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

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Abstract

A number of theoretical research papers in both micro- and macroeconomics model and analyze attention, but direct empirical evidence is scarce. In this paper, we analyze the determinants of attention to financial accounts using panel data from a financial-management software provider including 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, they suggest that information- or belief-dependent utility generates selective attention and Ostrich effects. First, we find that individuals are considerably more likely to log in and pay attention to their finances because they get paid. Second, we show that attention is decreasing in spending and overdrafts and increasing in cash holdings, savings, and liquidity *within* individuals' own histories. Third, attention jumps discretely when balances change from negative to positive. We finally show that some of our findings can be explained by a recent influential model of belief-dependent utility developed by Kőszegi and Rabin (2009).

Keywords: attention, personal finance, consumer debt, liquidity, spending
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*Department of Finance, Copenhagen Business School. ao.fi@cbs.dk

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

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1 Introduction

Recent theoretical literature in asset pricing and macroeconomics introduces attention as an explanatory mechanism and shows that it matters for aggregate dynamics (e.g., Woodford, 2009; Reis, 2006; Gabaix and Laibson, 2002; Van Nieuwerburgh and Veldkamp, 2009). Moreover, a number of microeconomic papers model attention (e.g., Caplin and Leahy, 2001; Golman and Loewenstein, 2015; Kőszegi and Rabin, 2009; Ely et al., 2015; 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 attention and inform the theoretical literature, we undertake a large-scale empirical study of individual attention to checking, savings, and credit card accounts.

We study the determinants of paying attention to financial accounts using data from a financial aggregation and service software from Iceland that individuals can use to check their bank accounts, but not to execute financial transactions.[1] We use online account and smartphone app logins to measure individual attention following three studies that analyze online account logins to retirement portfolios (Sicherman et al., 2015; Karlsson et al., 2009; Gherzi et al., 2014).[2] In addition to tracking attention, we also have high-frequency transaction-level data on income, spending, balances, and credit limits.

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, that is, by 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 illustrated in Figure 1, which shows how logins change with checking account balances. We see a positive correlation between account balances and logins and a jump when balances go from negative to positive. Furthermore, casual observation of the media suggests that fearing to check bank account balances is, in fact, common.

Standard economic models predict that information is more valuable when it helps individuals make better decisions. Theories of rational inattention posit that individuals trade off mechanical

[1] The present paper focuses solely on the determinants of paying attention and not on its consequences. For an analysis of the causal effect of paying attention to personal finances, we refer to Carlin et al. (2017).

[2] Logging in to financial accounts can be interpreted as paying attention to personal finances. Alternatively, it could be interpreted as deciding 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).

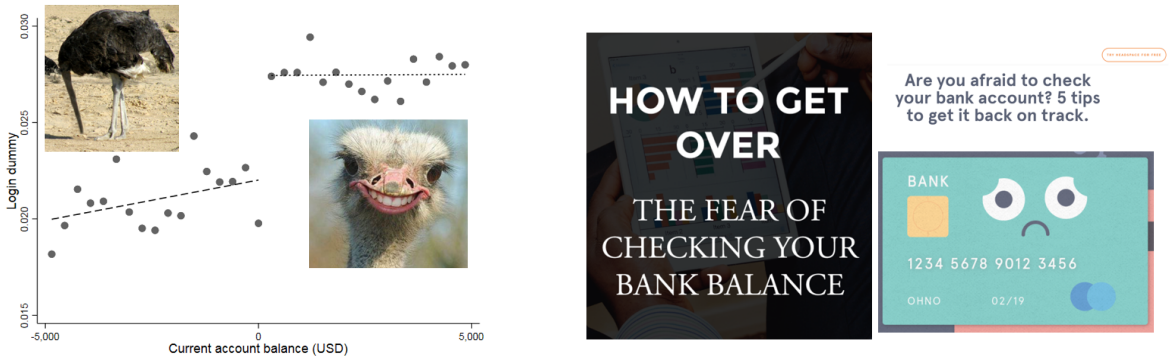


Figure 1: Binned averages of logins by checking account balances (raw data) and casual media observations (sources: www.wealthy-money.com and www.headspace.com)

costs and benefits of acquiring and processing information where the costs include information-processing costs and time and opportunity costs and its benefits include potential improvements in decision making. There are countless situations where information is useful and sought after, but situations also occur where people seek out apparently useless information or avoid useful information (see Golman et al., 2016, for a survey of the literature).[3] In light of this evidence, a literature on information-dependent and belief-dependent utility has emerged positing that information also has a hedonic impact on utility that goes beyond mechanical costs and benefits.[4] We 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.

Macroeconomic models of rational inattention would be likely to generate different aggregate dynamics if inattention were selective (additional studies assuming rational inattention include; Andrei and Hasler, 2014; Gabaix, 2016; Chien et al., 2012; Paciello and Wiederholt, 2013). Thus, our findings are important for the assumptions and implications of rational inattention models. Our

[3]There is a growing literature analyzing when people seek useless information or avoid useful information even when it is free. Casual observation and theoretical, laboratory, and field research suggest that this behavior is quite common. Specifically, investors are inattentive to their portfolios (Bonaparte and Cooper, 2009; Brunnermeier and Nagel, 2008) and may actively avoid looking at them when the stock market is down (Karlsson et al., 2009; Sicherman et al., 2015). Individuals at risk for health problems (e.g., serious genetic conditions or STDs) often avoid medical tests even when the information is costless and should, logically, help them 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, the laboratory findings of (Zimmermann, 2014; Falk and Zimmermann, 2014; Eliaz and Schotter, 2010; Powdthavee and Riyanto, 2015) underscore the importance of attention for belief-dependent utility.

[4]Starting with Loewenstein (1987), recent theoretical work has made substantial progress in modeling the notion that beliefs about and anticipation of future consumption can have direct utility consequences (in addition to the studies mentioned; Caplin and Leahy, 2004; Kőszegi and Rabin, 2006, 2009; Epstein, 2008; Dillenberger, 2010; Bénabou, 2012; Brunnermeier and Parker, 2005; Strzalecki, 2013).

findings are also relevant to the literature on information costs. If individuals are sometimes willing to pay in order not to receive information (which can be inferred from this study in connection with our companion paper Carlin et al., 2017),[5] then information costs are time-variant in non-trivial ways and sometimes effectively negative rather than positive (studies modeling information costs include; Abel et al., 2013; Alvarez et al., 2012; Huang and Liu, 2007; Van Nieuwerburgh and Veldkamp, 2009, 2010). Furthermore, because individuals in dire financial standings do not pay attention, which consequently exacerbates things, our findings relate to the literature on poverty traps (see Azariadis and Stachurski, 2005, for a literature survey) and on poverty and cognitive function (Mani et al., 2013; Carvalho et al., 2016). Finally, our findings are important for policy prescriptions or (field) experimental interventions where it is important to take into account that inattention is highly selective rather than rational (see DellaVigna, 2009, for a literature survey).

We first look at the individual propensity for paying attention to financial accounts in response to regular income payments–those that always arrive on the same day of the month. Because we use individual, day-of-week, day-of-month, holiday, and month-by-year fixed effects, we single out an exogenous source of variation in payment date due to weekends and holidays (i.e., the payday is moved when it would otherwise fall 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 because of getting paid.

To interpret this finding, we argue that a rationally inattentive agent, who is subject to information costs and benefits but does not experience information- or belief-dependent utility, would behave differently. We compare our empirical evidence to four rational hypotheses about when individuals log in:

1) irrespective of their transactions because there is either full uncertainty or no uncertainty associated with them,

2) for transaction verification,

3) to budget or to plan spending, and

4) when opportunity costs are low.

Hypothesis 1 can be ruled out, as we show that income arrival causes logins. Furthermore, a number of other empirical results are inconsistent with Hypothesis 2: (a) We find the same magnitude in log in responses to salary and to irregular or exogenous payments, for which the

[5] In Carlin et al. (2017), we find that an exogenous increase in logins causes a reduction in overdrafts, saving users approximately $2.50 in overdraft fees per login. Nevertheless, in this paper, we document that individuals log in less often when they hold large overdrafts relative to their personal histories of overdrafts.

transaction verification motive should be more relevant (recall that for identification purposes, we look only at salary payments that arrive on the same day of the month throughout the sample period). (b) We do not find a larger login response on paydays with many other transactions even though other transactions should increase the need for transaction verification. (c) The login response on paydays is higher when liquidity or cash holdings are high, but the verification motive should be negatively affected by liquidity. This finding is also inconsistent with Hypothesis 3, a higher login response on paydays when liquidity or cash holdings are high does not square with the fact that individuals should care more about budgeting when liquidity or cash holdings are low.[6] Here, it is important to note that we are identifying only within-individual variation, i.e., we sort every individual's observations of cash, liquidity, and spending into his or her personal deciles to compare individuals *within their own histories*. Finally, we can address Hypothesis 4 because the positive relationship between logins and income arrival is unaffected by spending, a potential measure of opportunity costs.[7] Finally, when we look at two or more logins, we find an even larger spike on paydays even though all payments post in the morning. We thus conclude that individuals log in because they enjoy seeing money in their bank accounts and probably experience a form of anticipatory utility.

