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

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Abstract

This paper investigates attention to personal financial accounts using panel data from a financial management software provider containing information on daily logins, income, spending, balances, and credit limits. We first explore whether individuals pay attention in response to the arrival of income payments. Here, we utilize that weekends and holidays generate exogenous variation in regular payment arrival using a fixed-effects approach. We find that individuals are five times more likely to log in on days when they get paid. Beyond looking at the causal effect of income on attention, we examine how attention depends on spending and individual financial standing, such as cash holdings, savings, and liquidity. We find that attention is decreasing in individual spending but increasing in cash holdings and liquidity. These results are consistent with selective attention and Ostrich effects with respect to financial accounts. To rationalize our findings, we set up a model assuming individuals experience utility over news, or changes in expectations about consumption, as proposed by Kőszegi and Rabin (2009). Because agents dislike bad news more than they like good news, paying attention to financial account is considered unpleasant especially when remaining cash holdings are low.

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1 Introduction

Individual attention to personal financial accounts can not only be an input into decision-making for spending and saving but also a source of anxiety or anticipatory utility. To better understand the determinants and effects of paying attention, this paper constitutes a first large-scale empirical study of individual checking of all financial accounts. More specifically, we try to shed light on the following questions: When and under what conditions do individuals pay attention to their financial accounts? To what extent is attention driven by anxiety or anticipatory utility? And what are the benefits of attention that drive individual demand for personal financial information?

Standard economic models predict that information is valuable when it helps to make better decisions. Theories of rational inattention posit that individuals trade off the costs and benefits of seeking information. The costs of attention include information-processing costs as well as time and opportunity costs, while a benefit of attention is the potential gains from improved decision-making and consumption smoothing. There exist countless situations in which information is useful and sought after but there also exist situations in which people seek out apparently useless information or avoid useful information (see Golman et al., 2016, for a survey of the literature). In light of this evidence a literature on information-dependent and belief-dependent utility emerged positing that information also has a hedonic impact on utility that goes beyond mechanical costs and benefits. Nevertheless, empirical evidence on the determinants and effects of getting informed lags behind the theoretical advances and remains scarce.

The digitization of budgeting processes with financial aggregation apps and the attendance tracking of online behavior allow direct measurement of individual attention in ways that previously were not possible. In this paper, we use online account logins to measure individual attention to financial accounts. More specifically, we look at the determinants and effects of checking financial accounts using data from a financial aggregation and service app from Iceland—a data source that not only allows individual tracking of attention but also provides high-frequency income and
spending data derived from the actual transactions and account balances of individuals; overcom-
ing the limitations of accuracy, scope, and frequency that existing data sources of consumption and income have. Gelman et al. (2014) and Baker (2014) were the first to advance the measurement of income and spending with such app data from the US. We use data from Iceland which has three main advantages: 1) Using Icelandic user data essentially eliminates the remaining limitation of app data—the absence of cash transactions—since Icelandic consumers use electronic means of payments almost exclusively, 2) the Icelandic app is marketed through banks thus covering a fairly broad fraction of the population, and 3) the spending and income data is pre-categorized and the categorization is very accurate with few uncategorized transactions.

We first look at the individual propensity to check financial accounts in response to regular and irregular income payments. To alleviate endogeneity concerns, we use indicator variables for the arrival of payments in addition to individual, day-of-week, day-of-month, holiday, and month-year fixed effects to utilize exogenous variation in payment arrival due to weekends and holidays. We find that individuals are five times more likely to pay attention in response to an income payment. In a recent contribution, Olafsson and Pagel (2016) show that individuals spend more on the days they get paid. To shed light on the mechanism by which income affects attention, we control for spending in additional specifications. However, we find that spending is not the mechanism by which income affects attention. In fact, spending is negatively correlated with attention within individuals.

