The Ostrich in Us: Selective Attention to Personal Finances

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Abstract

We analyze attention to personal finances using a high-frequency panel of bank data, including information on logins. We document a number of robust patterns. Relative to their personal histories, individuals pay more attention when holding more cash and liquidity and when receiving income. In contrast, attention decreases discretely as bank account balances go from positive to negative and then decreases further as overdraft debt increases. We conclude that Ostrich effects in a personal finance context, i.e., the avoidance of obtaining information on everyday personal finances, is a widespread phenomenon and explore a number of explanations for our findings.

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

JEL: G51, D12, D14, D81, D83

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1 Introduction

What determines individual attention to personal finances, such as transactions, bank account balances, credit lines, use of consumer credit, income arrivals, bill payments, and the incurrence of bank fees? Arguably, attention to personal finances influences individual financial standing. Recent studies analyze online account logins to retirement portfolios and brokerage accounts (Sicherman et al., 2016; Karlsson et al., 2009; Gargano and Rossi, 2018; Quispe-Torreblanca et al., 2024; Gargano et al., 2023). However, little is known about what drives attention to personal finances more broadly

We undertake a large-scale empirical study of individual attention to personal finances using a daily panel of bank account information that provides granular records of individuals' balances, transactions, credit lines, and consumer credit across all their bank accounts. The data stem from a financial aggregation app prevalent in Iceland and we measure attention by logins to the platform, online or via a smartphone app.[1] The platform is for informational purposes only; individuals cannot use it to transfer funds, pay bills, or perform other transactions.

By drawing on the high frequency and comprehensiveness of the information on individuals' financial circumstances, we document a number of very robust patterns in their attention. Individuals pay less attention when their checking account balances, savings account balances, and liquidity decrease.[2] Attention decreases discretely when individuals start overdrawing their checking accounts and decreases further as individuals roll over larger amounts of overdraft debt.[3] Finally, utilizing exogenous variation in regular income arrivals and bill payments, we document that attention increases on days of perfectly predictable income arrivals and more so than for bill payments.

[1] About 20% of the Icelandic adult population used the platform during our sample period.

[2] Liquidity is defined as cash plus credit and overdraft limits minus credit card balances and overdraft debt while cash is defined as savings account balances plus positive checking account balances.

[3] Overdraft debt are the predominant form of high-interest unsecured consumer debt in Iceland and is similar to credit card debt in the US. Banks charge interest monthly when the overdraft facility is utilized, but there is no discrete overdraft fee. We also observe credit card balances and payments, but credit card bills are almost always repaid in full each month. Figure C.8 shows the evolution of the average overdraft interest rates financial institutions charged individual customers over our sample period.

All these findings indicate that individuals pay less attention when they are doing worse financially, and this is consistent with individuals avoiding receiving information on their finances when they perceive their situation to be adverse.

These patterns do not reflect cross-sectional differences as they are identified using variation at the individual level, i.e., we split measures of individual financial standing into deciles *within each individual's history*, and we control for all observable and unobservable time-invariant factors by including individual fixed effects. Furthermore, these patterns are neither driven by aggregate nor individual-specific seasonality or trends as we include a set of calendar fixed effects (day-of-week, day-of-month, month-by-year, and holidays) and the interaction of individual and month-by-year fixed effects. Our empirical findings are also robust to sample splits by various factors, including income, but our analyses do not prove a direct relation, or establish causality, in the link between financial standing and attention.

We then draw upon features of the data to explore potential explanations for why individuals appear to avoid adverse financial information. This reveals new insights into what may drive financial attention. The extant literature shows that paying attention to personal bank accounts has beneficial impact on personal finances (e.g., Karlan et al., 2016b,a; Levi and Benartzi, 2020; Medina, 2020) and that there is a causal link between paying more attention and avoiding financial mistakes (Carlin et al., 2023).[4] Given that paying attention to bank accounts is helpful, it is important to understand why individuals do not do so when doing worse financially.

Theories of rational inattention posit that individuals trade off the expected benefits of information and the costs of acquisitions and processing, while theories of selective inattention posit

[4] In contrast, it is not as clear whether investor's degree of attention to their brokerage accounts benefits their returns through stock-picking or market-timing skill. Individuals increase their returns and reduce the risk of their portfolios by rebalancing, but Sicherman et al. (2016) rule out the rebalancing motive as a determinant of logging in after markets appreciate by referring to the generally low level of actual trading. Gargano and Rossi (2018) show that investors who pay more attention successfully exploit the momentum anomaly in a brokerage account dataset of frequent traders over the period from 2013 to 2014. Nevertheless, Barber and Odean (2000) show that over longer periods, investors who trade underperform their beginning-of-year portfolio by approximately their trading costs. Furthermore, Barber et al. (2022) shows that Robinhood investors face slightly lower returns when they trade attention-grabbing stocks.

that information also has a direct hedonic impact on utility.[5] Using the data, we examine some potential rational explanations for paying attention to personal finances as well as one form of selective attention referred to as the Ostrich effect – the avoidance of unpleasant information (Galai and Sade, 2006). The rational explanations considered are based upon i) uncertainty about transactions and balances, ii) information costs and transaction verification, iii) stakes, and iv) planning. Information on the empirical relevance of these is informative about the modeling assumptions in the theoretical literature on inattention, which is formally explored in a simple economic model of information costs in Olafsson and Pagel (2017). Our setting does not lend itself to examining other rational explanations for attention to personal finances, such as those based upon opportunity costs, as these are inherently difficult to measure. Our setting also does not lend itself to testing of best-fitting models. Still, our establishment of key empirical patterns in individual attention to personal finances provides valuable input into future theoretical research.

Our findings contribute to a small literature documenting Ostrich effects in a personal finance context.[6] Karlsson et al. (2009) show that retail investor attention to their portfolios decreases after negative returns on market indices.[7] We contribute to this literature by considering a new domain: everyday household finances. This includes, e.g., monitoring bank account transactions and balances, which are central components of household economic activity. The fact that the empirical patterns are consistent with Ostrich effects in standard everyday financial tasks for a broad sample of the population suggests that selective attention is more widespread than previously thought.[8] Our findings may be interesting to the literature on information costs as well.[9] When

[5]We define the term “selective attention” in this paper to refer to some variant of information-dependent utility following Karlsson et al. (2009) and Golman et al. (2016). In contrast, the term "rational inattention" refers to exogenous costs of information or information processing following the large literature around the seminal paper by Sims (2003).