We also examine the direct relationship between logging in, spending, and financial standing, such as liquidity and cash holdings. Again, we identify within-individual variation by constructing individual-specific deciles of spending and financial standing based on each individual's personal history. This allows us to analyze attention in different situations within that individual's own history. This means that none of the results reflect cross-sectional differences. Moreover, we control for individual fixed effects and thereby all self selection on observable or unobservable time-invariant characteristics. Furthermore, the inclusion of the aforementioned set of calendar fixed effects (day-of-week, day-of-month, month-by-year, and holidays) effectively identifies irregular variation within a given month that is not driven by week or holiday patterns. 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. Individual attention

1) decreases with individual spending and increases with individual savings,

2) increases with individual cash holdings and liquidity,

[6] In Section 5, we formally show that every risk-averse agent finds consumption smoothing more beneficial at low income or wealth levels if her utility function also features prudence.

[7] The fact that we document a negative relationship between logins and spending (especially time-consuming spending, such as restaurant meals and home improvement) suggests that spending can be used to measure opportunity costs.

3) decreases with individual overdrafts, especially of intermediate amounts,

4) jumps discontinuously when checking account balances change from negative to positive.

As before, we consider rational theories of inattention for all of these findings: transaction verification, budgeting, planning, and opportunity costs. However, for each case, we argue that the theory is inconsistent with the collection of our empirical findings.

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	✗	✗	✗	(✓)	✗	(✓)
Logins jump when balance turns positive	✗	✗	✗	(✗)	✗	✓

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

Table 1 summarizes our empirical findings and the theories we consider. We indicate whether each theory could easily be modified in coherence with our findings. Overall, we feel that most

of the findings are consistent with two specific forms of selective attention: anticipatory utility and the so-called 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–whether from income payments or wealth shocks–or large cash and liquidity holdings causing individuals to log in to their accounts more often. By contrast, in dire times, when individuals feel they have overspent and hold little cash or large overdrafts, they prefer not to pay attention.[8] Two important differences between logging in to retirement accounts, as analyzed by Karlsson et al. (2009), and logging in to bank accounts are the following: (1) We know that individuals can save money by paying more attention to their accounts (Carlin et al., 2017), but we are not sure whether individual investors have any skill in stock picking or market timing.[9] That is, logging in may be useless for portfolios but not for bank accounts. (2) Uncertainty about financial account balances is considerably lower than uncertainty about portfolios. Documenting selective attention in the domain of checking, savings, and credit card accounts is therefore of independent interest.

While our empirical findings point toward Ostrich effects and anticipatory utility as a first-order determinant for paying attention to financial accounts, we also think that the avoidance of fees is a determinant of logging in. The individuals in our sample incur substantial fees that they could avoid by logging in to their accounts more often, as established in Carlin et al. (2017). Furthermore, Stango and Zinman (2014) document that individuals respond to surveys about overdrafts by paying greater attention to account balances and incurring less in fees and Medina (2016) finds that reminders for timely payment reduce credit card late fees.

We thus try to reconcile and formalize intuitions consistent with our empirical evidence regarding attention: that individuals check their accounts more often when they have received income and hold more cash, and that individuals worry about incurring fees. To do so, we use the

[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. This is in spite of the fact, as shown by Olafsson and Pagel (forthcoming), that very few individuals are actually hitting their credit limits even right before regular paychecks. Nevertheless, individuals may have personal rules about how much consumer debt they will take. In fact, we see attention being U-shaped in overdrafts, and thus we find some reversal in attention when individuals hit their own personal records in overdrafts.

[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 period from 2013 to 2014. Nevertheless, over longer time periods, Barber and Odean (2000) show that individual investor who trade heavily underperform by approximately their trading costs.

belief-dependent utility model developed by Kőszegi and Rabin (2009). In this model, agents derive utility not only 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 hurts more than good news pleases. This assumption implies that expecting to receive news entails a first-order disutility. Thus, the agent is averse to receiving news even if the uncertainty is very low—which is likely to be the case for bank account balances.[10] However, if the agent is wealthier, news hurts 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 and the benefits of staying fully informed and avoiding fees, she may pay more attention in good financial standing. Thus, the model succeeds in explaining two key empirical findings: individuals are averse to paying attention to bank account balances even when uncertainty is low and especially when they are in dire financial standing.[11]

The remainder of the paper is organized as follows. We provide a data description and summary statistics in Section 2. In Section 3, we document all our empirical findings. In Section 4, we discuss in how far rational theories of inattention can explain our empirical findings. In Section 5, we analyze a theoretical framework for selective inattention. Finally, Section 6 provides our conclusions.

2 The financial management software and summary statistics

2.1 The financial management software

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 currently used by more than 50 million people in 20 countries. The company allows financial institutions to offer their online customers or smartphone app users a platform for connecting all their financial accounts, including bank accounts and credit card accounts, in a single location. Each day, the software automatically records all the users' bank and credit card transactions, including descriptions as well as balances, overdrafts, and credit limits. This data set has already been used for studying individuals' spending responses to income arrivals and the effect of increased

[10] By analyzing the jump in attention when balances change from negative to positive in a number of narrow bins, we can determine how well individuals predict their balance. It appears that individuals know their balances up to bins of approximately $50.

[11] Nevertheless, as the model is fully based on consumption, it cannot generate a response to perfectly predictable payments or a jump in logins when balances turn positive.

access to information about personal finances on individual financial fitness (Olafsson and Pagel, forthcoming; Carlin et al., 2017).

The digitization of budgeting processes with financial aggregation software and the attendant tracking of online and smartphone app behavior allow direct measurement of individual attention in ways that were not previously possible. The Meniga software allows the tracking of individual attention in addition to providing high-frequency income and spending data derived from the individuals' transactions and account balances. This data source overcomes the limitations of accuracy, scope, and frequency that earlier sources of consumption and income data face. Gelman et al. (2014) and Baker (2014) were the first to advance the measurement of income and spending using data of this sort from the US. We use data from Iceland, which has four main advantages: (1) It essentially eliminates the remaining limitation of the earlier app data–the absence of cash transactions–because Icelandic consumers use electronic means of payments almost exclusively.[12] (2) The software is marketed through banks, ensuring that it covers a fairly broad fraction of the population. (3) The spending and income data are pre-categorized, and the categorization is very accurate with few uncategorized transactions. (4) All the financial accounts are personal.

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 our analysis on daily user-level information on income by source, on spending by category, on logins by device, and on financial standing such as account balances, overdrafts, overdraft limits, credit card balances, and credit card limits. In January 2014, the population of Iceland counted 338,349 individuals, of whom 262,846 were above the age of 16. At that time, Meniga had 52,545 users, or 20 percent of the population above age 16. Because the software is marketed through banks, i.e., individuals can sign up when they sign up for online banking, the sample of Icelandic users is fairly representative. Moreover, the internet penetration is 97 percent in Iceland and almost everyone uses online banking. In addition to information on income, spending, account balances, and attention, the software collects some demographic information, such as age, gender, and postal codes. Moreover, we can infer whether individuals have (small) children, their employment status, and whether they own real estate.

Figure 2 displays screenshots of the app's user interface. The first shows background characteristics that the user provides, the second shows transactions, and the third shows bank account information. The first versions of the app did not include elements of financial advice, although Meniga advertised it as a tool for keeping track of individual finances. Later versions of the app, however, will flag certain events, such as unusually high transactions, deposits, or low balances. Examples of these flags are displayed in Figure 3. It is important to note, though, that the app does

[12] ATM withdrawals make up approximately 1 percent of spending transactions by volume.

not send push notifications. Users have to log in to see these messages. Furthermore, in the last two years, Meniga has expanded the app's merchant offer features.