These findings point to one specific form of selective attention called the Ostrich effect introduced by Galai and Sade (2006) and Karlsson et al. (2009). Karlsson et al. (2009) propose that attention amplifies the hedonic impact of information, which implies that investors should pay more attention to their finances after good news than after bad news. The authors show that individual investors’ attention to personal portfolios increases after positive returns on market indices. In the context of financial accounts, the existing evidence is thus consistent with cash inflows, be it from wealth shocks or income payments, causing individuals to check their accounts more often.
However, this empirical result stands in contrast to the idea that individuals pay more attention to their accounts when they have fewer resources and worry about hitting their liquidity constraints. In principle, given that checking your account is cost-free, we would not expect any effect of wealth on the propensity to check. If anything, we would expect a negative propensity to check as additional wealth reduces the need for budgeting. However, we find that individuals check their accounts in response to income payments even more often when their cash and liquidity holdings are large.

We also examine the direct relationship between checking accounts and individual liquidity and cash holdings. We document a number of patterns in investor attention and individual financial conditions controlling for individual and a variety of calendar fixed effects:

- attention is positively correlated with individual cash holdings
- attention is positively correlated with individual liquidity
- attention is u-shaped and generally reduced by individual debt holdings
- attention is u-shaped and generally increased by individual savings

While our previous findings about income payments point towards the Ostrich effect as an important determinant of the relationship between checking financial accounts and income or wealth, the descriptive statistics with respect to overdrafts also point towards budgeting and potential liquidity constraints as an additional determinant of checking. When overdraft holdings are high, individuals are close to their personal liquidity constraints.\(^1\) To avoid exceeding those limits or incur fee payments, individuals pay more attention. These findings are in line with Carlin et al. (2016) who document that the mobile app introduction of this personal finance software decreased financial penalty payments and Stango and Zinman (2014) who document that individuals respond to surveys about overdrafts by paying greater attention to account balances and incurring less fees.

\(^{1}\)Olafsson and Pagel (2016) find that less than three percent of individuals hold less than one day of their average spending in liquidity on the days they get paid.
To reconcile and formalize intuitions consistent with our two key empirical findings, 1) that individuals check their accounts more often if they received cash inflows and 2) that individuals worry about hitting their personal liquidity constraint or incur fees, we use the theoretical news-utility framework developed by K˝oszegi and Rabin (2009). In this model, individuals not only derive utility from current consumption but also from changes in expectations or news about present and future consumption. To generate attitudes towards wealth bets consistent with prospect theory, the model assumes that bad news hurt more than good news please. This assumption implies that expecting to receive news entails a first-order disutility. Thus, the agent is averse to receiving news. However, if the agent is more wealthy, news hurt less on average as the agent fluctuates around a less steep part of his or her concave utility function. Because the agent trades off the costs of expected news disutility with the benefits of staying fully informed and avoiding fee payments, he or she checks his or her accounts more often after income payments or wealth shocks. However, he or she also checks his or her accounts more often, if he or she holds little cash and worries more about fee payments. Thus, the model reconciles our two empirical findings.

The paper is organized as follows: first, we briefly review the literature to then provide a data description and summary statistics in Section 2. In turn, Section 3 documents the main analysis and Section 4 concludes.

Literature review

The most related papers are Sicherman et al. (2015) and Karlsson et al. (2009) who use online retirement account logins to measure investor attention to portfolios. However, to the best of our knowledge, to date no paper documents 1) the marginal propensity to check in response to cash inflows and 2) the relationship between paying attention and individual spending and financial standing.

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

In light of this evidence, starting with Loewenstein (1987), recent theoretical work has made substantial progress in modeling the notion that beliefs about or the anticipation of future consumption can have direct utility consequences (see, e.g., Caplin and Leahy, 2001, 2004; Brunnermeier and Parker, 2005; Kőszegi and Rabin, 2006; Epstein, 2008; Kőszegi and Rabin, 2009; Dillenberger, 2010; Bénabou, 2012; Strzalecki, 2013; Golman and Loewenstein, 2015; Golman et al., 2016; Ely et al., 2015). Moreover, there exists a small but growing theoretical literature that is incorporating attention and focus into economic decision-making (e.g., Bordalo et al., 2010; Kőszegi and Szeidl, 2013; Bushong et al., 2015). Additionally, the findings by Zimmermann (2014) and Falk and Zimmermann (2014) underscore the importance of attention for belief-based utility and support the idea that individuals can actively manage attention in a self-serving way, to increase or decrease anticipatory utility.
2 Data and summary statistics

