Mind the App: Mobile Access to Financial Information and Consumer Behavior

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Abstract

We use transaction data from an account aggregation company to study the impact of access to personal financial information from mobile devices on consumer behavior. We study consumers who installed the mobile app after using the app from a PC for several months. We utilize the gradual release of the app on different devices (iPhone, iPad, and Android) to establish a causal relationship conditional on adoption of a mobile app. Consistent with rational inattention models, we find that consumers increase their login frequency, especially during retail peak hours, and cut discretionary spending. Consistent with information-dependent utility models, these effects are stronger among lower-income and high-spending-to-income consumers.

JEL classification: D1, G4, G5.

Keywords: fintech, behavioral economics, household finance, consumption, spending, rational inattention, selective attention, information dependent utility.

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1 Introduction

Consumers' access to their personal financial information, such as account balance or recent transactions, have improved substantially over the past two decades. In the 1990s, consumers had to call their banks to obtain current financial information or wait for a slightly outdated bank statement to arrive in the mail. In the early 2000s, financial services providers introduced online financial accounts which offered up-to-date information at any time and from any location with a personal computer and internet access. It was only in the early 2010s that mobile apps were commonly offered by the financial industry. With the improvements in cellular data networks, consumers were able to access their financial information at any time and practically any place. Today, mobile financial apps are widely used around the world and the adoption rates are still increasing.[1]

In this paper, we study the effect of mobile financial apps on consumer behavior. Specifically, we test how access to personal financial information from a mobile device influences the behavior of consumers who already had access to the same information from a personal computer. There are several nonexclusive theories which predict the potential impact of mobile access to personal financial information.

According to the rational inattention literature, consumers face costs of acquiring, absorbing, and processing information. Consumers trade off the costs of obtaining information with the expected benefits and rationally choose to update their informa-

[1]In the U.S., 87% of the adult population have smartphones and 53% of all smartphone owners with bank accounts use mobile banking (Federal Reserve Board, 2016). In Kenya, almost 70% of adults gained access to a virtual bank account in less than three years after the introduction of a mobile banking app (Jack and Suri, 2011).

tion only sporadically, and remain inattentive in between updates (e.g. Brunnermeier and Nagel, 2008; DellaVigna, 2009; Reis, 2006; Sims, 2003). The introduction of mobile financial apps reduces the costs of obtaining information and therefore should lead to a higher optimal level of attention and better-informed consumption decisions. Consumer survey conducted by the Federal Reserve Board (2016) provides a practical example of this channel, showing that 62% of mobile banking users reported checking their account balances on their phones before making a large purchase in the 12 months prior to the survey. Half (50%) of them decided not to purchase an item as a result of their account balance or credit limit.

According to information-dependent utility models (selective attention, or reference-dependent utility models, e.g. Golman et al., 2017; Kőszegi and Rabin, 2007, 2009; Pagel 2017, 2018; Sicherman et al. 2016), information is not only a means to an end, but directly enters the agent's utility function. Consumers who are not at ease with their personal finances would prefer to check their accounts balance less frequently in order to avoid disutility. This information avoidance, or "ostrich effect", is predicted to be stronger among lower-income individuals due to the concavity of the utility function (Galai and Sade, 2006). Karlsson et al. (2009) propose that attention amplifies the hedonic impact of information. Therefore, if mobile apps increase the overall attention to personal finances, consumers who are displeased with their personal finances, such as low-income or high-spending-to-income consumers, would suffer a larger disutility from the availability of financial information on mobile devices, potentially driving them to reduce their spending level.

A significant body of work shows that household members have distinct preferences and their financial behavior is influenced by the visibility of their actions to the other household members (Ashraf, 2009; Browning and Chiappori, 1998; Hertzberg, 2016; Phipps and Burton, 1998; Schaner, 2015). Further, Hawkins et al. (2012) document that "how my spouse handles money" was quoted as a leading factor in 40% of divorce cases in the U.S. Mobile financial apps can improve the ability of household members to monitor the behavior of their spouses, and potentially lead to improved spending decisions of the household.

Mobile devices influence not only the availability of information, but also the users' ability to process that information. The screen size, spatial layout, and the touch screen of mobile devices have all been documented to decrease the users' decision quality (Brasel and Gips, 2014; Grant, 2019; Piolat et al., 1997). Further, the devices themselves promotes a "distracted frame of mind", a state where the individual has difficulty focusing on the task at hand (Bailey and Konstan, 2006; Brown et al., 2019; Misra et al., 2016; Trafton et al., 2003; Ward et al., 2017). According to this literature, consumers are expected to make worse decisions when switching to viewing their financial information using a mobile device instead of a personal computer. However, there is no clear prediction regarding the use of a mobile app in addition to a personal computer.

We obtain individual transaction-level data from a fintech company offering a free online personal financial management software that includes account aggregation technology. Account aggregation technology allows users to link all their financial accounts into one app, including checking, savings, retirement, investment, mortgage, loans, etc. This technology is commonly offered by all financial services providers and the collected data has been widely used in academic research.[2] Importantly, the app does not allow for any financial action other than viewing the financial information. This allows us to isolate the impact of information availability on consumer behavior.[3] We include in our sample users who have been using the software via a personal computer for at least three months prior to installing their first mobile app. This restriction allows us to isolate the mobile app effect from the potential effect of using the software in general.

Consumers make a conscious decision to install the mobile app. It is possible that the decision to install the mobile app is a consequence of a separate decision to increase attention to personal finances or decrease spending. In this case, the effect of the mobile app on behavior would be inseparable from the impact of the decision to change financial behavior. In order to isolate the effect of the mobile app installation, we use the gradual release of the mobile apps by the company, which is exogenous to the users of the software.

The company first released its personal computer (PC) app during 2011 and in the following year released three mobile apps for iPhone, iPad, and Android with at least two months between the release of any two mobile apps. In first two weeks following the release of each of the mobile apps, there was a spike in the number of

[2]Account aggregation technology is offered as a freemium (e.g., mint.com, future advisor), as paid advice (e.g. Ready for zero, YNAB), or as a complementary service (e.g., BBYA, Morgan Stanley). Examples of academic studies using account aggregation technology include: Baker (2018), Gelman et al. (2014), and Olafsson and Pagel (2018).

[3] Mobile banking apps are mainly used by consumers for viewing personal information. According to the Consumer and Mobile Services Survey (Federal Reserve Board 2016), 94% of consumers used their mobile banking app to check their account balances or recent transactions. Only 58% made a transfer between their own accounts, and 24% have made a mobile payment in the twelve months prior to the survey.

users installing the app on their phones. Beyond the first two weeks, there were only a handful of users installing the mobile app on a typical day (Figure 1). It is unlikely that a large group of users decided independently to install a mobile app in any given week. It is even less likely that this specific week happens to coincide with the release of the mobile app. And it is extremely unlikely that this same pattern arose in each of the different mobile app releases (iPhone, Android, and iPad). Hence, we believe that the large number of users installing the mobile app right after its release was triggered by the app release and not by an independent decision to suddenly cut spending.

Our main sample of interest consists of users who installed their first (or only) mobile app in the fourteen days after its release. This sample allows us to identify the causal impact of the mobile app on financial behavior. For robustness, we also test the impact of installing a mobile app among users who installed it more than two weeks after its release. We compare the behavior of consumers in the three months prior to installing the mobile app and the following thirteen months. Our empirical specifications include consumer fixed effects, which allow us to detect the change in behavior within an individual, and time fixed effects, which control for any seasonal effects.

We find that users drastically increase the attention to their personal finances upon the installation of the mobile app. Users increase their login frequency from four times per month before the mobile app installation to more than sixteen times per month immediately following the app installation. Further, this increase in login frequency persists over the following observed twelve months. Interestingly, there is no change in the login frequency from personal computers after the installation of the mobile app. That is, consumers keep using their personal computers with the same frequency after installation of the mobile app, and the entire increase in login activity is due to the usage of mobile devices.

We test the intraday login distributions of users in our sample (Figure 3). We find that on weekdays, users' PC login frequency peaks at 8 am, with a second lower peak around 2 pm. The PC login distribution does not change after the installation of the mobile apps. The login distribution on mobile devices also peaks for the first time at 8 am; however the second and highest peak is during retail peak time, between 4 pm to 6 pm on weekdays.

We test the change in spending behavior. Following Garmaise et al. (2019), we focus on discretionary spending, which is the sum of spending in categories over which consumers have relatively more control, such as restaurants and entertainment. We find that after the installation of the mobile app, consumers reduced their discretionary spending by 11.6 percent, which translates to about $430 per month for the average consumer in our sample. This effect is persistent over the observed twelve months following the app installation. We find a significant decline in spending on relatively spontaneous transactions such as entertainment, restaurants, and clothing. We do not find a change in spending on items such as utilities, telephone, rent, or mortgage. We also find a decline in traveling expenditure, which is likely to be a luxury item for many consumers. Consumers also reduce their cash withdrawals, which is another mechanism for maintaining higher balances in their bank accounts. This decline in cash withdrawal is consistent with consumers placing a higher subjective value on cash transactions relative to non-cash transactions and are therefore more likely to cut cash transactions first (Raghubir and Srivastava, 2008).

Next, we test which consumers are more likely to be affected by the mobile app installation. We find that lower-income individuals are more likely to cut their discretionary spending. Similarly, consumers with a high spending-to-income ratio are more likely to cut their spending and log in less frequently than low spending-to-income ratio consumers.

Overall, our results indicate that the availability of personal financial information on mobile devices has a profound impact on consumers' attention to their finances and their spending behavior. Our results are consistent with inattention: if consumers were always attentive, mobile app installation would not have any effect on login frequency or actual spending. The stability of logins from a PC after the installation of the mobile app and the increase in mobile login activity during the retail peak time is consistent with rational inattention models. Consumers have a demand for information during shopping time that was too costly to obtain without a mobile device. The observed decline in spending in categories that are relatively more spontaneous and the peak in login activity around retail rush hours suggests that the consumers might be influenced by the salience of their financial information rather than making a fully rational decision (e.g. Bordalo et al., 2012, 2013; Chetty et al., 2009; Frydman and Wang, 2020; Stango and Zinman, 2014). The lower effect on spending behavior and login frequency among lower-income and high-spending-to-income consumers is generally consistent with the predictions of information dependent utility models. Consumers with high spending-to-income ratio are likely to experience disutility when viewing their finances and therefore log in less frequently.