{Figures 2 and 3 around here}

It is important to reiterate that the app does not send reminders or notifications and users cannot perform transactions or pay bills through the app. Therefore, users do not see their credit card bills in the app and cannot receive push notifications due to unpaid bills, overdrafts, or low balances. They only see any notifications after they log in. Specifically, messages appear next to irregular transactions, if an account balance is very low, or an income transaction arrived saying "you got paid." However, as mentioned, users need to be logged in already to see these messages.[13]

2.2 Summary statistics

Income, spending, and demographics: We study all active users with complete records, i.e., for whom we see all balances as well as regular (at least once per month) salary and grocery transactions. Table 2 displays summary statistics including income and spending in US dollars across login and income terciles. It also displays some demographic statistics. Overall, the sample's characteristics with respect to age, gender, employment, income, and spending figures are remarkably similar to those in the representative national household survey conducted by Statistics Iceland, as can be seen in Table 3. This fact is reassuring because app data often come with a very selected sample of young and tech-savvy folks.[14]

{Table 2 and 3 around here}

It can be seen in Table 2 that individuals who use the software frequently are marginally wealthier, are slightly less indebted, and pay less financial fees, than those who do not. However, none of these differences are statistically significant. We thus conclude that not only does the overall sample look representative, but so does the sample of individuals causing most of the variation in logins.

[13] To ensure that our results are not driven by the smartphone app features, we can only look at the period where no smartphone app was available and individuals had to log in via a desktop. We find the same results in the pre and post smartphone app period.

[14] For instance, roughly half of our users are female, a much higher number than those in other papers using data of this kind.

Logins: Figure 4 shows the distribution of daily login rates by 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 beginning and end of the month and more on workdays than weekends. Figure 5 displays whether or not men and women log in on particular days when they receive different types of income payments. It can be seen that all individuals log in more often when they are paid, but also that there are large differences in the login responses to different payments. Again, men log in more often on average.

{Figures 4 and 5 around here}

3 Analyses and empirical findings

In this section we describe our empirical setting and the baseline identification strategy we employ to uncover the effects of income arrivals and of credit card due dates on logins. In turn, we explore how logins correlate with measures of individual financial standing, such as cash holdings, overdrafts, and liquidity, and with individual spending. We first present all empirical results and then discuss in how far they can be explained by various theories of rational or selective inattention.

3.1 Attention in response to income payments

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

$$I_i(Login_t) = \sum_{k=-14}^{14} \beta_k I_i(Paid_{t+k}) + \delta_{dow} + \phi_{dom} + \psi_{my} + \xi_h + \eta_i + \epsilon_{it} \quad (1)$$

where $I_i(Login_t)$ 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 one if individual i receives a payment at time $t+k$ and to zero otherwise. The β_k coefficients thus measure the fraction by which income arrival increases the probability of logging in on the four surrounding weeks. 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 of logins. The day-of-month dummies capture within-month patterns of logins. We restrict the income payments to regular payments that occur on a fixed day of the month. When a payday falls on a weekend or holiday, it is moved to the most recent working day or the next

one. Weekends and holidays generate therefore an exogenous source of variation in the day of the month that income arrives.[15] Standard errors are clustered at the individual level.

Figure 6 displays the effect of salary arrival on login rates in the four weeks surrounding the salary receipt. The β coefficient is five times larger on paydays than on days surrounding payment receipt. Compared to averages login rates, individuals are 62 percent more likely to log in on the day they get paid.[16] Figure 7 shows responses to irregular income payments, such as insurance claims, dividends, and grants, and plausibly exogenous income payments, such as lotteries and tax rebates. It can be seen that the login response is very similar in magnitude for irregular and regular payments.

{Figures 6 and 7 around here}

Furthermore, to analyze the effect of cash, liquidity, and spending on attention to financial accounts on paydays we run the following regression:

$$I_i(Login_t) = \sum_{d=1}^{10} \beta_d I_i(Paid_t) * I_i(Liq_{dt}) + \delta_{dow} + \phi_{dom} + \psi_{my} + \xi_h + \eta_i + \epsilon_{it} \qquad (2)$$

where the variables $I_i(Login_t)$, δ_{dow}, ϕ_{dom}, ψ_{my}, ξ_h, η_i, and $I_i(Paid_t)$ are as specified above and $I_i(Liq_{dt})$ is an indicator variable for each liquidity decile d of individual i (relative to individual i's own average liquidity) on date t. 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 examine the effect of cash holdings on attention to financial accounts. Figure 8 displays the relationship between logging in on paydays and on other days for different levels of individual cash and liquidity holdings. 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 than the baseline probability (around 3 percent per day) for low cash holdings, and are around 200 percent more likely to log in for large cash holdings or liquidity.

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

[16] We know from Olafsson and Pagel (forthcoming) 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, so we conclude that spending is not the mechanism by which income affects attention.

{Figure 8 around here}

Figure 9 (left side) shows the login response to regular income payments interacted with spending where no clear relationship between spending response on paydays and logins is visible. Moreover, Figure 6 suggests a unique spike on paydays, however, in the regression specification (1), the day-of-month fixed effects mask a payday cycle, as we will show now. Figure 9 (right side) 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 see a clear payday cycle that is not captured by the day-of-month fixed effects or the calendar cycle. In summary, individuals log in most often on paydays for regular payments, and their logins steadily decline after that.

{Figure 9 around here}

3.2 Attention in response to credit card bill payments

In Iceland, credit card bills are due on the 2nd of the month and weekends and holidays generate therefore an exogenous variation in bill payments in the same way as for paydays.[17] We can thus use the same identification strategy as before to assess the attention response to regular credit card bill payments. Figure 10 displays login responses to credit card due dates for different deciles of cash holdings and liquidity. Individuals are more likely to log in on the days they have to pay credit card bills, although the magnitude is only half of that of regular and irregular incoming payments. Furthermore, this login response to credit card payments is increasing in both cash holdings and liquidity (within individuals' personal histories).

{Figure 10 around here}

3.3 Attention, balances, liquidity, and spending

To estimate the effect of how much individuals spend and save on the probability of logging in, we run the following logit regression:

$$I_i(Login_t) = \sum_{d=0}^{10} \beta_d I_i(S_{dt}) + \psi_{my} + \phi_{dom} + \delta_{dow} + \xi_h + \eta_i + \epsilon_{it} \tag{3}$$

[17] The majority of credit cards are paid automatically.

where $I_i(Login_t)$, ψ_{my}, δ_{dow}, ϕ_{dom}, ξ_h, and η_i are as specified above. Thus, we control for individual, day-of-week, day-of-month, month-by-year, and holiday fixed effects. $I_i(S_{dt})$ is an indicator variable that is equal to 1 if individual i is in spending (savings) decile d on date t. The spending (savings) deciles are constructed by first calculating how much one individual spends (saves) in comparison to how much she spends (saves) on average and then we split this measure of individual's relative spending (savings) into 11 groups. The first group is zero spending (savings), and the remaining groups split the individual's spending (savings) into deciles. The estimated effect of being in each spending (savings) decile is therefore comparing the individual's propensity to log in to her probability of logging in when he spends (saves) nothing.

Although we are technically reporting correlations, in practice the set of fixed effects imposes a high bar for selection, omitted-variable bias, and reverse causality. All selection on time-invariant (un)observables is controlled for because we include individual fixed effects and only compare individuals within their own histories. Moreover, the calendar fixed effects, day-of-week, day-of-month, month-by-year, and holiday, control for all recurring planning motives. Therefore, we are left with variation within a given month that cannot be driven by calendar effects because the fixed effects pick up all recurring patterns in income and spending within a given month. Finally, we know from our companion paper (Carlin et al., 2017) that logins do not cause substantial changes in spending patterns at short horizons limiting the potential impact of reverse causality.[18]

Figure 11 displays the estimated effect of how much individuals spend (save) relative to their own average on the probability of logging in. We find that individuals are in general less likely to log in when they spend more. Spending increases the odds of logging in, but low spending less than high spending. The fact that the coefficient on high spending deciles is more than 0.2 lower for the highest spending deciles than the lowest spending decile means that the odds of logging in drop by more than 30 percent by going from the lowest spending decile to the highest. By contrast, individuals are more likely to log in when they have high levels of savings relative to their personal history.

{Figure 11 around here}

We reestimate specification (3) where we replace spending (savings) deciles with cash and liquidity deciles to uncover the effects of cash holdings and liquidity on the propensity to log in. Figure 12 displays the propensity to log in by decile of individual cash (savings plus positive

[18] Carlin et al. (2017) find that individuals reduce their payment of overdraft and late fees after logging in more frequently, however, this effect is observed over several months after the mobile app introduction of the financial management software. Such reverse causality would thus be picked up by the month-by-year fixed effects.

checking account balances) and liquidity (savings plus credit limits plus checking account balances minus credit card balances). Note that all balances are measured in the morning, so spending on that day does not affect balances. In the same way as before, each individual's cash holdings are split into 11 groups, group 0 for when the individual holds no cash and groups 1 to 10 are for deciles of cash or liquidity held within the individual's personal history. 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 see that cash holdings and liquidity are positively related to logging in, that is, individuals log in more often when they have more cash or liquidity.

