The Ostrich in Us: Selective Attention to Personal Finances

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Abstract

Attention plays an important role in both micro- and macroeconomic theory but direct empirical evidence is scarce. In this paper, we analyze the determinants of attention to financial accounts using panel data from a financial aggregation platform, including daily logins, discretionary spending, income, balances, and credit limits. We find that income arrivals cause individuals to log in and pay attention to their finances. Moreover, individual attention increases in cash holdings, savings, and liquidity, while it decreases in spending and overdrafts, and jumps discretely when balances change from negative to positive. We document these patterns within individuals by comparing each person within his or her own history. We argue that our findings cannot easily be explained by rational theories of inattention, i.e., information costs and benefits. Instead, they suggest that information-dependent utility generates selective attention and Ostrich effects. In turn, we formally discuss in how far the most highly-cited information-dependent utility model can explain our findings and what are its shortcomings. Furthermore, we show that a standard general-equilibrium model generates very different aggregate dynamics if inattention is assumed to be selective instead of rational.

Keywords: attention, personal finance, consumer debt, liquidity, spending

JEL: D12, D14, D81, D83

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1 Introduction

Standard economic models predict that information is always valuable because it helps individuals make better decisions. Theories of rational inattention posit that individuals trade off the direct costs of information acquisition with the expected benefits. Information costs include, e.g., the transaction costs of information processing, and its benefits include, e.g., potential improvements in decision making. Such rational inattention was introduced as an explanatory mechanism in a recent theoretical literature in asset pricing and macroeconomics, showing that it matters for aggregate dynamics (e.g., Woodford, 2009; Reis, 2006; Gabaix and Laibson, 2002; Van Nieuwerburgh and Veldkamp, 2009).

However, people often seek out apparently useless information or avoid useful information (see Golman et al., 2016, for a literature survey). In light of this evidence, a theoretical literature on information-dependent utility has emerged positing that information also has a hedonic impact on utility that goes beyond direct information costs and benefits (e.g., Golman and Loewenstein, 2015; Köszegi and Rabin, 2009; Caplin and Leahy, 2001; Ely et al., 2015; Van Nieuwerburgh and Veldkamp, 2010). Nevertheless, empirical evidence on the determinants of attention lags behind the theoretical advances and remains scarce.

Potentially because of a lack of empirical evidence, it is still an open question whether theories of rational inattention or theories of information-dependent utility are more successful in explaining everyday behavior. To answer this question is important because the different modeling assumptions majorly affect aggregate dynamics in macroeconomic models. To inform the theoretical literature and better understand the determinants of attention, we thus undertake a large-scale empirical study of individual attention to checking, savings, and credit card accounts.\(^1\)

We study the determinants of paying attention to financial accounts using data from a financial aggregation platform in Iceland that individuals use to check their bank accounts, but not to execute financial transactions.\(^2\) In addition to tracking attention, we also have high-frequency transaction-level data on income, spending, balances, and credit limits. Our empirical analysis is guided by the following questions: When and under what conditions do individuals pay attention to their financial accounts? Can our empirical findings be explained by "rational" theories of inattention,

\(^1\)We use online account and smartphone app logins to measure individual attention following three studies that analyze online account logins to retirement portfolios (Sicherman et al., 2015a; Karlsson et al., 2009; Gherzi et al., 2014).

\(^2\)The present paper focuses solely on the determinants of paying attention and not on its consequences. For an analysis of the causal effect of paying attention to personal finances, we refer to Carlin et al. (2017), who show that individuals reduce their consumer debt substantially in response to paying more attention to their financial accounts. More specifically, one additional login per month reduces the amount of consumer debt by approximately 14 percent over a 24-month period.
that is, by direct information costs and benefits? To what extent is inattention not "rational" but "selective," that is, driven by information-dependent utility? In sum, we argue that inattention appears mostly driven by selective rather than rational motives and that information-dependent utility generating Ostrich effects (the avoidance of adverse information) and anticipatory utility (an increase in current utility from looking forward to future consumption) are first-order important for individual attention to financial accounts. This conclusion is illustrated in Figure 1, which shows a positive correlation between bank account balances and logins and a jump when balances go from negative to positive in the raw data. Furthermore, casual observation of online media suggests that fearing to check bank account balances is indeed very common.

Our data allows us to sort every individual’s observations of cash holdings, liquidity, and spending into deciles to compare individuals within their own histories. This means that we can obtain results that do not reflect cross-sectional differences. Moreover, we control for individual fixed effects and thereby all self selection on observable or unobservable time-invariant characteristics. Furthermore, the inclusion of a set of calendar fixed effects (day-of-week, day-of-month, month-by-year, and holidays) effectively identifies irregular variation within a given month that is neither driven by week or holiday patterns nor slow-moving trends. We document a number of interesting patterns. First, individual attention increases with the arrival of perfectly predictable income. Second, attention increases as savings increase and decreases as spending increases. Third, attention increases with cash holdings and liquidity. Fourth, attention decreases with the amount of overdrafts individuals hold (again, relative to their own history) until individuals get into very dire financial standing where attention starts increasing again. Finally, attention jumps discontinuously when checking account balances change from negative to positive.

To interpret these findings, we carefully discuss how a rationally inattentive agent, who is subject to information costs and benefits, but does not experience information-dependent utility, would behave. More specifically, we compare our empirical evidence to four rational hypotheses about when individuals log in. The first one hypothesizes that individuals log in irrespective of their transactions because there is either full uncertainty or no uncertainty associated with them. The second one hypothesizes that individuals log in for transaction verification. The third hypothesis proposes that individuals log in to budget or plan their spending. Finally, the last one hypothesizes that individuals log in when their opportunity costs are low.

Based on all our empirical findings, we argue that none of the rational theories of inattention

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3Following the terminology in Golman et al. (2016).
4Cash is defined as savings account balances plus positive checking account balances and liquidity is defined as savings account balances plus credit limits plus checking account balances minus credit card balances. Checking account balances are negative when individuals hold an overdraft.
provide a dominant motive for individual attention to personal finances. For instance, hypothesis 1 can be ruled out because perfectly predictable income payments cause an increase in logins. Thus, individuals cannot be fully certain or uncertain about the transactions in their accounts. However, transaction verification (hypothesis 2) does not seem to be the main motivation for logging in as a number of additional findings suggest. For instance, we do not find a larger login response on paydays with many other transactions even though other transactions should increase the need for transaction verification. We also find that the login response on paydays is higher when cash holdings and liquidity are high, which is inconsistent with hypothesis 2 and 3, because individuals should care more about budgeting when cash holdings and liquidity are low. Finally, we can address hypothesis 4 because the response of logins on paydays is unaffected by concurrent spending, a potential measure of opportunity costs. In this manner, we carefully address and discuss all our findings and theories of rational inattention.

From this discussion, we conclude that most of our findings are consistent with two specific forms of selective rather than rational inattention: anticipatory utility and the so-called Ostrich effect introduced by Galai and Sade (2006) and Karlsson et al. (2009). Karlsson et al. (2009) propose that attention amplifies the hedonic impact of information, which implies that investors should pay more attention to their finances after good news than after bad news. The authors show that investor attention to personal portfolios increases after positive returns on market indices. In the context of financial accounts, cash inflows—whether from income payments or wealth shocks—or large cash and liquidity holdings can be considered good news and induce individuals to log in to their accounts. By contrast, little cash or large overdrafts can be considered bad news that individuals prefer not to pay attention to.

Three important differences between attention to portfolios, as analyzed by Karlsson et al. (2009), and our setting are the following: (1) We know that individuals can improve their financial standing by paying more attention to their accounts (Carlin et al., 2017; Stango and Zinman, 2014; Medina, 2016) while it is unclear whether investors have any skill in stock picking or market timing. This implies that attention to bank accounts may have more direct benefits than attention

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5The empirical finding in Carlin et al. (2017), that individuals save overdraft fees when they log in more, allows us to rule out a rationally attentive model in which all information costs are absent.

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

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

8Individuals can increase their returns and reduce the risk of their portfolios with rebalancing but Sicherman et al. (2015a) rule out this motive by referring to the general low level of actual trading. Gargano and Rossi (2017) show that investors who pay more attention successfully exploit the momentum anomaly in a brokerage account dataset of frequent traders over the period from 2013 to 2014. Nevertheless, over longer time periods, Barber and Odean (2000)
to portfolios. (2) Uncertainty about bank account balances should be considerably lower than uncertainty about portfolios. This makes inattention more difficult to rationalize theoretically and thus more surprising. (3) We document selective attention in a more standard "everyday" domain for a broad and representative sample of the population. This implies that selective attention is an even more widespread phenomenon than previous studies suggest.