[6]Such aversion to bad information has also been documented by several studies in the medical domain. Individuals at risk for health problems (for example, serious genetic conditions or sexually transmitted diseases) often avoid medical tests even when the information is costless and should, logically, help them make better decisions (Thornton, 2008; Oster et al., 2013; Ganguly and Tasoff, 2017; Sullivan et al., 2004; Lerman et al., 1996, 1999; Lyter et al., 1987).

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

[8]93 percent of American households have a bank account (the Federal Deposit Insurance Corporation (FDIC) reports). In contrast, investors who manage their portfolios in retirement accounts and groups of individuals who benefit from knowledge of adverse medical information are potentially more selected.

[9]Studies modeling information costs in personal finance settings include Abel et al. (2013); Alvarez et al. (2012);

our findings are interpreted as information avoidance, and individuals choose not to log in when in relatively bad financial standing, they are effectively willing to pay for not receiving information, which implies that information costs are time-variant in non-trivial ways and sometimes effectively negative. Furthermore, because individuals in bad financial situations pay less attention, which may exacerbate their situation, our findings relate to the literature on poverty traps (see Azariadis and Stachurski, 2005, for a literature survey) and on poverty and cognitive function (Mani et al., 2013; Carvalho et al., 2016). Finally, our findings are important for policy prescriptions or (field) experimental interventions where it is important to take into account that attention may be selective (see DellaVigna, 2009, for a literature survey).

The remainder of the paper proceeds as follows. We describe the data used in our analysis in Section 2. In Section 3, we report our empirical findings. In Section 4, we discuss the empirical support our results provide for some potential explanations of financial attention. Finally, Section 5 concludes the paper.

2 Data and summary statistics

This paper uses data from Iceland generated by Meniga, a European provider of financial aggregation software for banks and financial institutions. In Iceland, their aggregation platform allows individuals to observe all their financial accounts, including bank and credit card accounts, across all Icelandic banks in a single location. All adult individuals in Iceland must have a bank account,[10] the use of Internet banking is widespread,[11] and the platform is integrated into the services of all banks in Iceland. Arguably, this makes our data more representative of the underlying population than data based on similar platforms in other countries. However, some groups of individuals are surely underrepresented. This is confirmed in Table A.2 in the Online Appendix that shows that in

Huang and Liu (2007); Van Nieuwerburgh and Veldkamp (2009, 2010).

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

[11] According to Eurostat, 94 percent of Icelanders used Internet banking in 2018 (Source: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=isoc_bde15cbc&lang=en)

2017 the average age in our sample is 42, the share of women is 48%, and the individual monthly mean income is $4,141.[12] At the same time, Statistics Iceland reported that the average age among those above age 15 was 45.3, women constituted 50% of the population, and the average disposable income was $4,153.[13] Table A.2 also shows that the use of consumer debt in Iceland is quite similar to the US. Individuals in Iceland hold (conditionally) about $6,174 in overdraft debt, i.e., rolled-over interest-bearing debt which is the main form of consumer credit there. They still enjoy substantial liquidity via untapped credit lines, $13,938 on average. In comparison, the average credit card debt for individuals who roll it over is about $4,000 in the US and credit available is about $11,000, according to the Survey of Consumer Finances (SCF). We relegate the discussion of the advantages of working with data from Iceland and sample selection criteria to the Online Appendix A. Additionally, Online Appendix B.1 discusses cross-sectional differences in attention.

2.1 Concerns about selection or the platform

Table A.2 also shows that the sample of frequent users, i.e., those in the the top tercile of the login distribution, looks similar to the overall user sample. Among individuals who use the app frequently, the average share of days we observe at least one login is 6.1 percent (and 4.4 percent of days we see at least one login through a desktop).

One potential concern is that our findings may be restricted to subpopulations of high financial literacy as other studies (see, e.g., Haran Rosen and Sade, 2019) find that the use of financial aggregation apps is associated with high financial literacy. But we know that financial literacy is correlated with various other individual characteristics, e.g., income (Atkinson and Messy, 2012), and thus make sure in our analyses that the findings are robust across different income groups of the population.

To address any concerns about app features or notifications driving our results, we show that

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

[13] Olafsson and Pagel (2018), Carvalho et al. (2024), and Gathergood and Olafsson (2024) also provide a discussion of the representativeness of the platform's user population.

the patterns we document are the same pre-app release. Before the app release in November 2014, bank customers had access to an online version of the platform. This version did not feature notifications, as is made clear in a company statement displayed in Appendix D. Individuals could only sign for monthly summary emails (see Appendix E for an example). Later versions of the app, however, flagged certain events, such as unusually high transactions or low balances. Users had to sign in, however, to see those. In terms of notifications, to the best of our knowledge from having the app installed, the version of the app available during the sample period did not send any.[14] Additionally, users did not see their unpaid bills in the app and could not receive push notifications regarding unpaid bills.

3 Analyses and empirical findings

In this section, we document how within-individual variations in financial standing are associated with paying attention to bank accounts. Our set of fixed effects imposes a bar for selection, omitted-variable bias, and reverse causality. All regressions control for selection on time-invariant (un)observables by including individual fixed effects, and we always compare individuals' values to their averages. Moreover, the calendar fixed effects (day-of-week, day-of-month, month-by-year, and holiday) control for all aggregate recurring variation, seasonality, and any slow-moving trends. Finally, by including the interaction of individual and month-by-year fixed effects, we take care of the fact that different individuals may have different cyclical patterns, and they may have individual-specific trends.

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

3.1 The relationship between income receipts, bill payments, and attention

We estimate the relationship between paydays and bill due days on logins by running the following regression:

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

where $I_i(Login_t)$ is an indicator variable of whether individual i logged in to her account on date t, δ_{dow} is a day-of-week fixed effect, ϕ_{dom} is a day-of-month fixed effect, ξ_h is a holiday dummy, ψ_{my} is a month-by-year fixed effect, η_i is an individual fixed effect, and $I_i(P_{t+k})$ is either an indicator that is equal to 1 if individual i receives income at time $t+k$ and equal to zero otherwise or a credit card bill due indicator, equal to one on due dates and zero otherwise. The β_k coefficients measure the fraction by which paydays and bill due days increase the probability of logging in during the two surrounding weeks. Standard errors are double clustered at the individual and day levels.