{Figure 12 around here}

Next we reestimate specification (3) where we replace spending (savings) deciles with deciles of overdraft debt. As before, we thus split each individual's overdraft debt into 11 groups, group 0 for no debt holdings and groups 1 to 10 for deciles of the debt value. Figure 13 (left side) displays the propensity to log in by decile of overdraft debt. Here, we see that holding debt is always negatively correlated with logging in. Specifically, the coefficient on overdrafts is always negative, implying that individuals log in less often when they carry any overdraft. While overdrafts always reduce logins, the effect is U-shaped among negative overdrafts, that is, having little or a lot of overdraft reduces logins less than having an intermediate amount.

{Figure 13 around here}

Finally, we estimate the effect of deciles of checking account balances on the propensity to log in in the same way as before. In Figure 14 (left side), we first display the raw data showing that logins jump discretely when the checking account balance changes from negative to positive. It is important to note that the figure includes only individuals who have both positive and negative checking account balances at times 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. 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 bolsters the robustness of our previous findings.

Figure 14 (right side) illustrates the estimated jump from a regression controlling for individual and calendar fixed effects (and, in additional specifications, for the receipt of payments, overdraft limits, and savings account balances). Specifically, it displays the regression coefficients for each

decile of individual overdraft relative to the individual's personal history of overdrafts and the positive checking account balance relative to the individual's history of positive checking account balances. We clearly see a discontinuous increase at zero larger than the linear differences in the regression coefficients before and after the first deciles. Table 4 illustrates in detail how the regression coefficients change with the addition of controls, and documents standard errors to verify that all the regression coefficients are statistically significantly different from each other.

{Figure 14 and Table 4 around here}

4 Theories of rational inattention

Our findings are informative about the modeling assumptions in the theoretical literature on inattention. The theoretical predictions differ majorly depending on how inattention is modeled: inattention can be driven by exogenous information costs–what we call rational inattention–or psychological costs–what we call selective inattention. To evaluate existing theories in light of the empirical evidence, we first discuss how a rationally inattentive agent, one who is subject to mechanical information costs and benefits but does not experience information- or belief-dependent utility, would behave. As we outlined in the introduction, we consider a number of rational benchmarks and provide additional empirical evidence for or against each of them.

4.1 Perfect information or perfect uncertainty

A basic benchmark to consider is one where individuals could log in irrespective of their transactions because there is either full uncertainty or no uncertainty about them. We argue that this hypothesis can be ruled out because income arrival causes logins and we find specific patterns between balances, spending, and logins despite controlling for individual and calendar fixed effects. Therefore, we conclude that individuals face some intermediate uncertainty about their transactions and balances.

4.2 Transaction verification

Transaction verification is certainly a reason to log in to financial accounts. However, we do not think that it is of first-order importance for the login response to income payments we see for the following six reasons. (1) For identification, we only use payments that arrive on a fixed day of the

month to ensure that weekends and holidays generate exogenous variation in the day of the month that income arrives. Moreover, by using only payments that arrive on a fixed day of the month throughout the sample period, we can address transaction verification as a motive for logging in, as there should be no news associated with the payment arrival. (2) We find almost the same responses in magnitude to both irregular and exogenous payments, for which the transaction verification motive should be more relevant. Figure 7 shows responses to irregular income payments, such as insurance claims, dividends, and 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 reflect a transaction-verification motive, which we thus do 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 (also in Figure 7). (3) 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 login is unlikely to be explained by individuals not being able to verify the payment upon the first login because the vast majority of income payments are posted early in the morning. (4) The login response to income arrival is increasing in cash holdings and liquidity (see Figure 8) even though transaction verification should be more important when liquidity is low. (5) As we show in Figure 9, there is no relationship between other transactions, such as spending, and the login response even though the motive for verification should be stronger when there are many other transactions. (6) Finally, very generally, there is a negative relationship between transactions, such as spending, and logging in (see Figure 11).

4.3 Budgeting

Individuals in dire financial straits might log in to budget their spending. However, the following three empirical findings stand in stark contrast to the predictions of the budgeting hypothesis. (1) Empirically, we find that the login response to paydays is higher when cash holdings and liquidity are large, but the budgeting hypothesis implies that individuals in relatively good financial standing should care less about budgeting. Individuals should care more about budgeting and pay more attention when liquidity and cash holdings are low because, theoretically, agents with prudent utility functions benefit more from consumption smoothing at low wealth levels (as we formally show in Section 5). (2) We find that both large incoming and large outgoing payments, that is, credit card payments on due dates, cause spikes in attention but incoming payments two times more so than outgoing ones. Although the spike in attention on credit card due dates would seem

to be consistent with individuals worrying about liquidity constraints, we also find that this increase in attention is increasing in cash holdings and liquidity, which is inconsistent with budgeting as a motive for logging in (see Figures 7 and 10). Furthermore, the variation in logins in response to low versus high liquidity appears to dominate the response in logins due to credit card payments. Individuals are around 30 percent more likely to log in in response to a credit card payment but the response varies from 10 percent to 100 percent for low versus high liquidity holdings. (3) Figure 13 (left side) shows that overdrafts always reduce logins and there is a U-shaped relationship of logging in as a function of overdrafts. Because logins are always reduced by overdrafts, and holding a relatively small amount of overdraft still reduces logins less than having a relatively large amount of overdrafts, we conclude that budgeting or liquidity constraints are not the main motivation for logging in.

4.4 Planning

Large cash holdings relative to individual's own histories imply future spending. Thus, the question is whether individuals use the app to rationally plan future spending. Although 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 account 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 (see Figures 11 and 12).

The relationship between logins and spending on paydays versus other days sheds further light on the validity of the planning hypothesis. There is less need to plan for future spending if individuals spent a lot on paydays. However, as shown in Figure 9, there is no relationship between the login response on paydays and individual spending on paydays.

4.5 Opportunity costs

Individual logins could be driven by opportunity costs. Clearly, opportunity costs are difficult to measure in our data. One potential measure of opportunity costs is how much individuals spend (relative to their personal history of spending). After all, contemporaneous spending reflects what individuals are doing.[19] Thus, an opportunity costs explanation for paying attention would suggest

[19]In Iceland, all spending transactions post immediately without delay, as there exists only one financial clearing house in the country processing all transactions.

that individuals log in less often when they are busy spending. As an alternative to concurrent spending, one can consider cash holdings as a measure of opportunity costs, as they reflect past spending (when spending has been high, cash holdings are low, so opportunity costs should be low).

We show (see Figure 11) that individuals tend to log in less when they spend a lot relative to their own history of spending, which is consistent with opportunity costs having an effect on logins. However, the positive relationship between the login response to regular payments and cash holdings in Figure 8 is inconsistent with opportunity costs driving logins because opportunity costs are low when cash holdings are low (as individuals spent a lot in the past).[20] Furthermore, the positive effect of income arrival is unaffected by spending (see Figure 9, left side), suggesting that opportunity costs are not of first-order importance when logging in.

We can further analyze the opportunity costs explanation by looking at overall spending versus restaurant spending. Figure 15 compares the variation in logins for deciles of overall spending and restaurant expenses within individual's own histories of overall and restaurant spending controlling for individual and calendar fixed effects. We can see that the reduction in logins is around 30 percent relative to the baseline probability of logging in for overall spending. For restaurant spending, by contrast, it is almost 100 percent. Thus, as suggested by an opportunity costs theory, time-consuming spending has a larger effect on the probability of logging in. Nevertheless, spending may also reduce available cash and liquidity which may be driving the reduction in logins. In fact, in Figure 16, we show that the variation in available cash or liquidity and the contemporaneous log in response appears to dominate the increase in logins due to high or low overall spending (again, all deciles and splits are constructed relative to individual's own histories).[21]

{Figures 15 and 16 around here}

4.6 Other potential explanations

4.6.1 Obtaining information by other means

Some of our findings, for instance, that overdrafts reduce logins, could be explained by the following: individuals cannot perform transactions using the app; therefore, when they want to transfer

[20] In principle, low cash today implies either high past spending or low past income. But we pick up the variation in past spending because we control for the monthly cycle using day-of-month fixed effects.

[21] Note that, in Figure 16, we analyze a linear probability model instead of a logit model just to illustrate the magnitudes more straightforwardly and also document the robustness of our results for different specifications.

money to repay large overdrafts, they have to log in to their online bank accounts. Thus, they obtain information about their balances and do not need to log in through the app or software additionally. To address this concern, we can look exclusively at individuals who have little or no savings (and hence cannot transfer money to their checking account). Focusing solely on this group of individuals, we find that the documented negative U-shape of overdrafts on attention is very robust. This result can be seen in Figure 13 (right side) which depicts regression results for individuals without transferable savings. More generally, we find that the U-shaped pattern is robust to controlling for savings account balances, other account balances, income payments, and overdraft limits in Table 4.