In addition to the contribution to the rational inattention, information-dependent utility, and salience literature discussed above, our paper contributes to the literature on the impact of technology on consumer and investor behavior. Investors switching to trade online exhibit a more active and speculative behavior attributed to the illusion of knowledge and control that the new platform provides (Barber and Odean, 2001, 2002; Choi et al., 2002). The introduction of mobile banking accounts in Kenya significantly reduced the unbanked portion of the population and assisted individuals to share income shocks risk (Jack and Suri, 2011, 2014). Dolfen et al. (2019) show that e-commerce applications permanently boost household consumption by over 1% per household. Carlin et al. (2019) use the release of a mobile financial app in Iceland to show that consumers increase the level of attention to their personal finance and reduce their financial fee expense. Our paper contributes by establishing a causal relationship between the availability of financial information on mobile devices and consumer behavior.

Our paper also contributes to a wide cross-disciplinary literature on the effects of mobile phones on behavior. The use of mobile devices was found to be related to lower grades among university students (Jacobsen and Forste, 2011), unsafe behavior while crossing the road by pedestrians (Thompson et al., 2013), inattentional blindness among drivers (Caird et al., 2008; Strayer and Johnston, 2001), magnifying the endowment effect (sense of ownership) among consumers assessing a product (Brasel and Gips, 2014), and investors' information processing (Brown et al., 2019). Einav et al. (2014) show that the mobile adaptation of e-commerce applications (e.g.

eBay) is associated with both an immediate and sustained increase in total platform purchasing. Our paper shows that mobile devices affect consumer attention to their personal finances and their spending behavior.

It is important to highlight that the effects estimated in this paper are conditional on adoption of the app. It is not the effect of introducing the app to a group of consumers or even forcing them to install it. The interpretation of our results is that the mobile apps have a causal impact on the attention and spending behavior among consumers that decided to adopt it. A close analogy is a series of studies showing the impact of mobile health related apps on health outcomes such as weight loss among people that chose to use these apps (See Chin et al., 2016 for an example and literature review).

The rest of the paper is organized as follows. Section 2 introduces the data and the identification strategy. Section 3 presents our empirical specification. Section 4 presents our results, and section 5 concludes. An online appendix provides additional tests and detailed results.

2 Data and Identification Strategy

We obtain individual transaction-level data from a fintech company which provides a free online personal financial management software to the general public. The software includes an account aggregation feature that allows users to link all their financial accounts to the app including checking, savings, retirement, investment, mortgage, loans, etc. The data includes transaction data from the users' accounts and a classification of the transactions into categories, such as restaurants or entertainment, based on the merchant's identity. In addition, we observe the users' login activity, including the login time and the device used by the user.

Our sample includes users who have used the PC app at least three months before installing their first mobile app. We require three months of activity before the installation of the mobile app in order to isolate the effect of the mobile app from the general effect of using the software or any other pre-event trend in behavior. We keep in our sample active users who have logged in the app at least once after their first registration to the app and before the mobile app installation, and that have linked at least one bank account and one credit card account. We keep users with average monthly spending of at least $500 during the three months before the mobile app installation and with positive expenditure in each of the sixteen months, starting from three months before the mobile app installation until twelve months after.

We use the gradual release of the mobile apps by the company, which is exogenous to the users, to isolate the effect of the mobile app installation. The company released its PC app during 2011 and in the following year released three mobile apps for iPhone, iPad, and Android, with at least two months between the release of any two mobile apps.[4] Figure 1 shows the daily installation count for each of the mobile apps after their release by users in our sample. In all three releases, there was a large number of installations in the first few weeks after the app release. We attribute the spike in daily installations following release of each the mobile apps to the release itself, and not to an independent decision to suddenly cut spending.

[4]Following Einav et al. (2014), we define tablet computers as mobile devices.

We split our selected users into two samples:

- **Sample X**: (for "X"-ogenous) consists of users who installed their first (or only) mobile app, in the 14 days after its release.

- **Sample N**: (for "N"-dogenous) consists of users who installed their first (or only) mobile app more than 14 days after its release.

Sample X is our primary sample of interest and it allows us to identify the causal impact of using the mobile app. Sample N is larger and therefore provides more statistical power; however, the observed change in behavior in this sample includes both the mobile app installation effect and the potential effect of a decision to change financial behavior.

Table 2 presents summary statistics for samples X and N. Sample X consists of 729 consumers, out of which 400 users installed the iPhone app as their first mobile app, 132 installed the iPad app, and 197 installed the Android app. The average login frequency for users in sample X is 14.7 per month (median 5.4) from all devices (mobile and PC). iPhone users log in from their mobile devices on average 10.2 times per month, Android users log in on average 6.7 times per month and iPad users log in about 2.4 times per month. The average income for users in Sample X is $16.9K (median $12.8K) and their total spending is around $12K (median $10.5). Following Garmaise et al. (2019), we define discretionary spending as the sum of spending in specific categories such as restaurants, clothing and entertainment. The full list of categories with example vendors for each category is in Table 1. Users in sample X spend on average $3.7K on discretionary spending, out of which $542 on restaurants,

$316 on clothing, $189 on entertainment, and $769 on travel. Users in sample X withdraw on average $976 in cash per month.

Sample N consists of 6,873 consumers, out of which 3,345 installed the iPhone app as their first mobile app, 2430 installed the Android app, and 1094 installed the iPad app. The average monthly login frequency is 9.29 (median 3.31) and their average income is around $14.3K (median $10.2K). The average monthly spending is $10.8K (median $8.5K) and their average discretionary spending is $2.5K (median $2K).

Overall, the consumers in both samples are relatively wealthy and tech-savvy.[5] Consumers in our sample are not representative of the general U.S. population, but are similar to the bottom of the highest income quintile of consumers based on income levels and expenditure.[6]

3 Empirical Specification

Our main empirical specification is,

$$y_{i,t} = \beta Post_{i,t} + \delta_i + \gamma_j + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is an outcome variable such as spending or logins for a consumer i in event month t. *Post* is a binary variable with the value of zero for the three months prior to the mobile app instalation month and one for the mobile app installation

[5]In untabulated tests, I use the Understanding America Study panel and find that people who use account aggregation software tend to be more educated, financially literate, rational, financially sophisticated, and score higher on numeracy tests.

[6]Based on the Consumer Expenditures Survey of the BLS in 2014.

month, and each of the following twelve months. δ_i are individual fixed effects, and γ_j are calendar month fixed effects. β captures the average effect of the mobile app installation.

In addition, we estimate a similar specification with event month indicator variables:

$$y_{i,t} = \sum_{t=-3}^{t=12} \beta_t I(t) + \delta_i + \gamma_j + \epsilon_{i,t} \tag{2}$$

$I(t)$ are event month indicator variables. This specification reveals the time dynamics of the mobile app effect and the pre-event trend in behavior. For robustness, we test this specification with no time fixed effects, with month of year, or quarter of year fixed effects. In all specifications, we cluster the standard errors at the individual level.

4 Results

4.1 Attention to Financial Information

Table 3 shows the analysis for login behavior. Column 1 shows that users in Sample X increased their monthly login frequency by a significant 10.7 logins. Columns 2 to 4 show that the increase in login activity started immediately during the month of the mobile app insulation and is relatively constant in each of the subsequent months. Sample N shows the same pattern in login frequency with an increase in login frequency of 7.3 times per month.

Figure 2 shows a graphical representation of the event month dummy coefficients and mean fitted values for samples X and N. Panel c shows that the average monthly logins before the mobile installation was about four times per month for users in Sample X. Users in Sample X quadrupled their login frequency to about 16 logins per month following the installation of the mobile app. Users in Sample N increased their average monthly logins from about four times per month to about ten times per month (Panel d). In addition to analyzing the total amount of logins, Figure 2 also shows the same analysis for logins from a personal computer only (formal analysis of PC logins in Table A1). The was no change in the PC login frequency of users in Sample X which remained constant at about four logins per month before and after the mobile app installation. In comparison, users in Sample N increased their PC logins in the three months around the mobile app installation and over time, dropped their PC logins to the base level of four logins per month.

Overall, the logins analysis suggests that consumers significantly increased their attention to their finances after the installation of the mobile app, with a four-fold increase for Sample X and more than a two-fold increase for Sample N. The increase in logins before and during the event month for users in sample N is consistent with an endogenous decision to pay additional attention to their finances, which potentially led to the installation of the mobile app. Consumers use their mobile devices to check their finances in addition to, and not as a substitution for, the PC logins. That is, the consumers are still using their PC devices to monitor their finances after the installation of the mobile app. However, the mobile app seems to provide needed access to information at times or in locations that rendered it impossible or too costly to obtain with a PC alone.

Figure 3 shows the intraday login patterns separated into PC or mobile logins, and weekday or weekend logins. Panel A shows the login patterns before the installation of the mobile apps. The pick time of logins during the weekdays is at the start of the workday around 8 am, and a second lower pick in logins around 2 pm. There are significantly fewer logins over the weekends, with a single peak in logins at the beginning of the day, around 8 am. Panel B shows the logins distributions after the installation of the mobile device. The PC logins distribution is similar to the distributions before the mobile app installation both on weekdays and weekends. The mobile login activity during the weekdays peacks for the first time around 8 am as well, with a similar magnitude to that of the PC login activity. The second peak in mobile logins is around 4 pm to 6 pm, which is the retail peak time or commute rush hours. This mobile login pattern is consistent with the survey evidence in Federal Reserve Board (2016) of consumers checking their finances at the store before making a purchase. Overall, the mobile logins distribution is strictly dominating the PC logins distribution both on weekdays and weekends, apart from 8 am to 2 pm on weekdays, which are normal working hours.

4.2 Spending Behavior

Next, we test if the increased attention to financial information led users to change their spending behavior. Many items in household spending, such as utilities, mortgage, or rent, are difficult to adjust, especially over a short period of time. We focus our analysis on discretionary items over which the household had relatively more control. Following Garmaise et al. (2019), we define discretionary spending as the sum of spending on categories such as restaurants, clothing, and entertainment. Table 1 presents the full list of categories that constitute discretionary spending with vendor examples for each of the categories.

Table 4 presents the analysis of log discretionary spending. Users in Sample X decrease their spending on discretionary items by 11.6 percentage points after the installation of the mobile app. Using the mean discretionary items spending of \$3.7K, this effect translates into reductions of around \$430 per month. Columns 2-4 show that the reduction in spending starts immediately during the event month and remains relatively constant in the following 12 months (graphical representation of the event months dummy coefficients in panels a and g of Figure 4). Users in Sample N decreased their spending on discretionary items by a significant 7.6 percentage points, which corresponds to an average reduction of about \$192 in discretionary spending following the installation of the mobile device.