Figure 1 (A) displays the β_k coefficients for paydays and reveals it is five times larger on paydays than on the surrounding days. Compared to average login rates, individuals are about 30% more likely to log in on the day they get paid. (B) displays the propensity to log in more than once per day during the two surrounding weeks (note that income transactions post at the beginning of the day). We find that the propensity to log in twice also spikes on paydays. Appendix C provides additional results to alleviate concerns that the response might be driven by the mobile app or a specific part of the income distribution. Figure 1 (C) and (D) also show responses to irregular income, such as investment transactions, insurance claims, and dividends, and plausibly exogenous income, such as lotteries and tax rebates. The login response is a bit smaller in magnitude than for regular paydays. (E) displays the login response to credit card due dates, which is above half the magnitude of that of paydays. However, when we generate the same figure as (E) but drop paydays (see (F)), the response to credit card due dates halves.

{Figure 1 around here}

Our identification uses that individuals always receive their regular income on a fixed day of the month unless that is a weekend or holiday, which generates an exogenous source of variation in the day of the month income arrives. To exclusively single out this exogenous variation, everyone must be paid on the same day of the month or we need individual interacted with day-of-month fixed effects. Most individuals are paid on the 1st of the month and all our results are robust to restricting our sample to these individuals and also to the inclusion of individual interacted with day-of-month fixed effects. Additionally, we use an indicator for paydays as the regressor rather than the income amount to alleviate potential endogeneity concerns associated with the amount of income received that could arise from the fact that individuals may have some control over how much income they receive each month, e.g., by working extra hours. In Iceland, credit card bills are due on the 2nd of the month if that day does not fall on a weekend or a holiday[15] Thus, we use the same identification strategy for credit card bill due days.

To analyze how the login responses on paydays and credit card bill due days vary with cash, liquidity, and spending, we run the following regression:

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

where the variables $I_i(Login_t)$, δ_{dow}, ϕ_{dom}, η_i, ψ_{my}, ξ_h, and $I_i(P_t)$ are as specified above and $I_i(Dec_{dt})$ is an indicator variable for each cash, liquidity, or spending decile d of individual i on date t.[16] It is important to highlight that the deciles are constructed for each individual relative to their own history. We are, therefore, utilizing within-individual across-own-deciles variation. The β_d coefficients, displayed in Figure 2, capture the login responses of paydays and credit card bill due days for each (individual) cash, liquidity, or spending decile.

{Figure 2 around here}

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

[16] Liquidity is defined as cash plus credit and overdraft limits minus credit card balances and overdraft debt while cash is defined as savings account balances plus positive checking account balances.

We find that logins respond more strongly to paydays and bill due days when cash and liquidity holdings are relatively high. Logins do not respond much to paydays and bill due days when cash holdings are relatively low, while the response is substantial when cash holdings are high. Note that this is not a mechanical relationship where paydays cause high balances, as same-day income is excluded. The relationship between cash/liquidity and logins on other days is also positive and we note that for bill due days, the positive relation with cash or liquidity appears to dominate those with due dates. That is, the difference between average login rates within deciles of cash and liquidity on bill due days and not bill due days are not significant while the difference between login rates for the bottom and top deciles of cash and liquidity is.

Figure 2 also shows how logins respond to paydays and bill due days when same-day spending is relatively high or low. There is no clear relationship between logins on paydays and bill due days and the amount of spending. The same holds for logins on other days.

3.2 The relationship between balances, liquidity, spending, and attention

To estimate the relation between financial standing, namely checking and savings account balances, cash, as well as liquidity, and logins, we run the following regression:

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

where $I_i(Login_t)$, δ_{dow}, ϕ_{dom}, η_i, ψ_{my}, and ξ_h are as specified above. $I_i(S_{dt})$ is an indicator variable equal to 1 if individual i is in decile d of a measure of financial standing on date t. We construct 11 categories of financial standing. The first category is zero, and the remaining categories are individual (daily values normalized by individual average values) deciles. As before, we are therefore utilizing within-individual across-own-deciles variation.

Figure 3 displays the estimated coefficients of being in each decile of checking and savings account balances, cash, and liquidity on the probability of logging in. High values relative to one's history increase the login probability considerably. For instance, going from the bottom to the top decile of savings almost doubles the login probability (the difference between the coefficients is statistically significant employing a Wald test). The increases in the probability to log in are also large for the other variables, around 50% for checking account balances, 30% for cash, and 50% for liquidity relative to the baseline propensity to log in of around three percent.

{Figure 3 around here}

To test if spending influences attention to financial accounts we also estimate Specification (3) where $I_i(S_{dt})$ now represent deciles of spending. We split individuals' spending into 11 categories in the same way as the measures of financial standing. To test whether logins respond to upcoming expenses, we also estimate the relationship between spending and the propensity to log in the day before. Figure 3 shows there does not appear to be a relationship between the propensity to log in and spending deciles of the current or the following day.

Next, we investigate the relationship between overdraft debt and the propensity to log in by estimating Specification (3) where $I_i(S_{dt})$ now represents deciles of overdraft debt. Figure 4 displays the propensity to log in by deciles of overdraft debt for individuals with and without available savings. This shows a negative relationship with overdraft debt in both cases; when individuals have more overdraft debt, they are less likely to log in.

{Figure 4 around here}

The raw data Figure 4 (A) suggest that logins jump discretely when checking account balances go from negative to positive. It is important to note that the figure includes only individuals who experience both positive and negative checking account balances during our sample period. Therefore, the discontinuous jump around zero does not just reflect cross-sectional differences, with different groups of individuals being on each side of zero.

To investigate this discrete jump in logins in the raw data in a regression framework, we split all positive balances into 11 equally sized bins and do the same for negative balances. The lowest category of positive balances (where individuals hold $< \approx 2\%$ of their average positive balance) and the lowest overdraft category (where individuals have $< \approx 6\%$ of their average overdraft debt) are then merged with the exact-zero observations.[17] We then compare deciles of positive and negative balances to this "almost-zero" threshold.

Figure 4, panel B, illustrates the estimated jump from this specification.[18] The figure displays the regression coefficients for the individual deciles of overdraft debt or positive account balances added to the coefficient of the omitted category, an almost-zero checking account balance. As in the raw data, we see a discrete increase in the propensity to log in around zero. In the raw data, the slope in the positive cash domain is only marginally positive; however, (B) singles out individual-level variation, we see a positive slope both above and below zero.