2.1 Data

This paper exploits new data from Iceland generated by Meniga, a provider of financial aggregation software for European banks and financial institutions. Meniga has become Europe’s leading private financial management (PFM) provider. Their PFM solution is currently used by more than 20 million individuals in 15 countries, with more already scheduled to be added, in partnership with retail banks and financial institutions. The company allows financial institutions to offer their online customers a platform for connecting all their financial accounts, including bank accounts and credit card accounts, in a single location. Each day, the application automatically records all the bank and credit card transactions including balances and descriptions. We use the entire de-identified population of active users in Iceland and data derived from their records from 2011 until 2016 and perform the analysis on normalized and aggregated user-level data for different income and spending categories. In January 2014, the Icelandic population counted 325,671 individuals–254,538 of which were above the age of 16. At the same time, Meniga had 35,855 users–approximately 14% of individuals above the age of 16. Because the app is marketed through banks, the sample of Icelandic users is fairly representative. The app collects some demographic information such as age, gender, and marital status. Moreover, we can infer the number of (small) children, employment status, and geographical region. The user population is a substantial fraction of the population and very heterogeneous, including large numbers of users of different ages, education levels, and geographic location.

2.2 Summary statistics

Income, spending, and demographics: Table 1 displays summary statistics of the Icelandic users, including income and spending in US dollars across four income quartiles. Moreover, it displays
some demographic statistics. The average user is 40 years old, with 15% of users being pensioners. This information is reassuring: besides the young and tech-savvy using this app, we also observe the older generation. Moreover, roughly 50% of users are female – a much higher number than the one seen in other papers using data of this kind – with 20% having children. Overall, the characteristics of the sample with respect to age, gender, employment, income, and spending figures are remarkably similar to the ones of the representative national household survey conducted by Statistics Iceland.

(Table 1 around here)

Logins: Figure 1 shows the distribution of the daily propensity to log in, i.e., a dummy variable equal to one if the individual logs in that day, over the month and week for male and female users. It can be seen that men log in more often than women and all individuals log in more often around the end and beginning of the month and more on workdays than weekends. Figure 2 displays whether or not men and women log in on a particular day when they receive different types of income payments. It can be seen that all individuals log in more often when they get paid but also that there are large differences in the login responses of different payments. Again, men log in more often on average.

(Figure 1 around here)

3 Analyses and results

Here we describe our empirical setting and baseline identification strategy to uncover the effects of getting paid on logins.
3.1 Propensity to check in response to income arrival

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

\[ x_{it} = \sum_{k=-7}^{7} \beta_k I_i(Paid_{t+k}) + \delta_{dow} + \phi_{wom} + \psi_{my} + \eta_i + \epsilon_{it} \]  

(1)

where \( x_{it} \) is an indicator variable of whether individual \( i \) logged in to his or her account on date \( t \), \( \delta_{dow} \) is a day-of-week fixed effect, \( \phi_{wom} \) is a day-of-month fixed effect, \( \psi_{my} \) is a month-by-year fixed effect, \( \eta_i \) is an individual fixed effect, and \( I_i(Paid_{t+k}) \) is an indicator that is equal to 1 if individual \( i \) receives a payment at time \( t + k \) and that is equal to 0 otherwise. The \( \beta_k \) coefficients thus measure the fraction by which income arrival increases the probability of logging in on the days surrounding the receipt of a payment. We use indicator variables for income payments to alleviate potential endogeneity concerns at the income level. The day-of-week dummies capture within-week patterns for logins. The day-of-month dummies capture within-month patterns for logins. We restrict the income payments to regular payments that always occur on a certain day of the month and thus use exogenous variation in the pay date due to weekends and holidays as identifying variation. Standard errors are clustered at the individual level.

