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THE OSTRICH IN US:
SELECTIVE ATTENTION TO FINANCIAL ACCOUNTS, INCOME, SPENDING, AND LIQUIDITY

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ABSTRACT

We analyze attention to personal financial accounts using panel data that includes logins, spending, income, balances, and credit limits. We find that income arrivals cause individuals to log in and that attention is positively correlated with cash holdings and liquidity, is negatively correlated with consumer debt holdings, and increases when bank account balances change from negative to positive. We discuss how our findings relate to theories of rational and selective inattention and conclude that ostrich effects in a personal finance context, i.e., the fear of paying attention to bank account balances, is a more widespread phenomenon than previously thought.

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1 Introduction

Empirical evidence on what determines individual attention is scarce. A few recent studies analyze online account logins to retirement portfolios and brokerage accounts (Sicherman et al., 2015; Karlsson et al., 2009; Gargano and Rossi, 2018; Quispe-Torreblanca et al., 2020; Gargano et al., 2020), however, little is known about attention to personal finances more broadly. What determines individual attention to everyday financial tasks, such as monitoring transactions, balances, and payments, for a broad sample of the population?

We undertake a large-scale empirical study of the determinants of individual attention to personal finances using highly-disaggregated panel data from a widely used financial management platform in Iceland.[1] The data includes transaction-level information on all spending, income, use of unsecured consumer credit, and credit limits. To measure attention, we look at logins to the platform, online or via a smartphone app.

We document a number of very robust patterns in individual attention. First, individuals pay less attention when their checking account balances, savings account balances, and liquidity decrease. Second, attention decreases when individuals start overdrawing their checking accounts. Third, attention decreases further as individuals roll over larger amounts of overdraft debt.[2] Fourth, attention increases due to the arrival of perfectly predictable income payments. We single out a causal effect of income payments on attention by utilizing exogenous variation in regular income arrival due to weekends and holidays and plausibly exogenous irregular payments such as lotteries.

All of these findings indicate that individuals pay less attention when they are doing worse financially.

These patterns do not reflect cross-sectional differences as they are identified using variation at

[1]The financial aggregation platform is used by 20% of the Icelandic adult population after it was founded in 2009.

[2]Overdrafts are the predominant form of high-interest unsecured consumer debt in Iceland and is similar to credit card debt in the US. Banks charge interest monthly when the overdraft facility is utilized, but there is no discrete overdraft fee. We also observe credit card balances and payments but credit card bills are almost always repaid in full each month. Individuals thus use their overdrafts and roll those over to repay their credit card balances, if they do not have a large enough balance in their checking account.

the individual level exclusively. More specifically, we split individual savings, cash, liquidity, and spending into deciles *within each individual's own history*.[3] Because all our regressions include individual fixed effects, we also control for all observable and unobservable time-invariant factors. Furthermore, these patterns are neither driven by aggregate nor individual-specific seasonality or trends as we include a set calendar fixed effects (day-of-week, day-of-month, month-by-year, and holidays) as well as the interaction of individual and month-by-year fixed effects. We also show that our empirical findings are the same across a number of sample splits, for instance, by individual income and savings levels. Finally, we show specifications using a number of additional control variables.

One potential concern is that the empirical patterns we document are driven by specific features of the app or restricted to individuals engaging in mobile banking. To address this concern, we show that all patterns are the same for the period when the aggregation platform was not yet accessible via the smartphone app, i.e., when individuals had to log in through a desktop computer. During that period, individuals were not engaged via user-event specific smartphone app features or notifications about what is going on in their bank accounts. Our setting also isolates attention from action as the software is for informational purposes only and does not offer transaction functionalities.

Our findings contribute to a small literature documenting "ostrich effects" – the avoidance of adverse information (Galai and Sade, 2006) – in a personal finance context.[4] Karlsson et al. (2009) show that retail investor attention to their personal portfolios decreases after negative returns on market indices.[5] We contribute to this literature by considering a new domain: daily household

[3] Cash is defined as savings account balances plus positive checking account balances and liquidity is defined as cash plus credit and overdraft limits minus credit card balances and overdrafts. Checking account balances are negative when individuals hold an overdraft.

[4] Such aversion to bad information has also been documented by several studies in the medical domain. Individuals at risk for health problems (for example, serious genetic conditions or sexcually transmitted deseases) often avoid medical tests even when the information is costless and should, logically, help them make better decisions (Thornton, 2008; Oster et al., 2013; Ganguly and Tasoff, 2014; Sullivan et al., 2004; Lerman et al., 1996, 1999; Lyter et al., 1987).

[5] Additionally, investors are generally inattentive (Bonaparte and Cooper, 2009; Brunnermeier and Nagel, 2008).

finances. This includes monitoring bank account balances, credit card transactions, and bill payments, which are central components of household economic activity. The fact that we document selective attention in standard "everyday" financial tasks for a broad sample of the population suggests that selective attention is an even more widespread phenomenon than previously thought.[6]

This paper documents when and why individuals pay attention to their bank accounts. There exists a literature showing that paying attention to personal bank accounts has meaningful impact on important financial behaviors. We also show that, cross-sectionally and within-individuals, paying more attention is correlated with good financial traits. We also know from the existing literature that paying attention is beneficial. Furthermore, Carlin et al. (fthc) show that there is a causal link between paying more attention and avoiding financial mistakes. Additionally, several other studies (e.g., Karlan et al., 2016b,a; Levi and Benartzi, 2020; Medina, 2020), show that attention to personal finances is beneficial.[7] The question is: given we know that individuals are helped when they pay attention to their bank accounts, why do they not do so when they are doing worse financially?

To answer this question we turn to economic theory. Many standard economic models predict that information is always valuable because it enables individuals to make better decisions. Theories of rational inattention posit that individuals trade off the expected benefits of information and the costs of acquisition and processing. Additionally, a theoretical literature on selective attention has emerged, positing that information also has a direct hedonic impact on utility.[8]

[6]93 percent of American households have a bank account (the Federal Deposit Insurance Corporation (FDIC) reports), whereas investors who manage their portfolios in retirement accounts and groups of individuals who benefit from knowledge of adverse medical information are potentially more selected.

[7]It is not as clear that the same holds true for investment accounts, i.e., whether investor's degree of attention impacts their returns through stock-picking or market-timing skills. Individuals increase their returns and reduce the risk of their portfolios with rebalancing, but Sicherman et al. (2015) rule out the rebalancing motive as a determinant of logging in after markets appreciate by referring to the general low level of actual trading. Gargano and Rossi (2018) 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 periods, Barber and Odean (2000) show that individual investors who trade underperform their own beginning-of-year portfolio by approximately their trading costs. Furthermore, Barber et al. (2021) shows that Robinhood investors face slightly less high returns when they trade attention-grabbing stocks.

[8]We define the term "selective attention" in this paper to refer to some variant of information-dependent utility fol-

Clearly, different individuals have different motives to log in at different times. We start by discussing six hypotheses when individuals pay attention to their finances and formally outline a simple economic model of information costs. The hypotheses propose that logins are (1) independent of transactions and balances, (2) driven by transaction verification, (3) due to budgeting, (4) to plan spending, (5) driven by opportunity costs, and (6) driven by high uncertainty about transactions and balances.[9] We argue that none of these theories of inattention appear to provide a dominant explanation for why individuals pay attention to their personal finances and we therefore concede that individuals have different motives for paying attention.

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 (for instance, Caplin and Leahy, 2001, 2004; Brunnermeier and Parker, 2005; Kőszegi and Rabin, 2006, 2009; Van Nieuwerburgh and Veldkamp, 2009; Golman and Loewenstein, 2015; Ely et al., 2015; Andries and Haddad, 2017; Strzalecki, 2013; Kőszegi and Rabin, 2009; Barberis and Xiong, 2012). We formally investigate how far models of information-dependent utility offer intuitions consistent with our empirical findings and what are their main shortcomings.

Beyond informing the theoretical literature on the empirical relevance of selective attention, we argue that our findings are important for the macroeconomic literature that models rational inattention (Woodford, 2009; Reis, 2006; Gabaix and Laibson, 2002; Van Nieuwerburgh and Veldkamp, 2009). These models would generate very different aggregate dynamics if inattention were selective instead of rational.[10] Our findings also contribute to the literature on information costs.[11]

lowing Karlsson et al. (2009) and Golman et al. (2016). In contrast, the term "rational inattention" refers to exogenous costs of information or information processing following the large literature around the seminal paper by Sims (2003).

[9] We find that uncertainty about transactions and balances is not a major determinant of logging in. This suggest that salience beyond information matters for individuals. Logging in to financial accounts could be interpreted as deciding to make one's financial standing more salient (see, e.g., Bordalo et al., 2010; Kőszegi and Szeidl, 2013; Bushong et al., 2015).

[10] We can show this in a Lucas (1979) tree model with time-varying attention (following Andrei and Hasler, 2014). The results are available on request.

[11] Studies modeling information costs include Abel et al. (2013); Alvarez et al. (2012); Huang and Liu (2007); Van Nieuwerburgh and Veldkamp (2009, 2010).

When individuals choose to not log in in dire financial standing they are effectively willing to pay in order not to receive information, which implies that information costs are time-variant in non-trivial ways and sometimes effectively negative rather than positive. Furthermore, because individuals in dire financial situations do not pay attention, which may exacerbate their situation, 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 attention may be selective (see DellaVigna, 2009, for a literature survey).

The remainder of the paper proceeds as follows. We provide a data description and summary statistics in Section 2. In Section 3, we report our empirical findings. In Section 4, we discuss how far the six main hypotheses of when people log in can explain our findings. In turn, in Section 5, we discuss the empirical relevance of theories of selective attention and how far the most widely applied model of information-dependent utility goes in explaining our findings. Finally, Section 6 concludes the paper.

2 Data

This paper exploits data from Iceland generated by Meniga, a European provider of financial aggregation software for banks and financial institutions. The company allows financial institutions to offer their customers a platform for connecting all their financial accounts, including bank accounts and credit card accounts, in a single location. The software is used by all the major banks in Iceland and offered to individuals through their online bank account interface. All adult individuals in Iceland need to have a bank account.[12] According to Eurostat, 94 percent of Icelanders used internet banking in 2018 and all individuals with an online bank have access to the Meniga soft-

[12]Checks are not used in Iceland. If individuals want to receive salary payments or state benefits, they need a bank account.

ware.[13] Arguably this makes our data more likely to be representative of the underlying population than data based on similar platforms in other countries. We refer the reader to Olafsson and Pagel (2018) and Carvalho et al. (2019) for an in-depth discussion of the characteristics of our sample. That said, surely some groups of individuals are underrepresented and the variation in logins is driven by a subset of the population, individuals that are younger and potentially more financially literate, as we will discuss in Subsection 2.1.

The digitization of budgeting processes with financial aggregation services and the attendant tracking of online and app behavior allow direct measurement of individual attention in ways that were not previously possible. Our data is derived from individual transactions and account balances and provide high-frequency information on individual attention, income, spending, balances, borrowing, and credit limits. Such data 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. Using data from Iceland has four main advantages. First, 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.[14] Second, as discussed earlier, the software is marketed through banks and is offered to a large subset of the population. Third, the spending and income data are pre-categorized, and the categorization appears accurate with few uncategorized or misclassified transactions. Finally, bank accounts are personal and cannot be shared, that is, each bank account belongs to only one individual.

Before the app was released in November 2014, a desktop software was available for individuals that looked similar. This software and early versions of the app did not feature notifications as is made clear in a company statement displayed in Appendix D. Back then, individuals could only sign up to receive monthly summaries of their income and expenses via email. An example

[13]Source: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=isoc_bde15cbc&lang=en

[14]ATM withdrawals make up approximately one percent of spending transactions by amounts or transactions volume.

of a summary email sent in August 2015 is displayed in Appendix E. Later versions of the app, however, flag certain events, such as unusually high transactions, deposits, or low balances. Users have to sign in, however, to see this messages. In terms of notifications, the current version of the app asks for permission to send push notifications, but to the best of our knowledge from having the app installed, it does not actually send any.[15] Additionally, users do not see their unpaid bills in the app and cannot receive push notifications due to unpaid bills.

To address any concerns about whether app features or notifications are driving our results, we show that all our documented patterns are the same pre- and post-app release. That said, we are interested in when individuals pay attention to their finances. That includes being interested in when individuals plan to pay attention to their finances, for instance, by setting up notifications.[16] Additionally, we also consider it interesting when individuals log in to see, for instance, an income payment even if they know they received it (say, because they received a notification).

2.1 Summary statistics

We use data derived from the records of active users of the platform from January 2011 to January 2017. We perform our analysis on daily user-level information on income by source, spending by category, logins by type of device, and on financial standing (account balances, overdrafts, overdraft limits, credit card balances, and credit card limits). In January 2017, 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. In addition to information on income, spending, account balances, and attention, the platform collects some demographic information, such as age, gender, and postal codes.

All individuals in our final sample have passed an "activity test" that is designed to verify

[15] The “international demo" and some of the advertisements on the Meniga homepage do not accurately reflect how the platform looks and functions in Iceland during our sample period.

[16] Several existing studies look at experiments in which individuals are sent notifications and reminders (for instance, Karlan et al., 2016b; Medina, 2016; Stango and Zinman, 2014; Levi, 2014).

that we are capturing all of their financial pictures. Specifically, our sample of Meniga users is restricted to individuals with complete records, defined by four requirements. First, we restrict our sample to individuals for whom we see bank account balances and credit lines. Second, we restrict our sample to individuals for whom we observe income arrivals (this includes not only salaries but also unemployment benefits, pension payments, invalidity benefits, and student loans). The third requirement is that key demographic information about the user is available (age, sex, and postal code). The final requirement is that the consumption of each user must be credible, which we ensure by requiring at least 5 food transactions in each of at least 23 months of each 24 months period. Our final sample consists of 11,699 individuals and all tables and figures are based on this final sample of active users with complete records.