In Table 5, we test the average spending response in different spending categories. The table presents the average monthly response for each of the tested categories as specified in Equation (1). Graphical representation of the event month coefficients from the estimation of Equation (2) is in Figure 4 and the formal analysis is in the online appendix (tables A2 to A6)

We find that consumers in Sample X decreased their spending on restaurants by 13.2%. In panel B, we present the same analysis for Sample N and in column 1 we see that the consumers decreased their monthly spending by 8.8%. Restaurant spending is relatively easy to adjust by visiting less expensive restaurants or dinning at home. Next, we consider clothing expenditure (columns 2). Users in Sample X reduced their clothing expenses by a significant 22.7% while users in sample N reduces this spending by 12.2%. Clothing can be easily adjusted as well by reducing the frequency of purchase or the price range of the clothes. In columns 3 we find that users in sample X reduced entertainment expenditure by 20.4% and users in Sample N reduced their spending by 11.4%. In column 4, we show that users in Sample X reduced their traveling expense by 19.7% while users in sample N reduced it by 13.3%. Travel is likely to be a luxury item for many consumers that can be adjusted by choosing a more modest vacation or skipping it all together. Finally, in column 5, we find that consumers significantly reduced their cash withdrawals. Users in sample X reduced their cash withdrawals by 27.6% and users in sample N reduced it by 21.5%. Decreasing cash withdrawals is another form of maintaining a higher account balance. In addition, consumers tend to place a higher subjective value on cash transactions and are therefore more likely to cut these transactions first (Raghubir and Srivastava, 2008).

4.3 Heterogeneous Response

In Table 6 we explore which consumers are more likely to be affected by the mobile app installation. In Panel A we consider the income level of the consumers. On the one hand, lower-income individuals are likely to be conscious of their financial situations and therefore might attempt make the best use of the new information availability on their phones to cut spending. On the other hand, low-income individuals have a higher MPC and might not be able to cut their spending any further

(Mian et al., 2013). We estimate equation 2 and add an interaction term between Post and an indicator variable with the value of one for users with above-median average monthly income and zero otherwise. In column 1 we find that the coefficient on the interaction term is positive and similar in magnitude to the coefficient on Post alone. That is, while users in general are more likely to cut their spending after the installation of the mobile app, the effect is mostly due to the response of lower-income individuals. We find no significant differences in the login patterns between high- and low-income users in Sample X. Lower-income individuals in Sample N are also more likely to change their discretionary spending after the installation of the mobile app, and are less likely to increase their login frequency relative to higher-income individuals in that sample.

In panel B we repeat the same analysis with interaction between the Post variable and spending-to-income ratio. Users with higher spending-to-income ratio are more likely to cut their discretionary spending levels but are less likely to increase their login frequency relative to low spending-to-income ratio consumers. The lower login frequency among lower-income or high spending-to-income individuals is consistent with information-dependent utility models. These consumers are likely to suffer a greater disutility from viewing their financial information and would prefer to avoid viewing it frequently.

4.4 Additional Tests and Alternative Explanations

4.4.1 Total Spending

We test if total spending is affected by the installation of the mobile app. We find that consumers in Sample X reduce their overall spending by 5.4 percent, however this result is only significant at the 10% level. Consumers in Sample N reduce their spending by 3.3 percent (see table A7, column 1). These estimated effects are mostly mechanical since the discretionary spending are a large portion of the overall spending. However, these results reveal that consumers do not simply shift their spending into non-discretionary categories but rather reduce their spending and therefore, increase their saving rate.

4.4.2 Falsification Tests

As a falsification test, we tested if there is a change in spending categories that are difficult to adjust, especially in the short run. We find no significant changes in spending on utilities, telephone, or rent (columns (2) to (4) in Table A7).

4.4.3 Trends in Outcome Variables

Users in sample X installed the mobile app immediately after its release. Since the release date of the app was determined by the company, it is exogenous to the users in the sample. It is possible that these users decided to change their financial behavior before the release of the mobile app and installed the app when it was first available. In this case, the installation of the app would be correlated with the change in financial behavior even though there is no causal relationship.

Our empirical specification in equation 2 addresses this concern by testing the pre-installation behavior. In table 3, columns 2-4, we see that there is no economically significant change in the login behavior between any of the pre-installation event months ($t = -3, t = -2$, and $t = -1$), meaning that there was no pre-event trend in login behavior. The same pattern arose in the discretionary spending analysis (Table 4, columns 2-4) and in each of the specific spending categories (Figure 4, and tables A2-A6).

Note, our main results include year-month fixed effect that absorb any seasonal effects and potential time trends. In addition, we report the coefficients for the event month indicator variables as specified in Equation (2). These results reveal the the mobile effect is not gradually increasing in magnitude, but rather immediate and constant after the installation of the mobile app.

As an additional robustness test, we conduct our main analysis with the inclusion of matched sample of consumers that were using the PC app over the same time period of 16 months (from t=-3 to t+12) but did not install the mobile during that window (Results in Appendix B). Consumers in the matched sample slightly decreased their login frequency and did not change their expenditure on discretionary spending. As a results, the estimated effects for the main sample of mobile adopters remain almost unchanged when compared to the effects on the matched sample.

5 Conclusion

In this paper, we establish a causal relationship between the access to personal financial information on mobile devices on consumer behavior. We find that users drastically increase the attention to their finances immediately after installing the mobile app. The increase in login frequency is due to use of mobile devices, which do not substitute for the logins from a PC. The peak time of mobile devices use is during retail peak time, 4 pm to 6pm on weekdays. We find that consumers cut their spending on discretionary items. These effects are stronger among lower-income and high spending-to-income consumers.

Our results are consistent with inattention: if consumers were always attentive, mobile app installation would not have any effect on login frequency or actual spending. The stability of logins from a PC device after the installation of the mobile app and the increase in login activity during the retail peak time is consistent with rational inattention models. Consumers have a demand for information during shopping time that was too costly to obtain using a personal computer. The lower effect on spending behavior and login frequency among lower-income and high spending-to-income consumers is generally consistent with the predictions of information dependent utility models. Consumers with high spending-to-income ratio are likely to experience disutility when viewing their finances and therefore login less frequently.

Our paper motivates several directions for future research. First, future research can isolate the exact psychological mechanism driving the impact of mobile devices. The availability of financial information on mobile devices might influence consumers by providing up-to-date information that is relevant for a fully rational spending decision, or by providing a salient reminder of the already known bank account balance just before a large transaction. Second, our study provides evidence from a natural experiment among relatively high-income tech-savvy individuals, which are probably responsible for a large fraction of the consumption in the U.S. and are likely to be representative of the retail investor population. It is important to study the effects of mobile devices in different populations, especially among low-income individuals, and in developing countries where the general population does not own a PC. Third, our study explores the impact of the information availability feature of mobile phones. Future work can focus on the effect of other features of mobile devices, such as the ability to trade stocks, or transfer funds. Fourth, future research can explore the impact of financial apps on intrahousehold dynamics. The improved monitoring ability of household members might improve the household's quality of financial decisions and can potentially lead to an increase or a decrease in divorce rates.

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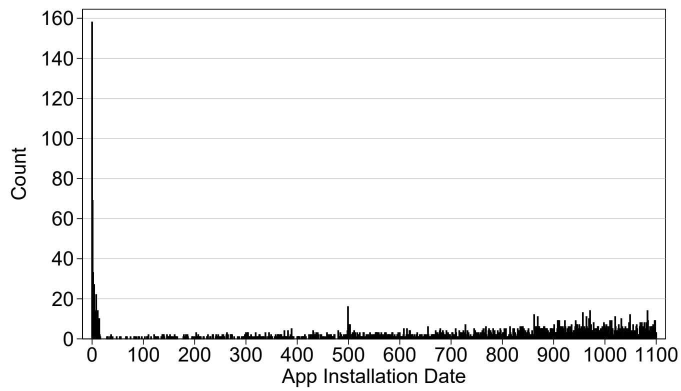
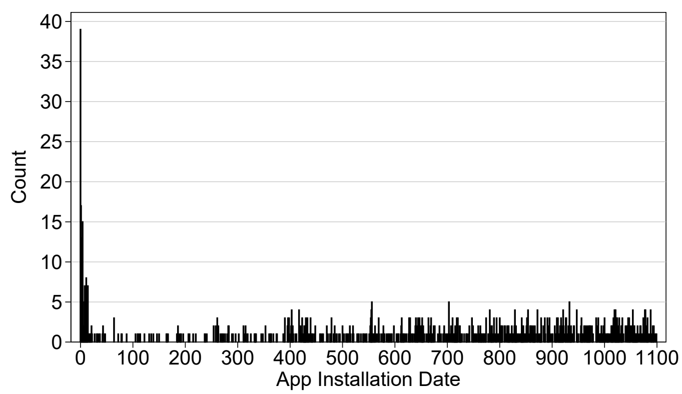
Figure 1. Mobile Apps Daily Installations