Furthermore, in Figure 17, we display the endogenous response to credit card payments. We use a dummy to represent days after which credit card balances decrease by at least 50 percent. We can see that making a payment increases 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 further alleviates the concern that individuals simply log in by other means when we see fewer logins through the app. Additionally, we can control for changes in balances to pick up potential transfer activity when individuals log in through their bank accounts.

{Figure 17 around here}

4.6.2 Worrying about finances implies less logins

It could be that if individuals have overdrafts, they worry about their personal finances and do not need to log in. In other words, individuals with overdrafts may be more aware of their financial standing and do not need to log in for extra information. However, this theory is inconsistent with our finding that individuals have a larger login response to income payments when they are in good financial standing (see Figure 8). A larger login response to regular income payments, varying because of weekends and holidays, implies that individuals can predict the income arrival better when they have high liquidity and cash rather than low levels of liquidity and cash.

When we analyze the jump in logins when balances turn from negative to positive in a range of narrow bins, we can determine how well individuals predict their balances. It appears that individuals know their balance up to bins of approximately $50.

5 Theories of selective inattention

From the previous discussion of rational-inattention theories, that is, mechanical costs and benefits, we conclude that overall the evidence appears to be more consistent with selective-inattention motives. Our results on income payments and cash holdings imply that individuals appear to log in because they enjoy seeing money in their bank accounts; that is, they experience a form of anticipatory utility. Figure 6 suggests a unique spike on paydays, however, an anticipatory utility story would suggest that logins should be higher on the following days too. Figure 9 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 see a clear payday cycle that is not captured by the day-of-month fixed effects or the calendar cycle.

The jump in logins suggests that as soon as individuals cease to 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. Moreover, even within overdrafts, individuals dislike logging in when they hold large amounts relative to little amounts of overdrafts. The same is true for cash holdings and savings: individuals dislike logging in when they have little cash or savings. These findings support the idea that Ostrich effects play a role in deciding whether or not to pay attention. On the other hand, we know from Carlin et al. (2017) that paying more attention causes a reduction in financial penalty payments and overdrafts so we know that paying attention is beneficial.

To back up our argument for selective inattention more formally, we now analyze a theory of selective inattention driven by 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 (forthcoming). This theory has been broadly applied in a number of domains and we are interested in how far it is able to explain our empirical findings. We will show that the model formalizes intuitions for two key empirical results: individuals dislike paying attention to their accounts, especially when cash holdings are low, but they also worry about fees. In the process, we also show formally that a rationally inattentive agent subject to exogenous attention costs would pay more attention if her wealth and income were low.

The agent experiences news utility as modeled by Kőszegi and Rabin (2009) and given by $\nu(u(c) - u(\tilde{c}))$ with $c \sim F_c$ representing his or her fully rational expectations about consumption. The agent may be positively or negatively surprised 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 $\nu(\cdot)$, which 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. In the following, we will formally show that the agent dislikes paying attention in general as it generates news disutility in expectation because bad news hurts more than good news pleases. This holds true even if uncertainty is very small—as likely to be the case for checking account balances. Moreover, we will show that the agent is more willing to pay attention when her income is high because paying attention is less painful on a less steep part of the concave utility curve.

We assume that if the agent does not check her accounts, she may incur a financial fee f whenever $\tilde{y} - \tilde{b} < 0$. If that happens, the fee will be subtracted from future consumption. By contrast, if she checks her accounts, we assume that she can avoid all financial fees simply by transferring money from other accounts, which does not affect her consumption. Thus, when she pays attention, she will not pay fees. All consumption takes place in the future and future consumption utility is discounted by $\beta < 1$. Furthermore, news utility about future consumption is discounted by $\gamma\beta$ and $\gamma < 1$.[22] In addition, $I(a)$ is an indicator variable equal to one 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 of paying attention is greater than the expected utility of being inattentive: that is,

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

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

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

[22] For the sake of exposition, we omit expected news utility in the future. Expected future news utility would only be another reason to pay attention in the present beyond avoiding the fee payment.

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

And we can easily establish the following comparative statics. When the fee is increased, so $f \uparrow \Rightarrow -\beta f F(-\frac{\mu}{\sigma}) \downarrow$, then paying attention is more likely. When overall cash holdings are increased and thereby the fee payment is less likely, i.e., $\mu \uparrow \Rightarrow F(-\frac{\mu}{\sigma}) = Prob(\tilde{s} < -\frac{\mu}{\sigma}) \downarrow \Rightarrow -\beta f F(-\frac{\mu}{\sigma}) \uparrow$, then paying attention 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 paying attention 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 that utility is concave which is an appropriate assumption for large stakes. To formalize the intuitions for a general utility function $u(\cdot)$, consider the risk premium when the agent pays attention, that is the compensating utility differential for paying attention when knowing or not knowing that $\tilde{s} = 0$:

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

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 $\frac{\partial\pi}{\partial\sigma}|_{\sigma\to 0}$. □

Thus, expecting to pay attention 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, in this approximation the effect of cash holdings, μ, affects the agent only through higher expected consumption,

not a lower likelihood of the fee payment. 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 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: $Y \sim log - N(\mu_{ann}, \sigma^2_{ann})$ 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, $\mu = \sigma$, and we can calculate the fraction Δ of monthly expected 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 for explaining the evidence in Kahneman and Tversky (1979) among 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 we obtain a decrease of 24 percent, which makes the agent much more likely to check, in line with our empirical findings (that the increase in the probability of logging in when one goes from low cash holdings to high cash holdings is approximately 25 percent). We conclude that the first-order willingness to avoid fee payments predicted by news utility can be a reasonable explanation for the amount of fee payments we see in the data and the main comparative static we obtain with respect to the likelihood to check accounts in response to low versus high cash holdings.

Nevertheless, the news-utility model is fully based on rational expectations about present and future consumption. As such, it cannot rationalize an increase in attention at a fully expected income payment or a jump in the probability of logging in when balances turn from negative to positive. To explain these findings, one would have to consider a model of myopia or another model in which income payments affect utility not through future consumption but independently so. We nevertheless think that the news-utility model succeeds on two important dimensions: first, it generates aversion to paying attention even when uncertainty is low because the agent cares about fluctuations in beliefs to a first-order extent, and second, it generates realistic variation in the willingness to paying attention for low versus high income or wealth.

Let's return to the standard agent. As we have just seen, the standard agent's risk premium is 0 for small risks. For large risks, the premium is positive if the utility function is concave. It is also 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

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

His risk premium for paying attention, that is the compensating utility differential for paying attention when knowing or not knowing that $\tilde{s} = 0$, is thus

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

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 0 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, because 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 her monthly consumption to avoid all monthly income uncertainty, not just for avoiding the fee payment (this assumption provides us with an upper bound independent of calibrating the fee). The answer is only 0.66 percent 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 first-order prudence about fee payment uncertainty cannot generate the amount of fee payments and the aversion to paying attention to financial accounts that we see in the data. We need first-order risk aversion and prudence to explain our findings under realistic income uncertainty at a monthly level.

6 Conclusion

Beyond the mechanical costs and benefits of paying attention to financial accounts, attention may have a hedonic impact on utility by causing anxiety or anticipatory feelings. In response to casual observation and empirical evidence on information avoidance, predominantly in health and medical domains and the laboratory, a literature on information-dependent and belief-dependent utility has emerged. Moreover, there exists a sizable theoretical literature in asset pricing and macroeconomics showing that rational inattention, that is, information costs and benefits, matters for aggregate dynamics. The open question whether inattention is mostly selective as opposed to rational should be answered by more empirical evidence.

In this paper, we use data from a financial aggregation software and app that allows individuals to manage all their accounts and credit cards from multiple banks in a single place. The digitization of budgeting processes and the attendance tracking of online behavior allow us to directly measure individual attention in ways that were not possible before and simultaneously provides us with data on spending, income, balances, and credit limits that are characterized by outstanding accuracy and comprehensiveness.

Using this information on attention, income, spending and financial standing, we find evidence consistent with selective attention, more specifically, Ostrich effects and anticipatory utility. Income payments cause individuals to log in more often, and people log in less often when they have relatively low cash holdings or spend a lot. In addition, when individuals are indebted, they log in less often, which appears to be inconsistent with standard models and the need for budgeting as the first-order motivation for paying attention to 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 because they dislike paying attention when bad news hurts them more than good news pleases them. Moreover, paying attention becomes less painful in expectation when cash holdings are large.