Table 1 displays summary statistics, including information on demographics, income, spending, cash, liquidity, and use of consumer credit across terciles of logins. Cash is defined as savings account balances plus positive checking account balances and liquidity is defined as cash plus credit and overdraft limits minus credit card balances and overdrafts. Note that, our sample period for balances covers only the later part of our sample period for spending and income transactions, which explains why the number of individuals and observations decreases when we analyze balances. Additionally, the number of individuals and observations varies with different control and outcome variables as we cluster standard errors and drop singleton observations to be conservative.

{Table 1 around here}

According to Table 1, the average age in our sample is 42, the share of women is 48 percent, and the individual monthly mean income in our sample is $4,141.[17] Furthermore, it can be seen that the use of consumer debt is quite similar to the US. Individuals in Iceland hold approximately $6,174 in overdrafts conditional on having overdraft debt. It is important to note that in Iceland,

[17] This is income after labor income taxes deflated to 2017.

individuals typically pay off their credit card in full and use overdrafts to roll-over debt. Nevertheless, they still enjoy substantial liquidity because they have additional borrowing capacity before hitting their limits, \$13,938 on average. In comparison, in the US, the average credit card debt for individuals who roll it over is approximately \$4,000 in the Survey of Consumer Finances (SCF) data. Americans also enjoy substantial space until they hit their credit limits, approximately \$11,000 in the SCF.

Table 1 also shows that individuals who use the platform frequently earn a bit more, are slightly less indebted, and pay less financial fees, than those who do not. Overall, the sample of individuals causing most of the variation in logins looks similar to the overall sample of users. Clearly, we observe many individuals who do not use the platform actively, which decreases the average number of logins. However, for those individuals who use the app frequently, the average share of days on which we observe at least one login is 6.1 percent (and 4.4 percent of days we see at least one login through a desktop). The average frequency of logins we observe is similar to the average logins of individuals to their retirement accounts documented in Sicherman et al. (2015).

2.2 Cross-sectional patterns in attention to personal bank accounts

Figure 1 shows that attention to bank accounts is associated with various important financial behaviors. More specifically, we show that logins to bank accounts are positively associated with individuals overdrawing their checking accounts less frequently, overdrawing lower amounts on average, and incurring less overdraft interest. We also document that individuals that check their bank accounts more frequently are less likely to take payday loans and they borrow less on average using payday loans. In addition, we show that individuals that check their bank accounts more frequently are less likely to incur late fees (these fees occur when bills are paid after their due date) and late payment interest (these fees occur when credit card bills are paid after their due date). We also show that checking bank accounts more frequently is associated with greater savings and cash holdings.

{Figure 1 around here}

While it is likely better for consumers to avoid late and overdraft fees, as established in Stango and Zinman (2009) and Jørring (2019), the ability to borrow money and pay late may indeed convey the benefit of short-term borrowing. It might be the case that individuals who pay more attention to their bank accounts get a greater benefit from short-term borrowing, which would explain the documented relationships. In that case attention would not be associated with better financial behaviors or fewer financial mistakes. However, Carlin et al. (fthc) show that attention causally reduces an unambiguous financial mistake, the accrual of insufficient fund fees. In Iceland, if a consumer attempts to make a purchase without sufficient balance or limit on her account, she incurs an NSF fee but her purchase is denied. This represents an unambiguous mistake because the consumer suffers a cost with no benefit (Carvalho et al., 2019). Additionally, several other studies such as Karlan et al. (2016b,a); Levi and Benartzi (2020); Medina (2020), show that receiving information about and paying attention to personal finances is indeed beneficial.

In this paper, we thus analyze the determinants of attention to personal finances.

3 Analyses and empirical findings

In this section we describe our empirical setting and the regression framework employed to uncover the effects of events, like income arrival and credit card bill payments, and measures of financial standing, such as cash holdings, overdrafts, liquidity, and spending, on logins.

3.1 Attention in response to income payments

We estimate the effect of income arrival on attention by running the following regression:

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

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, ξ_h is a holiday dummy, ψ_{my} is a month-by-year fixed effect, 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 equal to zero otherwise. Note that, $\eta_i \times \psi_{my}$ denotes controlling for the interaction of individual and month-by-year, i.e., individual-by-month-by-year fixed effects. Thus, we estimate a linear probability model and control for individual, day-of-week, day-of-month, month-by-year, and holiday fixed effects as well as the interaction of individual and month-by-year fixed effects. The β_k coefficients measure the fraction by which income arrival increases the probability of logging in during the two surrounding weeks. The day-of-week dummies capture within-week patterns of logins, the day-of-month dummies take care of within-month patterns of logins, and the month-by-year dummies capture any slow-moving trends. Furthermore, the inclusion of the interaction of individual and month-by-year fixed effects takes care of any individual-specific trends. Standard errors are double clustered at the individual and daily level.

Figure 2 graph (A) displays the effect of salary arrival on logins in the two weeks surrounding the salary receipt. The β coefficient is five times larger on paydays than on the surrounding days. Compared to average login rates, individuals are around 30 percent more likely to log in on the day they get paid. Figure 2 graph (B) displays the propensity to log in more than once per day in the two weeks surrounding the salary receipt (note that, salary payments post at the beginning of the day but after the balances are recorded). We find that the propensity to log in twice spikes on paydays as well. Figure A.7 graphs (A) and (B) in Appendix A shows the payday effects for the periods before and after the release of the mobile application of the aggregation platform and Figure A.8 in Appendix A shows the payday responses by a cross-sectional split on salary terciles. We see that the response is remarkably similar across time periods and subsamples, which alleviates concerns that the average response is driven by the mobile app or individuals that belong to a particular part of the income distribution.

For identification, we use the fact that regular income payments always arrive on a fixed day of the month unless that is a weekend or holiday.[18] All public employees are paid on the first working day of the month and benefits are paid then as well. Private sector employees are usually paid on one of the last or first days 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. Therefore, weekends and holidays generate an exogenous source of variation on which day income arrives. To exclusively single out this exogenous variation, everyone must be paid on the same day of the month or we need individual interacted with day-of-month fixed effects. All our results are virtually unchanged when we restrict our sample to individuals who are paid on the 1st of the month or when we include individual interacted with day-of-month fixed effects. Additionally, we use an indicator for income payments as the regressor rather than the income amount to alleviate potential endogeneity concerns associated with the amount of income received that could arise from the fact that individuals may have some control over how much income they receive every month. [19]

Figure 2 graphs (C) and (D) also shows responses to irregular income payments, such as investment transactions, insurance claims, dividends, and grants, and plausibly exogenous income payments, such as lotteries and tax rebates. The login response is a bit smaller in magnitude for irregular than for regular payments.

Regular income payments are made on predetermined days so individuals know about them and, in most cases, are paid via a salary or benefits processing system and not subject to human action or error at the time of payment. However, we cannot know for certain whether the irregular payments are fully expected or known to arrive on a certain date. Many types of irregular payments, such as investment transactions, dividends, or tax rebates, are likely to be fully expected and known to arrive or, at a minimum, individuals are likely to have some probability distribution about what the payment date will be and are correct on average. Additionally, the payer may notify individuals

[18]These are mostly salary payments but also unemployment benefits, pension payments, invalidity benefits, and student loans.

[19]For instance, individuals might decide to work extra hours when they want to earn more.

about when the irregular payment will arrive.

To analyze how the attention response on paydays varies with cash, liquidity, and spending, we run the following regression:

$$I_i(Login_t) = \sum_{d=0}^{10} \beta_d I_i(Dec_{dt}) * I_i(Paid_t) + \delta_{dow} + \phi_{dom} + \eta_i \times \psi_{my} + \xi_h + \epsilon_{it}, \tag{2}$$

where the variables $I_i(Login_t)$, δ_{dow}, ϕ_{dom}, η_i, ψ_{my}, ξ_h, and $I_i(Paid_t)$ are as specified above and $I_i(Dec_{dt})$ is an indicator variable for each cash, liquidity, or spending decile d of individual i on date t. It is important to highlight that the deciles are constructed for each individual relative to their own history. Therefore, we are utilizing within-individual across-own-deciles variation. The β_d coefficients, displayed in Figure 3, capture the fraction by which income arrival increases the probability of logging in by each (personal) cash, liquidity, or spending decile. For comparison, Figure 3 also displays the β_d coefficients when we consider all days except paydays, i.e., in Specification (2), we replace $I_i(Paid_t)$ with $I_i(NotPaid_t)$. Standard errors are double clustered at the individual and daily level.

{Figure 3 around here}

We find that the login response to paydays is stronger when individuals have relatively larger cash holdings and liquidity. On non-paydays, we also find a positive relationship between cash holdings and logins, but it is not as steep. Thus, individuals log in more when cash holdings and liquidity are high, both on their paydays and on other days. We see that logins do not respond much to paydays, when cash holdings are relatively low, but the response is substantial when cash holdings are high.

Note that, we do not observe a mechanical relationship here in the sense that paydays cause higher balances. The balances, cash holdings, and liquidity variables are all measured at the beginning of the day and exclude any payments that post on that day.

Figure 3 also shows how logins respond to regular income payments when spending on the same day is relatively high or low. There is no clear relationship between logins on paydays and the amount of spending. The same holds for logins on non-paydays.

Note that, we control for day-of-month fixed effects in these regressions which account for the variation in logins over the course of the month. In Figure 3 graph (D), we show the coefficients of an individual fixed-effects regressions of logins on the day-of-the month. We show that individuals log in often at the beginning of the month (when a lot of individuals receive their monthly salary) and at the very end of the month (when some other individuals receive their monthly salary). Thus, the propensity to log in is higher for some days after individuals receive their income and then decreases over the course of the month.

3.2 Attention in response to credit card bill payments

In Iceland, credit card bills are due on the 2nd of the month, so weekends and holidays generate an exogenous variation in timing of bill payments in the same way as for paydays.[20] Thus, we use the same identification strategy as before to assess the attention response to regular credit card bill payments.

Figure 4 graph (A) displays the login response to the credit card due dates and the two surrounding weeks and Figure 4 graphs (B) and (C) display the 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. However, they are even more likely to log in on due dates if their cash and liquidity holdings, relative to their own histories, are high. Note that, in graphs (B) and (C), the difference between average login rates (per decile of cash or liquidity) on due dates versus other dates are not significant, however, the difference between login rates between low cash or liquidity days versus high cash or liquidity days is. Therefore, it seems that cash

[20] The majority of credit cards are mandated by the bank to be paid automatically.

or liquidity dominates the due date versus other days effects.

{Figure 4 around here}

3.3 Attention, balances, liquidity, and spending

To estimate the effect of financial standing on the probability of logging in, we run the following regression:

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

where $I_i(Login_t)$, δ_{dow}, ϕ_{dom}, η_i, ψ_{my}, and ξ_h are as specified above. Thus, we estimate a linear probability model and control for individual, day-of-week, day-of-month, month-by-year, and holiday fixed effects as well as the interaction of individual and month-by-year fixed effects. $I_i(S_{dt})$ is an indicator variable that is equal to 1 if individual i is in decile d of the measure of financial standing under consideration on date t. The deciles are constructed by first comparing current values to individual average values. We split this measure of individual's relative standing into 11 categories. The first category is zero, and the remaining categories split the individual's standing relative to their own historical standing into deciles. As before, we are therefore utilizing within-individual across-own-deciles variation. For instance, the estimated effect of being in each savings decile is then comparing the individual's propensity to log in to her probability of logging in when she has no savings.

Splitting individual observations into deciles within individuals' own histories is much more informative than splitting observations cross-sectionally. Observing how an individual's behavior differs depending on whether she is in relatively good or bad (compared to their own history) uncovers patterns at the individual level that are not driven by any cross-sectional differences across individuals.

Although we are technically reporting correlations, in practice our set of fixed effects imposes a bar for selection, omitted-variable bias, and reverse causality. All regressions control for selection on time-invariant (un)observables because we include individual fixed effects and we compare individuals' savings only to their own savings at other points in time. Moreover, the calendar fixed effects (day-of-week, day-of-month, month-by-year, and holiday) control for all aggregate recurring variation and seasonality as well as all slow-moving trends. Finally, by including the interaction of individual and month-by-year fixed effects, we take care of the fact that different individuals may have different cyclical patterns of payments or attention and they may have individual-specific trends.

Figure 5 displays the estimated effect of being in each decile of savings, current account balances, cash, and liquidity holdings on the probability of logging in. Having high savings, current account balances, cash, or liquidity holdings relative to one's own history increases the probability of logging in considerably. For instance, going from the lowest decile of savings to the highest almost doubles the probability of logging in (the difference between the coefficients in the first and the 10th decile are statistically significant employing a Wald test). The increases in the probability to log in are also large in the case of the other outcomes under consideration, around 50 percent for current account balances, 30 percent for cash, and 50 percent for liquidity relative to the baseline propensity to log in of around three percent. Again, the absolute levels of logins are low because of users who sign up once but do not use the software or app much. However, all our effects are driven by those individuals who use the app or software frequently and we document large increases relative to the baseline probability to log in when individuals have more financial resources.

As mentioned, there is no mechanical relationship between payments on a given day and that day's balances as the balances are scraped in the very beginning of the day before all other activities take place, e.g., income payments. Additionally, note that these results are different from the payday effects we documented earlier, these graphs look the same if we control for income payments (as done in Figure 6 graph (B)).

{Figure 5 around here}

Note that, this analysis is similar to the one in Specification (2) except that we do not condition on either paydays or non-paydays. In Figure 3, we show the increasing relationship between logins as well as cash and liquidity separately for paydays and non-paydays. The relationship is steeper on paydays but also positive on non-paydays. We thus conclude that, on average, not only on paydays, individuals log in more when holding more cash or being more liquid.

To test whether spending influences attention to financial accounts we also estimate Specification (3) in which we replace savings deciles with deciles of total spending. As before, we split each individual's average daily spending into 11 categories where the null category consists of days with zero spending and categories 1 to 10 are deciles of the individual's average daily spending. Figure 5 shows that the amount of daily spending does not affect the probability of logging in. In order to test for login activity before expenses take place, we also estimate the effect of spending deciles on a certain day on the propensity to log in the day before in this figure and the patterns there are similar those in the same-day spending figure. Overall, there does not appear to exist a relationship between spending deciles of the current or the following day and the propensity to log in.[21] Furthermore, we see that increases in available cash or liquidity has the same effect when spending is high and when spending is low.