We think that our results make a general case for information-dependent utility models generating Ostrich effects and anticipatory utility. But more specifically, we are interested in how far the most widely-applied information-dependent utility model, the one developed by Kőszegi and Rabin (2006, 2007, 2009), can reconcile and formalize intuitions consistent with our empirical evidence regarding attention: that individuals incur substantial fees by being inattentive, but check their accounts more often when they have received income and hold more cash. We formally analyze this specific model because it is not only the most highly-cited model of information-dependent utility but it also combines features of influential previous models (such as the time inconsistency in Caplin and Leahy (2001) and Brunnermeier and Parker (2005) via the equilibrium concept in Kőszegi (2010)) and assumes first-order risk aversion, which is important as uncertainty about bank account balances is likely to be small. We do not aim to provide a satisfactory rationalization of our empirical results, but are rather interested in how far we get in terms of explaining our findings using a prototype of these models and what are its main shortcomings.

In the model by Kőszegi and Rabin (2009), agents derive utility not only from present consumption but also from changes in expectations or news about present and future consumption. To generate attitudes towards wealth gambles consistent with prospect theory, the model assumes that bad news hurts more than good news pleases. This assumption implies that expecting to receive news entails a first-order disutility. Thus, the agent is averse to receiving news even if the uncertainty is very low—which is likely to be the case for bank account balances. However, this expected news disutility decreases in wealth if the agent’s utility function is concave. Because the agent trades off the costs of expected news disutility and the benefits of staying fully informed and

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9 All the existing models of selective attention assume some uncertainty or risk, but any second-order risk averse agent will become risk-neutral when uncertainty goes to zero.

10 93 percent of American households have a bank account (Federal Deposit Insurance Corporation (FDIC) reports), while investors who have Vanguard retirement accounts are a potentially more selected group of individuals.

11 In terms of google scholar citation counts, the model in Kőszegi and Rabin (2006) alone far exceeds other very influential models, such as Caplin and Leahy (2001), Brunnermeier and Parker (2005), or Van Nieuwerburgh and Veldkamp (2009).

12 By analyzing the jump in attention when balances change from negative to positive in a number of narrow bins, we can determine how well individuals predict their balance. It appears that individuals know their balances up to bins of approximately $50.
avoiding fees, she may pay more attention in good financial health. Thus, the model succeeds in explaining two key empirical findings: individuals are averse to paying attention to bank account balances even when uncertainty is low and especially when they are in dire financial standing. While the model is able to generate some of our empirical findings, it cannot generate others (for instance, a jump in logins when balances turn positive), which calls for extending the model to off-equilibrium or otherwise irrational expectations about consumption.

Our findings are informative about the assumptions of rational inattention in macroeconomic models, which would generate different aggregate dynamics if inattention were selective instead of rational. We formally show this in a simple general-equilibrium model. More specifically, we consider a Lucas (1979) tree model and add time-varying attention as commonly done in the asset-pricing literature, e.g., Andrei and Hasler (2014), by simply assuming that the length of the agent’s upcoming time period varies with the consumption shock. Because any agent with a prudent utility function finds consumption smoothing more beneficial at low wealth levels, a rationally inattentive agent should pay more attention, i.e., smooth consumption at a higher frequency, in the event of an adverse consumption shock, while the selectively inattentive agent is assumed to do the opposite. We in turn show that the model’s predictions about the risky and risk-free returns as well as the equity premium and its volatility are substantially affected when we assume selective as opposed to rational inattention.

Our findings thus also contribute to the literature on information costs.13 If individuals are in some instances willing to pay in order not to receive information (which can be inferred from this study in connection with our companion paper Carlin et al., 2017), then information costs are time-variant in non-trivial ways and sometimes effectively negative rather than positive. Furthermore, because individuals in dire financial standings do not pay attention, which consequently exacerbates things, our findings relate to the literature on poverty traps (see Azariadis and Stachurski, 2005, for a literature survey) and on poverty and cognitive function (Mani et al., 2013; Carvalho et al., 2016). Finally, our findings are important for policy prescriptions or (field) experimental interventions where it is important to take into account that inattention is selective rather than rational (see DellaVigna, 2009, for a literature survey).

There is a growing literature analyzing when people seek useless information or avoid useful information even when it is free. Casual observation and theoretical, laboratory, and field research suggest that this behavior is quite common. Specifically, investors are inattentive to their portfolios (Bonaparte and Cooper, 2009; Brunnermeier and Nagel, 2008) and may actively avoid looking at

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13Studies modeling information costs include Abel et al. (2013); Alvarez et al. (2012); Huang and Liu (2007); Van Nieuwerburgh and Veldkamp (2009, 2010)
them when the stock market is down (Karlsson et al., 2009; Sicherman et al., 2015a). Individuals at risk for health problems (e.g., serious genetic conditions or STDs) often avoid medical tests even when the information is costless and should, logically, help them make better decisions (Ganguly and Tasoff, 2014; Sullivan et al., 2004; Lerman et al., 1996, 1999; Lyter et al., 1987; Oster et al., 2013; Thornton, 2008). Finally, the laboratory findings of Zimmermann (2014), Falk and Zimmermann (2014), Eliaz and Schotter (2010), and Powdthavee and Riyanto (2015) underscore the importance of attention for information-dependent utility.

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 (see (in addition to the studies already mentioned), e.g., Caplin and Leahy, 2004; Kőszegi and Rabin, 2006, 2009; Epstein, 2008; Dillenberger, 2010; Andries and Haddad, 2017; Bénabou, 2012; Brunnermeier and Parker, 2005; Strzalecki, 2013).

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

The remainder of the paper proceeds as follows. We provide a data description and summary statistics in Section 2. In Section 3, we document all our empirical findings. In Section 4, we discuss in how far rational theories of inattention can explain our findings and formally discuss a simple model of information costs, and in Section 5, we analyze in how far the most widely applied model of information-dependent utility can do so. Furthermore, in Section 6, we show that rational versus selective inattention matters in general equilibrium. Finally, Section 7 concludes the paper.

2 The financial aggregation platform and summary statistics

2.1 The financial aggregation platform

This paper exploits new data from Iceland generated by Meniga, Europe’s leading provider of financial aggregation software for banks and financial institutions. Meniga’s PFM solution is currently used by more than 50 million people in 20 countries. The company allows financial institutions to offer their online customers or smartphone app users a platform for connecting all their financial accounts, including bank accounts and credit card accounts, in a single location. Each day, the software automatically records all the users’ bank and credit card transactions, including
descriptions as well as balances, overdrafts, and credit limits. This data set has already been used for studying individuals’ spending responses to income arrivals and the effect of increased access to information about personal finances on individual overdrafts (Olafsson and Pagel, 2018; Carlin et al., 2017).

The digitization of budgeting processes with financial aggregation services and the attendant tracking of online and smartphone app behavior allow direct measurement of individual attention in ways that were not previously possible. The Meniga platform allows the tracking of individual attention in addition to providing high-frequency income and spending data derived from individual transactions and account balances. This data source overcomes the limitations of accuracy, scope, and frequency that earlier sources of consumption and income data face. Gelman et al. (2014) and Baker (2014) were the first to advance the measurement of income and spending using data of this sort from the US. We use data from Iceland, which has four main advantages. First, it essentially eliminates the remaining limitation of the earlier app data—the absence of paper money transactions—because Icelandic consumers use electronic means of payments almost exclusively. Second, the software is marketed through banks, ensuring that it covers a fairly broad fraction of the population. Third, the spending and income data are pre-categorized, and the categorization is very accurate with few uncategorized transactions. Finally, bank accounts are personal and cannot be shared, i.e., each bank account can only belong to one individual.

We use the entire de-identified population of active users in Iceland and data derived from their records from January 2011 to January 2017 and perform our analysis on daily user-level information on income by source, on spending by category, on logins by device, and on financial standing such as account balances, overdrafts, overdraft limits, credit card balances, and credit card limits. In January 2014, the population of Iceland counted 338,349 individuals, of whom 262,846 were above the age of 16. At that time, Meniga had 52,545 users, or 20 percent of the population above age 16. Because the platform is marketed through banks, i.e., individuals can sign up when they sign up for online banking, the sample of Icelandic users is fairly representative. Moreover, the internet penetration is 97 percent in Iceland and almost everyone uses online banking. In addition to information on income, spending, account balances, and attention, the platform collects some demographic information, such as age, gender, and postal codes. Moreover, we can infer whether individuals have (small) children, their employment status, and whether they own real estate.