Table 1 shows the same regression coefficients as Figure 4 (B) along with the results from a Wald test of the null hypothesis that the estimated coefficients of each decile 1 to 10 and the corresponding negative (overdraft) decile -1 to -10 are equal. The difference between the first overdraft decile (a small overdraft) versus the first positive checking account decile is significant. The regressions are, therefore, consistent with what we see in the raw data; when checking accounts go into the red, individuals log in less.

{Table 1 around here}

In sum, individuals are less likely to log in when doing worse financially, as captured by cash and liquidity holdings, bank account balances, and overdraft debt. Furthermore, there is a discontinuity in their attention when their checking account balances become negative. These patterns

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

[18] Additionally, we control for income receipt.

are very robust and we refer the reader to Online Appendix B for additional robustness checks and cross-sectional splits.

4 Explanations and mechanisms

In this section, we discuss various potential drivers of attention to personal finances in light of our empirical findings.

4.1 Uncertainty about transactions and balances

A basic benchmark to consider is that individuals log in irrespective of their transactions because they are either fully certain or uncertain about them. Our findings suggest that logins are not unrelated to transactions though. That is, we find that income arrival is associated with an increase in logins and that there is a robust relationship between logins and financial standing. These patterns dispel the notion that individuals are fully certain or uncertain about their bank transactions. The jump in logins when balances turn from negative to positive in a range of narrow bins (Figure 4 (A)) may give us an idea of how well individuals predict their balances. The jump in the raw data, when considering narrow bins of approximately $50, suggests that individuals can, to some extent, predict on which side of zero they are. Seeing a jump in logins around zero implies that individuals must know – to some extent – before logging in that they have a positive account balance. These patterns are thus consistent with individuals facing some intermediate uncertainty about their transactions and balances.

In principle, individuals should log in more when there is more uncertainty about their balances. We can specifically look at attention in situations without uncertainty around bank account balances. Uncertainty is arguably low when individuals log in the second time on any given day. While the first login of the day resolves a lot of uncertainty about bank account balances, additional logins resolve less uncertainty, and the information acquired by an additional login that day is likely to contain a larger hedonic component. Figure 1 shows the propensity to log in at least once and at least twice within a day in a two-week window around income arrival. We see a smaller response of second logins to income arrivals, but it is just as pronounced as the first. However, when compared to the baseline probability of logging in at least once and at least twice, the coefficient estimate of the second login is much larger: the propensity to log in at least once increases by about 37 percent on days with an income arrival, whereas the propensity to log in at least twice increases by about 62 percent. As discussed earlier, there is arguably less uncertainty surrounding regular than irregular income. However, individual attention responds more to the former ones (see Figure 1), which is inconsistent with uncertainty being a leading driver for logging in. Our findings are thus not consistent with attention increasing with uncertainty.

4.2 Transaction verification

One natural explanation for logging in on paydays is that individuals want to verify their income arrival. However, there are also information costs of logging in, most obviously time and effort. We argue though that the following findings are inconsistent with the trade-off between information costs and the benefits of transaction verification being a key driver behind the payday response.

If individuals were worried that their income was not paid, we would expect them to check not only on the day of the salary arrival but also on the days just after, especially when individuals have a liquidity buffer (which they do as shown in Olafsson and Pagel, 2018). Transaction verification therefore does not appear to be a key driver of the pronounced spike in logins on paydays we see in Figure 1 (A). Furthermore, as mentioned, individuals tend to log in multiple times on paydays even though salaries post at the very beginning of the day, and, compared to the baseline probability of logging in at least once and at least twice, the coefficient estimate on the second login is much larger.

We find a larger response to regular than to irregular income. However, for irregular income, the transaction verification motive should be more relevant as they are likely more uncertain. As opposed to regular income arrivals, we cannot know for certain whether the irregular income was fully expected or known to arrive on a certain date.[19] Additionally, the risk of mistakes is presumably larger as they are more often executed manually. Figure 1 (C) and (D) show responses to irregular income. The relationship is similar to the one of regular paydays. If anything, it is smaller for irregular paydays even if we add the coefficients on the surrounding days to it. It thus appears that individuals have a larger spike when there is less uncertainty about income arrivals.

In the next subsection, we discuss the evidence for individuals logging in when their credit card bills are due in Figure 1 (E). However, we note that this response is increasing in the available resources individuals have (see Figure 2) and goes away when dropping regular paydays.

4.3 Stakes

We define high stakes as situations of planning spending and income when financial resources are low. Under this hypothesis, individuals who have more at stake, as captured by their financial standings relative to their personal histories, should pay more attention. However, the following four findings suggest that stakes are not a dominant driver of attention to financial accounts.

First, the login response to paydays is greater when cash holdings and liquidity are large but overdrafts are small (Figures 3 and 4). Second, although the spike in attention on credit card due dates would seem to cohere with individuals worrying about liquidity constraints, we do not find that this spike in attention is more pronounced when cash holdings and liquidity are low (see Figure 2). Third, Figure 2 also suggests that going from low to high cash or liquidity holdings has a larger impact on logins than having a credit card bill due.

As an alternative hypothesis, individuals in worse financial standing may have a higher marginal value of time and therefore larger opportunity costs to pay attention. This would explain the observed patterns. The marginal cost of attention might also increase if people respond to financial

[19] Although many types of irregular income, such as investment transactions, dividends, or tax rebates, are likely to be fully expected or, at a minimum, individuals are likely to have some probability distribution about what the transaction date will be and are correct on average.

constraints by trying to earn more income.

4.4 Planning

Individuals with larger financial resources or recent income may log in to their accounts to plan future expenses. We evaluate this explanation by looking at logins on the day of or prior to spending. Specifically, we look at the propensity to log in on the same day and the day prior to spending by within-individual spending deciles. If individuals were logging in to plan spending, we would expect a positive relationship between logins on a given day and spending deciles that day or the next day. However, there is no clear relationship between current day or next-day spending and logins in Figure 3. Thus, while individuals log in more when they have more financial resources, as can be seen in Figure 3 as well, we do not find direct evidence for the planning hypothesis when we look at current or next-day spending. Logins may be driven by investment planning. Our setting does not lend itself to testing this hypothesis though.

As mentioned in the previous subsection, we do not find that the spike in attention on bill days is more pronounced when cash holdings and liquidity are low (see Figure 2). Additionally, the response depends on when bill pay dates coincide with salary paydays (see (E) and (F) in Figure 1).