Next, we estimate the effect of deciles of overdrafts on the propensity to log in using the same method as before. We estimate Specification (3) where $I_i(S_{dt})$ now represents deciles of overdraft debt. Figure 6 displays the propensity to log in by decile of overdraft debt for individuals with and without available savings to repay some of their overdrafts. This shows that the effect of overdrafts is negative, that is, when individuals have larger overdrafts they are less likely to log in.

[21] Note that, the difference between the 1st and 10th deciles in both figures is insignificant as the dotted lines display standard errors rather than 95% confidence intervals. Also note that we have a larger sample size for spending as our spending and income data covers a longer time period than our data on account balances.

{Figure 6 around here}

The raw data displayed in Figure 6 suggests that logins jump discretely when the checking account balance goes from negative to positive. It is important to note that the figure includes only individuals who experience both positive and negative checking account balances during our sample period. Therefore, the discontinuous jump around zero is not just reflecting cross-sectional differences, with one group of individuals being on the left side of zero and another group being on the right side.

This jump at the zero balance threshold is visible in the raw data, but it remains to be shown in a formal regression analysis. For that, we split all positive balances into 11 categories with equal number of observations and we do the same for negative balances. The lowest category of positive balances (where individuals hold less than approximately 2 percent of their average positive balance) and the lowest overdraft category (where individuals have less than approximately 6 percent of their average overdrafts) are then merged with the exact-zero observations.[22] We then compare deciles of positive and negative balances to this "almost-zero" threshold.

Figure 6, panel A, illustrates the estimated jump from this specification, controlling for individual, calendar, and their interaction fixed effects. In addition, we control for whether individuals receive income that day because we know that receiving payments has an impact on the propensity to log in. The figure displays the regression coefficients for each decile of individual overdrafts or positive checking account balance (relative to the individual's own history) added to the coefficient of the omitted category, an almost-zero checking account balance. As in the raw data, we see an increase in the propensity to log in around zero, which is in line with the monotonic increase in logins when checking account balances increase that (Figure 5). Table 2 shows the same regression coefficients as the figure along with the results from a Wald test of the null hypothesis that the estimated coefficients of each decile 1 to 10 and the corresponding negative (overdraft) decile -1 to

[22]Because there are few observations with exactly zero checking account balances, we include the slightly positive and slightly negative balances in the zero-balance category.

-10 are equal. The difference between the first overdraft decile (a small overdraft) versus the first positive checking account decile is significant. The regressions are therefore consistent with what we se in the raw data; when current accounts go into the red, individuals log in less.

{Table 2 around here}

To sum, individuals are less likely to log in when they are doing worse financially, as captured by cash, liquidity, bank account balances, and the size of overdrafts. Furthermore, there is a discontinuity in their attention when their current account goes into the red.

4 Discussion of theories of rational inattention

In this section, we discuss various theories of rational versus selective attention in light of our empirical findings. Our findings are informative about the modeling assumptions in the theoretical literature on inattention. Inattention may be formalized in existing models via exogenous information costs – what we call rational inattention – or psychological costs or benefits – what we call selective attention. To evaluate existing theories in light of the empirical evidence, we first discuss how a rationally inattentive agent would behave, i.e., an agent who is subject to exogenous information costs and benefits but does not experience information-dependent utility.

4.1 Perfect information or perfect uncertainty

A basic benchmark to consider is one where individuals log in irrespective of their transactions because there is either full uncertainty or no uncertainty about them. We find that income arrival causes an increase in logins and robust relationships between logins and financial standing. These patterns dispel the notion that individuals are fully certain or uncertain about the transactions in their accounts, as they would either not need the confirmation in the case of full certainty or would randomly distribute their logins in the case of full uncertainty. The jump in logins when balances turn from negative to positive in a range of narrow bins may give us an idea of how well individuals predict their balances. The jump in the raw data when we consider narrow bins of approximately \$50, suggests that individuals can, to some extent, predict on which side of zero they are. Seeing a jump in logins around zero balances implies that individuals must know – to some extent – before logging in that they have a positive checking account balance as opposed to a negative one. We conclude that individuals must face some intermediate uncertainty about their transactions and balances.

4.2 Information costs and transaction verification

One natural explanation for logging in on paydays is that individuals need to verify that transactions are posted. However, there are also information costs of logging in, most obviously time and effort. In the following, we argue that our empirical findings suggest that the trade-off between information costs and the benefits of transaction verification do not appear to be first-order important for the login response on paydays. In particular, we argue the following seven findings suggest that other motives dominate transaction verification as the main reason for logging in on paydays.

First, in Figure 3, we display the tendency to log in throughout the month. We find that individuals log in more in the beginning and very end of the month, when the vast majorities of salaries are paid, and logins decrease over the course of the month when financial resources are depleted. Because these regressions control for individual fixed effects, this variation is not driven by differences across individuals. Furthermore, Figure A.9 in Appendix A suggests that the attention on paydays is driven by the fact that on paydays, financial standing of individuals is relatively good. In this figure, we see how logins and personal finances vary throughout the month. The close resemblance between logins and liquidity, cash holdings, current and savings account balances, and indicators for drops in current account balances over the month suggest that it is indeed the good financial standing, which is associated with paydays, that drives the increase in logins on paydays. Individuals appear to know that their financial standing is good on (and soon after) paydays and therefore log in more. If logins were the same in the days after salary arrival as it is on days towards the end of the month, then we might fear that logins on paydays were rather driven by verification motives but we believe that the strong association between good financial standing and logins alleviates this concern.

Second, in Figure 2, we find that that individuals log in more than once on paydays even though salary payments post at the very beginning of the day (and all logins therefore take place after salaries are paid). When compared to the baseline probability of logging in at least once and at least twice, the effect on the second login is much larger: the propensity to log in at least once increases by about 37 percent whereas the propensity to log in at least twice increases by about 62 percent.

Third, the probability of mistakes in the case of income arrivals is extremely low as most income payments are made through a payment system where all the information has been entered long time before the salary arrives and machines execute the payment. There is therefore little room for mistakes regarding the payments of income.[23] Additionally, any mistakes would be easy to correct as all relevant information about the payments is readily available. Further, if individuals were worried that their income was not paid, we might expect them to check not only on the day of the salary arrival but the logins would be evenly distributed in the days just after, especially when individuals have a liquidity buffer the days around their income payment (which they do as we show in Olafsson and Pagel, 2018). Finally, we observe login responses to regular paydays that always occur on the same day of the month (where weekends and holidays generate exogenous variation in the day income arrives). Uncertainty around regular paydays should be low and individuals should therefore be unlikely to actually worry and verify the payment each time.

Fourth, we find a larger response to regular than to irregular payments. However, for irregu-

[23]In an attempt to figure out how common missing salary payments are, we calculated the share of months with missing salary payments and two payments in the coming month. That is 0.0075 which is very small. Additionally, this share is largely explained by weekends and holidays moving the payments so this would be an upper bound for "errors" in income payments.

lar payments, the transaction verification motive should be more relevant. Even though irregular transactions are typically for smaller amounts than regular ones, the risk of mistakes is larger so the expected loss from mistakes is higher. Figure 3 graphs (C) and (D) show responses to irregular income payments, such as investment transactions, insurance claims, dividends, and grants, as well as lotteries and tax rebates. The estimated effect is similar to the estimated effect of regular paydays. If anything, it is smaller for irregular paydays even if we add the coefficients on the surrounding days to it. It appears that individuals have a larger spike when they can easily predict the payment even though the actual payment verification is less important.

Fifth, as we show in Figure 3, there is no positive relationship between spending and the login response on paydays, even though the motive for verification should be stronger when there are many other transactions (captured by spending).

Sixth, there does not appear to be a relationship between spending and logins (Figure 5). If individuals log in after spending transactions for verification purposes, we would expect a positive relationship.

Seventh, the login response to income arrival increases with cash holdings and liquidity, relative to own average cash and liquidity (see Figure 3), even though transaction verification should be more important when liquidity is low. If the verification motive were the driving force behind logins on paydays then logins should increase less when individuals are more liquid as a bad scenario resulting from a late income arrival is less likely to happen when households are more liquid.

To back up this last point, we formally show that a rationally inattentive agent (subject to exogenous information costs) pays more attention if her wealth and income is low in Appendix B. Specifically, we have a simple model featuring uncertainty about income and bill payments as well as exogenous information costs and financial fees. In this model, we show that consumption smoothing is more beneficial at low income and wealth levels, because a prudent utility function implies that the standard agent wants to allocate the risk of paying a financial fee to the wealthy states (Proposition 1 in Appendix B).

Additionally, we show that the exogenous information cost model faces another shortcoming in our setting. The model predicts that any risk premium (the premium an agent is willing to pay for avoiding the risk of incurring a financial fee) goes to zero whenever risk becomes low. The reason is that the standard agent's utility function is linear or risk-neutral for small risks. This is formally shown in Proposition 2 in Appendix B. Low uncertainty is a plausible assumption in our context because uncertainty about bank account balances should be relatively small. Thus, any model featuring second-order risk aversion is unlikely to generate enough aversion to monitoring bank account balances to explain why individuals incur substantial financial fees that would be reduced if they would check their accounts more often (as shown in Carlin et al., fthc).

To sum, we argue that a number of the empirical patterns we document are not perfectly consistent with transaction verification as the dominant determinant of attention to financial accounts.

4.3 Budgeting

As discussed in the previous subsection and formally shown in Appendix B, if agents are prudent, they pay more attention when liquidity and cash holdings are low in the presence of exogenous information costs and benefits. Theoretically, agents with prudent utility functions benefit more from consumption smoothing and want to avoid the risk of incurring financial fees at low wealth levels. We refer to this behavior as budgeting, that is, planning spending and income when financial resources are low. In contrast, we refer to the activity of planning expenses in the presence of financial resources as planning. We will discuss expenditure planning in the next subsection.

Under the budgeting hypothesis, individuals who have more at stake, in terms of their financial standings relative to their own personal histories, should pay more attention. However, we do not find empirical evidence in support of this. Specifically, the following five findings suggest that budgeting is not a dominant determinant of logging in to financial accounts.

First, the login response to paydays is higher when cash holdings and liquidity are large, whereas the budgeting hypothesis implies that individuals in relatively good financial standings should care less about budgeting. Second, both large incoming and large outgoing payments (credit card payments on due dates) cause spikes in attention but the effect for incoming payments is significantly larger than for outgoing ones (see Figures 3 and 4). Although the spike in attention on credit card due dates would seem to cohere with individuals worrying about liquidity constraints, we do not find that this spike in attention is more pronounced when cash holdings and liquidity are low (see Figure 4).[24] Third, it appears that going from low to high cash or liquidity holdings has a larger impact on logins than having a credit card bill due in the first place. Fourth, having a small overdraft instead of a positive checking account balance reduces logins. But if budgeting were an important determinant of logins, then the opposite would be true because budgeting is more important when bank balances are in the red.

Finally, there is a negative relationship between logins and the size of overdrafts in Figure 6 graph (C) (which displays the response for individuals who do not have liquid savings available). When individuals have large overdrafts relative to their own history, they should budget more carefully. Yet, empirically, logins decrease with the size of overdrafts.

4.4 Planning

Do individuals log in to the app to rationally plan future spending? As discussed earlier, budgeting is a type of planning, but we distinguish the two by defining budgeting as planning when financial resources are low. We discussed budgeting in the previous subsection. In this subsection, we focus on planning in the presence of financial resources.

Individuals with adequate financial resources may log in to the platform to plan expenses in the future. We evaluate this explanation by looking at logins on the day of or prior to spending. Specifically, we look at the propensity to log in on the same day and the day prior to spending by

[24] Figure 4 shows the payday coefficient for each cash and liquidity decile (within individual's own histories). Both lines are increasing. The figure also shows the increasing relationship between cash or liquidity and logins on non-paydays, but what is important is not the difference in the two lines but the fact that the lines are increasing.

within-individual deciles of spending. If individuals were in fact logging in to plan spending, we would expect a positive relationship between logins on a given day and spending deciles that day or the next day. However, there is no clear relationship between current day or next-day spending and logins in Figure 5. Thus, while individuals in general log in more when they have more financial resources, as can be seen in Figure 5, we do not find direct evidence for the planning hypothesis when we look at current or next-day spending.

Individuals may also be planning how to save their current account balances. However, when we look at how attention varies with savings account balances (Figure 5), it appears that relatively high savings have a larger effect on attention (in absolute terms) than relatively high current account balance. Thus, money that has already been placed in a savings account has a larger effect on logins. That said, this could also mean that individuals are thinking about making other investments, for example, buying stocks and bonds. Unfortunately, we cannot identify such investments in the data, but it is reasonable to expect that individuals would keep the resources for such investments in the current account rather than transferring them to a savings account first.

4.5 Opportunity costs

Individuals' logins could be driven by opportunity costs. Opportunity costs are inherently difficult to measure but our data provides us with some plausible proxies to test whether opportunity costs are an important reason for why individuals log in to their financial accounts. We first look at a standard measure of opportunity costs, namely cross-sectional variation in earnings. Individuals of different income levels presumably have different opportunity costs of time. Figures A.8 and A.8 in Appendix A show the relationship between logins and income arrivals and between logins and deciles of cash, respectively, for different terciles of earnings. We see that the within-individual variation appears to dominate the cross-sectional variation, suggesting that opportunity costs, as reflected by average salaries, are not playing a dominant role in driving attention to financial accounts.

Another potential measure of opportunity costs is spending (relative to own history). After all, contemporaneous spending reflects how individuals are spending time on a given day.[25] An opportunity cost explanation for paying attention may suggest that individuals log in less or more often when they spend a lot (because high spending may imply that they are busy or that when they are not spending they are working a lot). However, we show in Figure A.7 graphs (C) and (D) in Appendix A that logins are unaffected by contemporaneous spending levels. On the other hand, spending may reduce available cash and liquidity, which would reduce logins. It is therefore important to look at the interaction of cash and liquidity with spending. In Figure A.7 graphs (C) and (D), we show that increases in available cash or liquidity has the same effect when spending is high and when spending is low. Furthermore, as shown in Figure 3, moving from low to high cash holdings increases the payday login response substantially, whereas it appears unaffected by concurrent spending. In summary, if one believes that the amount of spending has some relation to what an individual is doing on that day, which seems plausible, then attention should be correlated with spending. Our results, however, suggest that there is no relationship between the two.

