu(x) = \eta\lambda x$ for $x \leq 0$ with $\eta > 0$ and $\lambda > 1$. The agent thus cares about good and bad news but dislikes bad news more than she likes good news. Because bad news hurt more than good news please, the agent dislikes checking in general as it generates news disutility in expectation. Moreover, the agent is more willing to check if income is high because checking becomes less painful on a less steep part of the concave utility curve.

If the agent does not check her accounts, then she may incur a financial fee f whenever $\tilde{y} - \tilde{b} < 0$. If that happens, the fee will be subtracted from future consumption. If she checks her accounts, she can avoid all financial fees by simply transferring money from other accounts, which does not affect her consumption. Thus, when she pays attention, she will not pay a fee. All consumption takes place in the future, with utility given by $\beta u(c)$ with $\beta < 1$ and $\gamma < 1$. $I(a) = 1$ if the agent pays attention to her accounts and zero otherwise. The agent maximizes

$$E[\gamma\beta \int \nu(u(c) - u(\tilde{c}))dF_c(\tilde{c})I(a) + \beta u(c)I(a) + \beta u(c)(1 - I(a))]$$

$$\text{with } c = \tilde{y} - \tilde{b} - fI(\tilde{y} - \tilde{b} > 0)(1 - I(a)).$$

The agent pays attention to her accounts, if the expected utility from checking is greater than the expected utility from being inattentive

$$E[\gamma\beta \int \nu(u(\tilde{y} - \tilde{b}) - u(\tilde{Y} - \tilde{B}))dF_{YB}(\tilde{Y} - \tilde{B}) + \beta u(\tilde{y} - \tilde{b})] > E[\beta u(\tilde{y} - \tilde{b} - fI(\tilde{y} - \tilde{b} < 0))]$$

which can be rewritten as

$$E[\gamma\beta\eta(\lambda-1)\int_{\tilde{s}}^{\infty}(u(\mu+\sigma\tilde{s})-u(\mu+\sigma\tilde{S}))dF(\tilde{S})]+E[\beta u(\mu+\sigma\tilde{s})]$$

$$>E[\beta u(\mu+\sigma\tilde{s}-fI(\mu+\sigma\tilde{s}<0))].$$

Suppose utility is linear, which can be seen as a good approximation for small stakes. In turn, the comparison becomes

$$E[\gamma\beta\eta(\lambda-1)\sigma\int_{\tilde{s}}^{\infty}(\tilde{s}-\tilde{S})dF(\tilde{S})]+\beta\mu>\beta(\mu-fProb(\mu+\sigma\tilde{s}<0))$$

$$\Rightarrow E[\gamma\beta\eta(\lambda-1)\sigma\int_{\tilde{s}}^{\infty}(\tilde{s}-\tilde{S})dF(\tilde{S})]>-\beta fF(-\frac{\mu}{\sigma}).$$

And we can easily establish the following comparative statics. When the fee is increased, i.e., $f\uparrow\Rightarrow -\beta fF(-\frac{\mu}{\sigma})\downarrow$, then checking is more likely. When overall cash holdings are increased and thereby the fee payment is less likely, i.e., $\mu\uparrow\Rightarrow F(-\frac{\mu}{\sigma})=Prob(\tilde{s}<-\frac{\mu}{\sigma})\downarrow\Rightarrow -\beta fF(-\frac{\mu}{\sigma})\uparrow$, then checking is less likely. When the news-utility parameters are increased, i.e., $\eta\lambda\uparrow\Rightarrow E[\gamma\beta\eta(\lambda-1)\sigma\underbrace{\int_{\tilde{s}}^{\infty}(\tilde{s}-\tilde{S})dF(\tilde{S})]}_{<0}\downarrow$, then checking is less likely. And finally when the cash variance is increased, then news disutility is increased but the likelihood of a fee payment is increased too.

Now, suppose utility is concave and exponential $u(c)=-\frac{1}{\theta}e^{-\theta c}$, which is an appropriate assumption for large stakes,

$$E[\gamma\beta\eta(\lambda-1)e^{-\theta\mu}\int_{\tilde{s}}^{\infty}(e^{-\theta\sigma\tilde{s}}-e^{-\theta\sigma\tilde{S}})dF(\tilde{S})]+E[\beta e^{-\theta(\mu+\sigma\tilde{s})}]<E[\beta e^{-\theta(\mu+\sigma\tilde{s}-fI(\mu+\sigma\tilde{s}>0))}]$$

For this case, we can establish the following comparative statics. When the fee is increased, i.e., $f\uparrow$, then checking is more likely. When overall cash holdings are increased, i.e., $\mu\uparrow$, then expected news disutility is decreased $E[\gamma\beta\eta(\lambda-1)e^{-\theta\mu}\int_{\tilde{s}}^{\infty}(e^{-\theta\sigma\tilde{s}}-e^{-\theta\sigma\tilde{S}})dF(\tilde{S})]\uparrow$, which makes checking more likely, but expected fee payments are decreased too $(E[\beta e^{-\theta(\mu+\sigma\tilde{s})}]-E[\beta e^{-\theta(\mu+\sigma\tilde{s}-fI(\mu+\sigma\tilde{s}>0))}])\downarrow$, which makes checking less likely. When the news-utility parameters are increased, i.e., $\eta\lambda\uparrow\Rightarrow E[\gamma\beta\eta(\lambda-1)e^{-\theta\mu}\int_{\tilde{s}}^{\infty}(e^{-\theta\sigma\tilde{s}}-e^{-\theta\sigma\tilde{S}})dF(\tilde{S})]\uparrow$, then checking is less likely. Finally, if the cash variance is increased, i.e., $\sigma\uparrow$, then news disutility is increased $E[\gamma\beta\eta(\lambda-1)e^{-\theta\mu}\int_{\tilde{s}}^{\infty}(e^{-\theta\sigma\tilde{s}}-e^{-\theta\sigma\tilde{S}})dF(\tilde{S})]\uparrow$ and checking is less likely but expected fee payments are increased $(E[\beta e^{-\theta(\mu+\sigma\tilde{s})}]-E[\beta e^{-\theta(\mu+\sigma\tilde{s}-fI(\mu+\sigma\tilde{s}>0))}])\uparrow$, which makes checking more likely.