4.5 Beliefs-based utility

Starting with Loewenstein (1987), recent theories model the notion that beliefs about and anticipation of future consumption can have direct utility consequences (for instance, Caplin and Leahy, 2001, 2004; Brunnermeier and Parker, 2005; Kőszegi and Rabin, 2006, 2009; Van Nieuwerburgh and Veldkamp, 2009; Golman and Loewenstein, 2015; Ely et al., 2015; Andries and Haddad, 2020; Strzalecki, 2013). Olafsson and Pagel (2017) formally investigate how far one of these models, the one developed by Kőszegi and Rabin (2009), offers intuitions consistent with our empirical findings. This specific model may be a good candidate for three reasons: First, it is the most widely-applied and highly-cited model of information-dependent utility.[20] Second, it combines features of previous influential models, specifically, the notion of "anticipatory utility" – an increase in current utility from looking forward to future consumption (Loewenstein and Elster, 1992; Caplin and Leahy, 2001; Brunnermeier and Parker, 2005) and the resulting time inconsistency solved via the equilibrium concept in Kőszegi (2010). Third, the model features first-order risk aversion (as do the models by Dillenberger, 2010; Andries and Haddad, 2020), which is important because uncertainty about bank account balances is likely to be low. Inattention is more difficult to rationalize theoretically and thus more surprising in a setting with less uncertainty.[21]

Olafsson and Pagel (2017) 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 and provide a back-of-the-envelope calculation showing that the agent is willing to give up three percent of cash holdings to not experience news disutility, which amounts to $47 per month. In turn, as an out-of-sample test of this calibration, the decrease in monthly news disutility when the agent goes from high to low cash holdings to be 24 percent, which is in line with the empirical findings.

Finally, Olafsson and Pagel (2017) relate the empirical findings to the macroeconomic literature on rational inattention (Woodford, 2009; Reis, 2006; Gabaix and Laibson, 2002; Van Nieuwerburgh and Veldkamp, 2009) and formally show in a simple general-equilibrium model that aggregate dynamics are majorly affected if inattention is assumed to be selective instead of rational.

[20] In Google Scholar citations, the model in Kőszegi and Rabin (2006) alone exceeds other influential models, such as Caplin and Leahy (2001), Brunnermeier and Parker (2005), or Van Nieuwerburgh and Veldkamp (2009). Additionally, the laboratory findings of Zimmermann (2015), Falk and Zimmermann (2023), Eliaz and Schotter (2010), and Powdthavee and Riyanto (2015) underscore the importance of attention for information-dependent utility.

[21] Almost all the existing models of selective attention assume second-order risk aversion. But the agents will become risk-neutral when uncertainty goes to zero and the models lose their bite. Olafsson and Pagel (2017) formally prove that a second-order risk-averse agent becomes risk-neutral when uncertainty about financial fee payments becomes small in the presence of information costs.

5 Conclusion

In this paper, we explore what drives attention to everyday financial decisions, such as monitoring bank account balances, transactions, and bill payments. Paying attention to bank accounts is important as it is associated with various important financial behaviors (Karlan et al., 2016b,a; Levi and Benartzi, 2020; Medina, 2020; Carlin et al., 2023).

We use data from a financial management software that provides us with logins as a measure of attention, spending, income, balances, use of consumer credit, and credit limits. We document four empirical patterns in attention to personal finances: 1) attention is positively correlated with bank account balances and liquidity, 2) attention decreases discretely when individuals start overdrawing their checking accounts, 3) attention decreases further as consumer debt grows, and 4) predictable income arrivals are associated with attention.

Our findings are consistent with attention to personal finances being partly explained by individuals trading off exogenous information costs and benefits. However, our empirical evidence also indicates that Ostrich effects are a meaningful driver of attention to everyday personal finances.

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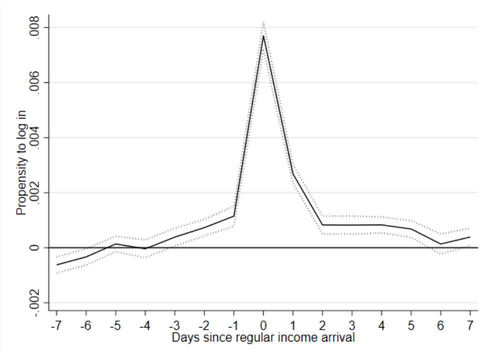
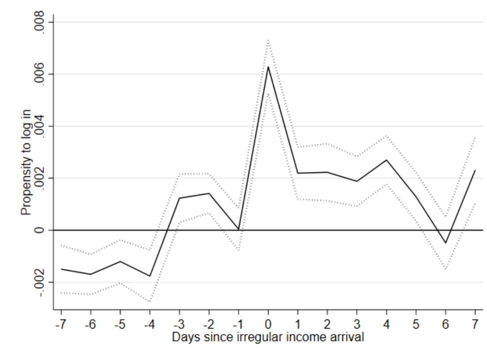
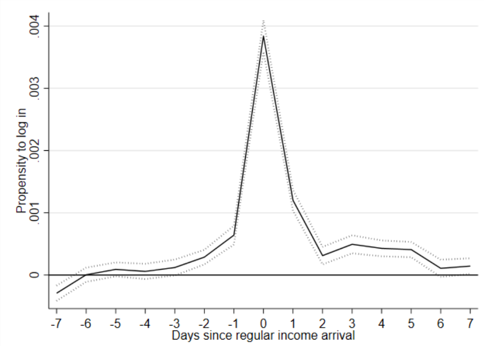
Figure 1: Logins around the arrival of regular and irregular income as well as credit card bill payments