Figure 2 displays screenshots of the app’s user interface. The first shows background characteristics that the user provides, the second shows transactions, and the third shows bank account information. The first versions of the app did not include elements of financial advice. Later ver-

14 ATM withdrawals make up approximately 1 percent of spending transactions by volume.
sions of the app, however, will flag certain events, such as unusually high transactions, deposits, or low balances. Examples of these flags are displayed in Figure 3. It is important to note, though, that the app does not send push notifications. Users have to log in to see these messages. Furthermore, in the last two years, Meniga has expanded the app’s merchant offer features, which are independent of individual financial standing though.

(Figures 2 and 3 around here)

It is important to reiterate that the app does not send reminders or notifications and users cannot perform transactions or pay bills through the app. Therefore, users do not see their credit card bills in the app and cannot receive push notifications due to unpaid bills, overdrafts, or low balances. They only see any notifications after they log in. Specifically, messages appear next to irregular transactions, if an account balance is very low, or an income transaction arrived saying "you got paid." However, as mentioned, users need to be logged in already to see these messages. Furthermore, to ensure that our results are not driven by the smartphone app features, we can only look at the period where no smartphone app was available and individuals had to log in via a desktop. We find the same results in the pre and post smartphone app period. Finally, banks may notify individuals of certain bill payments or transactions but this is not the default or norm.

### 2.2 Summary statistics

**Income, spending, and demographics:** We study all active users with complete records. All individuals in our sample have passed an "activity test" that is designed to verify that we are capturing all of their financial picture. More 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 does not only include labor market income but also, e.g., 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 at least 23 months of

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15Contrary to some of the advertisements on the app’s website (the “international demo” on the Meniga homepage does not accurately reflect how the platform looks and functions in Iceland), users have to log in initially to see all messages and warnings. The current version of the international app asks for permission to send push notifications, but, to the best of our knowledge from having the app installed, does not actually send any. Moreover, no push notifications were featured in the app during our sample period.
a 24 months period. Table 2 displays summary statistics including income and spending in US dollars across login and income terciles. It also displays some demographic statistics. Overall, the sample’s characteristics with respect to age, gender, employment, income, and spending figures are remarkably similar to those in the representative national household survey conducted by Statistics Iceland, as can be seen in Table 3.16 This fact is reassuring because app data often come with a very selected sample of young and tech-savvy folks.17

{Table 2 and 3 around here}

It can be seen in Table 2 that individuals who use the platform frequently are a bit wealthier, are slightly less indebted, and pay less financial fees, than those who do not. We thus conclude that not only does the overall sample look representative, but so does the sample of individuals causing most of the variation in logins. 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 percentage of individual-day observations on which we see at least one login is 6.1 percent. This number is in the same ballpark as the number of logins per individual per month to retirement accounts in Sicherman et al. (2015a).

Beyond being representative for the Icelandic population as a whole, our summary statistics on demographics, income, and consumer debt are also in line with the US. According to Table 2, the average age of our sample is 41 whereas the average age in the US population in 2015 was 38. The percentage of women in our sample is 48% whereas the US representative was 51% in 2015. The mean income in the U.S. population in 2015 dollars per adult member was $3,266, whereas the individual monthly mean income in our sample is $3,547.18 Furthermore, individuals in Iceland hold approximately $3,000 in overdrafts and credit card debt conditional on having overdraft debt (in Iceland, individuals typically pay off their credit card in full and use overdrafts to roll-over debt). Nevertheless, they still enjoy substantial liquidity because they have additional borrowing capacity before hitting their limits, i.e., $10,000 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 and individuals also enjoy substantial space until they hit their credit limits.

Logins: In the cross section of individuals, better financial standing is positively correlated

16 All the income statistics are post tax and deductions as these are subtracted at the source.
17 For instance, roughly half of our users are female, a much higher number than those in other papers using data of this kind.
18 All US numbers stem from the US Census Bureau’s American Community Survey (ACS) in 2015.
with logins. Figure 4 shows that higher income as well as more cash\(^{19}\) and liquidity\(^{20}\) is positively correlated with logins while Figure 5 shows that the number of logins drops with total bank fees, late fees, and overdraft interest. Furthermore, Figure 6 shows the cross-sectional relationship between liquidity and logins for three different income groups and shows that there is a positive relationship between logins and financial standing within all income groups. These are just binned averages of the raw data to illustrate the basic cross-sectional patterns we see.

{Figures 4 to 6 around here}

It is important to note that the average number of logins is very low. The reason is some silent users, i.e., we observe an individual’s spending, income, and transactions but no logins because he or she signed up once but never used the platform or the smartphone app. As we discussed, the average logins are in line with other papers such as Sicherman et al. (2015a) but of course all of the identifying variation stems from the group of regular users. As can be seen in Figure 5, which shows binned logins, some individuals use the app almost every other day. Nevertheless, as can be seen in Table 2, the group of individuals logging in frequently does not look very different from those who never use the app.

Because an uncountable number of differences in individual circumstances and histories can cause logins to vary cross-sectionally, we now turn to individual-level variation in the propensity to pay attention to personal finances to learn more about what determines attention to financial accounts.

3 Analyses and empirical findings

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

\(^{19}\)Cash is defined as: savings account balances + positive checking account balances.

\(^{20}\)Liquidity is defined as: savings account balances + credit limits + checking account balances − credit card balances. Checking account balances are negative when individuals hold an overdraft.
3.1 Attention in response to income payments

We estimate the response of attention to income arrival by running the following regression:

\[ I_i(\text{Login}_t) = \sum_{k=-14}^{14} \beta_k I_i(\text{Paid}_{t+k}) + \delta_{dow} + \phi_{dom} + \psi_{my} + \xi_h + \eta_i + \epsilon_{it}, \tag{1} \]

where \( I_i(\text{Login}_t) \) is an indicator variable of whether individual \( i \) logged in to her account on date \( t \), \( \delta_{dow} \) is a day-of-week fixed effect, \( \phi_{dom} \) is a day-of-month fixed effect, \( \psi_{my} \) is a month-by-year fixed effect, \( \xi_h \) is a holiday dummy, \( \eta_i \) is an individual fixed effect, and \( I_i(\text{Paid}_{t+k}) \) is an indicator that is equal to one if individual \( i \) receives a payment at time \( t + k \) and to zero otherwise. The \( \beta_k \) coefficients thus measure the fraction by which income arrival increases the probability of logging in on the four surrounding weeks. The day-of-week dummies capture within-week patterns of logins, the day-of-month dummies capture within-month patterns of logins, and the month-by-year dummies any slow-moving trends. We use indicator variables for income payments to alleviate potential endogeneity concerns at the income level. Furthermore, we restrict the income payments to regular payments that occur on a fixed day of the month. For most individuals, these are salary payments but they can also be unemployment benefits, pension payments, invalidity benefits, and student loans. When a payday falls on a weekend or holiday, it is moved to the most recent working day or the next one. Weekends and holidays generate therefore an exogenous source of variation in the day of the month that income arrives.\(^{21}\)

Standard errors are clustered at the individual level.

Figure 7 displays the effect of salary arrival on login rates in the four weeks surrounding the salary receipt. The \( \beta \) coefficient is five times larger on paydays than on the surrounding days. Compared to averages login rates, individuals are 62 percent more likely to log in on the day they get paid.\(^{22}\) Figure 8 shows responses to irregular income payments, such as insurance claims, dividends, and grants, and plausibly exogenous income payments, such as lotteries and tax rebates. It can be seen that the login response is very similar in magnitude for irregular and regular payments.

\( \text{Figures 7 and 8 around here} \)

\(^{21}\)Theoretically, we need individual-by-day-of-month fixed effects to single out this exogenous variation or everyone must be paid on the same day of the month. In practice, 85 percent of individuals are paid within a few days of the beginning or the end of the month, and we can restrict our sample to individuals who are paid on the same day of the month. For instance, the figures are virtually unchanged when we consider only individuals who are paid on the first of the month.

\(^{22}\)We know from Olafsson and Pagel (2018) that spending responds to income arrival. To single out the effect of income, we control for spending in additional specifications. While controlling for spending constitutes a bad controls problem, it is still informative about the mechanism if the coefficients are not affected. We find that controlling for spending does not change our coefficients, so we conclude that spending is not the mechanism by which income affects attention.
Furthermore, to analyze the effect of cash, liquidity, and spending on attention to financial accounts on paydays we run the following regression:

\[ I_i(\text{Login}_t) = \beta_d I_i(\text{Liq}_{dt}) \times I_i(\text{Paid}_t) + \delta_{dow} + \phi_{dom} + \psi_{my} + \xi_h + \eta_i + \epsilon_{it}, \]  

(2)

where the variables \( I_i(\text{Login}_t) \), \( \delta_{dow} \), \( \phi_{dom} \), \( \psi_{my} \), \( \xi_h \), \( \eta_i \), and \( I_i(\text{Paid}_t) \) are as specified above and \( I_i(\text{Liq}_{dt}) \) is an indicator variable for each cash or liquidity decile \( d \) of individual \( i \) (relative to individual \( i \)'s own average cash or liquidity) on date \( t \). The \( \beta_d \) coefficients thus measure the fraction by which income arrival increases the probability of logging in for each cash or liquidity decile. Figure 9 displays the relationship between logging in on paydays and on other days for different levels of individual cash and liquidity holdings. Individuals are more likely to log in on paydays, especially when their cash holdings and liquidity are relatively large. Here, one can nicely see the effects of income arrivals and its interaction with cash or liquidity: individuals are around 30 percent more likely to log in on paydays than the baseline probability (around 3 percent per day) when cash holdings are low, and are around 200 percent more likely to log in when cash holdings or liquidity are high.