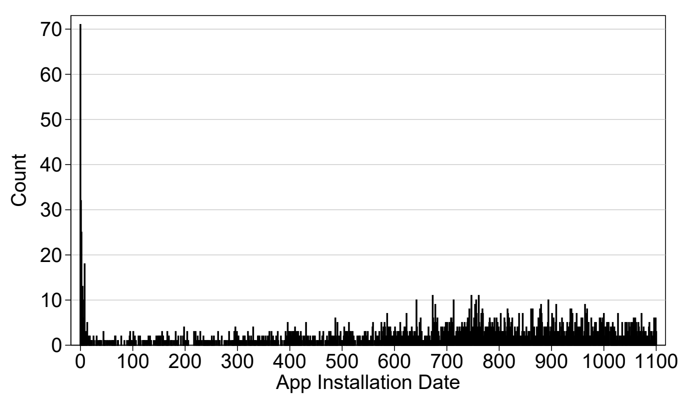
(a) iPhone



(b) iPad

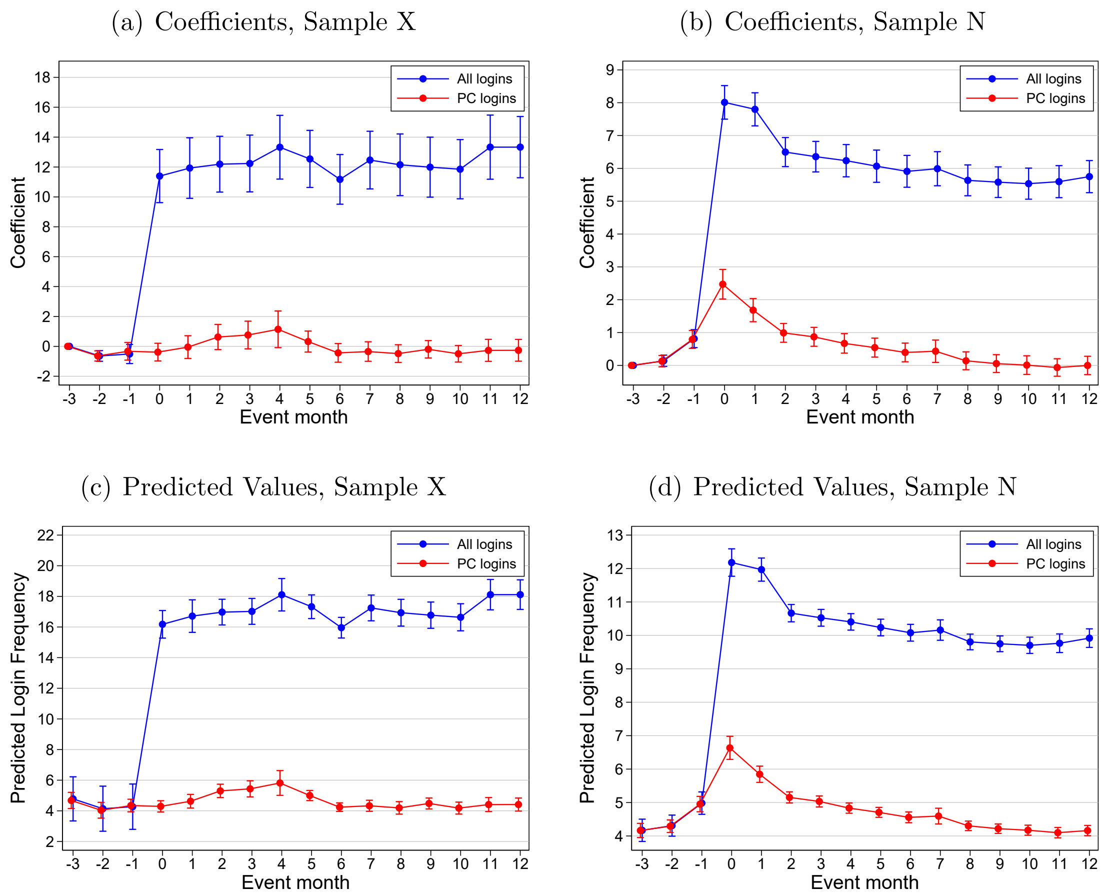


(c) Android



The figure shows the daily count of mobile app installations by all users (Sample X and Sample N), relative to the corresponding app release date.

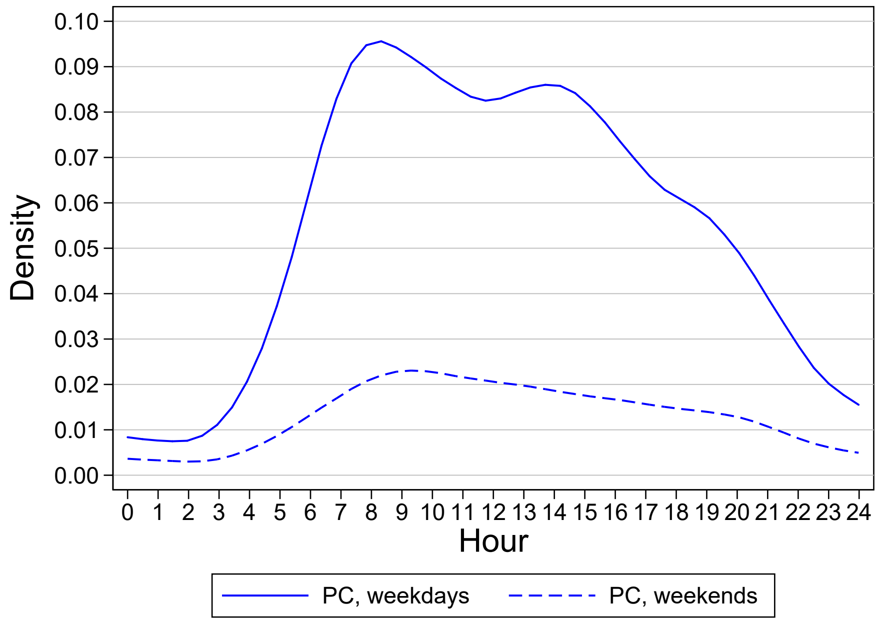
Figure 2. Mobile App Installation and Login Behavior



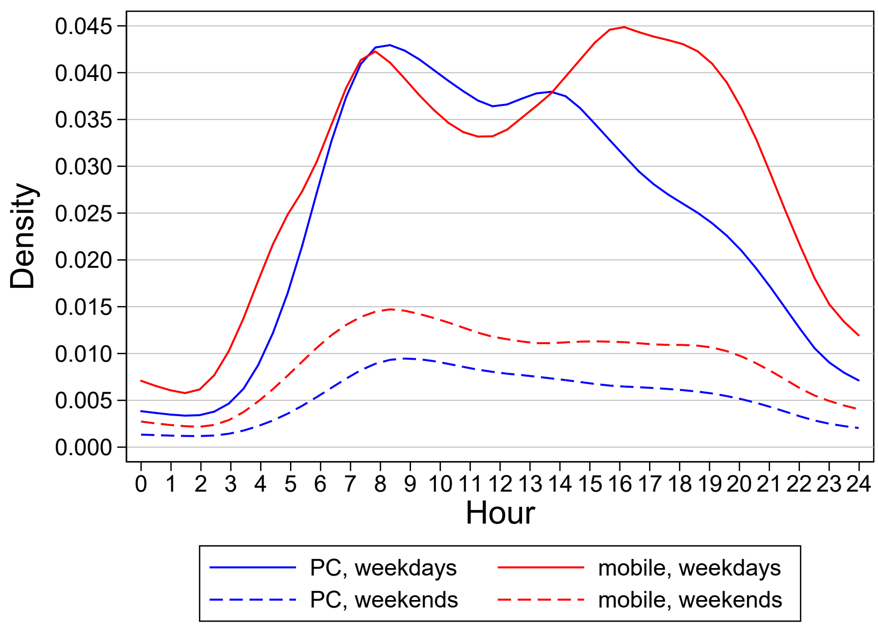
Panels (a) and (b) show the coefficients in the regressions of total monthly logins (in blue), and monthly PC logins (in red) on event month indicator variables in Sample X and Sample N, respectively. Regressions include consumer and quarter fixed effects. Standard errors are clustered at the consumer level. Full regression results are reported Table 3 (total logins), and Table A1 (PC logins). Panels (c) and (d) show the predicted values for these regressions in Sample X and Sample N, respectively.

Figure 3. Logins Distributions by Time of Day

(a) Before Launch of Mobile Apps



(b) After Launch of Mobile Apps

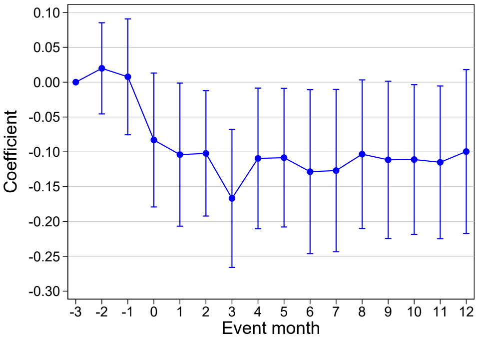


The figure shows the distributions of logins by time of day, separated into mobile device/PC logins, and weekday/weekend logins. Both Sample X and Sample N are included in each of the panels. Panel (a) shows the logins distributions in the three months before the installation of the mobile app, and Panel (b) shows the distributions in the 12 months after. The distributions are scaled by their relative weight in each panel.

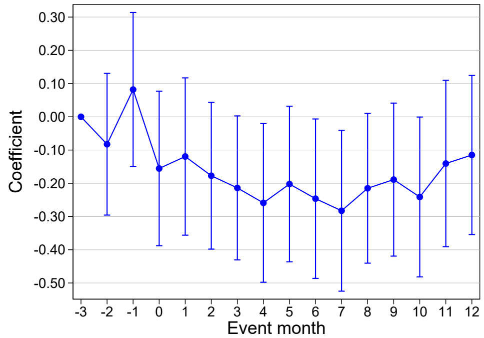
Figure 4. Mobile App Installation and Spending Behavior