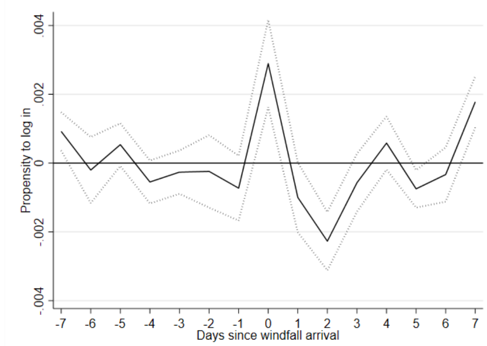
(A) Regular income, first log in



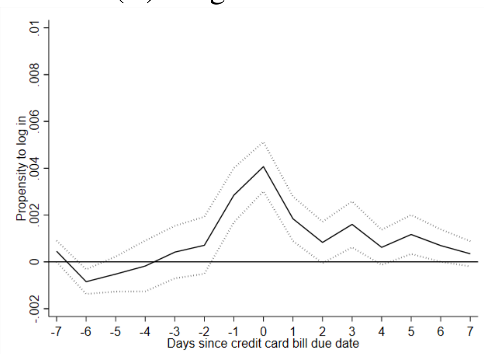
(B) Regular income, second login



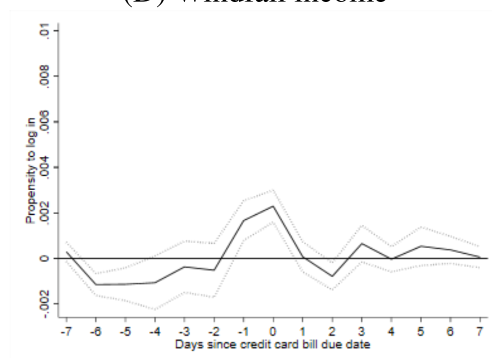
(C) Irregular income



(D) Windfall income



(E) Login response to credit card payments



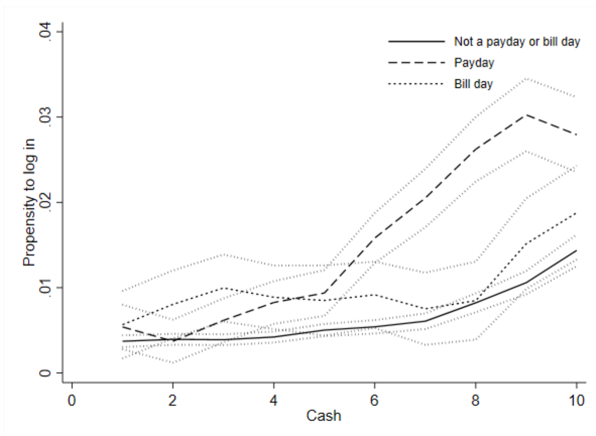
(F) Graph (E) but dropping paydays

Graphs (A) and (B) show the coefficient estimates of logging in at least once (A) and at least twice (B) from regular income arrival for two weeks around the income arrival. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week, and holiday fixed effects. Standard errors are double-clustered at the individual and daily levels. *Number of individuals:* 11,699. *N:* 22,076,013. R^2: 0.38228 for (A) and R^2: 0.2711 for (B).

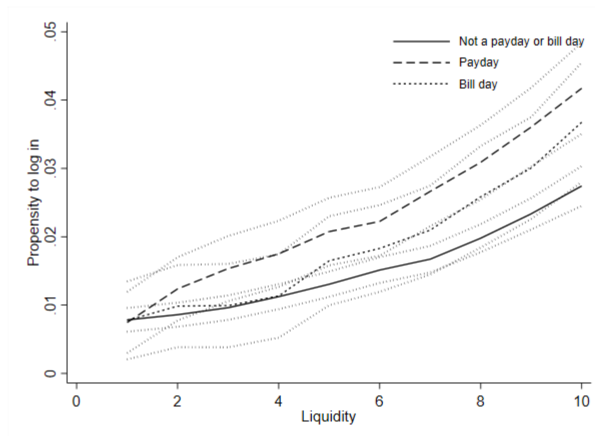
Graphs (C) and (D) show the propensity to log in in response to irregular income arrival (investment transactions, insurance claims, dividends, and grants) and for plausibly exogenous income arrival (lotteries and tax rebates) for two weeks around the income arrival. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week, and holiday fixed effects. Standard errors are double-clustered at the individual and daily levels. *Number of individuals:* 11,699. *N:* 22,239,799. R^2: 0.38227.

Graphs (E) and (F) show the response of the propensity to log in to credit card payments for two weeks around the payment date. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week, and holiday fixed effects. Standard errors are double-clustered at the individual and daily levels. *Number of individuals:* 11,699. *N:* 12,634,240. R^2: 0.38257. Graph (F) does not include due dates that coincide with paydays. *Number of individuals:* 11,699. *N:* 12,634,240. R^2: 0.3257.

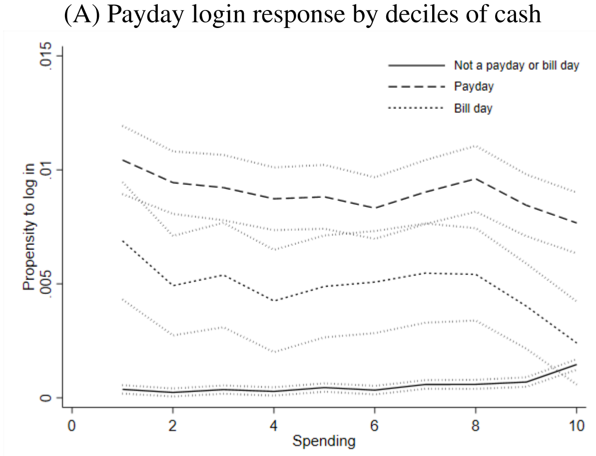
Figure 2: Logins and cash, liquidity, and spending on paydays, bill due days, and other days



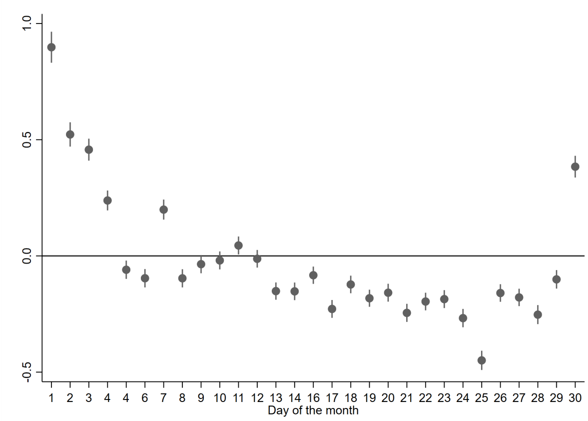
(A) Payday login response by deciles of cash