\{Figure 9 around here\}

The same approach can be used to examine the effect of spending on attention to financial accounts. Figure 10 shows how logins respond to spending when receiving regular income payments and when not, documenting that there is no clear relationship between spending and logins.

\{Figure 10 around here\}

### 3.2 Attention in response to credit card bill payments

In Iceland, credit card bills are due on the 2nd of the month and weekends and holidays generate therefore an exogenous variation in bill payments in the same way as for paydays.\(^{23}\) We can thus use the same identification strategy as before to assess the attention response to regular credit card bill payments. Figure 11 displays login responses to credit card due dates for different deciles of cash holdings and liquidity. Individuals are more likely to log in on the days they have to pay credit card bills, although the magnitude is only half of that of regular and irregular incoming payments and the response is much less tightly estimated. Furthermore, this login response to

\(^{23}\)The majority of credit cards are mandated by the bank to be paid automatically.
credit card payments is not decreasing in both cash holdings and liquidity (within individuals’ personal histories) but is in fact larger for the highest decile of cash and liquidity than for the lowest decile.

{Figure 11 around here}

### 3.3 Attention, balances, liquidity, and spending

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

\[
I_i(\text{Login}_t) = \sum_{d=0}^{10} \beta_d I_i(S_{dt}) + \psi_{my} + \phi_{dom} + \delta_{dow} + \xi_h + \eta_i + \epsilon_{it},
\]

(3)

where \( I_i(\text{Login}_t) \), \( \psi_{my} \), \( \delta_{dow} \), \( \phi_{dom} \), \( \xi_h \), and \( \eta_i \) 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. \( I_i(S_{dt}) \) is an indicator variable that is equal to 1 if individual \( i \) is in savings decile \( d \) on date \( t \). The savings deciles are constructed by first calculating how much savings an individual has in comparison to how much savings she has on average and then we split this measure of individual’s relative savings into 11 groups. The first group is zero savings, and the remaining groups split the individual’s savings into deciles. For instance, an individual’s savings are in the first decile if he or she held this small but positive amount of savings 10 percent of the time. The estimated effect of being in each savings decile is therefore comparing the individual’s propensity to log in to her probability of logging in when she has no savings.

Although we are technically reporting correlations, in practice the set of fixed effects imposes a high bar for selection, omitted-variable bias, and reverse causality. All selection on time-invariant (un)observables is controlled for because we include individual fixed effects and we only compare individuals’ savings with 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 recurring planning motives as well as all slow-moving trends. Therefore, we are left with variation within a given month that cannot be driven by recurring patterns in income and spending within a given month because these are picked up by the fixed effects. Finally, we know from our companion paper (Carlin et al., 2017) that logins do not cause substantial changes in spending patterns at short horizons limiting the potential impact of reverse causality. But even under the premise that all

\(^{24}\text{Carlin et al. (2017) find that individuals reduce their overdrafts after logging in more frequently, however, this effect is observed over several months after the mobile app introduction of the aggregation platform. Such reverse}\)
our results are correlations, to document these patterns is still useful in distinguishing between the relevance of theories of rational versus selective inattention and informing the theoretical literature, which is our goal in this paper.

Figure 12 displays the estimated effect of being in each savings decile on the probability of logging in plus the constant, i.e., the average probability of logging in if the individual has no savings. Savings relative to own personal histories of savings increase the probability of logging in considerably. When going from the lowest decile of savings to the highest one the probability of logging in increases by about 27 percent. The same is true for checking account balances, with an estimated increase of approximately 10 percent.

We reestimate specification (3) where we replace savings deciles with individual cash and liquidity deciles to uncover the effects of cash holdings and liquidity on the propensity to log in. Figure 13 displays the propensity to log in by decile of individual cash and liquidity. We see that cash holdings and liquidity are positively related to logging in, that is, individuals log in more often when they have more cash or liquidity. The increases in the probability to log in are large, around 17 percent for cash and 30 percent for liquidity. Again, the absolute levels of logins are low because of silent users whose income and spending we observe but who never use the app or software and never log in. For those individuals who use the app or software frequently, we see large effects rather than marginal deviations.

We also reestimate specification (3) where we replace savings deciles with deciles of total spending and restaurant spending, which is arguably a more time-consuming spending. As before, we split each individual’s average daily spending into 11 groups where group 0 consists of days with zero spending and groups 1 to 10 are deciles of the individual’s average daily spending. Figure 14 shows that the amount of daily spending does not affect much the probability of logging in. Compared to the baseline probability of logging in, the probability of logging in drops by about 5 percent when going from the lowest spending decile to the highest. For restaurant spending, the effect is around 9 percent.

causality would thus be picked up by the month-by-year fixed effects.
Moreover, we estimate the effect of deciles of checking account balances on the propensity to log in in the same way as before. As discussed earlier, Figure 1 displays the raw data showing that logins jump discretely when the checking account balance changes from negative to positive. It is important to note that the figure includes only individuals who have both positive and negative checking account balances at times during our sample period. Therefore, the discontinuous jump at zero is not just reflecting cross-sectional differences, with one group being on the left side of zero and another group being on the right side. This figure also shows a negative correlation between overdrafts and logins and a positive correlation between cash holdings and logins in the raw data, which bolsters the robustness of our previous findings.

Figure 15 illustrates the estimated jump from a regression controlling for individual and calendar fixed effects (in additional specifications we also control for the receipt of payments, overdraft limits, and savings account balances). Specifically, it displays the regression coefficients for each quintile of individual overdraft relative to the individual’s personal history of overdrafts and the positive checking account balance relative to the individual’s history of positive checking account balances. We clearly see a discontinuous increase at zero larger than the linear differences in the regression coefficients before and after the first deciles. Table 4 illustrates in detail how the regression coefficients change with the addition of controls, including the standard errors to verify that all the regression coefficients are statistically significantly different from each other.

Next we reestimate specification (3) where we replace savings deciles with deciles of overdraft debt. Figure 16 displays the propensity to log in by decile of overdraft debt for individuals with and without available savings to repay some of their overdrafts. Figure 15 shows that individuals always log in less when they carry any overdraft. While overdrafts always reduce logins, Figure 16 shows that the effect is U-shaped among negative overdrafts, that is, having little or a lot of overdraft reduces logins less than having an intermediate amount.

4 Theories and empirical evidence of rational inattention

Our findings are informative about the modeling assumptions in the theoretical literature on inattention. Inattention can be driven by direct information costs—what we call rational inattention—or
psychological costs—what we call selective inattention. To evaluate existing theories in light of the empirical evidence, we first discuss how a rationally inattentive agent, one who is subject to direct information costs and benefits, but does not experience information-dependent utility, would behave. We then then compare the behavior of the rationally inattentive agent to our empirical evidence. Table 1 summarizes our empirical findings and the theories we consider. We indicate whether each theory could easily be modified in coherence with our findings.

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 argue that this hypothesis can be ruled out because income arrival causes logins and we find specific patterns between balances, spending, and logins despite controlling for individual and calendar fixed effects. Therefore, we conclude that individuals face some intermediate uncertainty about their transactions and balances. When we analyze the jump in logins when balances turn from negative to positive in a range of narrow bins, we may get an idea of how well individuals predict their balances. We observe a jump in the raw data when we consider narrow bins of approximately $50, suggesting that individuals know their balance up to bins of approximately $50.

4.2 Information costs and transaction verification

The information costs of logging in, say time and effort, to verify transactions is a potential reason to log in to financial accounts in response to income payments for instance. In the following, we argue that information costs and transaction verification do not appear to be first-order important for the login response for six main reasons and formally discuss a simple model of information costs.

First, we observe a login response to paydays that always happen on the same day of the month (where weekends and holidays generate exogenous variation in the day of the month that income arrives). Uncertainty around such paydays, that arrive on the same day of the month throughout the sample period, should be small and individuals should therefore be unlikely to actually worry and verify the payment arrival each time.