To formalize these intuitions for a general utility function $u(\cdot)$, consider the risk premium when the agent pays attention, i.e., the compensating utility differential for paying attention if or if not knowing $\tilde{s}=0$:

$$\pi = E[\beta u(\mu)] - E[\gamma\beta\eta(\lambda-1)\int_{\tilde{s}}^{\infty}(u(\mu+\sigma\tilde{s})-u(\mu+\sigma\tilde{S}))dF(\tilde{S})] - E[\beta u(\mu+\sigma\tilde{s})].$$

Taking the derivative with respect to the amount of risk σ yields

$$\frac{\partial\pi}{\partial\sigma} = -E[\gamma\beta\eta(\lambda-1)\int_{\tilde{s}}^{\infty}(\tilde{s}u'(\mu+\sigma\tilde{s})-\tilde{S}u'(\mu+\sigma\tilde{S}))dF(\tilde{S})] - E[\beta\tilde{s}u'(\mu+\sigma\tilde{s})]$$

and for small risks:

$$\frac{\partial\pi}{\partial\sigma}|_{\sigma\to 0} = -E[\gamma\beta\eta(\lambda-1)u'(\mu)\int_{\tilde{s}}^{\infty}(\underbrace{\tilde{s}-\tilde{S}}_{<0})dF(\tilde{S})] - \underbrace{E[\beta\tilde{s}u'(\mu)]}_{=0} > 0.$$

Proposition. *For the standard agent or hyperbolic-discounting agent ($\eta=0$ or $\eta>0$ and $\lambda=1$), the risk premium for paying attention in the presence of small risks is zero (the agents are second-order risk averse). In contrast, for the news-utility agent ($\eta>0$ and $\lambda>1$), the risk premium for paying attention is always positive. Additionally, the risk premium for paying attention is decreasing in expected cash holdings μ if $u(\cdot)$ is concave.*

Proof. See derivation. $\square$

Thus, expecting to check causes a first-order decrease in expected utility and the agent has a first-order willingness to incur fees even when uncertainty is small. Note that, the effect of cash holdings, μ, only affects the agent through higher expected consumption, not a lower likelihood of the fee payment in this approximation. Thus, news disutility is lower when income or wealth and therefore consumption is large.

We can now do a back-of-the-envelope calculation to assess in how far the avoidance of news utility can explain the amount of fee payments we see empirically. Average monthly fee payments amount to approximately \$40. We assume that individuals experience news disutility at a monthly level and utility is given by $u(c) = \frac{c^{1-\theta}}{1-\theta}$ with $\theta = 4$. In turn, we calibrate annual labor income uncertainty in line with the life-cycle literature, for instance, Carroll (1997), as follows: $Y \sim log - N(\mu_{ann}, \sigma_{ann}^2)$ with $\mu_{ann} = 0$ and $\sigma_{ann} = 0.2$. At the monthly level, income uncertainty is then given by $\sigma = \sqrt{12}\sigma_{ann}$. Moreover, we assume that cash holdings are given by one standard deviation in monthly income, i.e., $\mu = \sqrt{12}\sigma_{ann}$, and can calculate the fraction Δ of monthly consumption the news-utility agent would be willing to give up to avoid news disutility:

$$\Delta e^{\mu+\frac{1}{2}\sigma^2} = u^{-1}(E[\eta(\lambda-1)\int_{\tilde{s}}^{\infty}(u(e^{\mu+\sigma\tilde{s}}) - u(e^{\mu+\sigma\tilde{S}}))dF(\tilde{S})]).$$

We obtain a fraction of 3 percent of cash holdings which amounts to \$47 per month for $\eta = 1$ and $\lambda = 2$ (which are standard parameters in the prospect-theory and news-utility literature explaining the evidence in Kahneman and Tversky (1979) among many others). In turn, as an out-of-sample calibrational test, we compute the decrease in monthly news disutility when the agent goes from $\mu = \sigma$ to $\mu = -\sigma$ of cash holdings and obtain a decrease of 24 percent, which thus makes the agent much more likely to check in line with our empirical findings (the increase when one goes from low cash holdings to high cash holdings in the probability to log in is approximately 25

Nevertheless, the news-utility model is fully based on rational expectations about present and future consumption. As such, it is not able to rationalize an increase in attention at a fully expected income payment or a jump in the probability to log in when balances turn from negative to positive. To address these findings, one has to consider a model of myopia or another model in which the income payments affects utility not through future consumption but independently so.

Let's now return to the standard agent. As just seen, any standard agent's risk premium is zero for small risks. Moreover, for large risks, the risk premium is positive if the utility function is concave. Moreover, the risk premium is increasing in wealth or income if the utility function is prudent (refer to Gollier, 2004, for a more in depth analysis). To see this, simply assume that the standard agent pays an exogenous attention cost a. In turn, he will pay attention if

$$E[\beta u(\mu + \sigma\tilde{s} - a)] > E[\beta u(\mu + \sigma\tilde{s} - fI(\mu + \sigma\tilde{s} > 0))].$$

In turn, the standard agent's risk premium for paying attention is

$$\pi = E[\beta u(\mu + \sigma\tilde{s} - a)] - E[\beta u(\mu + \sigma\tilde{s} - fI(\mu + \sigma\tilde{s} < 0))]$$

For each increment of risk σ, we obtain

$$\frac{\partial \pi}{\partial \sigma} = -E[\beta f\delta(\mu + \sigma\tilde{s})\tilde{s}u'(\mu + \sigma\tilde{s} - fI(\mu + \sigma\tilde{s} < 0))]$$

where δ is the negative dirac delta function, the derivative of the indicator function (which is constantly zero in $\tilde{s}$ except at the point $\tilde{s} = -\frac{\mu}{\sigma}$ where the function is positive and infinitely large). In turn,

$$\begin{aligned}\frac{\partial \frac{\partial \pi}{\partial \sigma}}{\partial \mu} &= -E[\beta f\delta(\mu + \sigma\tilde{s})\tilde{s}u''(\mu + \sigma\tilde{s} - fI(\mu + \sigma\tilde{s} < 0))] \\ &= \underbrace{E[\beta\tilde{s}]E[f\delta(\mu + \sigma\tilde{s})u''(\mu + \sigma\tilde{s} - fI(\mu + \sigma\tilde{s} < 0)))]}_{=0} \\ &- \underbrace{Cov(\beta\tilde{s}, f\delta(\mu + \sigma\tilde{s})u''(\mu + \sigma\tilde{s} - fI(\mu + \sigma\tilde{s} < 0))))}_{>0 \text{ if } u'''>0} < 0\end{aligned}$$

Thus, the standard agent's risk premium is decreasing in consumption or wealth μ if he is prudent $u''' > 0$. In other words, consumption smoothing is more beneficial at low income and wealth levels, as prudence implies that the standard agent wants to allocate risk to the wealthy states.