(B) Payday login response by deciles of liquidity



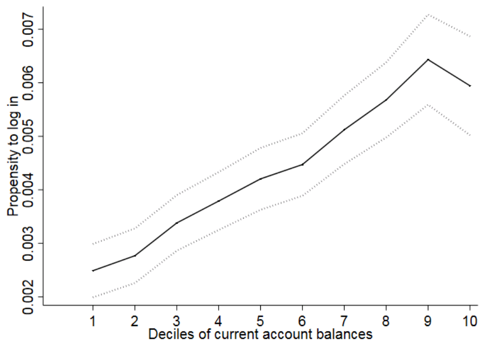
(C) Payday login response by deciles of spending



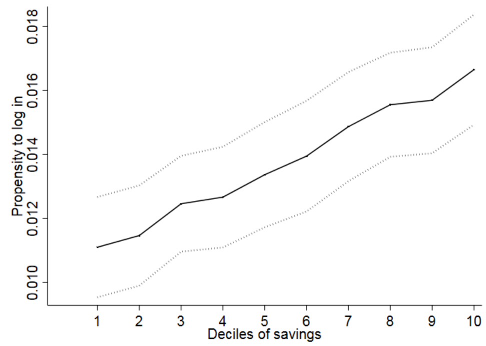
(D) Logins throughout the month

Graphs (A) to (C) show the regression coefficients and standard errors for deciles of cash holdings (positive checking account balance and savings balance), liquidity (cash plus credit card limit minus credit card balance plus overdraft limit minus overdraft debt), and daily total spending (all relative to own history of cash, liquidity, or spending) on paydays, bill due days, and other days. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week, and holiday fixed effects. Standard errors are double-clustered at the individual and daily levels. Cash: *Number of individuals:* 11,007. *N:* 9,730,188. R^2: 0.38223. Liquidity: *Number of individuals:* 11,007. *N:* 9,730,188. R^2: 0.38227. Spending: *Number of individuals:* 11,698. *N:* 22,401,670. R^2: 0.38227.
Graph (D) shows the regression coefficients and standard error bars for regressing logins on day-of-the-month dummies, controlling for individual, month, and year fixed effects. The vertical axis coefficients represent the number of daily logins relative to the middle of the month (the 15th of the month). *Number of individuals:* 11,698. *N:* 22,403,585. R^2: 0.0027.

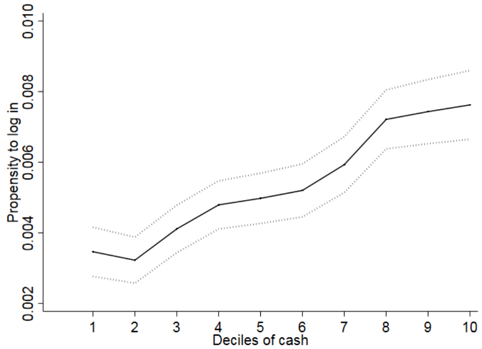
Figure 3: Logins and deciles of account balances and spending