Sample X

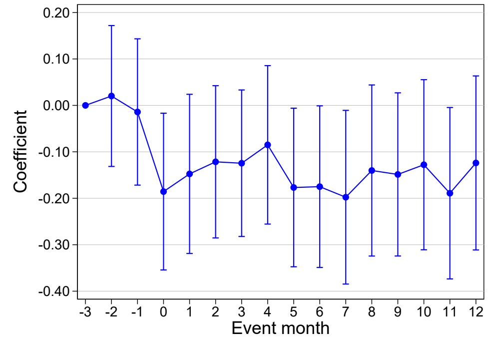
(a) Discretionary Spending



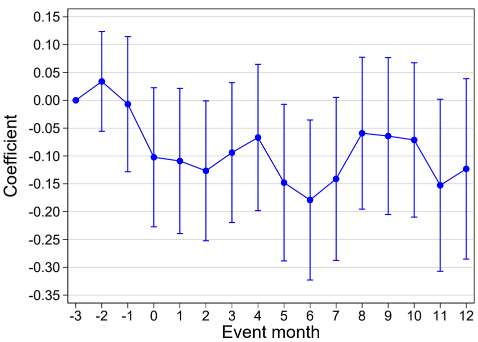
(b) Clothing



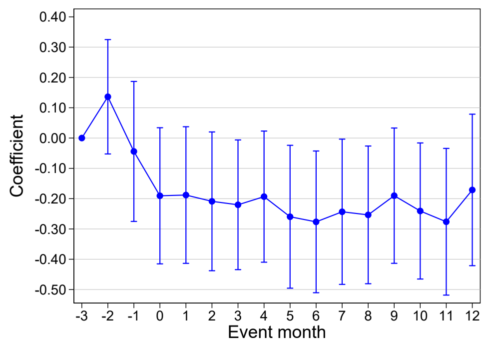
(c) Entertainment



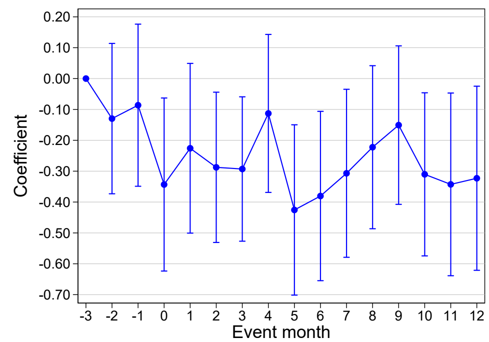
(d) Restaurants



(e) Travel

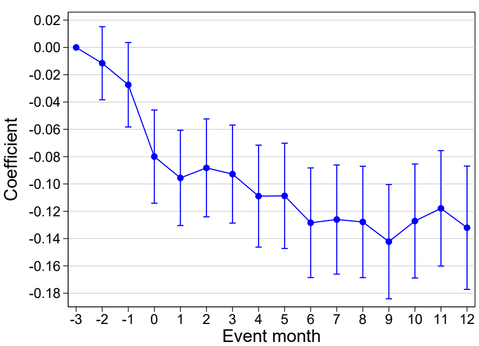


(f) Cash Withdrawals

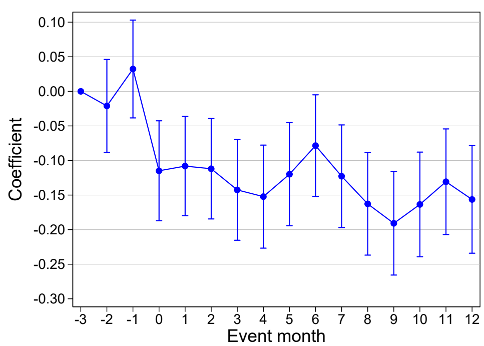


Sample N

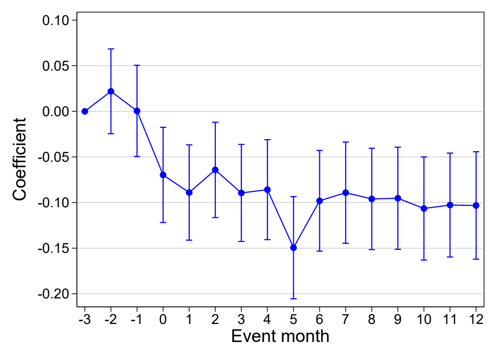
(g) Discretionary Spending



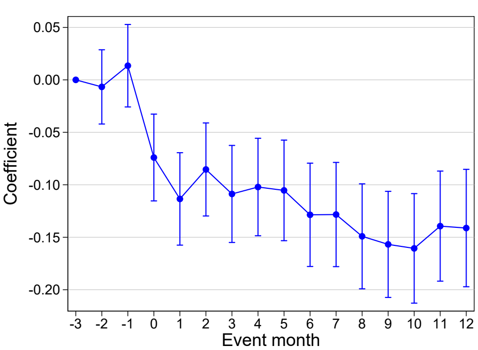
(h) Clothing



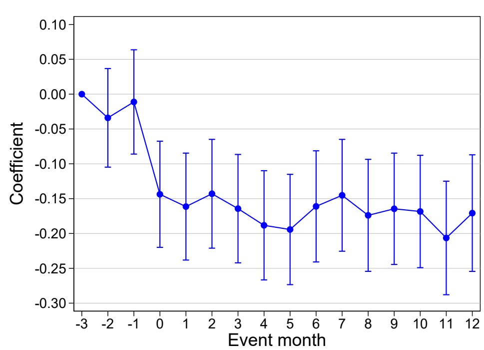
(i) Entertainment



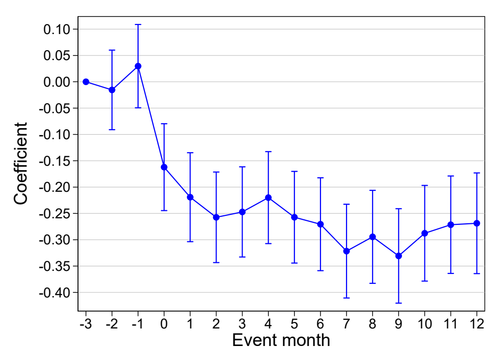
(j) Restaurants



(k) Travel



(l) Cash Withdrawals



Panels (a)-(f) show the coefficients in the regressions of different spending categories on event month indicator variables in Sample X. Panels (g)-(l) show the same coefficients for Sample N. Regressions include consumer and quarter fixed effects. Standard errors are clustered at the consumer level. Full regression results are reported Table 4 and Tables A2-A6.

Table 1. Discretionary Spending Categories

Spending Categories	Vendor Examples
Automotive Expenses	Autozone, Honda, Pep Boys
Cable/Satellite Services	Comcast, DirecTV, Time Warner Cable
Charitable Giving	Compassion International, Feed The Children, Greenpeace
Child/Dependent Expenses	Children's Place, Gymboree, Toys "R" Us
Clothing/Shoes	Kohl's Corporation, Macy's, Nordstrom
Dues and Subscriptions	Consumer Reports, The New York Times, The Wall Street Journal
Electronics	Apple Inc., Best Buy Co., Fry's Electronics
Entertainment	Redbox, Regal Cinemas, StubHub
Gifts	Godiva Chocolatier Inc, Hallmark, ProFlowers
Hobbies	Camping World, Inc., Guitar Center, Hobby Lobby
Home Improvement	Bed Bath & Beyond, Home Depot, Williams And Sonoma
Home Maintenance	Merry Maids, Stanley Steemer Intl. Inc., Terminix Intl. Company
Online Services	Google Play, Skype, TransUnion
Personal Care	Bath & Body Works, Great Clips, Ulta Salon, Cosmetics & Fragrance
Pets/Pet Care	Petco's, PetSmart, Wag.com
Restaurants/Dining	McDonald's Corporation, Starbucks, Subway
Travel	Delta Air Lines, Hilton Hotels, Southwest Airlines

Table 2. Summary Statistics

	Sample X				Sample N			
	N	mean	med	sd	N	mean	med	sd
Logins	729	14.70	5.38	24.63	6,873	9.29	3.31	16.52
PC Logins	729	4.61	1.19	10.44	6,873	4.73	1.13	10.68
iPhone Logins	400	10.24	1.81	22.84	3,346	4.63	1.06	9.98
iPad Logins	132	2.43	0.69	4.65	1,097	2.07	0.50	4.90
Android Logins	197	6.72	1.38	11.47	2,430	4.11	1.00	10.33
income	729	16,936.66	12,875.52	13,936.18	6,873	14,372.56	10,228.83	13,793.98
spending	729	11,980.76	10,502.66	7,679.99	6,873	10,866.62	8,478.06	8,121.86
Discretionary Spending	729	3,698.08	2,960.02	2,822.12	6,873	2,524.86	1,985.44	1,995.11
Restaurants	729	541.90	443.57	411.93	6,873	409.16	325.16	323.07
Clothing	729	315.78	167.73	368.67	6,873	225.07	134.09	270.27
Entertainment	729	188.87	130.69	207.90	6,873	131.88	87.79	144.05
Travel	729	768.74	500.91	821.97	6,873	544.69	328.60	668.14
Cash Withdrawal	704	975.80	471.77	1,535.56	6,530	966.44	351.48	1,749.45

Summary statistics describe the monthly mean values for each consumer estimated over the period of three months before the app installation until 12 months after. *Logins* is the number of monthly logins from all devices (PC and mobile). *PC Logins* is the number of monthly logins from a personal computer. *iPhone Logins*, *iPad Logins*, and *Android Logins* are the number of monthly logins in each of the coresponsing mobile apps, among users who installed that app as a first (or only) mobile app. *Income* is the monthly income from all sources. *Discretionary Spending* is the monthly spending in all spending categories listed in Table 1. *Restaurants*, *Clothing*, *Entertainment*, and *Travel* are monthly expenses in the corresponding spending category. *Cash Withdrawal* is monthly cash withdrawals from an ATM or a bank branch.

Table 3. Mobile App Installation and Login Behavior

	Sample X				Sample N			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	10.707***				7.331***			
	(10.44)				(33.73)			
I(t=-2)		-0.598***	-0.643***	-0.641**		0.122	0.140	0.130
		(-3.32)	(-3.55)	(-2.24)		(1.40)	(1.60)	(1.49)
I(t=-1)		-0.235	-0.511	0.742*		0.774***	0.814***	0.810***
		(-0.81)	(-1.57)	(1.89)		(5.56)	(5.88)	(5.87)
I(t=0)		11.671***	11.394***	10.913***		7.976***	8.010***	8.011***
		(13.09)	(12.63)	(12.02)		(30.56)	(30.90)	(31.07)
I(t=1)		12.277***	11.931***	11.309***		7.807***	7.799***	7.856***
		(12.29)	(11.60)	(11.54)		(30.22)	(30.50)	(30.79)
I(t=2)		12.163***	12.191***	10.743***		6.519***	6.496***	6.512***
		(13.08)	(12.87)	(11.87)		(28.69)	(28.91)	(29.04)
I(t=3)		12.210***	12.237***	12.284***		6.401***	6.357***	6.306***
		(12.98)	(12.69)	(12.45)		(26.99)	(26.95)	(26.80)
I(t=4)		13.192***	13.324***	13.492***		6.293***	6.235***	6.205***
		(12.79)	(12.31)	(12.30)		(25.04)	(25.00)	(24.93)
I(t=5)		12.619***	12.541***	12.910***		6.143***	6.067***	6.053***
		(12.90)	(12.93)	(12.76)		(24.44)	(24.33)	(24.27)
I(t=6)		11.251***	11.174***	11.560***		5.981***	5.910***	5.888***
		(13.21)	(13.24)	(12.70)		(24.15)	(23.99)	(23.88)
I(t=7)		12.531***	12.464***	11.343***		6.023***	5.990***	5.940***
		(12.71)	(12.73)	(12.46)		(22.83)	(22.74)	(22.47)
I(t=8)		12.151***	12.151***	11.074***		5.657***	5.636***	5.620***
		(11.61)	(11.61)	(11.41)		(23.69)	(23.63)	(23.55)
I(t=9)		11.990***	11.990***	11.990***		5.580***	5.580***	5.580***
		(11.77)	(11.77)	(11.77)		(23.57)	(23.57)	(23.57)
I(t=10)		11.898***	11.854***	11.855***		5.517***	5.534***	5.525***
		(11.95)	(11.79)	(11.48)		(22.97)	(23.02)	(22.98)
I(t=11)		13.606***	13.330***	14.583***		5.556***	5.596***	5.592***
		(12.32)	(12.23)	(12.28)		(22.50)	(22.60)	(22.56)
I(t=12)		13.608***	13.331***	12.849***		5.715***	5.749***	5.750***
		(12.98)	(12.82)	(12.41)		(23.09)	(23.17)	(23.17)
consumer FE	Y	Y	Y	Y	Y	Y	Y	Y
year-month FE	Y	N	N	N	Y	N	N	N
quarter FE	N	N	Y	N	N	N	Y	N
month FE	N	N	N	Y	N	N	N	Y
N	11,664	11,664	11,664	11,664	109,968	109,968	109,968	109,968
adj. R2	0.76	0.76	0.76	0.76	0.63	0.62	0.62	0.63