We believe that our findings are relevant for theories of rational inattention. In macroeconomics, for instance, theories of rational inattention would be likely to generate different aggregate dynamics if inattention were selective. Our findings also call into question the assumption that in-

formation costs are always positive. If individuals are willing to pay not to receive information (which could be inferred from this study in connection with Carlin et al., 2017) then information costs are time-varying in non-trivial ways and sometimes 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 and are informative for (field) experiments.

Logging in to financial accounts can be interpreted as paying attention to personal finances. It can also be interpreted as a decision to make one's financial standing more salient. A small but growing theoretical literature is incorporating salience and focus into economic decision-making (e.g., Bordalo et al., 2010; Koszegi and Szeidl, 2013; Bushong et al., 2015). Further exploring how salience affects economic decisions appears to be a promising avenue for future research.

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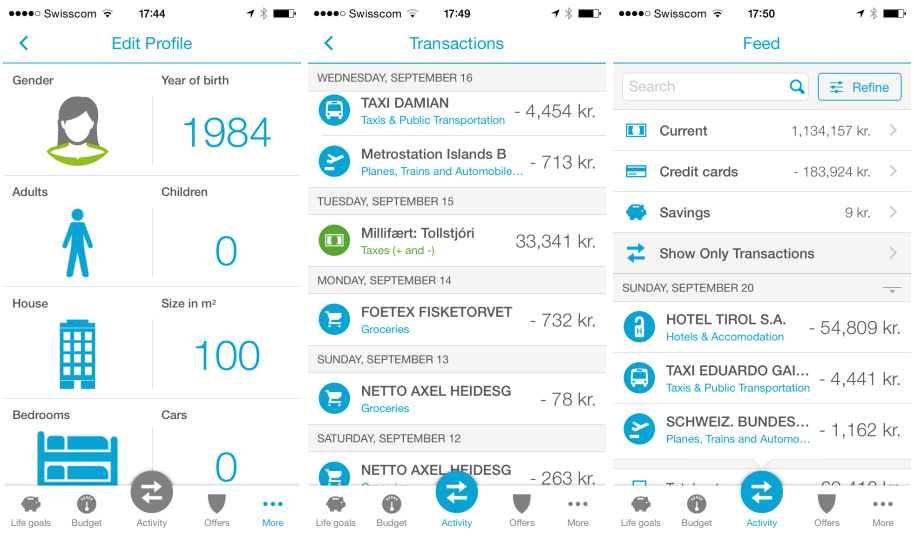


Figure 2: The financial aggregation app: screenshots of home screens

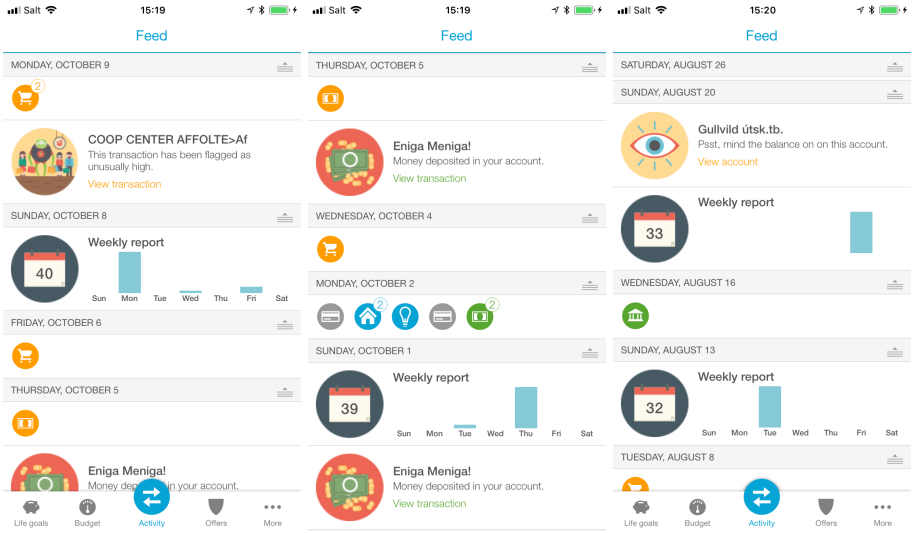


Figure 3: The financial aggregation app: screenshots of events flagged by the app

The app does not send push notifications and individuals have to log in to see these flags.

Table 2: Summary statistics by terciles of logins and income

	Login 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%

Note: All income, spending, and balance numbers are in US dollars.

Table 3: Summary statistics and comparison to Statistics Iceland

	Mean	Standard deviation	Statistics Iceland
Monthly regular income	3547	3717	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%

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

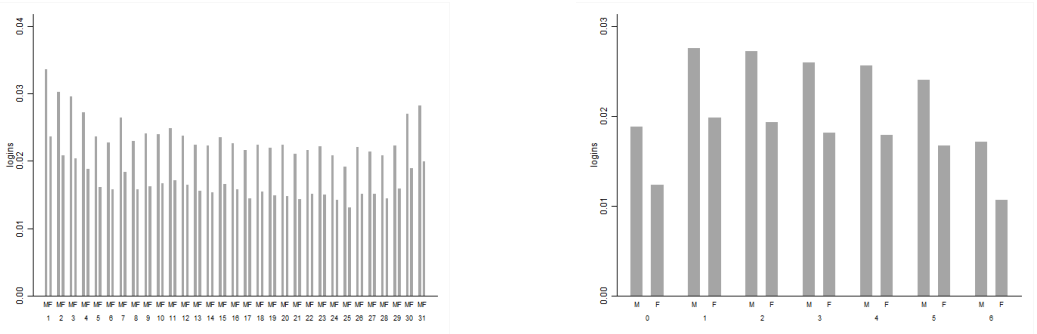


Figure 4: Distribution of logins over the month and by day of week (Sunday to Saturday) by men (M) and women (F)

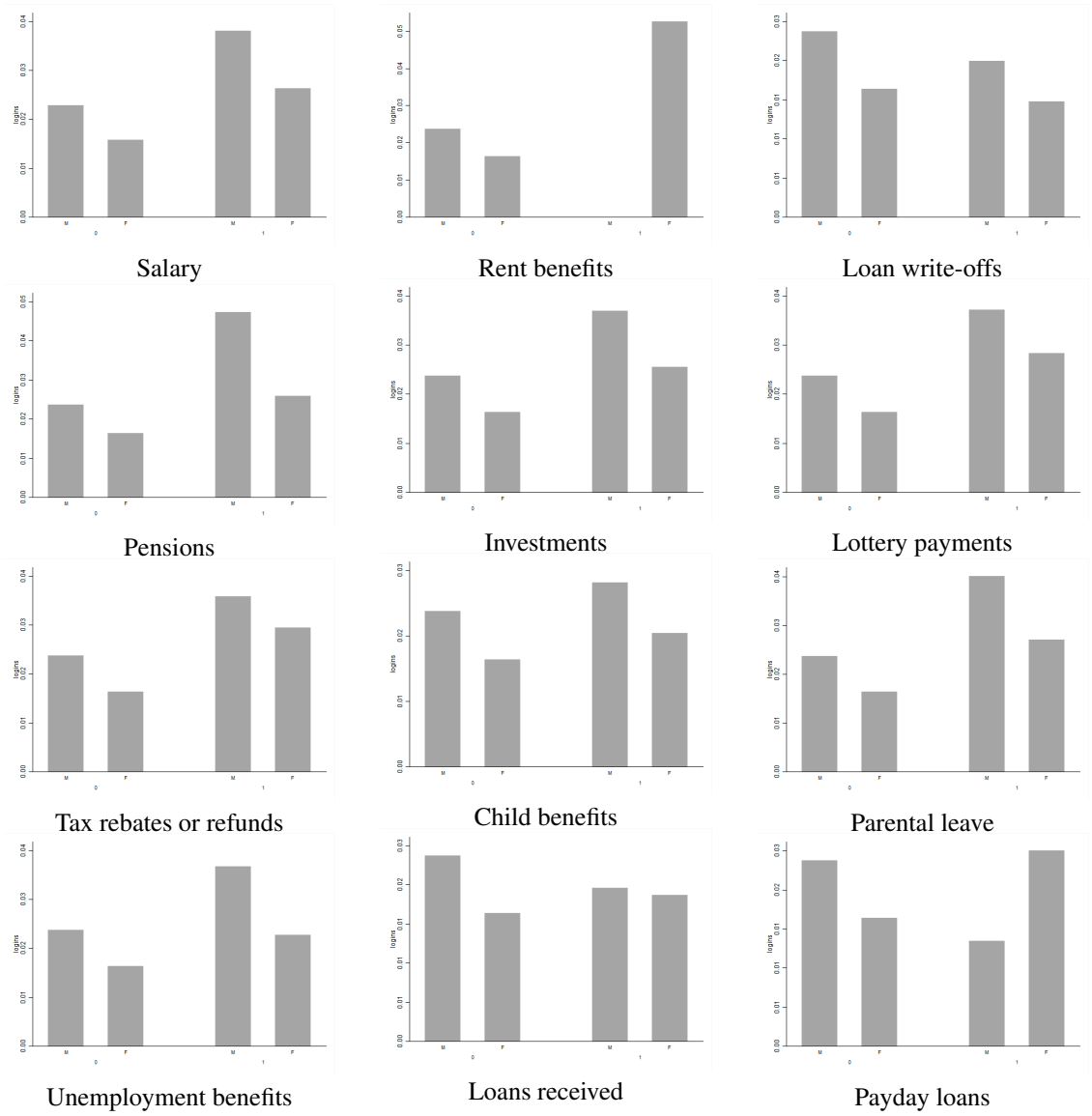


Figure 5: Average logins on regular days (left bars) and days with different income arrivals (right bars) by men (M) and women (F)