4.6 Uncertainty about balances

In principle, individuals should log in more when there is more uncertainty about their balances. Capturing measures of uncertainty in observational data is often challenging but our data provides several plausible proxies for uncertainty. A within-individual measure of uncertainty is the variation in the within-individual spending on a given day. If a lot is spent, individuals are presumably less certain about their ending balance.[26] However, Figure 5 shows that logins do not respond to the individuals' spending deciles, suggesting that uncertainty is not a major driver for logging in.

Another approach to evaluate the importance of uncertainty is to identify situations where there

[25]Our data contain the real point of sale of transactions and the transaction date in our data therefore accurately reflect the date of the spending.

[26]Either because the number of transactions is large or even if a lot is spent in just one transaction, individuals may find it more difficult to estimate their final balance.

is essentially no uncertainty about bank account balances and compare attention in those situations to attention in others. Uncertainty should be low when individuals are logging in the second time on any given day. While the first login of the day resolves a lot of uncertainty about bank account balances, additional logins resolve less uncertainty, and the information acquired by an additional login that day is likely to contain a larger hedonic component. Figure 2 shows the propensity to log in at least once and to log in at least twice within a day in a two-week window around income arrival. In this figure, we observe a smaller response of second logins to income arrivals, but it is just as pronounced as the first. However, when compared to the baseline probability of logging in at least once and at least twice, the effect on the second login is much larger: the propensity to log in at least once increases by about 37 percent on days with an income arrival, whereas the propensity to log in at least twice increases by about 62 percent.

Finally, we argue that individuals are more certain about the arrival dates of regular than irregular payments. However, individual attention responds more strongly to regular than the more uncertain irregular payments (see Figure 2), which is inconsistent with uncertainty being a leading driver for logging in.

4.7 Other potential explanations

Financial literacy. One potential concern is that our findings are restricted to subpopulations of high financial illiteracy. Other studies (see, e.g. Haran Rosen and Sade, 2019) have shown that the use of financial aggregation apps is associated with higher financial literacy. It is therefore very possible that our sample is more financially literate than the general population. However, as discussed earlier, our sample appears to be more representative of the underlying population, even regarding educational attainment (Carvalho et al., 2019) than samples of users of financial aggregation apps in other countries and it also covers a much larger share of the population. Furthermore, we know that financial illiteracy is correlated with various other individual characteristics, e.g., income (Atkinson and Messy, 2012) and cross-sectional splits of our sample by income reveal that the patterns we document are robust across different income groups of the population (see Figure A.8 in Appendix A).

Auxiliary sources of information. Some of our findings, for example, that logins decrease with the amounts of overdrafts, could be explained by individuals not being able to make transactions using the app or desktop software. If individuals want to transfer money to pay down their overdrafts, they have to log in to their online bank account. At the same time, they obtain information about their balances and do not need to log in through the app or their desktop. To address this concern, we look exclusively at individuals who have little or no savings (and hence cannot transfer money to their checking accounts). Focusing solely on this group of individuals, we find that the documented negative relationship between the size of overdrafts and attention is similar regardless of whether individuals have savings or not (see Figure 6).

To ensure that our results are not driven by features of the financial aggregation app or notifications, we look at the period before the smartphone app got introduced. Back then, individuals could only log in through a computer. The estimated effects of income arrivals on logins in the pre- and post-smartphone-app period are very similar (Figure A.7 in Appendix A). Furthermore, banks do not notify customers of income arrivals or low account balances. Individuals can only choose to receive notifications of automatic bill payments and bank transfers. Notifications are thus unlikely to explain the jump in logins at the zero-balances threshold in Figure 6. Furthermore, logging into the platform would be of no use just above the zero-balance threshold as individuals cannot transfer money through the app to avoid going into the red.

In the context of overdraft notifications, it is also important to note that overdrafts are the most common form of revolving consumer credit in Iceland. Half of our individuals hold an overdraft at any given point in time. Individuals pay interest for overdrafts, but there is no discrete overdraft fee as in the US. Therefore, banks do not offer overdraft protection features as in the US. Finally, even if individuals would receive notifications (for instance, in the event of irregular payments by the payer), we still think it is very interesting when individuals log in (or not) in response to such notifications. If individuals receive information by other means, then the first login to the app can be thought of as a second login because individuals should know they received the payment at the time of their first login.

It may still be possible that when we observe fewer logins, individuals are simply viewing their bank accounts through other platforms. However, the beginning and end of the month are periods when individuals log in more (see Figure 3), and these periods coincide with the days on which people would be most likely to log into their internet bank to initiate bill payments, transfer rents, etc. This suggests that logins through the app are positively rather than negatively correlated with logins to bank accounts. This is further supported in Figure 4 displaying the response to credit card bill payments on their due date and showing that credit card bill payments increase logins. Because some individuals do not have automatic bill payments, they will have to log in to their online bank account to pay off credit cards (so these individuals then also log in through the app). This further alleviates the concern that individuals simply obtain information by other means when we see fewer logins through the app.

Financial concerns imply better information and hence fewer logins. It could be that when individuals are doing relatively badly, i.e., when cash and liquidity is low, they worry and are therefore already more informed than when doing better. If this were the case, we would expect individuals to respond more strongly to income arrivals when they are in worse rather than better financial standings. However, we find the opposite; individuals in better financial positions have larger login responses to income payments than those in worse positions (see Figure 3). A larger login response to income payments may imply that individuals are better at predicting income arrivals when they have large holdings of cash and liquidity. This idea is also consistent with the fact that individuals are likely better at predicting when a regular payment arrives and that is consistent with us seeing a larger login response to regular than irregular paydays. In other words, if individuals with low cash holdings were more worried about their finances and thus better able to predict the income arrival, we should see a larger response to irregular income arrivals when liquidity is low. However, if anything, we find that large cash holdings allow people to more accurately predict the exact day of their income arrivals (as indicated by their login responses to income payments). Our results are thus more in line with the literature on poverty and cognitive function (Mani et al., 2013; Carvalho et al., 2016) saying that individuals in worse financial positions are worse at decision making.

5 Discussion of theories of selective attention

Individuals are heterogeneous in their motives for paying attention to their accounts. We have discussed several hypotheses, where exogenous information costs and benefits drive attention, but we conclude that our findings are not fully consistent with their predictions. As a result, we now turn to a discussion of whether the predictions of models assuming selective-inattention motives, such as anticipatory utility and ostrich effects, are supported by our empirical findings.

5.1 Anticipatory utility

Our results on income payments and cash holdings imply that individuals appear to log in because they enjoy seeing money in their bank accounts. Large bank account balances imply that they can afford future spending and consumption. Thus, individuals may experience a form of anticipatory utility. Figure 2 suggests a unique spike on regular (perfectly predictable) income arrivals that is even larger than the one of the irregular (not unexpected but potentially not perfectly predictable) income arrivals. Furthermore, when we look at how logins evolve throughout the month (Figure 3), we see a steady decrease over the course of the payday cycle. Both of these findings appear consistent with anticipatory utility because it suggests that individuals are looking forward to seeing the money in their accounts and dislike when it depletes.

To model anticipatory utility, one could augment the model we briefly discussed in Section 4 by assuming that the information costs are simply varying with the level of resources. But models offering a more developed micro foundation based on axioms or experimental and other micro evidence that may generate behavior consistent with our empirical findings also exist. We now want to explore how far such models of anticipatory utility go in explaining our empirical findings. The most highly cited existing models are Caplin and Leahy (2001) and Brunnermeier and Parker (2005). In both of these models, observing an overdraft may come at a utility cost due to anticipated fees, which would explain the jump in logins around zero and the decrease below zero. However, as agents are second-order risk averse in these models, they become risk neutral whenever uncertainty is low (which is arguably the case for bank account balances). In the model of Caplin and Leahy (2001), anticipatory utility and preferences change as time passes, which may result in time-inconsistent behavior. This time inconsistency is addressed in a highly-cited model by Kőszegi (2010), who assumes that agents follow a time-consistent "personal equilibrium" in which they expect their anticipatory utility and resulting behavior and choose an action that maps correct expectations into behavior and vice versa. This equilibrium concept was picked up in the information-dependent utility models generating anticipatory utility by Kőszegi and Rabin (2006, 2007, 2009). Moreover, the models in Kőszegi and Rabin (2006, 2007, 2009) feature loss aversion and thus first-order risk aversion, which bites even when uncertainty becomes small as is likely the case for bank account balances. Thus, we consider the model by Kőszegi and Rabin (2009) to be a promising candidate to explore further.

5.2 Ostrich effects

We find that individuals login less often when they have little cash, savings, or liquidity relative to their own personal histories. Furthermore, the jump in logins, as depicted in Figure 6, implies that individuals are more likely to look up their financial accounts when they go from a low overdraft to a low positive checking account balance. Individuals then log in even less as their overdrafts increase (see Figure 6). These findings support the idea that ostrich effects play a role in deciding whether or not to pay attention.

While no formal model of ostrich effects exists, many models generate behavior that is consistent with information avoidance in adverse states. For instance, the models of anticipatory utility outlined above generate potential aversion to negative information. The realization utility model in Barberis and Xiong (2012) assumes that the moment individuals sell assets, they experience utility over their monetary gains and losses and that they dislike losses more than they like gains. This results in individuals avoiding to sell assets whose values are below their purchase prices. In combination with the findings in Karlsson et al. (2009), this behavior could be explained by inattention to losses. Furthermore, the model in Andries and Haddad (2017) generates optimal inattention and ostrich effects, which are consistent with the evidence in Sicherman et al. (2015) and Karlsson et al. (2009). Andries and Haddad (2017) assume dynamic disappointment aversion preferences as in Dillenberger (2010). Pagel (2018) then shows that the preferences in Kőszegi and Rabin (2009) generate inattention similar to disappointment aversion as in Andries and Haddad (2017). Again, we thus consider the model by Kőszegi and Rabin (2009) to be a promising candidate to explore further.

5.3 Information-dependent utility

In Appendix C, we formally explore the information-dependent utility model developed by Kőszegi and Rabin (2006, 2007, 2009). We do not aim to provide a satisfactory rationalization of all our findings, but we ask whether the model explains some of our empirical findings and through which channels this happens. We also explore some of its shortcomings in the context of our empirical findings. As discussed, we consider this specific model because of three reasons: First, it is the most widely-applied and highly-cited model of information-dependent utility.[27] Second, it combines features of previous influential models. In particular, the notion of "anticipatory utility" –

[27] In Google Scholar citations, the model in Kőszegi and Rabin (2006) alone exceeds other influential models, such as Caplin and Leahy (2001), Brunnermeier and Parker (2005), or Van Nieuwerburgh and Veldkamp (2009). Additionally, the laboratory findings of Zimmermann (2014), Falk and Zimmermann (2014), Eliaz and Schotter (2010), and Powdthavee and Riyanto (2015) underscore the importance of attention for information-dependent utility.

an increase in current utility from looking forward to future consumption (Loewenstein and Elster, 1992; Caplin and Leahy, 2001; Brunnermeier and Parker, 2005) and the resulting time inconsistency solved via the equilibrium concept in Kőszegi (2010). Third, the model features first-order risk aversion (as do the models by Dillenberger, 2010; Andries and Haddad, 2017), which is important because uncertainty about bank account balances is likely to be low. Inattention is more difficult to rationalize theoretically and thus more surprising in a setting with less uncertainty.[28]

In Appendix C, we prove that the model by Kőszegi and Rabin (2009) is consistent with an increasing pattern between attention and wealth when uncertainty about balances is low and show that this pattern is quantitatively in line with our findings.[29] However, we cannot rationalize an attention response to predictable payments or overdrawing checking accounts in this model. That said, we think it is informative for future work to investigate which findings are explained by a typical belief-dependent utility model and what are its main shortcomings.

[28]Almost all the existing models of selective attention assume second-order risk aversion. But the agents will become risk-neutral when uncertainty goes to zero and the models would lose their bite. We formally prove that a second-order risk averse agent becomes risk-neutral when uncertainty about financial fee payments becomes small in the presence of information costs in Proposition 2 in Appendix B.

[29]Refer to Proposition 3 in Appendix C and the back-of-the-envelope calculation to assess the extent to which the avoidance of news disutility can explain the amount of fees we observe empirically. We calculate that the agent is willing to give up three percent of cash holdings to not experience news disutility, which amounts to $47 per month. In turn, as an out-of-sample test of this calibration, we compute the decrease in monthly news disutility when the agent goes from high to low cash holdings. Here, we obtain a decrease of 24 percent, which makes the agent 24 percent more likely to look up his or her accounts when his or her cash holdings are high. This is in line with our empirical finding that the probability of logging in when one goes from low cash holdings to high cash holdings increases by approximately 30 percent. We conclude that the first-order willingness to incur fees predicted by news utility may be a reasonable explanation for the amount of fees 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. We use the same calibration and the standard model in Appendix B to ask how much the standard agent would be willing to pay of his or 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 of consumption because income uncertainty at the monthly level is small. Furthermore, the standard agent becomes risk-neutral for small risks. This value changes only marginally for lower or higher values of consumption levels. Therefore, standard risk aversion and prudence about fee payment uncertainty can neither generate the amount of fees nor the aversion to paying attention to financial accounts that we see in the data. We need first-order risk aversion and first-order prudence to explain our findings under realistic uncertainty about monthly income.

6 Conclusion

In this paper we provide a comprehensive analysis of what determines attention to everyday financial decisions such as monitoring bank account balances, transactions, and bill payments. Paying attention to bank accounts is important as it is associated with various important financial behaviors (Karlan et al., 2016b,a; Levi and Benartzi, 2020; Medina, 2020) and there exists a causal link between attention and avoiding financial mistakes (Carlin et al., fthc).