Using the above calibration, we ask how much the standard agent would be willing to pay of monthly consumption to avoid all monthly income uncertainty, not only the fee payment (we want to avoid calibrating the fee). The answer is only 0.66% because income uncertainty at the monthly level is only $\sqrt{12}\sigma_{ann} = \sqrt{12}0.2$ as calibrated in Carroll (1997) and the standard agent becomes risk neutral for small risks. Moreover, this value changes only marginally for lower or higher values of consumption μ. Therefore, standard risk aversion and prudence about fee payment uncertainty is unlikely to generate the amount of fee payments and the aversion to check financial accounts we see in the data. We need first-order risk aversion and prudence for explaining our findings under realistic income uncertainty at a monthly level.

5 Conclusion

Beyond mechanical costs and benefits, paying attention to financial accounts may have a hedonic impact on utility by causing anxiety or anticipatory feelings. In response to casual observation and empirical evidence on information avoidance, a literature on information-dependent and belief-dependent utility emerged. Moreover, inattention has been shown to matter in the aggregate. However, empirical evidence on when individuals pay attention to their financial accounts remains scarce. In this paper we use data from a financial aggregation app that allows bank customers to manage all their bank accounts and credit cards across multiple banks in one place. The digitization of budgeting processes and the attendance tracking of online behavior allow us to directly measure individual attention in ways that previously were not possible. Moreover, we have access to spending, income, balances, and credit limits data that is characterized by outstanding accuracy and comprehensiveness.

We find evidence consistent with selective attention and Ostrich effects. Income payments cause individuals to log in more often and people log in less when they have relatively low cash holdings or spend a lot. Additionally, when individuals are very indebted, they log in less which appears inconsistent with standard models and the need for budgeting as the first-order motivation for checking financial accounts. To formalize intuitions for our key empirical findings, we analyze a model of news utility developed by Kőszegi and Rabin (2009). We establish that individuals have a first-order willingness to incur fees as they dislike checking when bad news hurt more than good news please. But, checking becomes less painful in expectation when cash holdings are large.

In terms of broader implications, our findings are relevant for theories of rational inattention. In macroeconomics, for instance, theories of rational inattention are likely to generate different aggregate dynamics if inattention would be selective. More generally, our findings question the assumption that information costs are always positive. If individuals are willing to pay to not receive information (which could be inferred from this study in connection with Carlin et al., 2017), then information costs are effectively negative rather than positive. Beyond rational inattention and information costs, our findings relate to the literature on poverty traps and cognitive function in poverty.

Logging in to financial accounts can be interpreted as paying attention to personal finances. Alternatively, it could be interpreted as a decision to make individual financial standing more salient. There exists a small but growing theoretical literature that is incorporating salience and focus into economic decision-making (e.g., Bordalo et al., 2010; Koszegi and Szeidl, 2013; Bushong et al., 2015). To further explore how salience affects economic decisions is a promising avenue for future research.

References

Abel, Andrew B, Janice C Eberly, and Stavros Panageas, "Optimal inattention to the stock market with information costs and transactions costs," *Econometrica*, 2013, *81* (4), 1455–1481.

Alvarez, Fernando, Luigi Guiso, and Francesco Lippi, "Durable consumption and asset management with transaction and observation costs," *The American Economic Review*, 2012, *102* (5), 2272–2300.

Andrei, Daniel and Michael Hasler, "Investor attention and stock market volatility," *Review of Financial Studies*, 2014, p. hhu059.

Azariadis, Costas and John Stachurski, "Poverty traps," *Handbook of economic growth*, 2005, *1*, 295–384.

Baker, Scott, "Debt and the Consumption Response to Household Income Shocks," Working Paper, Stanford University 2014.

Bénabou, Roland, "Groupthink: Collective delusions in organizations and markets," *The Review of Economic Studies*, 2012, p. rds030.

Bonaparte, Yosef and Russell Cooper, "Costly portfolio adjustment," *National Bureau of Economic Research*, 2009.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, "Salience theory of choice under risk," Technical Report, National Bureau of Economic Research 2010.

Brunnermeier, Markus K and Jonathan A Parker, "Optimal expectations," *The American Economic Review*, 2005, *95* (4), 1092–1118.

_ **and Stefan Nagel**, "Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals' asset allocation," *The American Economic Review*, 2008, *98* (3), 713–736.

Bushong, Benjamin, Matthew Rabin, and Joshua Schwartzstein, "A model of relative thinking," Technical Report, Working paper 2015.

Caplin, Andrew and John Leahy, "Psychological expected utility theory and anticipatory feelings," *Quarterly Journal of economics*, 2001, pp. 55–79.

_ **and** _ , "The supply of information by a concerned expert," *The Economic Journal*, 2004, *114* (497), 487–505.

Carlin, Bruce, Arna Olafsson, and Michaela Pagel, "Technology Adoption Across Generations: Financial Fitness in the Information Age," *Working Paper*, 2017.

Carroll, Christopher D, "Buffer-Stock Saving and the Life Cycle/Permanent Income Hypothesis," *The Quarterly Journal of Economics*, February 1997, *112* (1), 1–55.

Carvalho, Leandro S, Stephan Meier, and Stephanie W Wang, "Poverty and economic decision-making: Evidence from changes in financial resources at payday," *The American Economic Review*, 2016, *106* (2), 260–284.

Chien, YiLi, Harold Cole, and Hanno Lustig, "Is the Volatility of the Market Price of Risk Due to Intermittent Portfolio Rebalancing?," *The American Economic Review*, 2012, *102* (6), 2859–2896.

Dillenberger, David, "Preferences for One-Shot Resolution of Uncertainty and Allais-Type Behavior," *Econometrica*, 2010, *78* (6), 1973–2004.

Eliaz, Kfir and Andrew Schotter, "Paying for confidence: An experimental study of the demand for non-instrumental information," *Games and Economic Behavior*, 2010, *70* (2), 304–324.

Ely, Jeffrey, Alexander Frankel, and Emir Kamenica, "Suspense and surprise," *Journal of Political Economy*, 2015, *123* (1), 215–260.

Epstein, Larry G, "Living with risk," *The Review of Economic Studies*, 2008, *75* (4), 1121–1141.

Falk, Armin and Florian Zimmermann, "Beliefs and utility: Experimental evidence on preferences for information," Technical Report, Working paper 2014.

Gabaix, Xavier, "Behavioral Macroeconomics Via Sparse Dynamic Programming," Technical Report, National Bureau of Economic Research 2016.

_ and David Laibson, "The 6D bias and the equity-premium puzzle," in "NBER Macroeconomics Annual 2001, Volume 16," MIT Press, 2002, pp. 257–330.

Galai, Dan and Orly Sade, "The ostrich effect and the relationship between the liquidity and the yields of financial assets," *The Journal of Business*, 2006, *79* (5), 2741–2759.