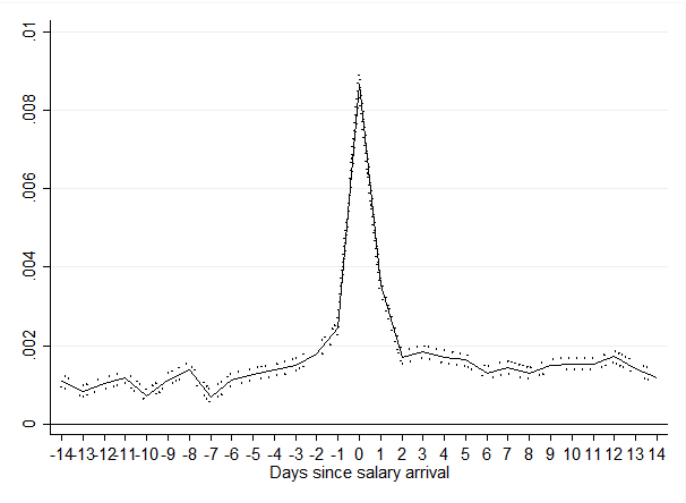


Figure 6: Propensity to log in around paydays of regular salary payments

Linear probability model of propensity to log in on dummies for 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.

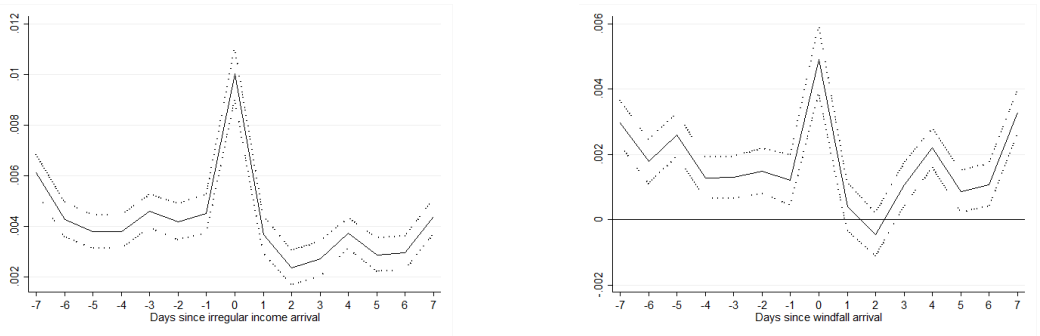


Figure 7: Propensity to log in around paydays of irregular payments and plausibly exogenous payments

Linear probability model of propensity to log in on dummies for the two weeks around irregular income arrival (left side) or plausibly exogenous income arrival (lotteries and tax rebates) (right side) 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.

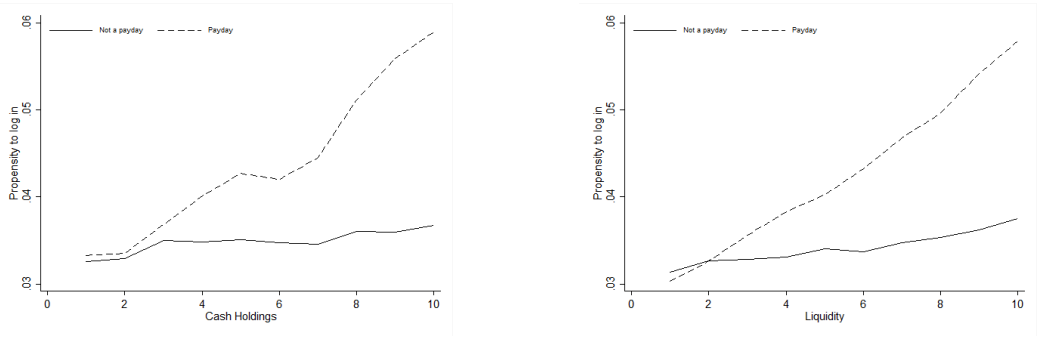


Figure 8: Differences in propensity to log in on paydays versus other days as functions of individual cash holdings and liquidity

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. Standard errors are clustered at the individual level and very tight (omitted for visibility).

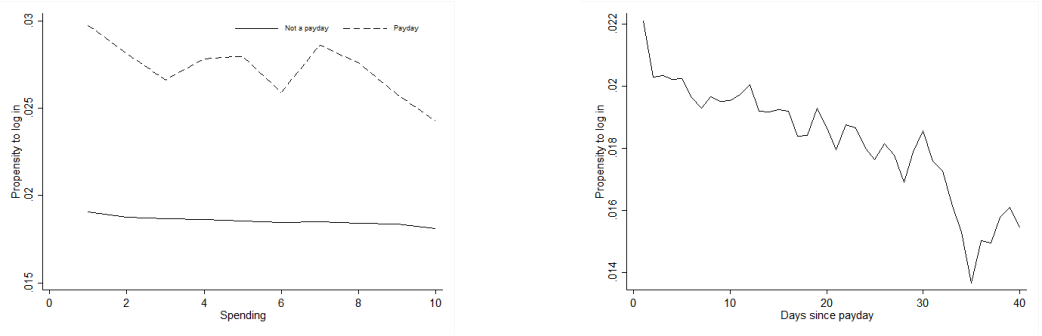


Figure 9: Differences in propensity to log in on paydays versus other days as functions of individual spending and as a function of days since regular paydays

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. Standard errors are clustered at the individual level and very tight (omitted for visibility).

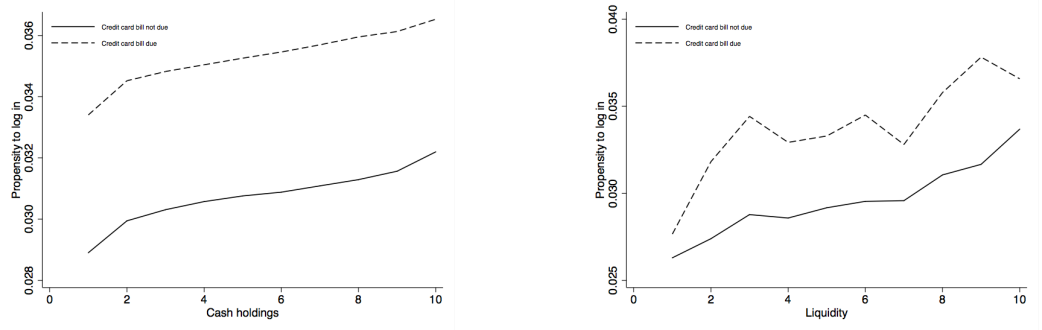


Figure 10: Differences in propensity to log in on paydays versus other days as functions of individual spending and on credit card due dates versus other days as functions of individual cash holdings and liquidity

Coefficients on day of credit card due date of propensity to log in in linear probability model for ten deciles of individual cash holdings and 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). Standard errors are clustered at the individual level and very tight (omitted for visibility).

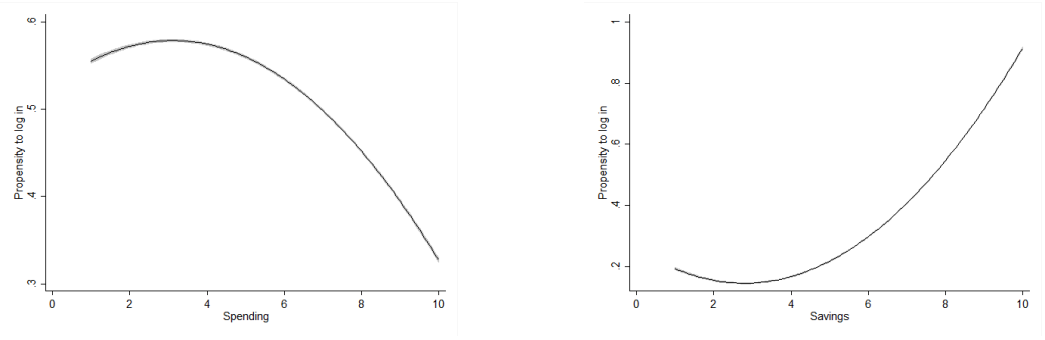


Figure 11: Propensity to log in by deciles of spending and savings

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. Standard errors are clustered at the individual level and displayed but very tight.