We use data from a financial management software which provides accurate and comprehensive information on attention (captured by logins), spending, income, balances, and credit limits. We identify salient empirical patterns in attention to personal finances: 1) attention is positively correlated with bank account balances and liquidity, 2) attention decreases when individuals start overdrawing their checking accounts, 3) attention decreases further with larger consumer debt balances, and 4) income arrivals cause individuals to log in.

Our findings are consistent with attention to personal financial accounts being partly explained by individuals trading off exogenous information costs and benefits as formalized in existing models of rational inattention. However, our empirical evidence also indicate that the psychological costs of information or information-dependent utility generate selective attention. In particular, ostrich effects and anticipatory utility may be at play. Income payments cause individuals to log in more often, and relatively low savings and current account balances are associated with fewer logins. Individual attention decreases discretely when their current account balances go into the red and their attention decreases further with the amounts of overdraft debt they roll over. We carefully discuss that theories of rational inattention and models of selective attention explain some, but not all, of our findings.

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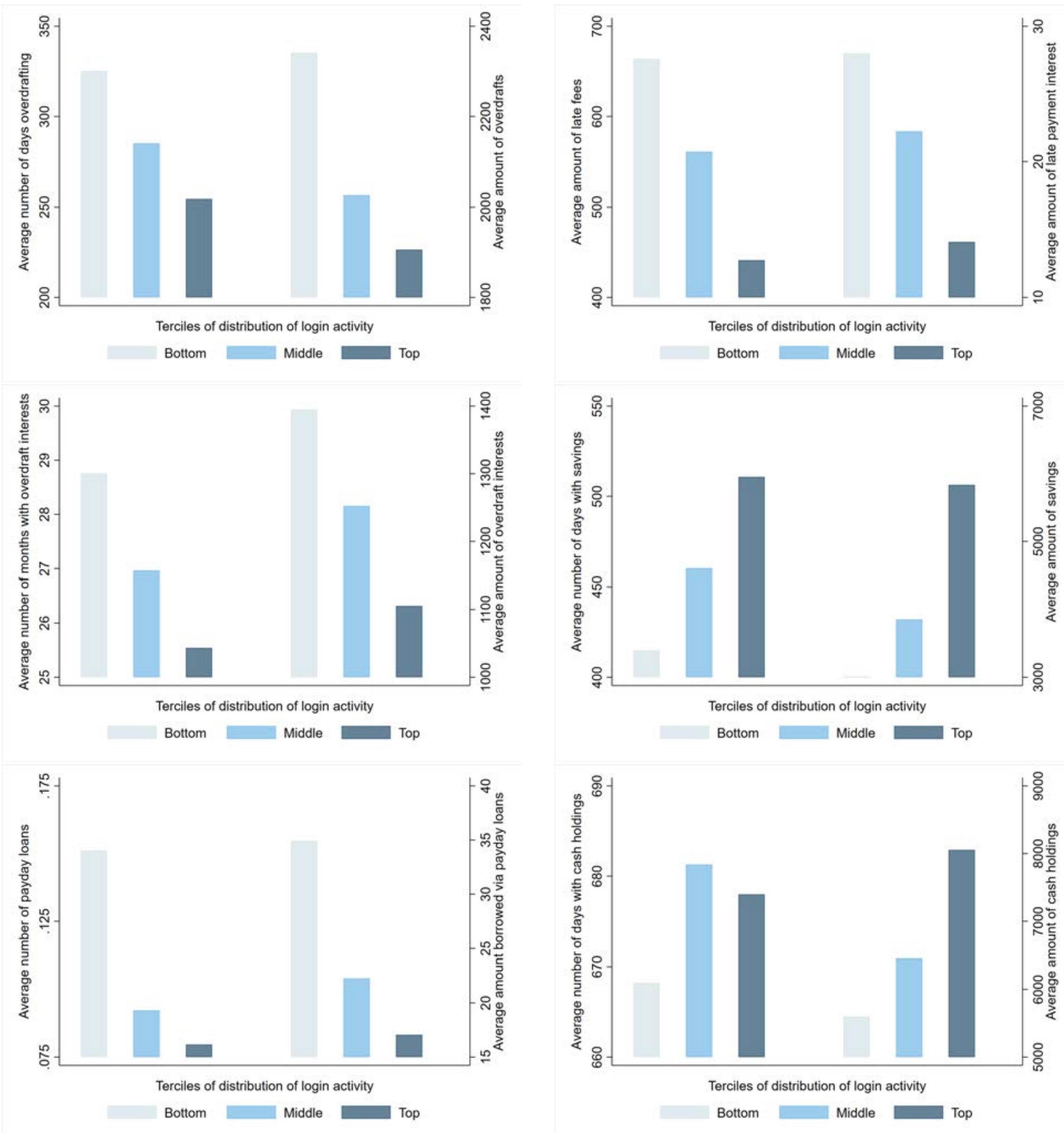
Table 1: Summary Statistics

	Full Sample	Login terciles			Differences	
		(1)	(2)	(3)	(2)-(1)	(3)-(1)
Female	0.48	0.51	0.47	0.41	0.04***	0.11***
Age	41.53	40.73	43.24	41.52	-2.52***	-0.79***
Income	4,141	3,564	4,508	4,950	-943***	-139***
Regular Income	4,004	3,434	4,365	4,806	-930***	-137***
Irregular Income	106	101	110	112	-9***	-104***
Bank Fees	0.91	0.91	0.98	0.83	-0.07***	0.08***
Overdraft Interest	0.60	0.58	0.66	0.58	-0.08***	0.00
Overdraft Interest (cond.)[a]	45.58	46.36	46.45	43.28	-0.09	3.08***
Overdraft	0.34	0.35	0.34	0.32	0.01***	0.03***
Overdraft Amount	2,110	2,088	2,148	2,119	-59.8***	-30.6***
Overdraft Amount (cond.)[a]	6,174	5,934	6,280	6,626	-346***	-692***
Overdraft Limit	4,454	3,673	4,088	6,487	-415***	-2,814***
Savings Account Balance	2,493	2,385	2,755	2,466	-370***	-81***
Current Account Balance	1,781	1,465	1,845	2,395	-379***	-93***
Credit Card Balance	3,161	2,909	3,352	3,511	-443***	-602***
Credit Card Limit	5,611	4,345	5,703	8,231	-136***	-3,887***
Cash Holdings	6,947	6,058	6,843	8,952	-785***	-2,895***
Liquidity	13,938	11,846	14,053	18,300	-2,207***	-6,454***
Discretionary Spending	1,847	1,651	1,992	2,103	-341***	-452***
Number of individuals	9,006	3,248	2,796	2,962		

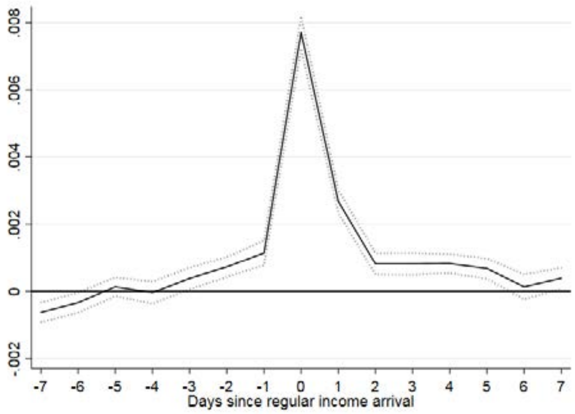
This table shows summary statistics for our sample of users of the financial aggregation platform and also split up by terciles of logins to the platform. All financial variables have been converted into US dollars using the approximate exchange rate in 2017 (\$1 $\approx$ 100 ISK). Cash is defined as savings account balances plus positive checking account balances and liquidity is defined as cash plus credit and overdraft limits minus credit card balances and overdrafts. Checking account balances are negative when individuals hold an overdraft. The number of logins and propensity to log in refer to the number per day or percentage of days individuals log in. Our sample consists of 11,699 active individuals with complete records. [a] We calculate both average overdraft interest and overdraft amount for everybody in the sample and also conditional on having an overdraft.

Figure 1: Financial Behaviors and Attention

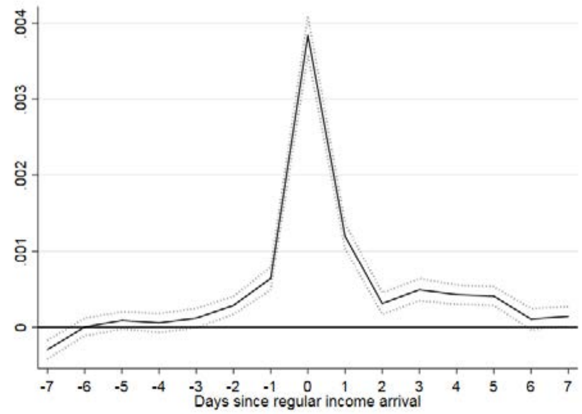


Note: This figure shows financial behaviors by frequency of logins. The three bars represent the bottom, middle, and top terciles of the frequency of login distribution. Cash is defined as savings account balances plus positive checking account balances. Checking account balances are negative when individuals hold an overdraft. The average amount of overdraft interest is the total overdraft interest over the period. All financial variables have been converted into US dollars using the approximate exchange rate in 2017 ($\$1 \approx 100$ ISK). Our sample consists of 11,699 active individuals with complete records.

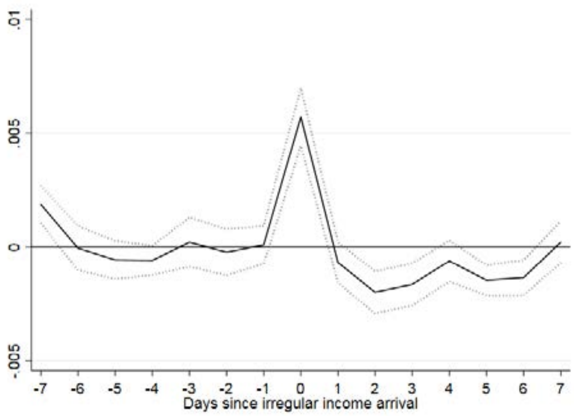
Figure 2: Logins around the arrival of regular and irregular salary payments



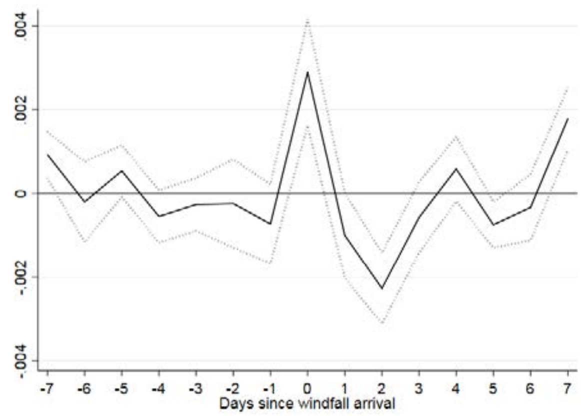
(A) Regular payments, first login



(B) Regular payments, second login



(C) Irregular payments

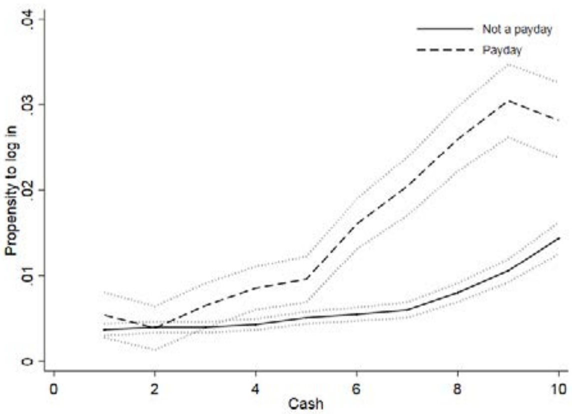


(D) Windfall payments

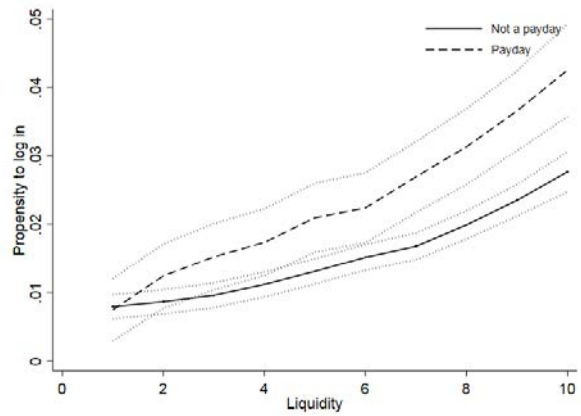
Graphs (A) and (B) show the response of an indicator for logging in at least once (A) and at least twice (B) to regular income arrival for two weeks around the income arrival. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. *Number of individuals:* 11,699. *Number of observations:* 22,076,013. R^2: 0.3228 for (A) and R^2: 0.2711 for (B).

Graphs (C) and (D) show the response of the propensity to log in to irregular income arrival (investment transactions, insurance claims, dividends, and grants) (C) or plausibly exogenous income arrival (lotteries and tax rebates) (D) for two weeks around the income arrival. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. *Number of individuals:* 11,699. *Number of observations:* 22,239,799. R^2: 0.3227.