Ganguly, Ananda and Joshua Tasoff, "Fantasy and Dread: An Experimental Test of Attentional Anticipatory Utility," *Working Paper*, 2014.

Gargano, Antonio and Alberto G Rossi, "Does it Pay to Pay Attention?," 2017.

Gelman, Michael, Shachar Kariv, Matthew D. Shapiro, Dan Silverman, and Steven Tadelis, "Harnessing naturally occurring data to measure the response of spending to income," *Science*, 2014, *345* (6193), 212–215.

Gherzi, Svetlana, Daniel Egan, Neil Stewart, Emily Haisley, and Peter Ayton, "The meerkat effect: Personality and market returns affect investors' portfolio monitoring behaviour," *Journal of Economic Behavior & Organization*, 2014, *107*, 512–526.

Gollier, Christian, *The economics of risk and time*, MIT press, 2004.

Golman, Russell and George Loewenstein, "Curiosity, information gaps, and the utility of knowledge," *Information Gaps, and the Utility of Knowledge (April 16, 2015)*, 2015.

_ , David Hagmann, and George Loewenstein, "Information Avoidance," *Journal of Economic Literature*, 2016.

Huang, Lixin and Hong Liu, "Rational inattention and portfolio selection," *The Journal of Finance*, 2007, *62* (4), 1999–2040.

Kahneman, Daniel and Amos Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica: Journal of the econometric society*, 1979, pp. 263–291.

Karlsson, Niklas, George Loewenstein, and Duane Seppi, "The ostrich effect: Selective attention to information," *Journal of Risk and uncertainty*, 2009, *38* (2), 95–115.

Koszegi, Botond and Adam Szeidl, "A Model of Focusing in Economic Choice," *The Quarterly Journal of Economics*, 2013, *128* (1), 53–104.

Kőszegi, Botond and Matthew Rabin, "A model of reference-dependent preferences," *The Quarterly Journal of Economics*, 2006, pp. 1133–1165.

_ and _ , "Reference-dependent consumption plans," *The American Economic Review*, 2009, *99* (3), 909–936.

Lerman, Caryn, Chanita Hughes, Bruce J Trock, Ronald E Myers, David Main, Aba Bonney, Mohammad R Abbaszadegan, Anne E Harty, Barbara A Franklin, Jane F Lynch et al., "Genetic testing in families with hereditary nonpolyposis colon cancer," *Jama*, 1999, *281* (17), 1618–1622.

— , **Steven Narod, Kevin Schulman, Chanita Hughes, Andres Gomez-Caminero, George Bonney, Karen Gold, Bruce Trock, David Main, Jane Lynch et al.**, "BRCA1 testing in families with hereditary breast-ovarian cancer: a prospective study of patient decision making and outcomes," *Jama*, 1996, *275* (24), 1885–1892.

Loewenstein, George, "Anticipation and the valuation of delayed consumption," *The Economic Journal*, 1987, *97* (387), 666–684.

— , "The psychology of curiosity: A review and reinterpretation.," *Psychological bulletin*, 1994, *116* (1), 75.

Lyter, David W, Ronald O Valdiserri, Lawrence A Kingsley, William P Amoroso, and Charles R Rinaldo Jr, "The HIV antibody test: why gay and bisexual men want or do not want to know their results.," *Public health reports*, 1987, *102* (5), 468.

Mani, Anandi, Sendhil Mullainathan, Eldar Shafir, and Jiaying Zhao, "Poverty impedes cognitive function," *science*, 2013, *341* (6149), 976–980.

Medina, Paolina, "Selective Attention in Consumer Finance: Experimental Evidence from the Credit Card Market," *Working Paper*, 2016.

Nieuwerburgh, Stijn Van and Laura Veldkamp, "Information immobility and the home bias puzzle," *The Journal of Finance*, 2009, *64* (3), 1187–1215.

— **and** — , "Information acquisition and under-diversification," *The Review of Economic Studies*, 2010, *77* (2), 779–805.

Olafsson, Arna and Michaela Pagel, "The Liquid Hand-to-Mouth: Evidence from Personal Finance Management Software," *Working Paper*, 2016.

Oster, Emily, Ira Shoulson, and E Dorsey, "Optimal expectations and limited medical testing: evidence from Huntington disease," *The American Economic Review*, 2013, *103* (2), 804–830.

Paciello, Luigi and Mirko Wiederholt, "Exogenous information, endogenous information and optimal monetary policy," *The Review of Economic Studies*, 2013, p. rdt024.

Pagel, Michaela, "A news-utility theory for inattention and delegation in portfolio choice," Technical Report, working paper 2014.

Powdthavee, Nattavudh and Yohanes E Riyanto, "Would you pay for transparently useless advice? A test of boundaries of beliefs in the folly of predictions," *Review of Economics and Statistics*, 2015, *97* (2), 257–272.

Reis, Ricardo, "Inattentive consumers," *Journal of Monetary Economics*, 2006, *53* (8), 1761–1800.

Schulz-Hardt, Stefan, Dieter Frey, Carsten Lüthgens, and Serge Moscovici, "Biased information search in group decision making.," *Journal of personality and social psychology*, 2000, *78* (4), 655.

Sicherman, Nachum, George Loewenstein, Duane J Seppi, and Stephen Utkus, "Financial attention," *Review of Financial Studies*, 2015, p. hhv073.

Stango, Victor and Jonathan Zinman, "Limited and varying consumer attention evidence from shocks to the salience of bank overdraft fees," *Review of Financial Studies*, 2014, p. hhu008.

Strzalecki, Tomasz, "Temporal resolution of uncertainty and recursive models of ambiguity aversion," *Econometrica*, 2013, *81* (3), 1039–1074.

Sullivan, Patrick S, Amy Lansky, Amy Drake, HITS-2000 Investigators et al., "Failure to return for HIV test results among persons at high risk for HIV infection: results from a multistate interview project," *JAIDS Journal of Acquired Immune Deficiency Syndromes*, 2004, *35* (5), 511–518.

Thornton, Rebecca L, "The demand for, and impact of, learning HIV status," *The American economic review*, 2008, *98* (5), 1829–1863.

Woodford, Michael, "Information-constrained state-dependent pricing," *Journal of Monetary Economics*, 2009, *56*, S100–S124.

Zimmermann, Florian, "Clumped or piecewise? evidence on preferences for information," *Management Science*, 2014, *61* (4), 740–753.