The dependent variable in all regressions is the count of monthly logins from all devices (PC and mobile). The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. $I(t = x)$ are event month indicator variables. Event month $t = -3$ is the baseline level in columns (2)-(4) and (6)-(8). Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Mobile App Installation and Discretionary Spending

	Sample X				Sample N			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.116**				-0.076***			
	(-2.44)				(-5.52)			
I(t=-2)		0.016	0.020	-0.005		-0.012	-0.013	-0.012
		(0.50)	(0.60)	(-0.12)		(-0.85)	(-0.95)	(-0.91)
I(t=-1)		-0.003	0.008	0.031		-0.027*	-0.032**	-0.033**
		(-0.07)	(0.18)	(0.68)		(-1.74)	(-2.02)	(-2.11)
I(t=0)		-0.093**	-0.083*	-0.130**		-0.080***	-0.083***	-0.087***
		(-2.17)	(-1.70)	(-2.27)		(-4.62)	(-4.77)	(-5.01)
I(t=1)		-0.120***	-0.104**	-0.079		-0.096***	-0.093***	-0.091***
		(-2.62)	(-1.99)	(-1.42)		(-5.40)	(-5.24)	(-5.15)
I(t=2)		-0.109**	-0.102**	-0.089		-0.088***	-0.081***	-0.084***
		(-2.39)	(-2.24)	(-1.59)		(-4.85)	(-4.46)	(-4.63)
I(t=3)		-0.174***	-0.167***	-0.172***		-0.093***	-0.085***	-0.089***
		(-3.45)	(-3.32)	(-3.24)		(-5.09)	(-4.67)	(-4.87)
I(t=4)		-0.113**	-0.109**	-0.123**		-0.109***	-0.105***	-0.108***
		(-2.24)	(-2.14)	(-2.16)		(-5.75)	(-5.55)	(-5.68)
I(t=5)		-0.104**	-0.108**	-0.123**		-0.109***	-0.108***	-0.113***
		(-2.23)	(-2.15)	(-2.31)		(-5.55)	(-5.49)	(-5.78)
I(t=6)		-0.124**	-0.128**	-0.144**		-0.128***	-0.128***	-0.132***
		(-2.22)	(-2.15)	(-2.22)		(-6.30)	(-6.30)	(-6.47)
I(t=7)		-0.116**	-0.127**	-0.117*		-0.126***	-0.126***	-0.134***
		(-2.15)	(-2.15)	(-1.81)		(-6.21)	(-6.22)	(-6.62)
I(t=8)		-0.103*	-0.103*	-0.060		-0.128***	-0.127***	-0.132***
		(-1.91)	(-1.91)	(-0.91)		(-6.18)	(-6.13)	(-6.39)
I(t=9)		-0.111*	-0.111*	-0.111*		-0.142***	-0.142***	-0.142***
		(-1.95)	(-1.95)	(-1.94)		(-6.70)	(-6.70)	(-6.70)
I(t=10)		-0.115**	-0.111**	-0.136**		-0.127***	-0.129***	-0.128***
		(-2.11)	(-2.04)	(-2.25)		(-6.00)	(-6.07)	(-6.04)
I(t=11)		-0.125**	-0.115**	-0.092*		-0.118***	-0.122***	-0.124***
		(-2.44)	(-2.07)	(-1.67)		(-5.49)	(-5.71)	(-5.78)
I(t=12)		-0.110**	-0.100*	-0.146**		-0.132***	-0.135***	-0.139***
		(-2.00)	(-1.67)	(-2.19)		(-5.76)	(-5.90)	(-6.10)
consumer FE	Y	Y	Y	Y	Y	Y	Y	Y
year-month FE	Y	N	N	N	Y	N	N	N
quarter FE	N	N	Y	N	N	N	Y	N
month FE	N	N	N	Y	N	N	N	Y
N	11,664	11,664	11,664	11,664	109,968	109,968	109,968	109,968
adj. R2	0.54	0.54	0.54	0.54	0.50	0.49	0.49	0.49

The dependent variable in all regressions is the log of the sum of monthly spending in all the categories listed in Table 1. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. $I(t = x)$ are event month indicator variables. Event month $t = -3$ is the baseline level in columns (2)-(4) and (6)-(8). Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Mobile App Installation and Spending Categories

Panel A: Sample X

Dependent	(1) Restaurants	(2) Clothing	(3) Entertainment	(4) Travel	(5) Cash Withdrawal
Post	-0.132**	-0.227**	-0.204***	-0.197*	-0.276**
	(-1.99)	(-2.19)	(-2.67)	(-1.86)	(-2.22)
consumer FE	Y	Y	Y	Y	Y
year-month FE	Y	Y	Y	Y	Y
N	11,664	11,664	11,664	11,664	11,264
adj. R2	0.59	0.42	0.43	0.43	0.45

Panel B: Sample N

Dependent	(1) Restaurants	(2) Clothing	(3) Entertainment	(4) Travel	(5) Cash Withdrawal
Post	-0.088***	-0.122***	-0.114***	-0.131***	-0.215***
	(-5.32)	(-5.04)	(-6.09)	(-4.94)	(-7.07)
consumer FE	Y	Y	Y	Y	Y
year-month FE	Y	Y	Y	Y	Y
N	109,968	109,968	109,968	109,968	104,480
adj. R2	0.52	0.37	0.42	0.40	0.43

The dependent variables in columns (1)-(4) are the log of monthly spending in the corresponding category, and the log of monthly cash withdrawal in column (5). The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Consumer Heterogeneity in Login and Discretionary Spending Behavior

Panel A: Income

	Sample X		Sample N	
	(1)	(2)	(3)	(4)
Dependent	Discretionary Spending	Logins	Discretionary Spending	Logins
Post	-0.201***	11.215***	-0.162***	6.102***
	(-3.85)	(8.46)	(-8.87)	(24.88)
*Post * Income*	0.223***	-1.201	0.170***	2.440***
	(3.65)	(-0.64)	(6.86)	(6.41)
consumer FE	Y	Y	Y	Y
year-month FE	Y	Y	Y	Y
N	11,664	11,664	109,968	109,968
adj. R2	0.54	0.76	0.50	0.63

Panel B: Spending/Income

	Sample X		Sample N	
	(1)	(2)	(3)	(4)
Dependent	Discretionary Spending	Logins	Discretionary Spending	Logins
Post	-0.032	13.950***	-0.045**	8.137***
	(-0.65)	(9.43)	(-2.47)	(27.09)
*Post * spending/income*	-0.169***	-6.536***	-0.061**	-1.624***
	(-2.68)	(-3.71)	(-2.44)	(-4.24)
consumer FE	Y	Y	Y	Y
year-month FE	Y	Y	Y	Y
N	11,664	11,664	109,968	109,968
adj. R2	0.54	0.76	0.50	0.63

Logins is the count of monthly logins from all devices (PC and mobile). *Discretionary Spending* is the sum of monthly spending in all the categories listed in Table 1. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. *Income* and $\frac{Spending}{Income}$ are binary variables that equals one if the mean monthly income, or the mean monthly spending to income ratio are above the cross-consumer median and zero when it is below. Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendices - For Online Publication

A Additional Tests

Table A1. Mobile App Installation and PC Login Behavior

	Sample X				Sample N			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.496				1.636***			
	(-1.05)				(11.83)			
I(t=-2)		-0.598***	-0.639***	-1.125***		0.122	0.129	0.123
		(-3.32)	(-3.69)	(-5.47)		(1.40)	(1.48)	(1.41)
I(t=-1)		-0.235	-0.330	-0.308		0.774***	0.790***	0.792***
		(-0.81)	(-1.10)	(-1.00)		(5.56)	(5.72)	(5.76)
I(t=0)		-0.289	-0.385	-0.773**		2.459***	2.472***	2.477***
		(-1.00)	(-1.28)	(-2.46)		(10.64)	(10.81)	(10.91)
I(t=1)		-0.011	-0.050	-0.389		1.688***	1.682***	1.710***
		(-0.03)	(-0.13)	(-0.91)		(9.27)	(9.39)	(9.62)
I(t=2)		0.339	0.624	0.093		1.003***	0.990***	1.003***
		(0.99)	(1.46)	(0.22)		(6.77)	(6.82)	(6.95)
I(t=3)		0.475	0.760	0.670		0.890***	0.869***	0.851***
		(1.26)	(1.62)	(1.33)		(6.04)	(5.94)	(5.83)
I(t=4)		0.743	1.141*	0.750		0.693***	0.670***	0.668***
		(1.55)	(1.83)	(1.24)		(4.57)	(4.44)	(4.43)
I(t=5)		0.401	0.323	0.141		0.570***	0.542***	0.542***
		(1.21)	(0.91)	(0.37)		(3.86)	(3.70)	(3.70)
I(t=6)		-0.359	-0.437	-0.675**		0.420***	0.394***	0.388***
		(-1.21)	(-1.38)	(-1.98)		(2.89)	(2.72)	(2.67)
I(t=7)		-0.141	-0.348	-0.710**		0.443**	0.431**	0.417**
		(-0.43)	(-1.05)	(-2.17)		(2.56)	(2.49)	(2.38)
I(t=8)		-0.484	-0.484	-0.866***		0.148	0.140	0.136
		(-1.61)	(-1.61)	(-2.84)		(1.07)	(1.01)	(0.98)
I(t=9)		-0.195	-0.195	-0.195		0.055	0.055	0.055
		(-0.66)	(-0.66)	(-0.66)		(0.40)	(0.40)	(0.40)
I(t=10)		-0.455	-0.496*	-0.983***		0.002	0.009	0.003
		(-1.59)	(-1.77)	(-3.39)		(0.01)	(0.06)	(0.02)
I(t=11)		-0.173	-0.268	-0.246		-0.080	-0.064	-0.062
		(-0.46)	(-0.72)	(-0.65)		(-0.60)	(-0.48)	(-0.46)
I(t=12)		-0.169	-0.264	-0.653*		-0.016	-0.003	0.002
		(-0.45)	(-0.71)	(-1.75)		(-0.11)	(-0.02)	(0.02)
consumer FE	Y	Y	Y	Y	Y	Y	Y	Y
year-month FE	Y	N	N	N	Y	N	N	N
quarter FE	N	N	Y	N	N	N	Y	N
month FE	N	N	N	Y	N	N	N	Y
N	11,664	11,664	11,664	11,664	109,968	109,968	109,968	109,968
adj. R2	0.78	0.78	0.78	0.78	0.60	0.60	0.60	0.60