Figure 3 displays the payday response for the two weeks and four weeks around paydays of regular salary payments. As can be seen, individuals are five times more likely to log in on the days they get paid relative to the days surrounding payment receipt. Moreover, in Figure 4, we look at the relationship between logging in on paydays relative to other days for different levels of individual cash and liquidity holdings. We can see that individuals are more likely to log in on paydays especially when their cash holdings and liquidity are relatively large.

We know from Olafsson and Pagel (2016) that spending responds to income arrival. To single out the effect of income, we control for spending in additional specifications. However, we do
not find any differences and thus conclude that the mechanism how income affects attention is not
spending. In fact, spending appears to be negatively correlated with logins on paydays and other
days too as can be seen in Figure 5.

{Figure 5 around here}

### 3.2 Checking, liquidity, and cash holdings

Figure 6 displays the propensity to log in, i.e., the change in a dummy variable for logging in that
day, as a function of deciles of individual spending. We first calculate how much one individual
spends compared to how much he or she spends on average and then split that individual’s spending
in 11 groups. The first group is zero spending and the remaining groups split spending up in deciles
1 to 10. Each point is therefore comparing the propensity to log in to the log-in rate when nothing is
spent; all within individuals. We control for month-by-year, day-of-week, and holiday fixed effects.
Additionally, the figure depicts the propensity to log in by deciles of savings within individuals.
We find that individuals are generally less likely to log in when they spend relatively much. In
contrast, individuals are more likely to log in when they have low or high levels of savings relative
to some intermediate range.

{Figure 6 around here}

Figure 7 displays the propensity to log in by deciles of individual cash (savings plus positive
checking balance). This graph splits one individual into 11 groups, group 0 is when the individual
holds zero cash and groups 1 to 10 are deciles of the his or her value of cash. Additionally, we
control for month-by-year, day-of-week, and holiday fixed effects. We can see that cash holdings
are positively related to logging in, i.e., individuals log in more often when they have more cash.
Figure 8 displays the propensity to log in by deciles of overdraft debt and overall consumer debt (overdraft plus credit card balances). This graph splits one individual into 11 groups, group 0 belongs to zero holdings of debt and groups 1 to 10 are deciles of the value of debt. Additionally, we control for month-by-year, day-of-week, and holiday fixed effects. Again, it can be seen that holding debt is always negatively correlated with logging in. However, we see that individuals log in more often when they have relatively little or a lot of debt relative to their average debt holdings.

Figure 9 displays the propensity to log in by deciles of cash (savings plus overdraft balance) and liquidity (savings plus overdraft and credit card balances plus overdraft and credit card limits). This graph splits all individuals into 11 groups, group 0 is everybody with zero holdings of cash or liquidity and groups 1 to 10 are deciles of the value of cash or liquidity. Everybody is thus included, not only individuals with positive holdings. Additionally, we control for year-by-month fixed effects. Moreover, we consider cash and liquidity normalized by individual spending, i.e., days of average spending left in cash or liquidity. While the cross-sectional graphs are more difficult to interpret, we also see that cash and liquidity relative to consumption are increasing in logins.

Figure 10 displays the propensity to log in by deciles of overdraft debt and overall consumer debt (overdraft plus credit card balances). Again, this graph splits all individuals into 11 groups, group 0 is everybody with zero holdings of debt and groups 1-10 are deciles of the value of debt. Cross-sectionally we see again that individuals log in more often when they have a lot or little
overdraft debt. Moreover, debt holdings generally decrease logins. For all consumer debt, we see a slightly different picture cross-sectionally. Potentially because rich individuals hold more credit-card debt on average as they spend more but also log in more often.