Table 2: Summary statistics by terciles of logins and income

	Log in terciles			Income terciles		
	(1)	(2)	(3)	(1)	(2)	(3)
Number of individual logins	0.00	0.01	0.10	0.02	0.04	0.05
Number of household logins	0.01	0.01	0.11	0.03	0.04	0.06
Propensity to log in	0.1%	0.4%	6.1%	1.2%	2.3%	3.1%
smartphone log in	0.0%	0.1%	2.0%	0.4%	0.7%	1.0%
desktop log in	0.1%	0.3%	4.4%	0.8%	1.7%	2.2%
tabloid log in	0.0%	0.0%	0.2%	0.0%	0.1%	0.1%
Monthly income	3217	3543	3939	448	2995	7240
Monthly regular income	3099	3426	3822	428	2933	6969
Monthly irregular income	92	90	92	20	60	193
Monthly financial fees	-24	-23	-19	-14	-22	-30
Overdraft	-1740	-1712	-1557	-1453	-1453	-2046
Savings account balance	2527	3220	4979	2428	2924	4939
checking account balance	1991	2060	1877	1590	1378	2837
Credit card balance	-1204	-1313	-1748	-1041	-1099	-1989
Overdraft limit	2446	2534	2546	1993	2067	3311
Credit card limit	3501	4080	5891	3178	3304	6492
Cash holdings	4518	5280	6856	4017	4302	7776
Liquidity	9261	10582	13545	8146	8575	15591
Monthly discretionary spending	1384	1478	1578	923	1432	2080
Age	41.7	42.2	40.7	37.3	42.2	45.1
Female	52%	48%	43%	51%	54%	38%
Spouse	19%	24%	40%	25%	28%	30%

Table 3: Summary Statistics and Comparison to Statistics Iceland

	Mean	Standard Deviation	Statistics Iceland
Monthly regular income	3,547	3,717	3,768
Monthly spending:			
Total	1,535	1,429	
Groceries	546	454	572
Fuel	276	302	(419)
Alcohol	72	141	99
Ready Made Food	198	202	(294)
Home Improvement	175	543	(267)
Transportations	68	817	77
Clothing & accessories	102	211	112
Sports & activities	51	173	(42)
Pharmacies	47	72	49
Age	42.2	11.5	37.2
Female	49%		48%
Retired	3.9%		

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

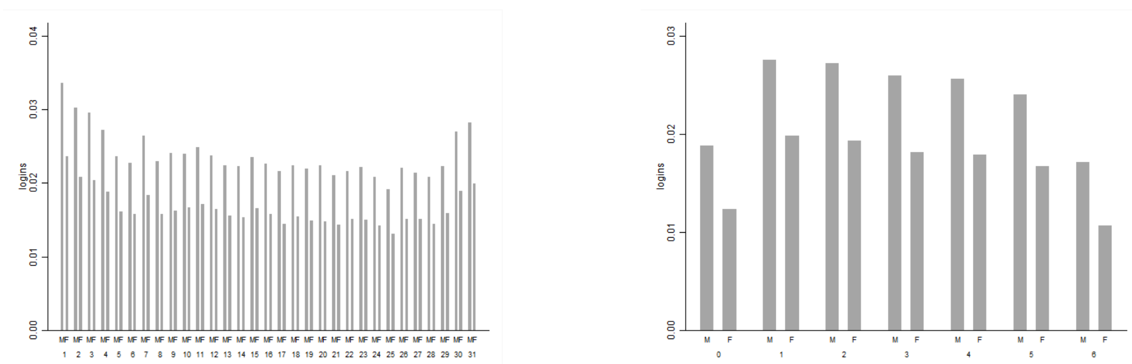

Figure 2: Distribution of logins over the month and by day of week (Sunday to Saturday) by men (M) and women (F)

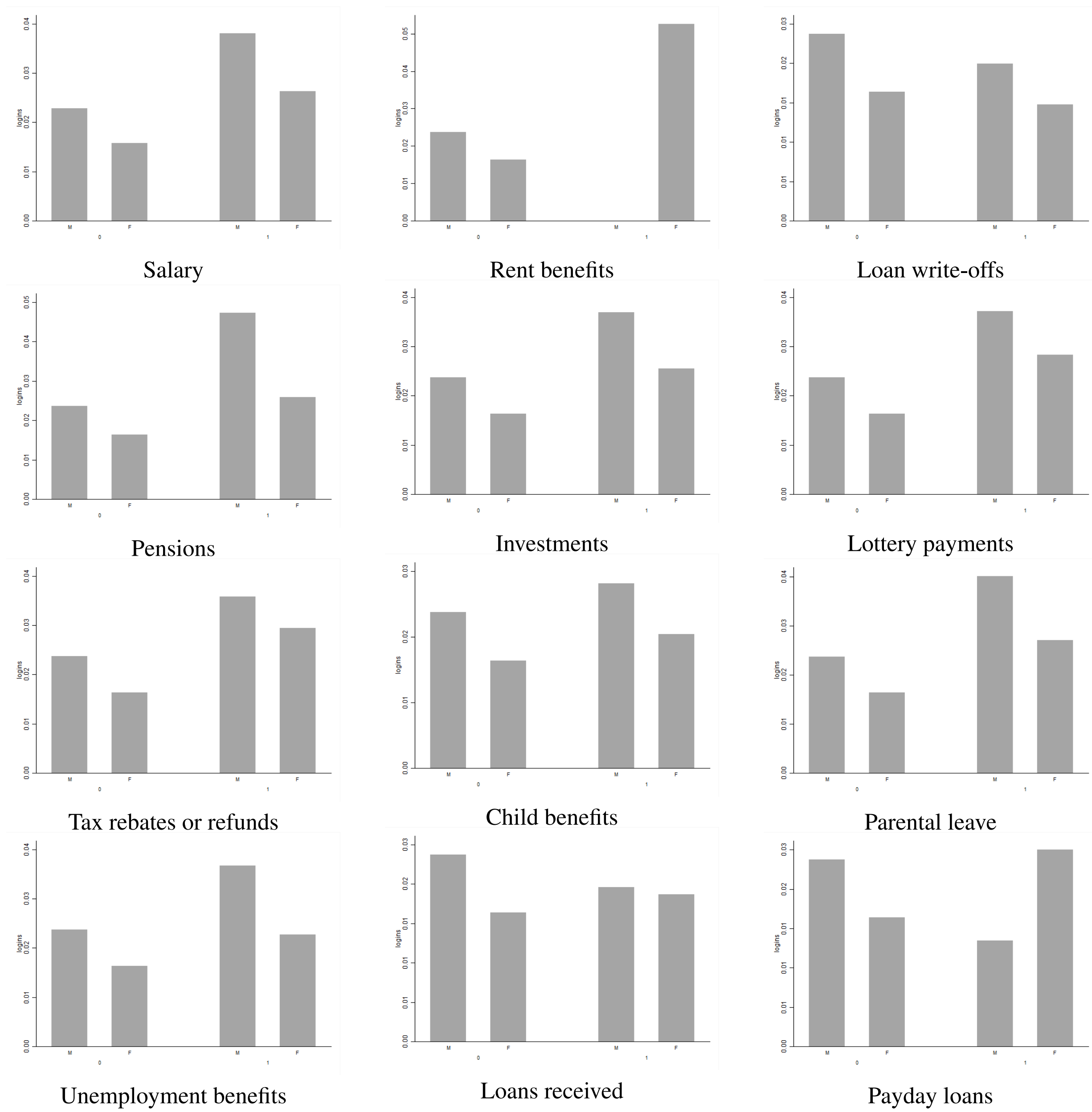

Figure 3: Average logins on regular days (left bars) and days with different income arrivals (right bars) by men (M) and women (F)