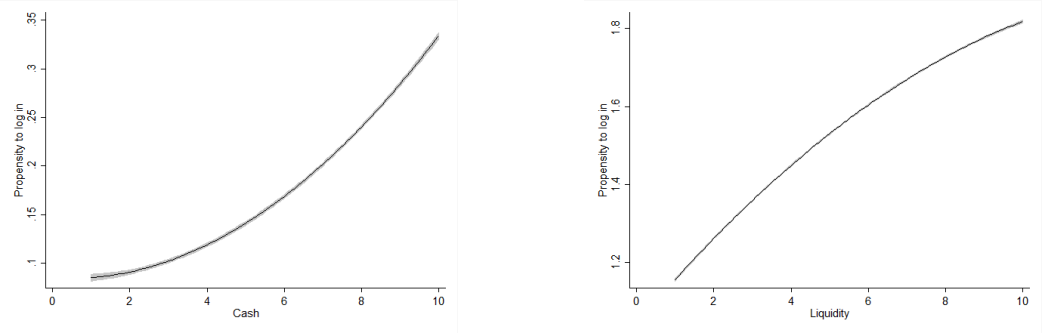


Figure 12: Propensity to log in by deciles of individual cash and liquidity holdings

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. Standard errors are clustered at the individual level and displayed but very tight.

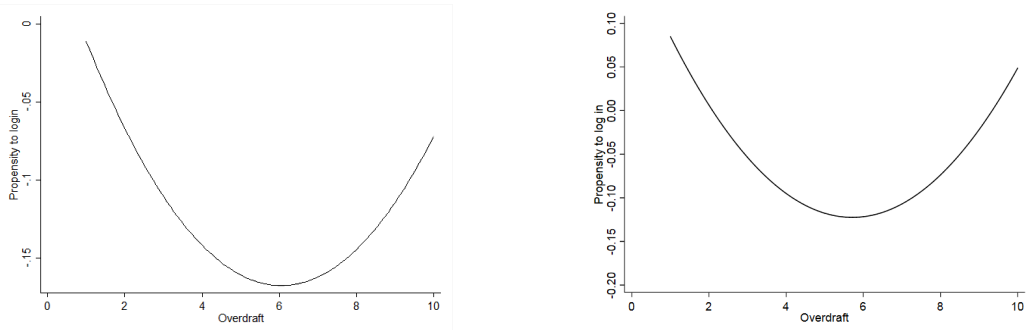


Figure 13: Propensity to log in by deciles of individual overdraft

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. The figure on the right side is based on regressions that only uses individuals without any savings. Standard errors are clustered at the individual level and displayed but very tight.

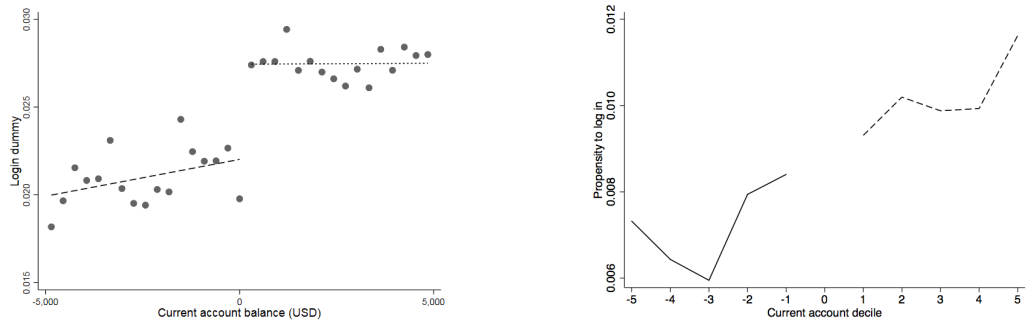


Figure 14: Propensity to log in by deciles of individual overdraft and by the checking account balance

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. Standard errors are clustered at the individual level and very tight (omitted but displayed in Table 4).

Table 4: Effects of relative bank account balances on logins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overdraft quintiles:										
-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 quintiles:										
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 quintiles (relative to individual's own histories) controlling for individual, month, and year fixed effects (in addition to the calendar 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 and displayed but very tight.
[b] Significance levels: * p<0.1 ** p<0.05 *** p< 0.01

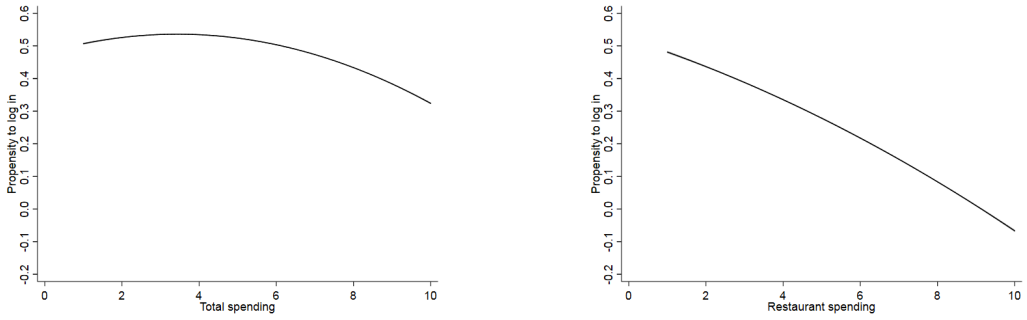


Figure 15: Propensity to log in by deciles of individual spending and restaurant spending

Quadratic fit of logit regression coefficients for each decile of individual spending and restaurant expenses relative to individual's own history, controlling for individual and calendar fixed effects. Standard errors are clustered at the individual level.

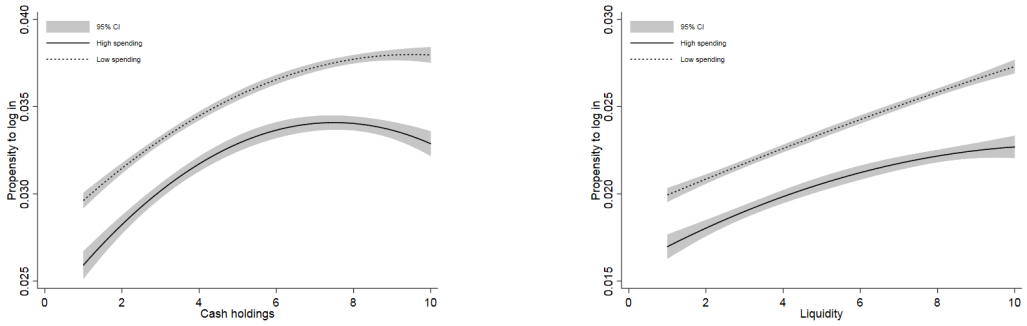


Figure 16: Propensity to log in by deciles of individual cash holdings and liquidity for low and high spending days (within individual)

Quadratic fit of linear probability model regression coefficients for each decile of individual cash holdings and liquidity relative to individual's own history for all days with within-individual relatively low spending and relatively high spending, controlling for individual and calendar fixed effects. Standard errors are clustered at the individual level.

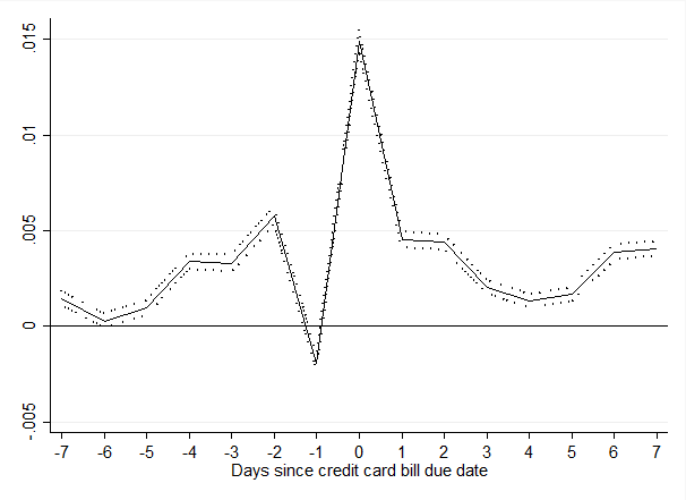


Figure 17: Endogenous log in response before reductions in credit card balances

Linear probability model of endogenous propensity to log in on dummies for two weeks around credit card payment days 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.