Second, in terms of magnitudes, we find almost the same responses to regular and irregular payments, for which the transaction verification motive should be more relevant. Figure 8 (left) shows responses to irregular income payments, such as insurance claims, dividends, and grants.\footnote{Alternatively, we can look at plausibly exogenous income payments, such as lotteries and tax rebates. As can be

16
The estimated effect is very similar to the estimated effect of regular paydays and the spike in attention on paydays appears to be only marginally larger on irregular paydays. This additional margin may reflect a transaction-verification motive, which we thus do not consider first-order important.

Third, we find that the effect of paydays is even larger for second or more logins than for one login. Compared to average logins, individuals are 62 percent more likely to log in once and 94.2 percent more likely to log in twice or more on a payday. These are not marginal deviations but substantial increases in the likelihood of logging in. Moreover, it is important to note that the second login cannot be explained by individuals not being able to verify the payment upon the first login because the vast majority of income payments are posted early in the morning.

Fourth, as we show in Figure 10, there is no relationship between spending and the login response on paydays, even though the motive for verification should be stronger when there are many other transactions.

Fifth, there is a negative relationship between transactions in general, such as spending, and logging in (see Figure 14).

Finally, the login response to income arrival is increasing in cash holdings and liquidity (see Figure 9) even though transaction verification should be more important when liquidity is low. We now briefly formally show that a rationally inattentive agent subject to exogenous attention costs would pay more attention if her wealth and income were low.

**A simple model of information costs:** We assume that the agent is subject to uncertainty about her income and bill payments: \( \tilde{Y} - \tilde{B} \sim F \) 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. In turn, she will pay attention if

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

Her risk premium for paying attention, that is the compensating utility differential for paying attention seen in Figure 8 (right), the login response to these payments is of similar magnitude.
tention when knowing or not knowing that $\bar{y} - \bar{b} = \mu$ or $\bar{s} = 0$, is thus

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

For each increment of risk $\sigma$, we obtain

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

where $\delta$ is the negative dirac delta function, the derivative of the indicator function (which is constantly 0 in $\bar{s}$, except at the point $\bar{s} = -\frac{\mu}{\sigma}$ where the function is positive and infinitely large). In turn,

$$\frac{\partial^2 \pi}{\partial \sigma^2} = -E[\beta f \delta(\mu + \sigma \bar{s}) \tilde{s} u''(\mu + \sigma \bar{s} - f I(\mu + \sigma \bar{s} < 0))]$$

$$= 0$$

Thus, $\delta u'' > 0$ 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.\(^{26}\)

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. To see this, note that:

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

That uncertainty is small is a plausible assumption in our context because uncertainty about bank account balances is generally very 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 (Carlin et al., 2017).

Overall, we thus conclude that transaction verification is unlikely to be the main determinant of paying attention to financial accounts.

\(^{26}\)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).
4.3 Budgeting

As we formally showed in the previous subsection, individuals should care more about budgeting and pay more attention when liquidity and cash holdings are low because, theoretically, agents with prudent utility functions benefit more from consumption smoothing at low wealth levels. In other words, individuals who have more at stake, in terms of their financial standing relative to their own personal history, should pay more attention. However, the following three empirical findings stand in stark contrast to the predictions of this budgeting hypothesis.

First, the login response to paydays is higher when cash holdings and liquidity are large, while the budgeting hypothesis implies that individuals in relatively good financial standing should care less about budgeting. Second, we find that both large incoming and large outgoing payments (credit card payments on due dates) cause spikes in attention but incoming payments two times more so than outgoing ones (see Figures 7 and 11). Although the spike in attention on credit card due dates would seem to be consistent with individuals worrying about liquidity constraints, we also find that this increase in attention is increasing in cash holdings and liquidity, which is inconsistent with budgeting as a motive for logging in (see Figure 11). Furthermore, the variation in logins in response to low versus high liquidity appears to dominate the response in logins due to credit card payments. Individuals are on average around 17 percent more likely to log in in response to a credit card payment but the response varies from 10 percent to 33 percent increases in the likelihood for low versus high liquidity holdings (see Figures 9 to 11). Lastly, having an overdraft always reduces logins and there is a U-shaped relationship between logins and the amount of overdraft, as can be seen in Figure 16 (left side). Because logins are always reduced by overdrafts, and holding a relatively small amount of overdraft still reduces logins less than having a relatively large amount of overdrafts, we conclude that budgeting or liquidity constraints are not the main motivation for logging in.

4.4 Planning

Do individuals log in to the app to rationally plan future spending? Although planning to spend in the future is very hard to distinguish from anticipatory utility, we can address this theory by noting that the positive relationship between the propensity to log in and balances is more pronounced for savings account than checking account balances. Given that a savings account is not dedicated to spending, as the debit card always subtracts from the checking account, we thus conclude that planning future spending is not the main determinant of logging in to financial accounts when cash holdings are large (see Figures 12 and 13).
The relationship between logins and spending on paydays versus other days sheds further light on the validity of the planning hypothesis. There is less need to plan for future spending if individuals spent a lot on paydays. However, as shown in Figure 10, the response of logins to income arrivals is unaffected by the spending of individuals (compared to their own average spending).

### 4.5 Opportunity costs

Individual logins could be driven by opportunity costs. Opportunity costs are inherently difficult to measure in any data, including ours. One potential measure of opportunity costs we can use is how much individuals spend (relative to their personal history of spending). After all, contemporaneous spending reflects what individuals are doing.\(^{27}\) Thus, an opportunity costs explanation for paying attention would suggest that individuals log in less often when they are busy spending. We show that individuals do indeed tend to log in less when they spend a lot relative to their own history of spending, which is consistent with opportunity costs having an effect on logins. Furthermore, spending on ready made food (including restaurant visits), which is arguably a more time consuming spending, reduces logins more (see Figure 14). However, looking at the magnitudes of these effects, we see that going from the the lowest decile of spending to the highest only reduces logins by about 5 percent when compared to the baseline probability of logging in. This is very small when compared to the effect of other determinants discussed above, e.g., cash holdings and liquidity.

Furthermore, spending may also reduce available cash and liquidity which may be driving the reduction in logins. In fact, in Figure 17, we show that the variation in available cash or liquidity and the contemporaneous log in response appears to dominate the increase in logins due to high or low overall spending (again, all deciles and splits are constructed relative to individual’s own histories). It can be seen that high versus low spending increases the probability of logging in by much less than moving from low to high cash holdings (and the difference between low and high spending is not statistically significant). Furthermore, as shown in Figure 9, moving from low to high cash holdings increases the payday login response substantially while it appears unaffected by concurrent spending (Figure 10).

\(^{27}\)In Iceland, all spending transactions post immediately without delay, as there exists only one financial clearing house in the country processing all transactions.
4.6 Other potential explanations

Financial literacy. One might worry that our findings are restricted to subpopulations where financial illiteracy is widespread. Lusardi and Mitchell (2011) document that women are less financially literate than men, the young and the old are less financially literate than the middle-aged, and more educated people are more financially knowledgeable. However, when we do cross-sectional splits, we find the documented patterns to be robust across different groups of the population, which is reassuring that the dominant motives appear to be the same across subgroups of the population (see Figure 6 for a basic illustration in the raw data using binned averages). Furthermore, the within-individual patterns we document appear to hold cross-sectionally as well (see Figures 4 and 6 showing the binned averages of logins relative to income, liquidity, and financial fees). The fact that our results are not restricted to subpopulations suggests that financial literacy is an unlikely explanation and that the patterns we document are robust features of human behavior.

Obtaining information by other means. Some of our findings, e.g., that logins reduce with overdrafts, could be explained by individuals not being able to make transactions using the app. If they want to transfer money to pay off their overdrafts, they therefore have to log in to their online bank accounts. At the same time they obtain information about their balances and do not need to log in through the app or on a computer additionally. To address this concern, we can look exclusively at individuals who have little or no savings (and hence cannot transfer money to their checking account). Focusing solely on this group of individuals, we find that the documented negative U-shape of overdrafts on attention is very robust. This result can be seen in Figure 16 (right side) which depicts regression results for individuals without transferable savings. More generally, we find that the decrease in logging in in response to holding an overdraft is robust to controlling for savings account balances, other account balances, income payments, and overdraft limits in Table 4.

Furthermore, in Figure 18, we display the response to all credit card payments not only automatic ones.\(^{28}\) We can see that credit card bill payments increases logins. Thus, this figure suggests that logins via the app are positively rather than negatively correlated with logins to bank accounts because some individuals do not have automatic bill payments and will therefore log into their online bank account to pay off credit cards because the app does not have a transaction functionality. This further alleviates the concern that individuals simply log in by other means when we see fewer logins through the app.