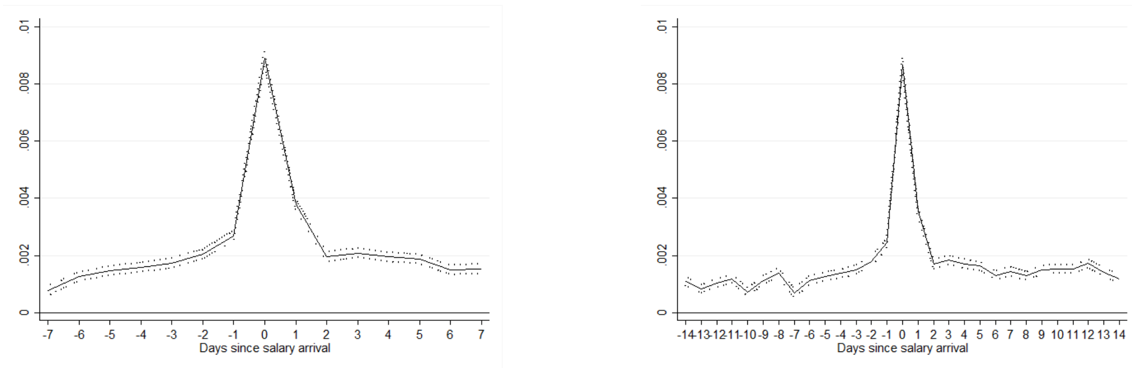

Figure 4: Propensity to log in around paydays of regular salary payments

Linear probability model of propensity to log in on dummies for the two or four weeks around regular paycheck arrival controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Standard errors are clustered at the individual level.

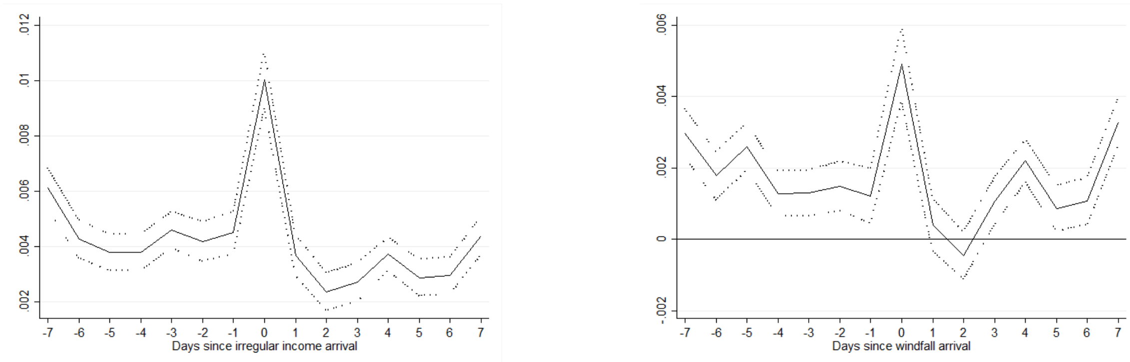

Figure 5: Propensity to log in around paydays of irregular payments and plausibly exogenous payments

Linear probability model of propensity to log in on dummies for the two weeks around irregular income arrival or plausibly exogenous income arrival (lotteries and tax rebates) controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Standard errors are clustered at the individual level.

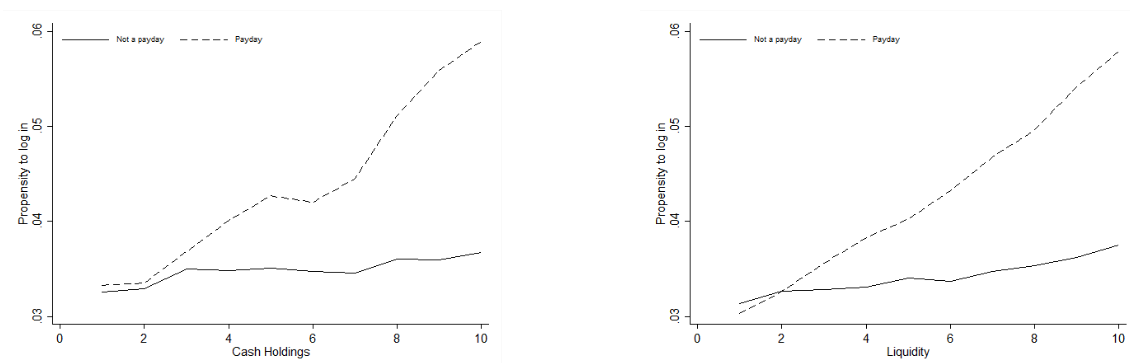

Figure 6: Differences in propensity to log in on paydays versus other days as functions of individual spending and as a function of days since regular paydays

Left side: Coefficients on day of paycheck of propensity to log in in linear probability model for ten deciles of individual spending relative to own history of individual spending controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Right side: Linear probability model of propensity to log in on days since regular paycheck arrival controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects.

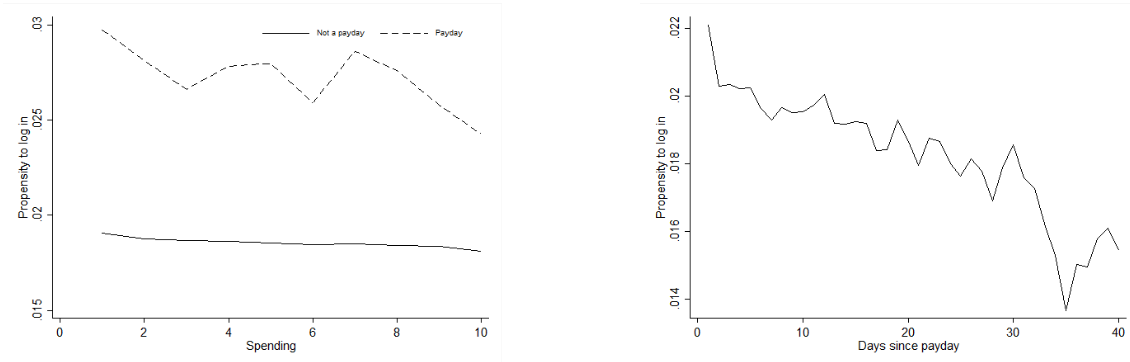

Figure 7: Differences in propensity to log in on paydays versus other days as functions of individual cash holdings and liquidity

Coefficients on day of paycheck of propensity to log in in linear probability model for ten deciles of individual cash (positive checking account balance and savings balance) or liquidity (checking account balance plus credit card balance plus overdraft and credit limits plus savings account balance) relative to own history of individual spending or liquidity controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects.