The dependent variable in all regressions is the count of monthly logins from a PC. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. $I(t = x)$ are event month indicator variables. Event month $t = -3$ is the baseline level in columns (2)-(4) and (6)-(8). Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Mobile App Installation and Clothing Expenditure

	Sample X				Sample N			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.227**				-0.122***			
	(-2.19)				(-5.04)			
I(t=-2)		-0.107	-0.083	0.018		-0.021	-0.038	-0.028
		(-1.00)	(-0.76)	(0.14)		(-0.62)	(-1.11)	(-0.82)
I(t=-1)		0.027	0.082	0.187		0.032	-0.002	-0.005
		(0.24)	(0.70)	(1.51)		(0.90)	(-0.04)	(-0.13)
I(t=0)		-0.210*	-0.155	-0.139		-0.115***	-0.147***	-0.168***
		(-1.86)	(-1.32)	(-1.02)		(-3.13)	(-4.01)	(-4.61)
I(t=1)		-0.206*	-0.119	-0.035		-0.108***	-0.117***	-0.128***
		(-1.86)	(-0.99)	(-0.27)		(-2.97)	(-3.22)	(-3.53)
I(t=2)		-0.205*	-0.177	-0.114		-0.112***	-0.107***	-0.121***
		(-1.87)	(-1.58)	(-0.85)		(-3.04)	(-2.90)	(-3.29)
I(t=3)		-0.241**	-0.214*	-0.191		-0.143***	-0.132***	-0.140***
		(-2.24)	(-1.95)	(-1.62)		(-3.86)	(-3.56)	(-3.80)
I(t=4)		-0.263**	-0.259**	-0.149		-0.152***	-0.146***	-0.154***
		(-2.24)	(-2.14)	(-1.15)		(-4.03)	(-3.87)	(-4.09)
I(t=5)		-0.167	-0.202*	-0.112		-0.120***	-0.118***	-0.134***
		(-1.44)	(-1.70)	(-0.87)		(-3.17)	(-3.12)	(-3.55)
I(t=6)		-0.211*	-0.246**	-0.159		-0.078**	-0.077**	-0.085**
		(-1.81)	(-2.02)	(-1.18)		(-2.10)	(-2.06)	(-2.29)
I(t=7)		-0.214*	-0.283**	-0.264**		-0.123***	-0.122***	-0.142***
		(-1.87)	(-2.30)	(-2.08)		(-3.26)	(-3.25)	(-3.79)
I(t=8)		-0.215*	-0.215*	-0.133		-0.163***	-0.155***	-0.173***
		(-1.88)	(-1.88)	(-0.99)		(-4.33)	(-4.13)	(-4.62)
I(t=9)		-0.189	-0.189	-0.189		-0.191***	-0.191***	-0.191***
		(-1.62)	(-1.62)	(-1.62)		(-5.03)	(-5.03)	(-5.03)
I(t=10)		-0.266**	-0.241**	-0.141		-0.164***	-0.180***	-0.170***
		(-2.19)	(-1.98)	(-1.03)		(-4.26)	(-4.70)	(-4.45)
I(t=11)		-0.195	-0.141	-0.036		-0.131***	-0.165***	-0.168***
		(-1.59)	(-1.11)	(-0.27)		(-3.37)	(-4.26)	(-4.36)
I(t=12)		-0.170	-0.115	-0.099		-0.156***	-0.188***	-0.209***
		(-1.46)	(-0.95)	(-0.72)		(-3.96)	(-4.80)	(-5.33)
consumer FE	Y	Y	Y	Y	Y	Y	Y	Y
year-month FE	Y	N	N	N	Y	N	N	N
quarter FE	N	N	Y	N	N	N	Y	N
month FE	N	N	N	Y	N	N	N	Y
N	11,664	11,664	11,664	11,664	109,968	109,968	109,968	109,968
adj. R2	0.42	0.42	0.42	0.42	0.37	0.35	0.36	0.36

The dependent variable in all regressions is the log of monthly spending on clothing. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. $I(t = x)$ are event month indicator variables. Event month $t = -3$ is the baseline level in columns (2)-(4) and (6)-(8). Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3. Mobile App Installation and Entertainment Expenditure

	Sample X				Sample N			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.204***				-0.114***			
	(-2.67)				(-6.09)			
I(t=-2)		0.025	0.020	-0.093		0.022	0.016	0.019
		(0.33)	(0.26)	(-0.99)		(0.93)	(0.69)	(0.80)
I(t=-1)		0.003	-0.014	-0.025		0.000	-0.010	-0.012
		(0.04)	(-0.18)	(-0.29)		(0.02)	(-0.41)	(-0.45)
I(t=0)		-0.168**	-0.186**	-0.327***		-0.070***	-0.081***	-0.089***
		(-2.06)	(-2.17)	(-3.22)		(-2.63)	(-3.04)	(-3.38)
I(t=1)		-0.136*	-0.147*	-0.087		-0.089***	-0.094***	-0.098***
		(-1.65)	(-1.70)	(-0.89)		(-3.36)	(-3.53)	(-3.69)
I(t=2)		-0.156*	-0.122	-0.180*		-0.064**	-0.066**	-0.071***
		(-1.87)	(-1.46)	(-1.72)		(-2.42)	(-2.47)	(-2.68)
I(t=3)		-0.159**	-0.125	-0.142		-0.089***	-0.089***	-0.093***
		(-2.00)	(-1.56)	(-1.65)		(-3.31)	(-3.29)	(-3.45)
I(t=4)		-0.135	-0.085	-0.142		-0.086***	-0.085***	-0.087***
		(-1.59)	(-0.98)	(-1.41)		(-3.09)	(-3.07)	(-3.12)
I(t=5)		-0.164*	-0.177**	-0.256***		-0.149***	-0.149***	-0.156***
		(-1.91)	(-2.04)	(-2.70)		(-5.26)	(-5.25)	(-5.50)
I(t=6)		-0.162*	-0.175**	-0.198*		-0.098***	-0.097***	-0.103***
		(-1.89)	(-1.98)	(-1.89)		(-3.50)	(-3.48)	(-3.67)
I(t=7)		-0.169*	-0.198**	-0.217**		-0.089***	-0.089***	-0.100***
		(-1.86)	(-2.08)	(-2.10)		(-3.17)	(-3.16)	(-3.55)
I(t=8)		-0.140	-0.140	-0.142		-0.096***	-0.094***	-0.103***
		(-1.50)	(-1.50)	(-1.25)		(-3.40)	(-3.32)	(-3.65)
I(t=9)		-0.149*	-0.149*	-0.149*		-0.095***	-0.095***	-0.095***
		(-1.67)	(-1.67)	(-1.67)		(-3.35)	(-3.35)	(-3.35)
I(t=10)		-0.123	-0.128	-0.241**		-0.107***	-0.112***	-0.109***
		(-1.33)	(-1.37)	(-2.25)		(-3.71)	(-3.91)	(-3.82)
I(t=11)		-0.172*	-0.189**	-0.200*		-0.103***	-0.114***	-0.115***
		(-1.93)	(-2.02)	(-1.96)		(-3.55)	(-3.93)	(-3.97)
I(t=12)		-0.106	-0.124	-0.266**		-0.103***	-0.114***	-0.123***
		(-1.17)	(-1.30)	(-2.41)		(-3.45)	(-3.82)	(-4.12)
consumer FE	Y	Y	Y	Y	Y	Y	Y	Y
year-month FE	Y	N	N	N	Y	N	N	N
quarter FE	N	N	Y	N	N	N	Y	N
month FE	N	N	N	Y	N	N	N	Y
N	11,664	11,664	11,664	11,664	109,968	109,968	109,968	109,968
adj. R2	0.43	0.43	0.43	0.43	0.42	0.41	0.41	0.42

The dependent variable in all regressions is the log of monthly spending on entertainment. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. $I(t = x)$ are event month indicator variables. Event month $t = -3$ is the baseline level in columns (2)-(4) and (6)-(8). Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4. Mobile App Installation and Restaurants Expenditure

	Sample X				Sample N			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.132**				-0.088***			
	(-1.99)				(-5.32)			
I(t=-2)		0.023	0.034	-0.049		-0.007	-0.005	-0.007
		(0.51)	(0.75)	(-0.86)		(-0.37)	(-0.26)	(-0.37)
I(t=-1)		0.017	-0.007	-0.035		0.013	0.015	0.014
		(0.32)	(-0.11)	(-0.53)		(0.68)	(0.73)	(0.70)
I(t=0)		-0.079	-0.102	-0.202***		-0.074***	-0.070***	-0.072***
		(-1.38)	(-1.61)	(-2.73)		(-3.52)	(-3.35)	(-3.41)
I(t=1)		-0.079	-0.109	-0.103		-0.113***	-0.105***	-0.101***
		(-1.33)	(-1.65)	(-1.43)		(-5.08)	(-4.71)	(-4.50)
I(t=2)		-0.109*	-0.127**	-0.244***		-0.085***	-0.073***	-0.074***
		(-1.70)	(-1.99)	(-3.21)		(-3.79)	(-3.25)	(-3.29)
I(t=3)		-0.076	-0.094	-0.097		-0.109***	-0.096***	-0.099***
		(-1.20)	(-1.47)	(-1.42)		(-4.63)	(-4.11)	(-4.21)
I(t=4)		-0.045	-0.067	-0.130*		-0.102***	-0.095***	-0.095***
		(-0.69)	(-1.00)	(-1.76)		(-4.33)	(-4.03)	(-4.03)
I(t=5)		-0.114*	-0.148**	-0.219***		-0.105***	-0.101***	-0.105***
		(-1.73)	(-2.07)	(-2.91)		(-4.33)	(-4.13)	(-4.33)
I(t=6)		-0.145**	-0.179**	-0.220***		-0.129***	-0.126***	-0.128***
		(-2.15)	(-2.45)	(-2.73)		(-5.15)	(-5.04)	(-5.12)
I(t=7)		-0.108	-0.141*	-0.170**		-0.128***	-0.127***	-0.134***
		(-1.62)	(-1.90)	(-2.15)		(-5.09)	(-5.04)	(-5.31)
I(t=8)		-0.059	-0.059	-0.101		-0.149***	-0.149***	-0.153***
		(-0.85)	(-0.85)	(-1.19)		(-5.87)	(-5.86)	(-6.01)
I(t=9)		-0.064	-0.064	-0.064		-0.157***	-0.157***	-0.157***
		(-0.90)	(-0.90)	(-0.90)		(-6.11)	(-6.11)	(-6.11)
I(t=10)		-0.082	-0.071	-0.155**		-0.161***	-0.159***	-0.160***
		(-1.17)	(-1.01)	(-1.97)		(-6.06)	(-5.99)	(-6.06)
I(t=11)		-0.129*	-0.153*	-0.181**		-0.139***	-0.138***	-0.139***
		(-1.78)	(-1.95)	(-2.21)		(-5.23)	(-5.20)	(-5.21)
I(t=12)		-0.100	-0.123	-0.222**		-0.141***	-0.138***	-0.139***
		(-1.29)	(-1.50)	(-2.47)		(-4.97)	(-4.85)	(-4.91)
consumer FE	Y	Y	Y	Y	Y	Y	Y	Y
year-month FE	Y	N	N	N	Y	N	N	N
quarter FE	N	N	Y	N	N	N	Y	N
month FE	N	N	N	Y	N	N	N	Y
N	11,664	11,664	11,664	11,664	109,968	109,968	109,968	109,968
adj. R2	0.59	0.59	0.59	0.59	0.52	0.51	0.51	0.51