\(^{28}\)We use a dummy to denote whether a credit card balance decreases by at least 50 percent. We include our set of calendar and individual fixed effects, but because we do not restrict the analysis to mandatory credit card due dates, the response is endogenous.
Worrying about finances implies less logins. It could be that if individuals have overdrafts, they worry and are more aware of their financial standing and do not need to log in for extra information. However, this is inconsistent with us finding that individuals have a larger login response to irregular income payments when they are in good financial standing. A larger login response to irregular income payments implies that individuals can predict the income arrival better when they have high liquidity and cash rather than low levels of liquidity and cash. In other words, if individuals were able to predict the income arrival better if they had low cash holdings, because they worry more about their finances, we should see a larger response. However, we find that large cash holdings allows people to more accurately predict the exact day of the income arrival (as indicated by their login response to income payments).

5 Theories of selective inattention

From the previous discussion of rational-inattention theories, i.e., where direct information costs and benefits drive attention, we conclude that their predictions do not appear to be dominant in explaining the empirical evidence. This is true not only for the overall average patterns in logins but also for subsamples such as income groups. We therefore turn to discussing whether selective-inattention motives, such as anticipatory utility and Ostrich effects, are more successful in explaining 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 future spending and consumption. Thus, individuals may experience a form of anticipatory utility. Figure 7 suggests a unique spike on regular (perfectly predictable) paydays while Figure 8 shows a bit of a run-up in logins before the irregular (not perfectly predictable) paydays. Furthermore, when we look at how logins evolve after the payday, we see a steady decrease over the course of the next month. 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 both anticipatory utility, one could augment the model in Section 4 by assuming that the information costs are simply varying with the level of resources. But there also exist models offering a more developed micro foundation based on axioms or experimental and other
micro evidence that generate behavior consistent with our empirical findings. We thus ask in how far models of anticipatory utility can explain 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 at zero as well as the decrease below zero. However, as agents are second-order risk averse in these models, they become risk-neutral whenever uncertainty is small as likely the case for bank account balances. Another highly-cited model is proposed by Kőszegi (2010) who addresses the time inconsistency generated by the model by Caplin and Leahy (2001). Kőszegi (2010) assumes that agents follow a time-consistent "personal equilibrium" in which they anticipate 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 likely the case for bank account balances. We thus consider the model by Kőszegi and Rabin (2009) as a promising one to explore further.

5.2 Ostrich effects

The jump in logins, as depicted in Figure 15, suggests that as soon as individuals go from a negative checking account balance to a positive one, they are more likely to look up their financial accounts. Individuals prefer to see a black checking account balance as opposed to a red one. Moreover, it is not just having an overdraft that reduces logins, larger overdrafts relative to their own history make individuals less likely to log in.29 The same is true for cash holdings and savings, individuals dislike logging in when they have little cash or savings. These findings support the idea that Ostrich effects play a role in deciding whether or not to pay attention. On the other hand, we know from Carlin et al. (2017) that paying more attention causes a reduction in financial penalty payments via a reduction in overdraft debt so we know that paying attention is beneficial.

While no formal model of Ostrich effects exist, 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 information on the downside. Furthermore, the model

29We see some reversal in attention when individuals hit their own personal maximum amount of overdrafts which may reflect some personal rules as the overdraft limits are still far away from the overdraft amounts for the large majority of individuals even right before their paychecks (see Olafsson and Pagel, 2018). Individuals may have their own personal rules as to when they would not be able to cope with sudden economic hardship and thus maintain a liquidity buffer.
in Andries and Haddad (2017) generates optimal inattention and Ostrich effects consistent with the evidence in Sicherman et al. (2015a) and Karlsson et al. (2009) via dynamic disappointment aversion preferences as in Dillenberger (2010). Pagel (2018) shows that the preferences in Kőszegi and Rabin (2009) generate inattention similar to disappointment aversion as in Andries and Haddad (2017). We thus again conclude that the model by Kőszegi and Rabin (2009) is a promising one to explore further to formally support our argument that information-dependent utility models can match some of our empirical findings but also to illustrate the shortcomings of the existing models.

5.3 A model of information-dependent utility

We now formally explore the information-dependent utility model developed by Kőszegi and Rabin (2006, 2007, 2009). In this section, we do not aim to provide a satisfactory rationalization of all our findings but rather ask whether the model can explain some of our empirical findings through which channels and what are its shortcomings. Again, we choose this particular model because it is the most highly-cited and widely-applied existing information-dependent utility model and combines various desirable aspects of previous models (as discussed in the previous two subsections). This model has been broadly applied in a number of domains (see Barberis, 2013, for a literature survey) and specifically assumed in a life-cycle model with inattention to brokerage accounts by Pagel (2018). 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. Thereafter, we will briefly discuss the model’s shortcomings and possible extensions.

The agent experiences news utility as modeled by Kőszegi and Rabin (2009).\textsuperscript{30} News utility is given by $\nu(\bar{c} - \tilde{c})$ with $\tilde{c} \sim F_c$ representing the agent’s fully rational expectations about consumption $c$.\textsuperscript{31} 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 $\tilde{s} = \frac{\tilde{y} - \tilde{b} - \mu}{\sigma} \sim F = \mathcal{N}(0, 1)$ 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 $\eta > 0$

\textsuperscript{30}We refer to Kőszegi and Rabin (2009) and Pagel (2018) for a more detailed introduction of the preferences in the interest of brevity.

\textsuperscript{31}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 are 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.
and $\lambda > 1$. The agent thus compares his actual consumption $c$ to his rational expectations about consumption $\bar{c}$ and thus cares effectively 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).\(^{32}\) In addition, $I(a)$ is an indicator variable equal to one if the agent pays attention to her accounts and zero otherwise. The agent maximizes

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

with $c = \tilde{y} - \tilde{b} - fI(\tilde{y} - \tilde{b} < 0)(1 - I(a))$. The agent pays attention to her accounts if the expected utility of paying attention is greater than the expected utility of being inattentive: that is,

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

which can be rewritten as

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

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

\(^{32}\)For the sake of exposition, we omit expected news utility in the future. Expected future news utility would only be another reason to pay attention in the present beyond avoiding the fee payment.
Suppose that utility is linear, the comparison becomes

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

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

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., $\mu \uparrow \Rightarrow F(-\frac{\mu}{\sigma}) \downarrow \Rightarrow -\beta fF(-\frac{\mu}{\sigma}) \uparrow$, then paying attention is less likely. When the news-utility parameters are increased, i.e., $\eta\lambda \uparrow \Rightarrow E[\gamma\beta\eta(\lambda - 1)\sigma \int_{\tilde{s}}^{\tilde{S}} (\tilde{s} - \tilde{S})dF(\tilde{S})] \downarrow$, then paying attention is less likely. And finally when the cash variance is increased, then news disutility is increased but the likelihood of a fee payment is increased too.

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 $\tilde{s} = 0$:

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

Taking the derivative with respect to the amount of risk $\sigma$ yields

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

and for small risks:

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

**Proposition.** 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 is decreasing in expected cash holdings $\mu$ if $u(\cdot)$ is concave.
Proof. See \( \frac{\partial \pi}{\partial \sigma} \big|_{\sigma \to 0} \).

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, \( \mu \), 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 \( \theta \), we calibrate annual labor income uncertainty in line with the life-cycle literature (see, e.g., Carroll, 1997) as follows: \( Y \sim \log N(\mu_{\text{ann}}, \sigma_{\text{ann}}^2) \) with \( \mu_{\text{ann}} = 0 \) and \( \sigma_{\text{ann}} = 0.2 \). At the monthly level, income uncertainty is then given by \( \sigma = \frac{\sigma_{\text{ann}}}{\sqrt{12}} \). Moreover, we assume that cash holdings equal the exponent of monthly income uncertainty, \( \mu = \sigma \), and we can calculate the fraction \( \Delta \) 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.\(^{33}\) In turn, as an out-of-sample calibration test, we compute the decrease in monthly news disutility when the agent goes from \( \mu = \sigma \) to \( \mu = -\sigma \) of cash holdings, and we obtain a decrease of 24 percent, which makes the agent much more likely to look up his accounts. This is 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 the standard

\(^{33}\)We refer to Pagel (2017) for examples of calculations of attitudes towards wealth gambles.
agent would be willing to pay of her monthly consumption to avoid all monthly income uncertainty, not just for avoiding the fee payment (this assumption provides us with an upper bound independent of calibrating the fee). The answer is only 0.66 percent because income uncertainty at the monthly level is only $\sigma_{\text{ann}}/\sqrt{12} = 0.2/\sqrt{12}$, 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 $\mu$. 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 news-utility model is fully based on rational expectations about present and future consumption. As such, it cannot rationalize an increase in attention at a fully expected income payment or a jump in the probability of logging in when balances turn from negative to positive. To explain these findings, one would have to consider a model of myopia or another model in which income payments affect utility not through future consumption but independently. Nevertheless, we argue that the news-utility model succeeds on two important dimensions. First, it generates aversion to paying attention even when uncertainty is low because the agent cares about fluctuations in expectations to a first-order extent. Second, it generates realistic variation in the willingness to paying attention for low versus high income or wealth. Thus, first-order risk aversion and first-order prudence appears to be a crucial ingredient in information-dependent utility models.