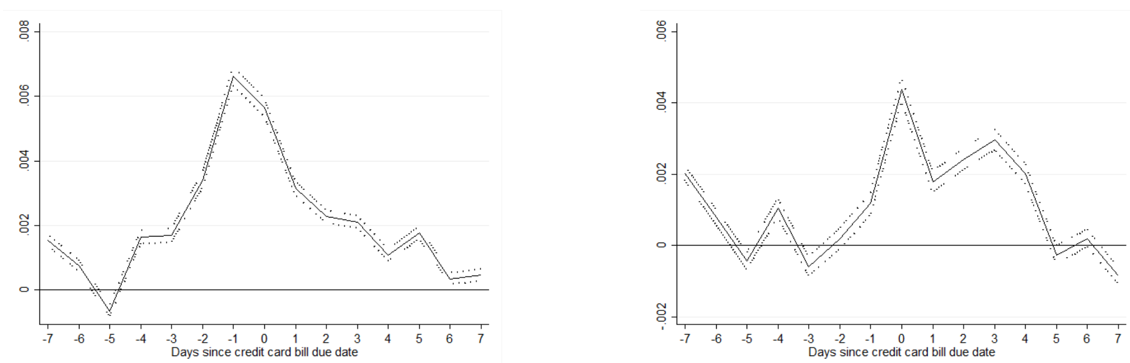

Figure 8: Propensity to log in around credit card bill due dates

Linear probability model of propensity to log in on dummies for the two weeks around credit card bill due dates controlling for individual and calendar fixed effects (on the left side we control for month-by-year, day-of-week, and holiday fixed effects, on the right side we control for month-by-year, day-of-month, day-of-week, and holiday fixed effects). Standard errors are clustered at the individual level.

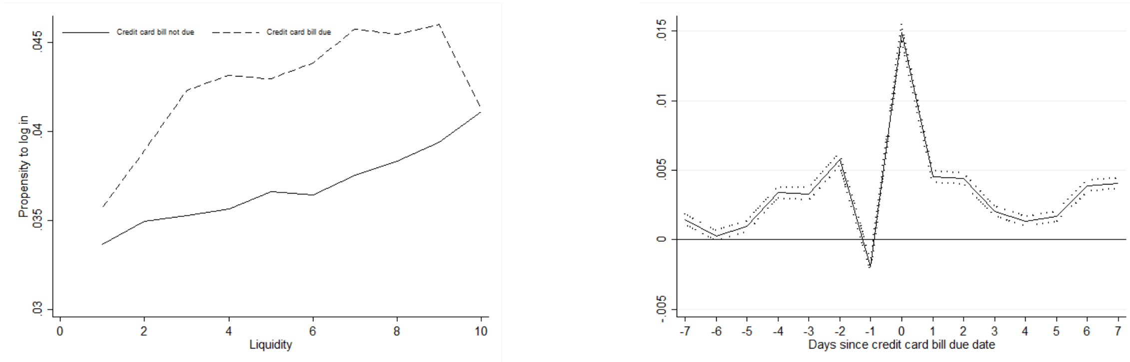

Figure 9: Differences in propensity to log in on paydays versus other days as functions of individual spending and on credit card due dates versus other days as functions of individual liquidity and endogenous log in response before reductions in credit card balances

Left side: Coefficients on day of credit card due date of propensity to log in in linear probability model for ten deciles of individual liquidity relative to own history of individual liquidity controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Right side: Endogenous logins before reductions in credit card balances.

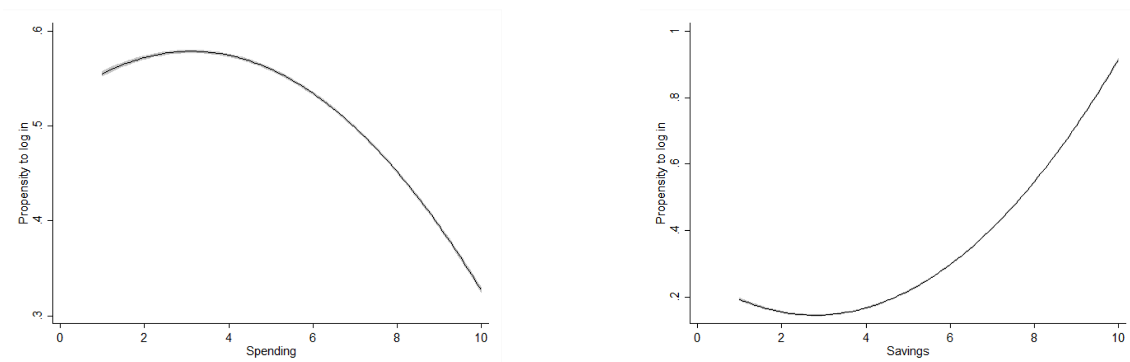

Figure 10: Propensity to log in by deciles of spending and savings

Quadratic fit of logit regression coefficients for each decile of individual spending or savings account balance relative to individual's own history of spending or saving controlling for individual and calendar fixed effects.

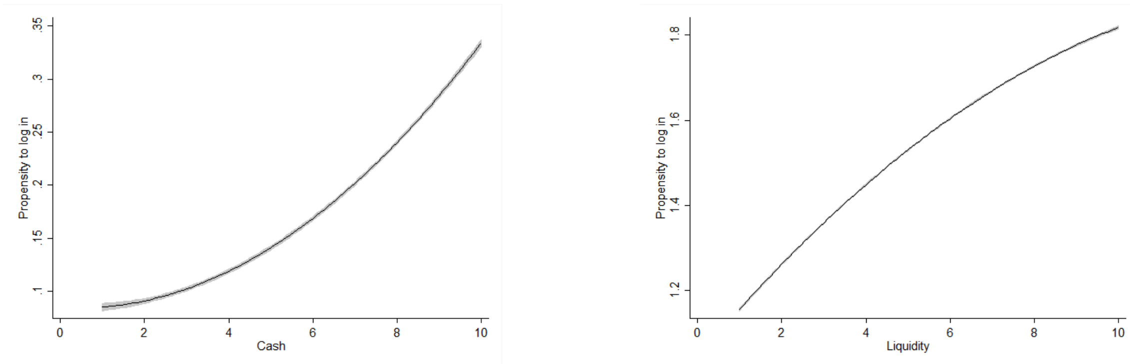

Figure 11: Propensity to log in by deciles of individual cash and liquidity holdings

Quadratic fit of logit regression coefficients for each decile of individual cash (positive checking account balance plus savings account balance) or liquidity (checking account balance plus credit card balance plus overdraft and credit limits plus savings account balance) relative to individual's own history of cash or liquidity controlling for individual and calendar fixed effects.