{Figure 10 around here}

Table 2 shows the effects of paycheck arrival and an indicator for the credit-card due dates. It can be seen that paycheck arrival and bill dates both increase logins. Moreover, controlling for liquidity decreases the number of logins for paycheck receipt but increases the number of logins for bill payments.

{Table 2 around here}

Overall, we conclude from the descriptive analysis that our causal results for selective attention with respect to income hold much more generally. Individuals do not pay attention when they spend a lot or have low cash holdings. On the other hand, individuals appear to worry somewhat when their debt levels are unusually high.

4 News-utility model

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

The marginal costs of checking is a simple effort cost \( a \) proportional to consumption utility \( u(-a) \). The benefit of checking is that the agent avoids fee payments. Additionally, she experiences news utility \( \gamma \beta \mu(u'(c) - u'(\hat{c})) \) with \( c \sim F_c(\hat{c}) \), as proposed in Kőszegi and Rabin (2009),
which is positive or negative depending on her income and bill payments $\bar{Y} - \bar{B} \sim F_{YB} = N(\mu, \sigma^2)$ with realization denoted by $\bar{y} - \bar{b}$ and $\tilde{S} = \frac{\bar{Y} - \bar{B} - \mu}{\sigma} \sim F = N(0, 1)$ with realization denoted by $\tilde{s}$. Kőszegi and Rabin (2009) generalize prospect-theory preferences via the function $\mu$ that is given by $\mu(x) = \eta x$ for $x > 0$ and $\mu(x) = \eta \lambda x$ for $x \leq 0$ with $\eta > 0$ and $\lambda > 1$. The agent thus cares about good and bad news but dislikes bad news more than she likes good news. Because bad news hurt more than good news please, the agent dislikes checking in general as news disutility is painful in expectation. Moreover, the agent is more willing to check if income is high because checking becomes less painful on a flatter part of the utility curve. If the agent does not check then she may incur a financial fee $f$ whenever $\bar{y} - \bar{b} < 0$. If that happens, the fee will be subtracted from future consumption. If she checks her accounts, she can avoid fees by simply transferring money from other accounts, which does not affect her consumption. Thus, when she pays attention, she will not pay a fee. All consumption takes place in the future, with utility given by $\beta u(c)$. $I(a) = 1$ if the agent pays attention to her accounts and zero otherwise. The agent maximizes

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

with $c = \bar{y} - \bar{b} - f I(\bar{y} - \bar{b} > 0)(1 - I(a))$.

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

$$E[(u(-a) + \gamma \beta \int \mu(u(\bar{y} - \bar{b}) - u(\bar{Y} - \bar{B}))dF_{YB}(\bar{Y} - \bar{B}) + \beta u(\bar{y} - \bar{b})) > E[\beta u(\bar{y} - \bar{b} - f I(\bar{y} - \bar{b} < 0))]]$$

which can be rewritten as

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

$$> E[\beta u(\mu + \sigma \tilde{s} - f I(\mu + \sigma \tilde{s} < 0))].$$
Suppose utility is linear, which can be seen as a good approximation for small stakes,

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

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

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

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

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

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

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

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

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

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

and for small risks:

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

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

**Proof.** See derivation.

Thus, expecting to check causes a first-order decrease in expected utility and the agent has a first-order willingness to incur fees even when uncertainty is small. This proposition will also hold for additive risks instead of the multiplicative risk that we considered here iff \(u(\cdot)\) is concave, i.e., \(u'' > 0\).
We can now do a back-of-the-envelope calculation to assess in how far the avoidance of news utility can explain the amount of fee payments we see empirically. Average monthly fee payments amount to approximately $30 or one day in average spending. We assume that individuals experience news disutility at a monthly level and utility is given by a log functional, i.e., $u(c) = \log(c)$. In turn, we calibrate annual labor income uncertainty in line with the life-cycle literature, for instance, Carroll (1997), as follows: $Y \sim log - N(\mu, \sigma^2)$ with $\sigma = 0.2$ and assume that 20 percent of the variation is uncertain. In turn, we assume that cash holdings are given by one year of annual income, i.e., $\mu = \sigma$, and can calculate the fraction of monthly income the news-utility agent would be willing to give up to avoid news-disutility. We obtain a fraction of 3 percent of monthly income which amounts to $60 per month for $\eta = 1$ and $\lambda = 2$, which are standard parameters in the prospect-theory and news-utility literature. We conclude that the first-order willingness to avoid fee payments predicted by news utility can be a reasonable explanation for the amount of fee payments we see in the data.