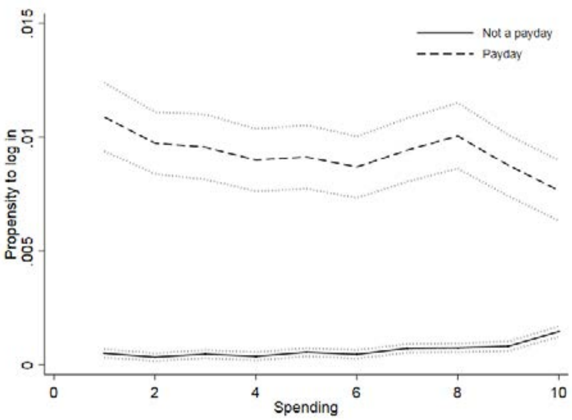
Figure 3: Logins and cash holdings, liquidity, and spending on paydays and other days



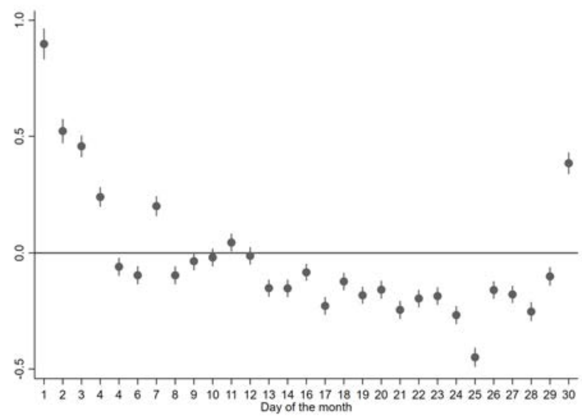
(A) Payday login response by deciles of cash



(B) Payday login response by deciles of liquidity



(C) Payday login response by deciles of spending

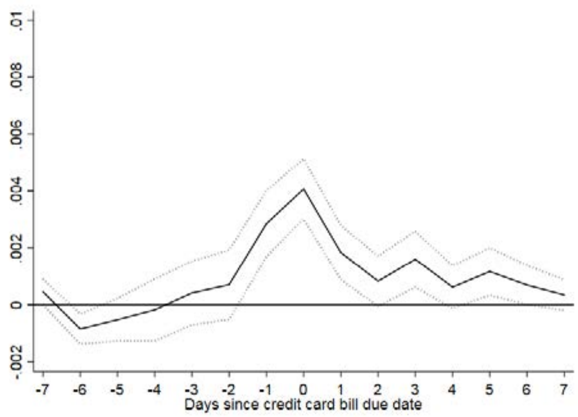


(D) Logins throughout the month

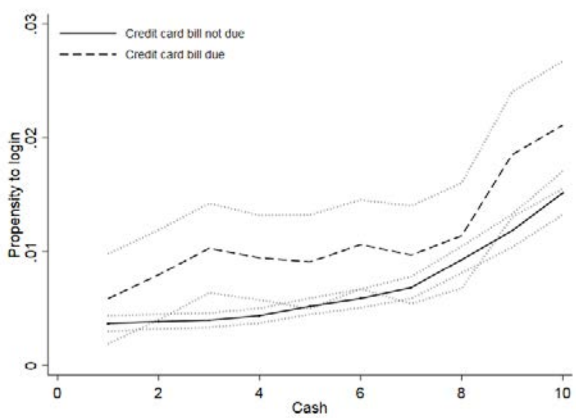
Graphs (A) to (C) show the regression coefficients and standard errors for deciles of cash holdings (positive checking account balance and savings balance), liquidity (cash plus credit card limit minus credit card balance plus overdraft limit minus overdrafts), and daily total spending (all relative to own history of cash, liquidity, or spending) on paydays and other days. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. Cash: *Number of individuals:* 11,007. *Number of observations:* 9,730,188. R^2: 0.3223. Liquidity: *Number of individuals:* 11,007. *Number of observations:* 9,730,188. R^2: 0.3227. Spending: *Number of individuals:* 11,698. *Number of observations:* 22,401,670. R^2: 0.3227.

Graph (D) shows the regression coefficients and standard error bars for regressing logins on day-of-the-month dummies, controlling for individual, month, and year fixed effects. The vertical axis coefficients represent the number of daily logins relative to the middle of the month (the 15th of the month). *Number of individuals:* 11,698. *Number of observations:* 22,403,585. R^2: 0.0027.

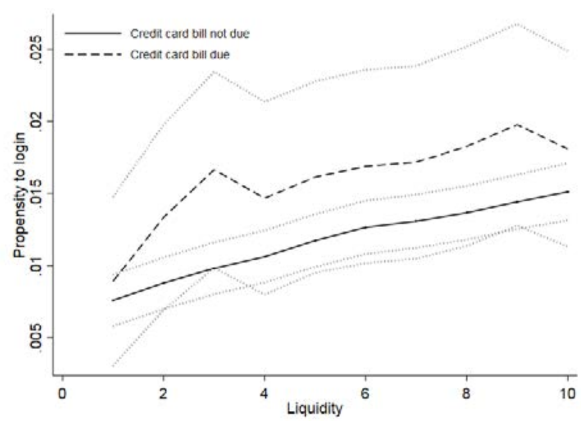
Figure 4: Logins around credit card due dates relative to cash holdings, liquidity, and spending on credit card due days and other days



(A) Login response to credit card payments



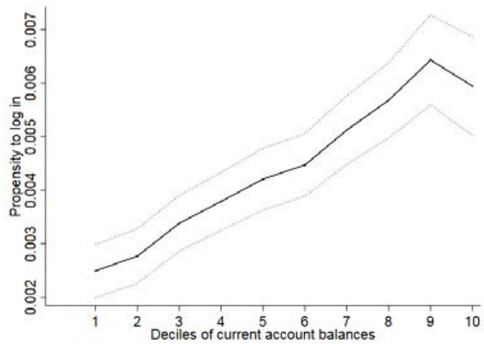
(B) Login response by deciles of cash



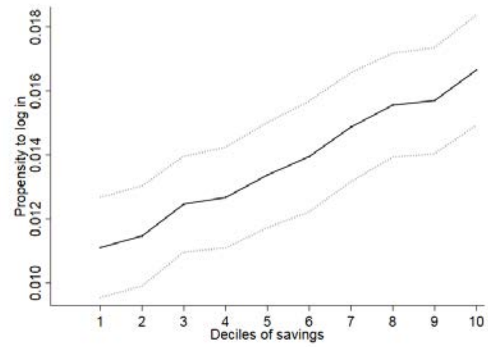
(C) Login response by deciles of liquidity

Graph (A) shows the response of the propensity to log in to credit card payments for two weeks around the payment date. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. *Number of individuals:* 11,699. *Number of observations:* 12,634,240. R^2: 0.3257.
Graphs (B) and (C) compare the propensity to log in on credit card due dates and other days by deciles of cash and liquidity by plotting the regression coefficients and standard errors of deciles of cash holdings and liquidity relative to own history of cash or liquidity on credit card due dates and other days. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. (B): *Number of individuals:* 11,007. *Number of observations:* 9,730,188. R^2: 0.3221. (C): *Number of individuals:* 11,006. *Number of observations:* 9,729,304. R^2: 0.3222.

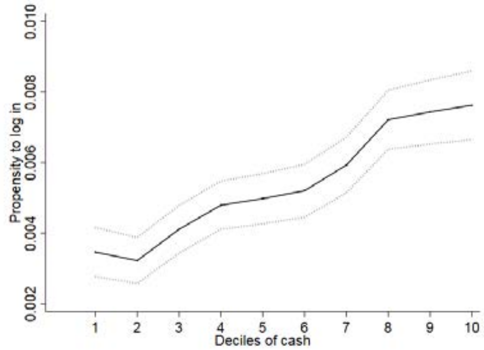
Figure 5: Logins and deciles of account balances and spending



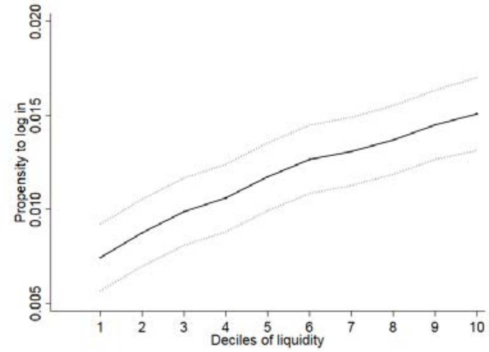
(A) Logins by checking account balance



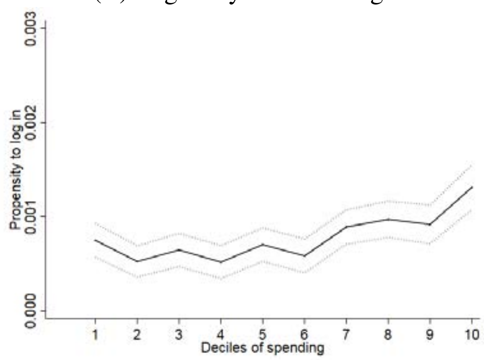
(B) Logins by savings account balance



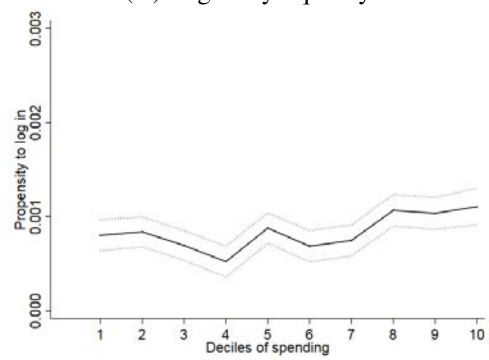
(C) Logins by cash holdings



(D) Logins by liquidity



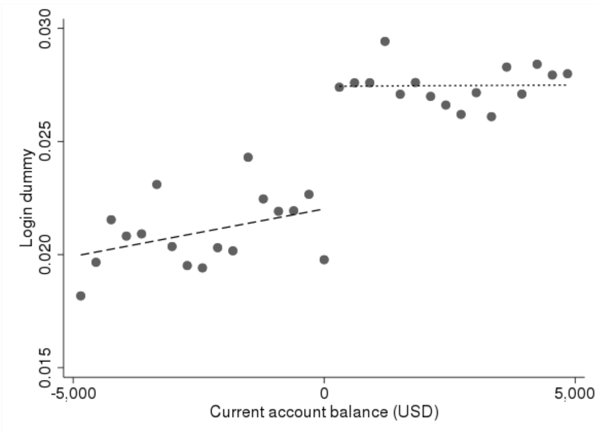
(E) Logins by spending



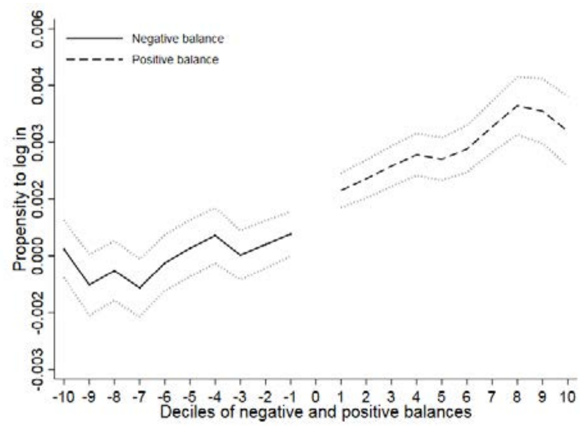
(F) Logins by following day spending

In all graphs, controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level.
Graphs (A) and (B) show the regression coefficients and standard errors for each decile of positive checking account balances and savings account balances relative to individual's own history of checking or savings account balances. (A): *Number of individuals:* 11,007. *Number of observations:* 9,730,188. R^2: 0.3222. (B): *Number of individuals:* 6,970. *Number of observations:* 6,161,480. R^2: 0.3273.
Graphs (C) and (D) show the regression coefficients and standard errors for each decile of cash (positive checking account balance plus savings account balance) or liquidity (cash plus credit card limit minus credit card balance plus overdraft limit minus overdrafts) relative to individual's own history of cash or liquidity. (C): *Number of individuals:* 10,850. *Number of observations:* 9,591,400. R^2: 0.3227. (D): *Number of individuals:* 11,006. *Number of observations:* 9,729,304. R^2: 0.3223.
Graphs (E) and (F) show the regression coefficients and standard errors for each decile of total spending relative to individual's own history. (E): *Number of individuals:* 11,698. *Number of observations:* 22,401,670. R^2: 0.3227. (F): *Number of individuals:* 11,698. *Number of observations:* 22,401,670. R^2: 0.3227.

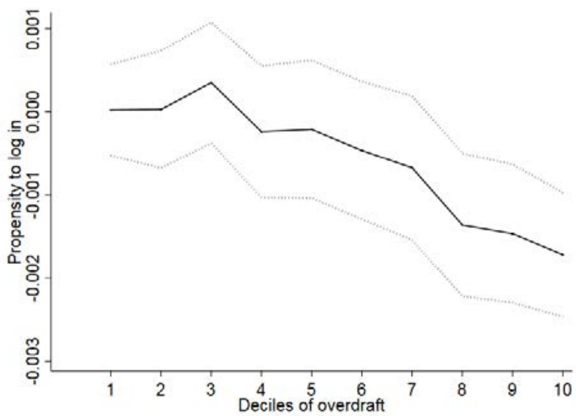
Figure 6: Logins by negative or positive checking account balances as well as deciles of overdrafts



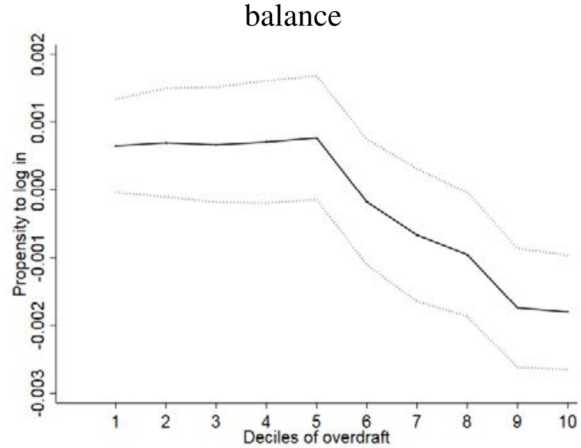
(A) Raw data login bins by checking account balance



(B) Logins by deciles of checking account balance



(C) Logins by deciles of overdrafts



(D) Logins by deciles of overdrafs

Graph (A) shows the raw average of the propensity to log in by bins of negative and positive checking account balance values for individuals who have both negative and positive checking account balances at some point over the sample period. Graph (B) shows the regression coefficients and standard errors for each decile of negative checking account balance or overdraft relative to individual's own history of overdrafts (decile -10 reflects the most negative checking account balance decile or largest amount of overdraft) and the positive checking account balance relative to individual's own history of positive checking account balances. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Additionally, all regressions control for whether payments were received that day. Standard errors are double-clustered at the individual and daily level. *Number of individuals:* 7,580. *Number of observations:* 5,931,362. R^2: 0.3240. We reject the Wald test of the null hypothesis that the estimated coefficients of deciles -1 versus 1 are equal with a p-value equal to 0.0027 (see Table 2).