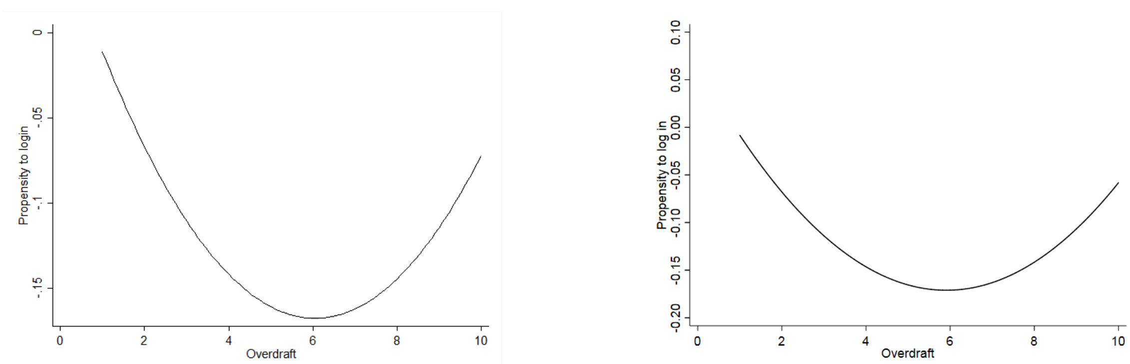

Figure 12: Propensity to log in by deciles of individual overdraft

Quadratic fit of logit regression coefficients for each decile of individual overdraft relative to individual's own history of overdrafts controlling for individual and calendar fixed effects, with and without controlling for savings account balances.

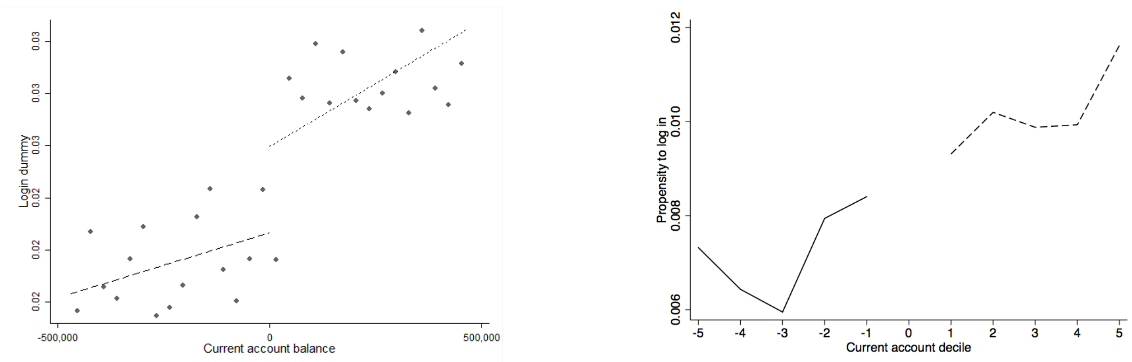

Figure 13: Propensity to log in by deciles of individual overdraft and by the checking account balance

Left side: Binned checking account balances in a cross-sectional comparison including only individuals who have negative and positive checking account balances. Right side: Regression coefficients for each decile of individual overdraft relative to individual's own history of overdrafts and the positive checking account balance relative to individual's own history of positive checking account balances, controlling for individual and calendar fixed effects as well as for the receipt of payments, overdraft limits, and savings account balances.

Table 4: Effects of relative bank account balances on logins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overdraft deciles:										
-1	0.0080***	0.0078***	0.0073***	0.0080***	0.0073***	0.0137***	0.0134***	0.0124***	0.0136***	0.0122***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
-2	0.0068***	0.0068***	0.0063***	0.0070***	0.0064***	0.0104***	0.0104***	0.0094***	0.0108***	0.0096***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
-3	0.0064***	0.0064***	0.0059***	0.0064***	0.0059***	0.0106***	0.0107***	0.0097***	0.0108***	0.0097***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
-4	0.0085***	0.0085***	0.0081***	0.0083***	0.0079***	0.0137***	0.0136***	0.0127***	0.0132***	0.0125***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
-5	0.0090***	0.0089***	0.0085***	0.0086***	0.0084***	0.0149***	0.0146***	0.0138***	0.0141***	0.0136***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
checking account balance deciles:										
1	0.0095***	0.0093***	0.0089***	0.0095***	0.0093***	0.0150***	0.0147***	0.0139***	0.0148***	0.0145***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
2	0.0105***	0.0104***	0.0101***	0.0103***	0.0102***	0.0159***	0.0158***	0.0151***	0.0157***	0.0154***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
3	0.0104***	0.0104***	0.0100***	0.0100***	0.0099***	0.0160***	0.0160***	0.0153***	0.0154***	0.0151***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
4	0.0107***	0.0107***	0.0104***	0.0101***	0.0099***	0.0176***	0.0175***	0.0169***	0.0165***	0.0162***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
5	0.0131***	0.0127***	0.0127***	0.0118***	0.0116***	0.0211***	0.0202***	0.0201***	0.0184***	0.0181***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
#obs	9,731,072	9,731,072	9,731,072	9,731,072	9,731,072	9,731,072	9,731,072	9,731,072	9,731,072	9,731,072
#individuals	11,008	11,008	11,008	11,008	11,008	11,008	11,008	11,008	11,008	11,008
Day of week FE			✓	✓	✓			✓	✓	✓
Day of month FE				✓	✓				✓	✓
Savings					✓					✓
Overdraft limit					✓					✓

Note: [a] This table shows regression results for logins on overdraft and checking account deciles (relative to individual's own histories) controlling for individual, month, and year fixed effects (in addition to the calendard fixed effects illustrated in the table). Additionally, all regressions except for (1) and (5) control for whether payments were received. Standard errors are clustered at the individual level.

[b] Significance levels: * p<0.1 ** p<0.05 *** p< 0.01