5 Conclusion

Beyond mechanical costs and benefits, paying attention to financial accounts may have a hedonic impact on utility by causing anxiety or anticipatory feelings. In response to casual observation and empirical evidence on information avoidance, a literature on information-dependent and belief-dependent utility emerged. However, empirical evidence on when individuals pay attention to their financial accounts remains scarce. We aim to fill this gap by using data from a financial aggregation app that allows bank customers to manage all their bank accounts and credit cards across multiple banks in one place. The digitization of budgeting processes and the attendance tracking of online behavior allow us to directly measure individual attention in ways that previously were not possible. To examine the determinants and effects of individual attention to financial accounts, we use data from Iceland and beyond information on logins look at spending and income data that is
characterized by outstanding accuracy and comprehensiveness since electronic payments are used almost exclusively there.

We find evidence consistent with selective attention and Ostrich effects. Income payments cause individuals to log in more often and people login less when they have relatively low cash holdings or spend a lot. Additionally, when individuals are very indebted, they login somewhat more consistent with liquidity constraints or a worry about fee payments. To formalize intuitions for our key empirical findings, we analyze a model of news utility developed by Kőszegi and Rabin (2009). We establish that individuals have a first-order willingness to incur fees as they dislike checking when bad news hurt more than good news please. But, checking becomes less painful in expectation when cash holdings are large and utility is concave.
References