6 A general-equilibrium model of selective and rational inattention

To formally illustrate that the modeling assumptions about inattention are important for aggregate dynamics in macroeconomic models, we consider a standard Lucas (1979) tree model in which the sole source of consumption is an everlasting tree that produces $C_t$ units of consumption each period $t$. We assume that consumption growth is log-normal, following Mehra and Prescott (1985), i.e.,

$$\log\left(\frac{C_{t+1}}{C_t}\right) = \mu_c + \varepsilon_{t+1} \quad \text{with} \quad \varepsilon_{t+1} \sim N(0, \sigma_c^2)$$

with the consumption growth parameters $\mu_c$ and $\sigma_c$ calibrated as standard in the literature. Furthermore, we assume that the agent’s instantaneous utility in period $t$ is given by

$$U_t = u(C_t) = C_t^{1-\theta} \frac{1}{1-\theta}$$

28
with $\theta$ the coefficient of risk aversion calibrated as standard in the literature. The price of the Lucas tree in each period $t$ is $P_t$. There also exists a risk-free asset in zero net supply with return $R^f_t$.

The period $t+1$ return of holding the Lucas tree is thus $R_{t+1} = P_{t+1} + C_{t+1}/P_t$. Each period $t$, the agent faces the price of the Lucas tree $P_t$ and the risk-free return $R^f_t$ and, acting as a price taker, optimally decides how much to consume $C^*_t$ and how much to invest in the Lucas tree as opposed to the risk-free asset $\alpha^*_t$.

Facing prices and returns, the agent’s maximization problem in period $t$ is given by

$$
\max_{C_t} \{u(C_t) + E_t[\sum_{\tau=1}^{\infty} \beta^\tau U_{t+\tau}]\}.
$$

Equation (6)

The agent’s wealth in the beginning of period $t$, $W_t$, is determined by his portfolio return $R^p_t$, which in turn depends on the risky return realization $R_t$, the risk-free return $R^f_t$, and the previous period’s optimal portfolio share $\alpha_{t-1}$. The budget constraint is

$$
W_t = (W_{t-1} - C_{t-1})R^p_t = (W_{t-1} - C_{t-1})(R^f_t + \alpha_{t-1}(R_t - R^f_t)).
$$

Equation (7)

In each period $t$, the agent optimally decides how much to consume $C^*_t$, how much to invest $W_t - C^*_t$, and how much to invest in the Lucas tree $\alpha^*_t$. In equilibrium, the price of the tree $P_t = W_t - C_t$ adjusts so that the single agent in the model always chooses to hold the entire tree, i.e., $\alpha^*_t = 1$ for all $t$, and to consume the tree’s entire payoff $C^*_t = C_t$ for all $t$ as determined by the consumption growth process in equation (4).

The equilibrium has a very simple structure and can be derived in closed form. In each period $t$, optimal consumption $C^*_t$ is a fraction of current wealth $W_t$ such that $C^*_t = W_t \rho_t$ and the consumption-wealth ratio $\rho_t$ is

$$
\rho_t = \frac{C^*_t}{W_t} = 1 - \beta \epsilon \mu(1-\theta) + \frac{1}{2} \theta (1-\theta)^2 \sigma^2_c.
$$

Equation (8)

We simply assume that the length of the agent’s upcoming time period varies with the consumption growth shock $\epsilon_t$, in the spirit of the time-variant attention model of Andrei and Hasler (2014). Andrei and Hasler (2014) assume that the agent pays more attention in the event of an adverse consumption shock, which would be the optimal response of any prudent agent who is rationally inattentive. We will show how the model’s predictions vary when instead we assume that the agent pays less attention in the event of an adverse consumption shock, i.e., a selectively attentive agent.
The environmental and preference parameters are calibrated as perfectly standard in the literature (for instance, Bansal and Yaron, 2004; Campbell and Cochrane, 1999), with $\mu_c = 0.89\%$ and $\sigma_c = 2.7\%$ as well as $\theta = 4$ and $\beta = 0.999$ in annualized terms to match the risk-free rate to the historical average of Moody’s municipal bond index, which is around 3 percent. In turn, the time-variant attention functional is assumed to be:

$$
att_t(\varepsilon_t, att_{t-1}) = (1 + \psi(\text{att}_{t-1} - 1))(1 + d(F(\varepsilon_t) - 0.5))
$$

with $F$ being the cumulative distribution function of $N(0, \sigma_c^2)$. We assume $\psi = 0.5$ and consider three values of $d \in \{-1, 0, 1\}$ which represents a selectively attentive agent (who pays less attention when consumption growth is negative), an agent who pays attention in constant intervals (independent of consumption growth), and a rationally inattentive agent (who pays more attention when consumption growth is negative). Thus, attention is characterized by an autoregressive process with a monthly frequency on average that may double or half for extreme realizations of the consumption growth shock $\varepsilon_t$, in line with the average frequency and variation that we observe in the data or documented in Sicherman et al. (2015b) and Karlsson et al. (2009). The model’s simulation frequency or the agent’s attention varies around one month, i.e., the model’s frequency is monthly if $\text{att}_t = 1$. The model’s simulation frequency determines $\mu_c$, $\sigma_c$, and $\beta$, i.e., we now redefine $\mu_{tc} := \text{att}_t \mu_c / 12$, $\sigma_{tc} := \sqrt{\text{att}_t \sigma_c^2 / \sqrt{12}}$, and $\beta_t := \beta^{\text{att}_t^{1/12}}$. We now have to solve the model numerically as the agent takes his time-variant attention into account when the price of the Lucas tree is determined in period $t$ and can then simulate returns. We report annualized moments for the mean and variation in the risky return, risk-free return, and equity premium for the three agents in Table 5.

While none of the models are able to match the historical equity premium and risky return volatility (known since Mehra and Prescott, 1985), one can easily see in Table 5 that the model’s simulated aggregate dynamics are significantly affected by the agent’s selective or rational inattention. If the agent is selectively inattentive the equity premium increases by 10 percent and it’s volatility increases by 50 percent. The intuition for this increase in the equity premium is again related to prudence: because consumption smoothing is more beneficial at low wealth levels, the agent should pay more attention, i.e., smooth consumption at a higher frequency when wealth and consumption is low. Thus, the rationally inattentive agent requires a less high equity premium.

In summary, the important conclusion of this exercise is that the predictions of macroeconomics models about aggregate fluctuations are likely to be affected by whether they assume that inattention is rational or selective.
7 Conclusion

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

We show that paying attention to financial accounts appears to have an effect beyond the direct information costs and benefits and find evidence consistent with selective attention, more specifically, Ostrich effects and anticipatory utility. Income payments cause individuals to log in more often, and people log in less often when they have relatively low cash holdings or spend a lot. In addition, when individuals are indebted, they log in less often. These findings are hard to reconcile with theories of rational inattention, but some of our findings can be explained by a recent influential model of information-dependent utility developed by Kőszegi and Rabin (2009).

Even though models of selective attention are more consistent with our findings than models of rational inattention, existing models of selective attention (e.g., the model by Kőszegi and Rabin, 2009) have trouble generating some of our results (e.g., a jump in logins when balances turn positive and a reaction to perfectly predictable payments) as they are fully based on rational expectations about consumption. Our formal analysis thus calls for extending information-dependent utility models to off-equilibrium or otherwise irrational expectations about consumption or some elements of myopia.