Graphs (C) and (D) show the regression coefficients and standard errors for each decile of overdraft relative to individual's own history (decile 10 reflects the largest amount of overdraft). Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Graph (D) is based on regressions that only uses individuals without any savings. Standard errors are double-clustered at the individual and daily level. (C): *Number of individuals:* 6,024. *Number of observations:* 3,264,399. R^2: 0.2986. (D): *Number of individuals:* 5,675. *Number of observations:* 1,444,681. R^2: 0.2386.

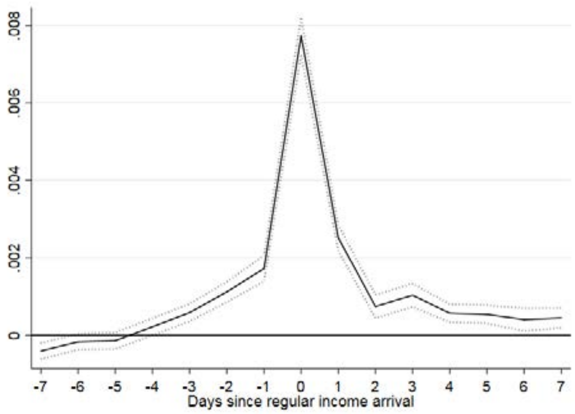
Table 2: Effects of relative bank account balances on logins

	(1)	(2)	(2)-(1)	(4)	(5)	(5)-(4)
Overdraft and current account deciles:						
-10 and 10	0.0002	0.0017***	0.0015***	0.0003	0.0017***	0.0014***
	-0.0008	-0.0005		-0.0008	-0.0004	
-9 and 9	-0.0008	0.002***	0.0028***	-0.0006	0.0021***	0.0027***
	-0.0008	-0.0005		-0.0008	-0.0005	
-8 and 8	-0.0004	0.0024***	0.0028***	-0.0002	0.0023***	0.0025***
	-0.0008	-0.0005		-0.0008	-0.0005	
-7 and 7	-0.0009	0.0027***	0.0036***	-0.0007	0.0028***	0.0035***
	-0.0008	-0.0006		-0.0008	-0.0005	
-6 and 6	-0.0002	0.0026***	0.0028***	-0.0001	0.0026***	0.0027***
	-0.0007	-0.0006		-0.0007	-0.0006	
-5 and 5	0.0002	0.0028***	0.0026***	0.0003	0.0029***	0.0026***
	-0.0007	-0.0006		-0.0007	-0.0006	
-4 and 4	0.0005	0.0034***	0.0029***	0.0007	0.0033***	0.0026***
	-0.0007	-0.0007		-0.0007	-0.0007	
-3 and 3	0.0000	0.004***	0.004***	0.0002	0.0038***	0.0036***
	-0.0007	-0.0008		-0.0006	-0.0007	
-2 and 2	0.0003	0.0038***	0.0035***	0.0001	0.0035***	0.0034***
	-0.0006	-0.0009		-0.0006	-0.0008	
-1 and 1	0.0006	0.0033***	0.0027*	0.0005	0.003***	0.0025*
	-0.0006	-0.0009		-0.0006	-0.0009	
#obs		5,931,362			6,169,038	
#individuals		7,580			8,985	
R^2		0.3240			0.3233	

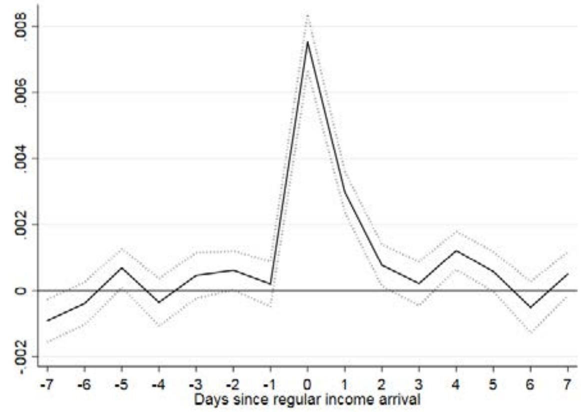
Notes: [a] This table shows regression results for logins on overdrafts and positive checking account balance deciles (relative to individual's own histories). Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Additionally, all regressions control for whether payments were received that day. Standard errors are double-clustered at the individual and daily level. [b] The estimates in Columns (1) and (4) are for negative checking account deciles or overdrafts while the estimates in Columns (2) and (5) are for positive checking account deciles. The estimates in Columns (1) and (2) include only individuals who, at some point during the sample period, have both positive and negative checking account balance. The estimates in Columns (4) and (5) also include individuals who are only observed with either positive or negative current account balances. [c] The stars in Columns (3) and (4) refer to the significance level at which we can reject the null hypothesis that the difference between the -x and x deciles is equal to zero using a Wald test. [d] Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

A Additional figures

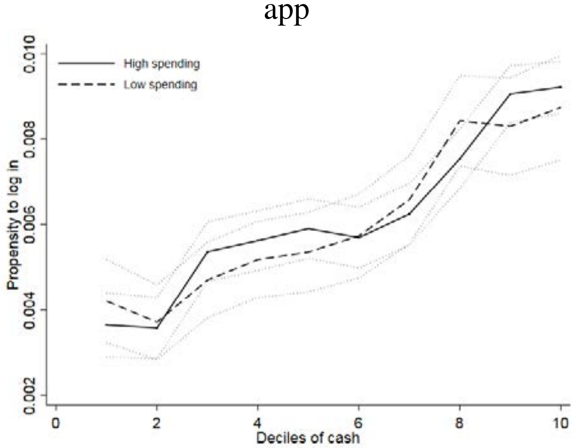
Figure A.7: Logins around the arrival of regular salary payments, before and after the introduction of the mobile app, and logins by cash and liquidity for low and high daily spending



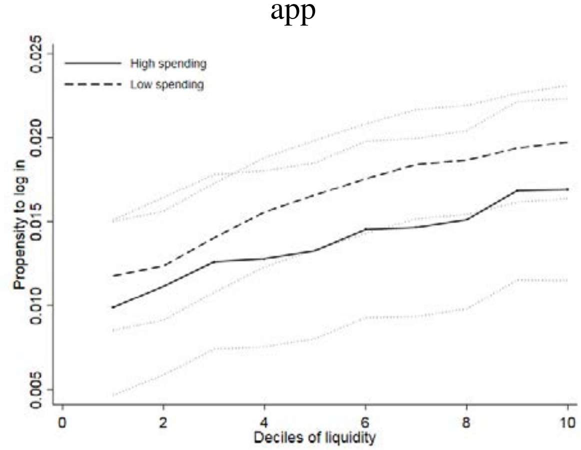
(A) Logins around the arrival of regular salary payments, before the introduction of the mobile app



(B) Logins around the arrival of regular salary payments, after the introduction of the mobile app



(C) Logins by deciles of cash

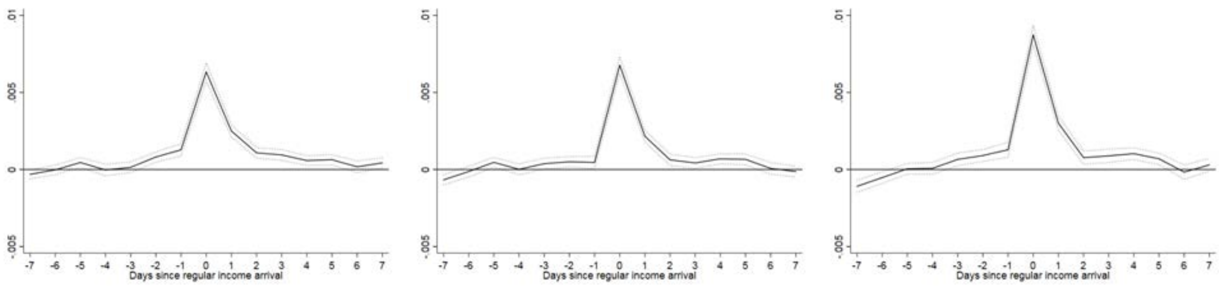


(D) Logins by deciles of liquidity

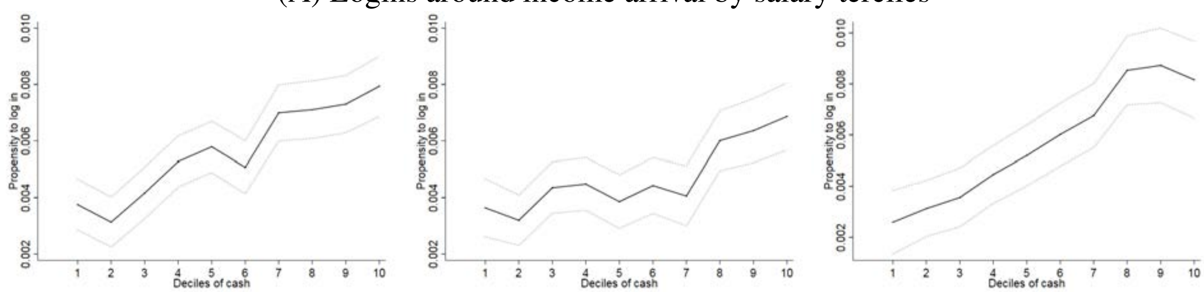
Graphs (A) and (B) show the response of the propensity to log in to regular income arrival for two weeks around the income arrival before and after the introduction of the mobile app. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. *Number of individuals:* 11,699. *Number of observations before:* 12,845,502. R^2 before: 0.3215. *Number of observations after:* 9,394,297. R^2 after: 0.3252

Graphs (C) and (D) show the regression coefficients and standard errors for deciles of cash holdings and liquidity relative to individual's own average cash and liquidity for (within-individual) low and high spending days. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. Cash, low spending: *Number of individuals:* 10,850. *Number of observations:* 4,513,080. R^2: 0.3575. Cash, high spending: *Number of individuals:* 10,850. *Number of observations:* 1,441,586. R^2: 0.3575. Liquidity, low spending: *Number of individuals:* 11,006. *Number of observations:* 4,576,8523. R^2: 0.3571. Liquidity, high spending: *Number of individuals:* 11,006. *Number of observations:* 1,444,681. R^2: 0.3145.

Figure A.8: Logins around income arrival by salary terciles and logins by cash deciles for three income terciles



(A) Logins around income arrival by salary terciles

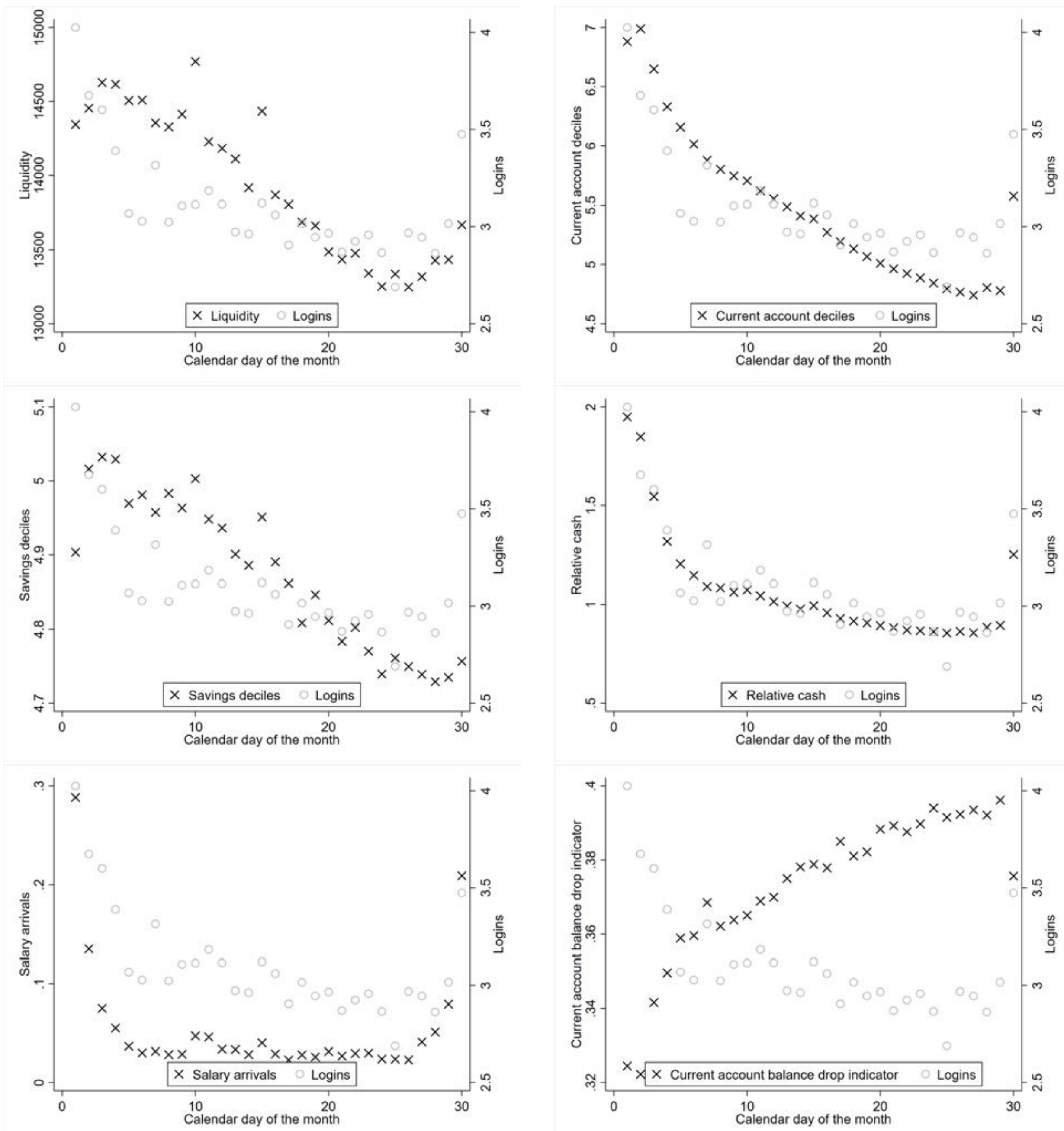


(B) Logins by cash deciles for three income terciles

The graphs in panel (A) show the response of the propensity to log in to regular income arrival for three salary terciles. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. Tercile 1: *Number of individuals:* 3,900. *Number of observations:* 7,413,900. R^2: 0.2966. Tercile 2: *Number of individuals:* 3,900. *Number of observations:* 7,413,900. Tercile 3: R^2: 0.3188. *Number of individuals:* 3,899. *Number of observations:* 7,411,999. R^2: 0.3343.