Table 1: Summary Statistics

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<th>All Individuals</th>
<th>1st quantile</th>
<th>2nd quantile</th>
<th>3rd quantile</th>
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<td>Monthly total income</td>
<td>3,256.06</td>
<td>3,530.50</td>
<td>857.11</td>
<td>2,045.13</td>
<td>2,652.88</td>
</tr>
<tr>
<td>Monthly regular income</td>
<td>3,083.24</td>
<td>3,184.27</td>
<td>665.73</td>
<td>1,487.27</td>
<td>2,487.45</td>
</tr>
<tr>
<td>Monthly irregular income</td>
<td>217.83</td>
<td>1,414.77</td>
<td>191.38</td>
<td>1,391.08</td>
<td>165.43</td>
</tr>
<tr>
<td>Monthly expenditures:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1,315.15</td>
<td>1,224.34</td>
<td>960.81</td>
<td>1,092.34</td>
<td>1,193.10</td>
</tr>
<tr>
<td>Groceries</td>
<td>468.29</td>
<td>389.30</td>
<td>342.01</td>
<td>353.99</td>
<td>447.42</td>
</tr>
<tr>
<td>Fuel</td>
<td>235.88</td>
<td>258.77</td>
<td>170.73</td>
<td>246.73</td>
<td>216.12</td>
</tr>
<tr>
<td>Alcohol</td>
<td>61.76</td>
<td>121.43</td>
<td>45.60</td>
<td>106.33</td>
<td>54.11</td>
</tr>
<tr>
<td>Ready Made Food</td>
<td>170.19</td>
<td>172.65</td>
<td>137.81</td>
<td>162.67</td>
<td>156.64</td>
</tr>
<tr>
<td>Home Improvement</td>
<td>150.16</td>
<td>464.94</td>
<td>103.86</td>
<td>379.45</td>
<td>118.55</td>
</tr>
<tr>
<td>Transportations</td>
<td>58.33</td>
<td>700.07</td>
<td>38.23</td>
<td>583.73</td>
<td>44.53</td>
</tr>
<tr>
<td>Clothing and Accessories</td>
<td>86.62</td>
<td>181.27</td>
<td>62.15</td>
<td>152.07</td>
<td>79.87</td>
</tr>
<tr>
<td>Sports and Activities</td>
<td>44.30</td>
<td>148.41</td>
<td>27.91</td>
<td>109.40</td>
<td>35.11</td>
</tr>
<tr>
<td>Pharmacies</td>
<td>39.62</td>
<td>62.08</td>
<td>32.52</td>
<td>58.94</td>
<td>40.75</td>
</tr>
<tr>
<td>Age</td>
<td>40.60</td>
<td>11.50</td>
<td>38.50</td>
<td>13.00</td>
<td>39.40</td>
</tr>
<tr>
<td>Female</td>
<td>0.45</td>
<td>0.50</td>
<td>0.49</td>
<td>0.50</td>
<td>0.58</td>
</tr>
<tr>
<td>Capital region</td>
<td>0.79</td>
<td>0.40</td>
<td>0.80</td>
<td>0.40</td>
<td>0.77</td>
</tr>
<tr>
<td>Number of days between check arrivals</td>
<td>17.30</td>
<td>17.00</td>
<td>20.50</td>
<td>26.60</td>
<td>17.60</td>
</tr>
<tr>
<td>Number of days between salary check arrivals</td>
<td>24.00</td>
<td>26.60</td>
<td>34.50</td>
<td>56.90</td>
<td>25.60</td>
</tr>
<tr>
<td>Unemployed</td>
<td>0.08</td>
<td>0.27</td>
<td>0.11</td>
<td>0.31</td>
<td>0.09</td>
</tr>
<tr>
<td>Parent</td>
<td>0.23</td>
<td>0.42</td>
<td>0.20</td>
<td>0.40</td>
<td>0.30</td>
</tr>
<tr>
<td>Parent of a young child</td>
<td>0.02</td>
<td>0.13</td>
<td>0.02</td>
<td>0.13</td>
<td>0.01</td>
</tr>
<tr>
<td>Pensioner</td>
<td>0.15</td>
<td>0.36</td>
<td>0.15</td>
<td>0.35</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Note: All numbers are in US dollars.
Figure 1: Distribution of logins over the month and by day of week (Sunday to Saturday) by men and women
Figure 2: Average logins on regular days and days with different income arrivals by men and women
Figure 3: Propensity to log in around paydays of regular salary payments

Figure 4: Differences in propensity to log in on paydays versus other days (when individuals receive (dashed line) and do not receive (solid line) a salary check) as functions of individual cash holdings and liquidity
Figure 5: Differences in propensity to log in on paydays versus other days as functions of individual cash holdings and liquidity and raw correlation between individual logins and spending

Figure 6: Propensity to log in by deciles of spending and savings
Figure 7: Propensity to log in by deciles of individual cash and liquidity holdings

Figure 8: Propensity to log in by deciles of individual overdraft
Figure 9: Propensity to log in by deciles of cash and liquidity holdings (absolute or measured in number of consumption days)

Figure 10: Propensity to log in by deciles of overdraft and all consumer debt
Table 2: Effect of Paydays and Credit Card Bill Due Dates on the Propensity to Log in

<table>
<thead>
<tr>
<th></th>
<th>Log in Dummy</th>
<th>Total Logins</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Paycheck</td>
<td>0.0094***</td>
<td>0.0082***</td>
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<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>Credit Card Bill Due</td>
<td>0.0036***</td>
<td>0.0052***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>individual fixed effects</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>month-by-year fixed effects</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>day-of-month fixed effects</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>day-of-week fixed effects</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>holiday dummies</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>liquidity</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>#groups</td>
<td>14,048</td>
<td>3,493</td>
</tr>
<tr>
<td>#obs</td>
<td>24,752,576</td>
<td>2,553,383</td>
</tr>
<tr>
<td>#obs per group</td>
<td>1,762</td>
<td>731</td>
</tr>
</tbody>
</table>

Note: * p<0.1, ** p<0.05, *** p<0.01