Our findings are informative on the empirical relevance of the assumptions made regarding inattention in macroeconomic models whose aggregate dynamics differ importantly depending on whether inattention is rational or selective as we formally show in a standard Lucas tree economy. Our findings also call into question the assumption that information costs are always positive. If individuals are willing to pay not to receive information (which can be inferred from this study in connection with Carlin et al., 2017) then information costs are time-varying in non-trivial ways and sometimes effectively negative rather than positive. Beyond rational inattention and information costs, our findings relate to the literature on poverty traps and cognitive function in scarcity situations and are informative for (field) experiments.
References


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Figure 1: Logins by bins of checking account balances

Average login by binned checking account balances including only individuals who have negative and positive checking account balances at some point in time.
Table 1: Empirical findings and possible theoretical explanations

<table>
<thead>
<tr>
<th>Event Description</th>
<th>No/perfect Information</th>
<th>Transaction Verification</th>
<th>Budgeting</th>
<th>Planning</th>
<th>Opportunity Costs</th>
<th>Selective Attention</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individuals log in because they get paid</td>
<td>x</td>
<td>✓</td>
<td></td>
<td>✓</td>
<td>(X)</td>
<td>✓</td>
</tr>
<tr>
<td>Individuals log in twice because they get paid</td>
<td>x</td>
<td>x</td>
<td>(X)</td>
<td>✓</td>
<td>(X)</td>
<td>✓</td>
</tr>
<tr>
<td>Income response similar for irregular payments</td>
<td>x</td>
<td>x</td>
<td>(X)</td>
<td>✓</td>
<td>(X)</td>
<td>✓</td>
</tr>
<tr>
<td>Income response increasing in cash and liquidity</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Income response unrelated to spending</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>✓</td>
</tr>
<tr>
<td>Individuals log in because they make a payment</td>
<td>x</td>
<td>✓</td>
<td>✓</td>
<td>x</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Response to payments increasing in cash and liquidity</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Logins decreasing with spending</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Logins increasing with cash and liquidity</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>✓</td>
<td>x</td>
<td>✓</td>
</tr>
<tr>
<td>Logins more increasing with savings than cash</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Logins U-shaped in overdrafts</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>(X)</td>
<td>x</td>
<td>✓</td>
</tr>
<tr>
<td>Logins jump when balance turns positive</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>(X)</td>
<td>x</td>
<td>✓</td>
</tr>
</tbody>
</table>

Note: x unlikely to explain, (X) explain with major modifications, ✓ explain with modifications, ✓ consistent with theory
The app does not send push notifications and individuals have to log in to see these flags.
Table 2: Summary statistics by terciles of logins and income

<table>
<thead>
<tr>
<th></th>
<th>Login terciles</th>
<th>Income terciles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Number of individual logins</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Number of household logins</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Propensity to log in</td>
<td>0.1%</td>
<td>0.4%</td>
</tr>
<tr>
<td>smartphone log in</td>
<td>0.0%</td>
<td>0.1%</td>
</tr>
<tr>
<td>desktop log in</td>
<td>0.1%</td>
<td>0.3%</td>
</tr>
<tr>
<td>tabloid log in</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Monthly income</td>
<td>3,217</td>
<td>3,543</td>
</tr>
<tr>
<td>Monthly regular income</td>
<td>3,099</td>
<td>3,426</td>
</tr>
<tr>
<td>Monthly irregular income</td>
<td>92</td>
<td>90</td>
</tr>
<tr>
<td>Monthly financial fees</td>
<td>-24</td>
<td>-23</td>
</tr>
<tr>
<td>Overdraft</td>
<td>-1,740</td>
<td>-1,712</td>
</tr>
<tr>
<td>Savings account balance</td>
<td>2,527</td>
<td>3,220</td>
</tr>
<tr>
<td>Checking account balance</td>
<td>1,991</td>
<td>2,060</td>
</tr>
<tr>
<td>Credit card balance</td>
<td>-1,204</td>
<td>-1,313</td>
</tr>
<tr>
<td>Overdraft limit</td>
<td>2,446</td>
<td>2,534</td>
</tr>
<tr>
<td>Credit card limit</td>
<td>3,501</td>
<td>4,080</td>
</tr>
<tr>
<td>Cash holdings</td>
<td>4,518</td>
<td>5,280</td>
</tr>
<tr>
<td>Liquidity</td>
<td>9,261</td>
<td>10,582</td>
</tr>
<tr>
<td>Monthly discretionary spending</td>
<td>1,384</td>
<td>1,478</td>
</tr>
<tr>
<td>Age</td>
<td>41.7</td>
<td>42.2</td>
</tr>
<tr>
<td>Female</td>
<td>52%</td>
<td>48%</td>
</tr>
<tr>
<td>Spouse</td>
<td>19%</td>
<td>24%</td>
</tr>
</tbody>
</table>

Note: All income, spending, and balance numbers are in US dollars. The number of logins and propensity to log in refer to the number per day or percentage of days individuals log in.
Table 3: Summary statistics and comparison to Statistics Iceland

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

Note: All income and spending numbers are in US dollars. Parentheses indicate that data categories do not match perfectly.
Figure 4: Number of monthly logins for deciles of income, cash holdings, and liquidity

Figure 5: Monthly financial fee payments by bins of monthly logins

Figure 6: Relationship between the propensity to log in within a month and deciles of liquidity (measured in average spending per day for each individual) for three terciles of income
Figure 7: Propensity to log in around the arrival of regular salary payments

Response of logins to regular income arrival for four weeks around the income arrival controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Standard errors are clustered at the individual level.
Figure 8: Propensity to log in around the arrival of irregular payments and plausibly exogenous payments

Response of logins to irregular income arrival (left side) or plausibly exogenous income arrival (lotteries and tax rebates) (right side) for two weeks around the income arrival, controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Standard errors are clustered at the individual level.

Figure 9: Differences in propensity to log in on paydays versus other days as functions of cash holdings and liquidity

Regression coefficients and standard errors of deciles of cash (positive checking account balance and savings balance) or liquidity (checking account balance plus credit card balance plus overdraft and credit limits plus savings account balance) relative to own history of spending or liquidity on paydays and other days, controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Standard errors are clustered at the individual level.
Figure 10: Differences in propensity to log in on paydays versus other days as functions of total spending

Regression coefficients and standard errors of deciles of cash holdings and liquidity relative to own history of cash or liquidity on paydays and other days, controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Standard errors are clustered at the individual level.

Figure 11: Differences in propensity to log in on credit card due dates versus other days as functions of cash holdings and liquidity

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, controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Standard errors are clustered at the individual level.
Figure 12: Propensity to log in by deciles of savings

Regression coefficients and standard errors for each decile of savings and current account balances relative to individual’s own history of savings or current account balances controlling for individual and calendar fixed effects. Standard errors are clustered at the individual level.

Figure 13: Propensity to log in by deciles of individual cash and liquidity holdings

Regression coefficients and standard errors for each decile of cash (positive checking account balance plus savings account balance) or liquidity (checking account balance (positive or negative) plus credit card balance (negative) plus credit limits plus savings account balance) relative to individual’s own history of cash or liquidity, controlling for individual and calendar fixed effects. Standard errors are clustered at the individual level.
Figure 14: Propensity to log in by deciles of total spending and restaurant spending

Regression coefficients and standard errors for each decile of total spending and restaurant spending relative to individual’s own history, controlling for individual and calendar fixed effects. Standard errors are clustered at the individual level.

Figure 15: Propensity to log in by quintiles of overdraft and checking account balance

Regression coefficients and standard errors for each quintile of overdraft relative to individual’s own history of overdrafts and the positive checking account balance relative to individual’s own history of positive checking account balances, controlling for individual and calendar fixed effects as well as for the receipt of payments, overdraft limits, and savings account balances. Standard errors are clustered at the individual level.
### Table 4: Effects of relative bank account balances on logins

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</table>

| Day of week FE                    | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         |
| Day of month FE                   | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         |
| Overdraft limit                   | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         |
| Savings                           | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         |

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

b Significance levels: * p<0.1 ** p<0.05 *** p< 0.01
Figure 16: Propensity to log in by deciles of individual overdraft

Regression coefficients and standard errors for each decile of overdraft relative to individual's own history of overdrafts, controlling for individual and calendar fixed effects. The figure on the right side is based on regressions that only uses individuals without any savings. Standard errors are clustered at the individual level.
Figure 17: Propensity to log in by deciles of cash and liquidity for low and high spending

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, controlling for individual and calendar fixed effects. Standard errors are clustered at the individual level.

Figure 18: Response of logins to credit card due dates

Response of logins to credit card payments for two weeks around the payment date, controlling for individual and calendar (month-by-year, day-of-month, day-of-week, and holiday) fixed effects. Standard errors are clustered at the individual level.
Table 5: Simulation results for annualized return moments in different asset pricing models

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<th>Risk-free return</th>
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<td>mean</td>
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<td>Selective inattention:</td>
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<td>Constant attention:</td>
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<td>Rational inattention:</td>
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</table>

Note: This table shows simulation results for the annualized risky and risk-free return moments in a standard Lucas tree model with either selective inattention (agent is less attentive after negative consumption growth shocks), constant attention intervals (agent is attentive at constant monthly frequency), or rational inattention (agent is more attentive after negative consumption growth shocks).