The graphs in panel (B) show the response of the propensity to log in to cash holdings (positive checking account balance and savings balance) deciles relative to own history of cash for three income terciles. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily level. Tercile 1: *Number of individuals:* 3,679. *Number of observations:* 3,252,236. R^2 : 0.2830. Tercile 2: *Number of individuals:* 3,611. *Number of observations:* 3,192,124. R^2 : 0.3231. Tercile 3: *Number of individuals:* 3,560. *Number of observations:* 3,147,040. R^2 : 0.3441.

Figure A.9: Personal finances and attention throughout the month



Note: This figure shows liquidity, bank account balances, frequency of salary arrivals, frequency of bank account balance reductions and logins throughout the month.

B A simple model of information costs

We assume that the agent is subject to uncertainty about 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 $\tilde{s}$. Furthermore, the rationally inattentive agent pays an exogenous attention cost a. 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. We describe the costs of being inattentive as a fee, but we remain agnostic about what it actually represents, it can be an actual financial penalty or any other costs that is incurred because the agent did not pay attention. In turn, the agent considers the expectation of paying a fee and will pay attention if

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

Her risk premium for paying attention, that is the linear difference in utility levels that compensates the agent for paying attention when knowing that $\tilde{y} - \tilde{b} = \mu$ or $\tilde{s} = 0$ as opposed to $\tilde{s}$ being uncertain, is thus

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

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,

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

Proposition 1. *The standard agent's risk premium decreases with consumption or wealth μ if she* *is prudent:* $u''' > 0$.

Proof. See $\frac{\partial \frac{\partial \pi}{\partial \sigma}}{\partial \mu} < 0$ if $u''' > 0$. □

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.[30]

Moreover, the above model faces another shortcoming in our setting. The model predicts that the risk premium goes to zero whenever risk becomes small as the standard agent's utility function is linear or risk-neutral for small risks.

Proposition 2. *The standard agent's risk premium goes to zero whenever risk becomes small, i.e.,* $\frac{\partial \pi}{\partial \sigma}|_{\sigma \to 0} = 0$.

Proof. To see this, note that:

$$\frac{\partial \pi}{\partial \sigma}|_{\sigma \to 0} = -E[\beta f \delta(\mu) \tilde{s} u'(\mu - f I(\mu < 0))] = 0.$$

□

That uncertainty is small is a plausible assumption in our context because uncertainty about bank account balances is generally small. Thus, any model featuring second-order risk aversion is unlikely to generate a large aversion against checking bank account balances that would explain why individuals incur substantial financial fees that would be reduced if they would check their accounts more often.

C A model of information-dependent utility

We now formally explore the information-dependent utility model developed by Kőszegi and Rabin (2006, 2007, 2009). We will show that the model formalizes intuitions for a key empirical result: individuals dislike paying attention to their accounts, especially when cash holdings are low. This holds even when uncertainty is low, which is a plausible assumption for uncertainty about bank account balances.

The agent experiences news utility as modeled by Kőszegi and Rabin (2009).[31] News utility is given by $\int \nu(u(c) - u(\tilde{c}))dF_c(\tilde{c})$ with $\tilde{c} \sim F_c$ representing the agent's fully rational expectations

[30] A standard agent's risk premium is positive if the utility function is concave and it is increasing in wealth or income if the utility function is prudent (refer to Gollier, 2004, for a more in-depth analysis).

[31] We refer to Kőszegi and Rabin (2009) and Pagel (2018) for a more detailed introduction of the preferences in the interest of brevity.

about consumption c.[32] As in the previous rational-inattention model, 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) define 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 compares her actual consumption c to her rational expectations about consumption $\tilde{c}$ and 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, which is 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, as we will explain in more detail below.

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. As in the previous model, we assume that 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 $\gamma\beta$, where $\gamma < 1$. The assumption $\gamma < 1$ implies that the agent cares less about news regarding future consumption relative to present consumption, which, for instance, generates realistic overconsumption in a life-cycle model, as shown in Pagel (2017).[33] In addition, $I(a)$ is an indicator variable equal to 1 if the agent pays attention to her accounts and zero otherwise. The agent maximizes

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

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

The agent pays attention to her accounts if the expected utility of paying attention is greater than

[32] The consumption level c can be a realization or an updated stochastic distribution function. Kőszegi and Rabin (2009) propose rational expectations as a benchmark for the reference point. In this situation, expecting to receive news, even if news is not mean zero, entails a first-order disutility. Alternatively, one may consider off-equilibrium beliefs or other reference points (such as the status quo or aspirations). We first see how the model fares using rational expectations and discuss potential modifications when we turn to the empirical findings the model as is cannot explain.

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

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, 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, so $f \uparrow \Rightarrow -\beta fF(-\frac{\mu}{\sigma}) \downarrow$, then paying attention is more likely. When overall cash holdings are increased and thereby the fee payment is less likely, i.e., $\mu \uparrow \Rightarrow F(-\frac{\mu}{\sigma}) = Prob(\tilde{s} < -\frac{\mu}{\sigma}) \downarrow \Rightarrow -\beta fF(-\frac{\mu}{\sigma}) \uparrow$, 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.

The linear case is helpful to understand the model's components and mechanisms in a simple setting. But we want to now move on to a concave utility function and a situation in which uncertainty is small, which is likely to be the case for bank account balances. To formalize intuitions for a concave 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 3. *For the standard agent ($\eta = 0$), the risk premium for paying attention in the presence of small risks is zero (the agent is 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 decreases with 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 disutility 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 $\theta = 4$. Beyond the coefficient of risk aversion θ, we calibrate annual labor income uncertainty in line with the life-cycle literature (e.g., 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 $\sigma = \sigma_{ann}/\sqrt{12}$. Moreover, we assume that cash holdings equal the exponent of monthly income uncertainty, $\mu = \sigma$, 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 calculate that the agent is willing to give up 3 percent of cash holdings to not experience news disutility, which amounts to \$47 per month for $\eta = 1$ and $\lambda = 2$. These parameters provide a lower bound of the standard parameters in the prospect-theory and news-utility literature for explaining the evidence in Kahneman and Tversky (1979), among others.[34] In turn, as an out-of-sample test of this calibration, 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 her accounts. This is in line with our empirical finding that the probability of logging in when one goes from low cash holdings to high cash holdings increases by approximately 25 percent. We conclude that the first-order willingness to incur 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. These predictions hold within-individuals but also cross-sectionally.

Using the same calibration but the standard model in Section 4, we ask how much of her monthly consumption the standard agent would be willing to forgo in order 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 ${}^{\sigma_{ann}}/\sqrt{12} = {}^{0.2}/\sqrt{12}$, 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 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 first-order prudence to explain our findings under realistic income uncertainty at a monthly level.

The finding that the willingness to pay to avoid uncertainty is much larger for the news-utility agent than for the standard agent also illustrates that the news utility motives would dominate standard motives for reducing uncertainty in a model that contains both. In other words, if we had a news-utility agent who also has a standard motive to avoid uncertainty about fee payments, then the news-utility preferences would dominate the behavior of this agent. I.e., if uncertainty is low, the agent would prefer to not pay attention even if doing so can reduce the risk of paying fees.

In the news-utility model, the agent maximizes her utility knowing that she derives disutility from fluctuations in beliefs about consumption and optimally trades those off. However, there is also a time-inconsistency problem associated with the preferences. If the agent were to maximize her utility from some initial period and could make an optimal contingency plan of when to pay attention, she would generally pay less attention, as shown in Pagel (2018). However, this prediction appears also at odds with some of the evidence we see, such as online resources that help individuals getting over the fear of checking bank account balances.

[34]We refer to Pagel (2017) for examples of calculations of attitudes toward wealth gambles.

D Statement by Meniga about the absence of notifications when only the desktop version of the software was available

Reykjavík January 7th, 2020

User Events and Notification in the Meniga App

Meniga PFM 2.20 was released on December 8th, 2015. The main features were User Events and Notification. The following features were supported in the release and were not included in previous versions:

- Available amount
- Unusual spending
- Deposit
- Merchant purchase count
- Threshold expenses
- Category budget watch
- Weekly report
- Monthly report
- Custom content

The definition of User Event:

User Events

A user event is personalized visually engaging content that is displayed to the end user, e.g. in a financial feed within an online bank or a mobile app. The contents of the user event can be pushed to the end user by sending a notification via email, mobile push, SMS or any other notification channel. Here you can manage the built-in user event types offered in the system. Each event has a system settings object that you can configure. The required format for the settings object is documented here

Best Regards

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meniga

E Monthly summary email of income and expenses sent by Meniga when only the desktop version of the software was available

From: **Meniga** noreply@meniga.is
Subject: Mánaðaryfirlit þitt í Meniga
Date: August 7, 2015 at 1:29 PM
To: arnavardar@gmail.com

meniga

07. Aug 2015 — Sérðu ekki póstinn? Skoðaðu yfirlitið á vefnum | Stilla tilkynningar sem berast í tölvupósti

Yfirlit yfir fjármál heimilisins

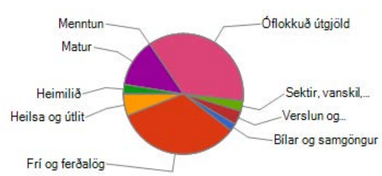
Tengjast Meniga

TEKJUR		ÚTGJÖLD		SPARNAÐUR
0	-	174,383	=	-174,383

Farðu varlega
Þú eyddir 174,383 kr. meira en þú aflaðir í síðasta mánuði. Þú gætir átt á hættu að lenda í fjárhagsvanda ef endar ná ítrekað ekki saman.

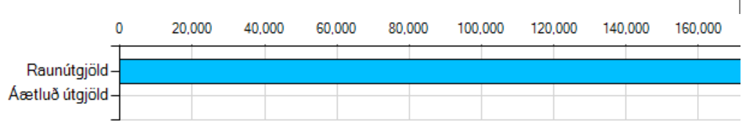
Útgjöld eftir flokkum

Bílar og samgöngur	12,972 kr.	7.4%
Frí og ferðalög	214,888 kr.	123.2%
Heilsa og útlit	37,490 kr.	21.5%
Heimilið	16,430 kr.	9.4%
Matur	82,231 kr.	47.2%
Menntun	270 kr.	0.2%
Óflokkuð útgjöld	-231,450 kr.	-132.7%
Sektir, vanskil, neyslulán	18,150 kr.	10.4%
Verslun og þjónusta	23,402 kr.	13.4%



Útgjöld og áætlun

Þú eyddir 174,383 kr. meira en áætlun síðasta mánaðar gerði ráð fyrir. Skoðaðu vel í hvaða flokkum þú fórst fram úr áætlun í listanum hér að neðan.



Áætluð útgjöld eru samanlögð markmið þín í öllum útgjaldaflokkum.

Útgjaldaflokkur	Útgjöld	Bókhald	Árangur
Frí og ferðalög	**214,888**	**0**	**-214,888**
Hótel og gisting	214,888	0	-214,888
Matur	**82,231**	**0**	**-82,231**
Matarinnkaup	71,831	0	-71,831
Veitingastaðir	10,400	0	-10,400

Smelltu á tölur í dálknum **Útgjöld** til að skoða færslur á bakvið hvern flokk.

Smelltu á tölur í dálknum **Áætlun** til að fara í bókhaldið þitt og

Heilsa og útlit	**37,490**	**0**	**-37,490**
Læknar og tannlæknar	30,000	0	-30,000
Líkamsrækt og íþróttir	7,490	0	-7,490
Verslun og þjónusta	**23,402**	**0**	**-23,402**
Verslun og þjónusta (annað)	13,606	0	-13,606
Áfengi	7,869	0	-7,869
Póstur og burðargjöld	1,630	0	-1,630
Sjónvarpsefni, bækur, tónlist o.þ.h.	297	0	-297
Sektir, vanskil, neyslulán	**18,150**	**0**	**-18,150**
Bankakostnaður og þjónustugjöld	18,150	0	-18,150
Heimilið	**16,430**	**0**	**-16,430**
Rafmagn og hiti	13,006	0	-13,006
Sími og internet	3,424	0	-3,424
Bílar og samgöngur	**12,972**	**0**	**-12,972**
Eldsneyti	9,051	0	-9,051
Leigubílar, strætó, samgöngur	3,921	0	-3,921
Menntun	**270**	**0**	**-270**
Skólabækur, efni og ritföng	270	0	-270
Óflokkuð útgjöld	**-231,450**	**0**	**231,450**
Óflokkaðar millifærslur	-1,450	0	1,450
Óflokkaðar peningaúttektir	-230,000	0	230,000
Samtals útgjöld	**174,383**	**0**	**-174,383**

setja þér þín eigin markmið. Gráu tölurnar eru útgjaldaspá sem byggir á eyðslu þinni í fortíðinni en bláu tölurnar sýna þín eigin útgjaldamarkmið.

Breyta dagsetningu á færslu

Ef launin þín eru stundum greidd út í lok mánaðar er lítið mál að breyta dagsetningu svo bókhaldið gefi rétta mynd. Skoða hjálparmyndband.

Tengjast öðrum notanda

Með samstarfi við fleiri banka er auðveldara að fá heildarmynd á fjármál heimilisins, sérstaklega ef makar eru í sitthvorum bankanum. Auðvelt er að stofna nýjan aðgang og tengja saman við maka sem er þegar skráður en einnig er hægt að gera það eftir á. Skoða hjálparmyndband

Fylgstu með á