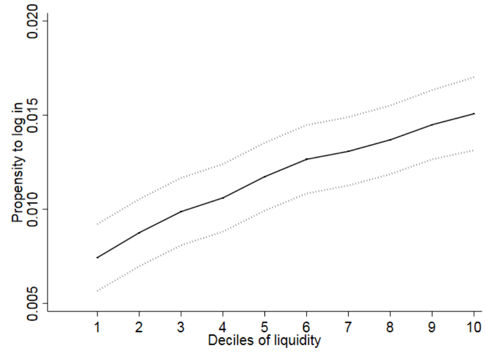
(A) Logins by checking account balance



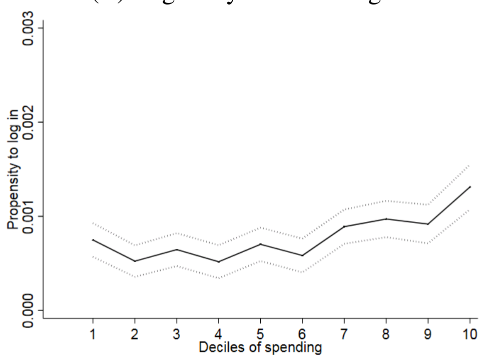
(B) Logins by savings account balance



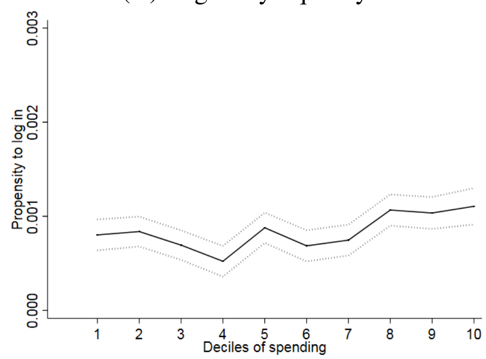
(C) Logins by cash holdings



(D) Logins by liquidity



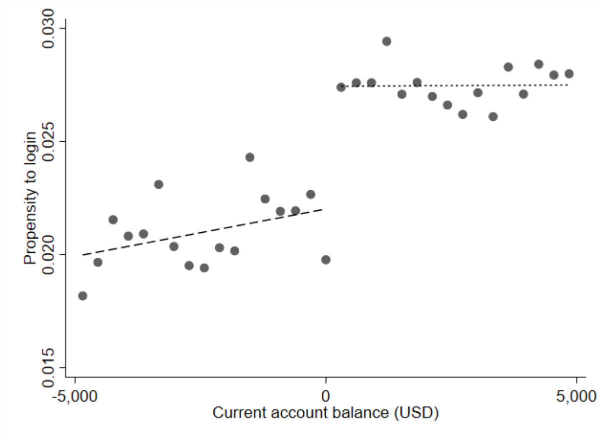
(E) Logins by spending



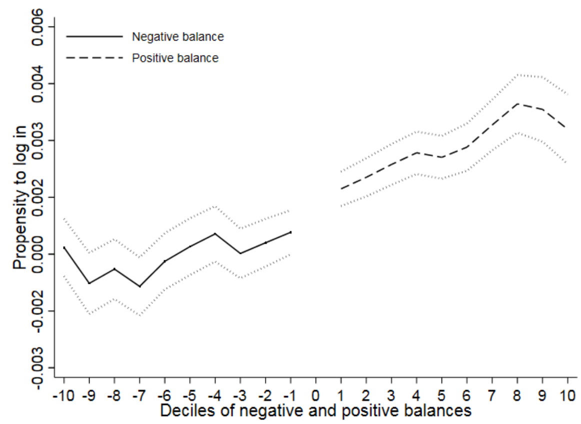
(F) Logins by following day spending

In all figures, controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week and holiday fixed effects. Standard errors are double-clustered at the individual and daily levels.
Graphs (A) and (B) show the regression coefficients and standard errors for each decile of positive checking account balances and savings account balances relative to individual's history of checking or savings account balances. (A): *Number of individuals:* 11,007. *N:* 9,730,188. R^2: 0.38222. (B): *Number of individuals:* 6,970. *N:* 6,161,480. R^2: 0.38273.
Graphs (C) and (D) show the regression coefficients and standard errors for each decile of cash (positive checking account balance plus savings account balance) or liquidity (cash plus credit card limit minus credit card balance plus overdraft limit minus overdraft debt) relative to individual's history of cash or liquidity. (C): *Number of individuals:* 10,850. *N:* 9,591,400. R^2: 0.38227. (D): *Number of individuals:* 11,006. *N:* 9,729,304. R^2: 0.38223.
Graphs (E) and (F) show the regression coefficients and standard errors for each decile of total spending relative to individual's history. (E): *Number of individuals:* 11,698. *N:* 22,401,670. R^2: 0.38227. (F): *Number of individuals:* 11,698. *N:* 22,401,670. R^2: 0.38227.

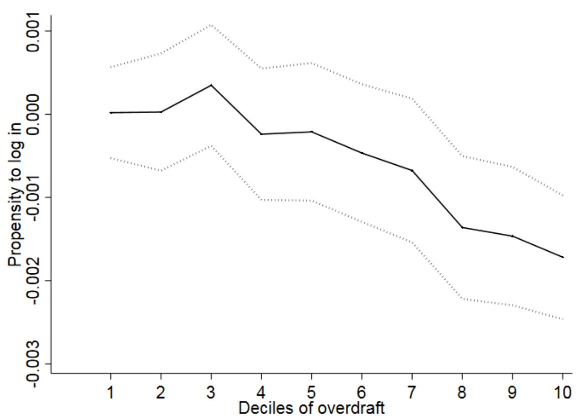
Figure 4: Logins by negative or positive checking account balances as well as deciles of overdraft debt



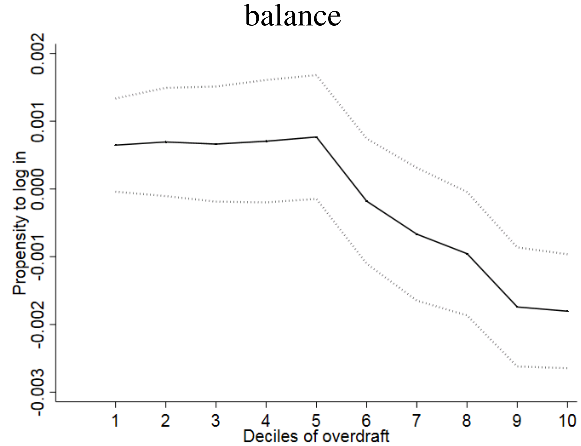
(A) Raw data login bins by checking account balance



(B) Logins by deciles of checking account balance



(C) Logins by deciles of overdraft debt



(D) Logins by deciles of overdraft debt

Graph (A) shows the raw average of the propensity to log in by bins of negative and positive checking account balance values for individuals who have both negative and positive checking account balances at some point over the sample period. Graph (B) shows the regression coefficients and standard errors for each decile of negative checking account balance or overdraft debt relative to individual's history of overdraft debt (decile -10 reflects the most negative checking account balance decile or the largest amount of overdraft debt) and the positive checking account balance relative to individual's history of positive checking account balances. Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week, and holiday fixed effects. Additionally, all regressions control for whether income was received that day. Standard errors are double-clustered at the individual and daily levels. *Number of individuals:* 7,580. *N:* 5,931,362. R^2: 0.38240. We reject the Wald test of the null hypothesis that the estimated coefficients of deciles -1 versus 1 are equal with a p-value equal to 0.0027 (see Table 1).
Graphs (C) and (D) show the regression coefficients and standard errors for each decile of overdraft relative to individual's history (decile 10 reflects the largest amount of overdraft). Controls include individual, month-by-year, and their interaction fixed effects as well as day-of-month, day-of-week, and holiday fixed effects. Graph (D) is based on regressions that only use individuals without any savings. Standard errors are double-clustered at the individual and daily levels. (C): *Number of individuals:* 6,024. *N:* 3,264,399. R^2: 0.2986. (D): *Number of individuals:* 5,675. *N:* 1,444,681. R^2: 0.2386.

Table 1: Relative bank account balances and logins

	(1)	(2)	(2)-(1)	(4)	(5)	(5)-(4)
Overdraft debt and checking account deciles:						
-10 and 10	0.0002	0.0017***	0.0015***	0.0003	0.0017***	0.0014***
	-0.0008	-0.0005		-0.0008	-0.0004	
-9 and 9	-0.0008	0.002***	0.0028***	-0.0006	0.0021***	0.0027***
	-0.0008	-0.0005		-0.0008	-0.0005	
-8 and 8	-0.0004	0.0024***	0.0028***	-0.0002	0.0023***	0.0025***
	-0.0008	-0.0005		-0.0008	-0.0005	
-7 and 7	-0.0009	0.0027***	0.0036***	-0.0007	0.0028***	0.0035***
	-0.0008	-0.0006		-0.0008	-0.0005	
-6 and 6	-0.0002	0.0026***	0.0028***	-0.0001	0.0026***	0.0027***
	-0.0007	-0.0006		-0.0007	-0.0006	
-5 and 5	0.0002	0.0028***	0.0026***	0.0003	0.0029***	0.0026***
	-0.0007	-0.0006		-0.0007	-0.0006	
-4 and 4	0.0005	0.0034***	0.0029***	0.0007	0.0033***	0.0026***
	-0.0007	-0.0007		-0.0007	-0.0007	
-3 and 3	0.0000	0.004***	0.004***	0.0002	0.0038***	0.0036***
	-0.0007	-0.0008		-0.0006	-0.0007	
-2 and 2	0.0003	0.0038***	0.0035***	0.0001	0.0035***	0.0034***
	-0.0006	-0.0009		-0.0006	-0.0008	
-1 and 1	0.0006	0.0033***	0.0027*	0.0005	0.003***	0.0025*
	-0.0006	-0.0009		-0.0006	-0.0009	
#obs		5,931,362			6,169,038	
#individuals		7,580			8,985	
R^2		0.38240			0.38233	

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