The dependent variable in all regressions is the log of monthly spending on restaurants. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. $I(t = x)$ are event month indicator variables. Event month $t = -3$ is the baseline level in columns (2)-(4) and (6)-(8). Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5. Mobile App Installation and Travel Expenditure

	Sample X				Sample N			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.197*				-0.131***			
	(-1.86)				(-4.94)			
I(t=-2)		0.123	0.136	0.010		-0.034	-0.026	-0.031
		(1.29)	(1.42)	(0.08)		(-0.95)	(-0.74)	(-0.86)
I(t=-1)		-0.016	-0.044	-0.059		-0.011	-0.002	-0.001
		(-0.15)	(-0.38)	(-0.44)		(-0.29)	(-0.05)	(-0.03)
I(t=0)		-0.162	-0.191*	-0.319**		-0.144***	-0.130***	-0.129***
		(-1.52)	(-1.67)	(-2.32)		(-3.72)	(-3.35)	(-3.35)
I(t=1)		-0.135	-0.188	-0.218*		-0.161***	-0.142***	-0.133***
		(-1.29)	(-1.64)	(-1.72)		(-4.14)	(-3.64)	(-3.41)
I(t=2)		-0.136	-0.209*	-0.379**		-0.143***	-0.118***	-0.116***
		(-1.18)	(-1.80)	(-2.45)		(-3.61)	(-2.97)	(-2.93)
I(t=3)		-0.147	-0.220**	-0.252**		-0.164***	-0.140***	-0.142***
		(-1.37)	(-2.03)	(-2.13)		(-4.16)	(-3.54)	(-3.60)
I(t=4)		-0.103	-0.193*	-0.269**		-0.188***	-0.174***	-0.168***
		(-0.95)	(-1.76)	(-2.01)		(-4.73)	(-4.37)	(-4.22)
I(t=5)		-0.239**	-0.260**	-0.384***		-0.194***	-0.184***	-0.188***
		(-2.11)	(-2.17)	(-2.84)		(-4.83)	(-4.57)	(-4.66)
I(t=6)		-0.256**	-0.277**	-0.300**		-0.161***	-0.155***	-0.159***
		(-2.29)	(-2.33)	(-2.13)		(-3.98)	(-3.83)	(-3.92)
I(t=7)		-0.251**	-0.243**	-0.323**		-0.145***	-0.142***	-0.151***
		(-2.28)	(-2.00)	(-2.48)		(-3.56)	(-3.49)	(-3.71)
I(t=8)		-0.254**	-0.254**	-0.345**		-0.174***	-0.175***	-0.180***
		(-2.20)	(-2.20)	(-2.20)		(-4.26)	(-4.28)	(-4.39)
I(t=9)		-0.190*	-0.190*	-0.190*		-0.165***	-0.165***	-0.165***
		(-1.68)	(-1.68)	(-1.68)		(-4.06)	(-4.06)	(-4.06)
I(t=10)		-0.254**	-0.241**	-0.367**		-0.168***	-0.161***	-0.165***
		(-2.22)	(-2.11)	(-2.54)		(-4.11)	(-3.93)	(-4.04)
I(t=11)		-0.248**	-0.276**	-0.291**		-0.206***	-0.197***	-0.197***
		(-2.13)	(-2.25)	(-2.11)		(-4.99)	(-4.77)	(-4.76)
I(t=12)		-0.143	-0.171	-0.299**		-0.171***	-0.157***	-0.157***
		(-1.20)	(-1.35)	(-2.03)		(-4.02)	(-3.69)	(-3.69)
consumer FE	Y	Y	Y	Y	Y	Y	Y	Y
year-month FE	Y	N	N	N	Y	N	N	N
quarter FE	N	N	Y	N	N	N	Y	N
month FE	N	N	N	Y	N	N	N	Y
N	11,664	11,664	11,664	11,664	109,968	109,968	109,968	109,968
adj. R2	0.43	0.43	0.43	0.43	0.40	0.40	0.40	0.40

The dependent variable in all regressions is the log of monthly spending on travel. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. $I(t = x)$ are event month indicator variables. Event month $t = -3$ is the baseline level in columns (2)-(4) and (6)-(8). Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6. Mobile App Installation and Cash Withdrawal

	Sample X				Sample N			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.276**				-0.215***			
	(-2.22)				(-7.07)			
I(t=-2)		-0.190	-0.130	0.162		-0.015	-0.010	-0.012
		(-1.55)	(-1.05)	(1.06)		(-0.40)	(-0.26)	(-0.31)
I(t=-1)		-0.093	-0.086	-0.011		0.030	0.033	0.034
		(-0.77)	(-0.65)	(-0.07)		(0.74)	(0.82)	(0.85)
I(t=0)		-0.350***	-0.343**	0.000		-0.162***	-0.152***	-0.151***
		(-2.65)	(-2.41)	(0.00)		(-3.87)	(-3.64)	(-3.60)
I(t=1)		-0.245**	-0.226	-0.221		-0.219***	-0.196***	-0.186***
		(-1.99)	(-1.62)	(-1.44)		(-5.11)	(-4.58)	(-4.34)
I(t=2)		-0.246**	-0.288**	-0.060		-0.257***	-0.226***	-0.226***
		(-2.00)	(-2.33)	(-0.41)		(-5.90)	(-5.19)	(-5.20)
I(t=3)		-0.252**	-0.293**	-0.356***		-0.247***	-0.212***	-0.215***
		(-2.14)	(-2.47)	(-2.88)		(-5.69)	(-4.88)	(-4.96)
I(t=4)		-0.022	-0.113	0.219		-0.220***	-0.193***	-0.188***
		(-0.17)	(-0.87)	(1.42)		(-4.96)	(-4.35)	(-4.25)
I(t=5)		-0.306**	-0.426***	-0.469***		-0.257***	-0.230***	-0.234***
		(-2.36)	(-3.04)	(-3.03)		(-5.82)	(-5.20)	(-5.29)
I(t=6)		-0.261**	-0.380***	0.026		-0.271***	-0.250***	-0.251***
		(-1.99)	(-2.73)	(0.16)		(-6.04)	(-5.57)	(-5.60)
I(t=7)		-0.164	-0.307**	-0.310**		-0.322***	-0.312***	-0.319***
		(-1.30)	(-2.22)	(-2.13)		(-7.12)	(-6.90)	(-7.05)
I(t=8)		-0.222*	-0.222*	0.028		-0.294***	-0.291***	-0.296***
		(-1.66)	(-1.66)	(0.18)		(-6.57)	(-6.49)	(-6.59)
I(t=9)		-0.151	-0.151	-0.151		-0.331***	-0.331***	-0.331***
		(-1.16)	(-1.16)	(-1.16)		(-7.26)	(-7.26)	(-7.26)
I(t=10)		-0.370***	-0.310**	-0.019		-0.288***	-0.282***	-0.284***
		(-2.79)	(-2.31)	(-0.12)		(-6.24)	(-6.12)	(-6.16)
I(t=11)		-0.350**	-0.343**	-0.267*		-0.271***	-0.268***	-0.267***
		(-2.48)	(-2.28)	(-1.72)		(-5.78)	(-5.71)	(-5.68)
I(t=12)		-0.330**	-0.323**	0.020		-0.269***	-0.259***	-0.257***
		(-2.35)	(-2.13)	(0.11)		(-5.54)	(-5.33)	(-5.30)
consumer FE	Y	Y	Y	Y	Y	Y	Y	Y
year-month FE	Y	N	N	N	Y	N	N	N
quarter FE	N	N	Y	N	N	N	Y	N
month FE	N	N	N	Y	N	N	N	Y
N	11,264	11,264	11,264	11,264	104,480	104,480	104,480	104,480
adj. R2	0.45	0.44	0.44	0.45	0.43	0.43	0.43	0.43

The dependent variable in all regressions is the log of monthly cash withdrawal. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. $I(t = x)$ are event month indicator variables. Event month $t = -3$ is the baseline level in columns (2)-(4) and (6)-(8). Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7. Mobile App Installation and Additional Spending Categories

Panel A: Sample X

Dependent	(1) Log Spending	(2) Log Utilities	(3) Log Telephone	(4) Log Rent
Post	-0.054*	0.082	-0.032	-0.120
	(-1.67)	(0.88)	(-0.38)	(-0.51)
consumer FE	Y	Y	Y	Y
year-month FE	Y	Y	Y	Y
N	11,664	10,624	11,136	5,248
adj. R2	0.60	0.52	0.51	0.49

Panel B: Sample N

Dependent	(1) Log Spending	(2) Log Utilities	(3) Log Telephone	(4) Log Rent
Post	-0.033***	-0.010	-0.010	0.044
	(-3.96)	(-0.40)	(-0.46)	(0.88)
consumer FE	Y	Y	Y	Y
year-month FE	Y	Y	Y	Y
N	109,968	94,064	101,488	46,512
adj. R2	0.60	0.51	0.53	0.47

The dependent variables are the log of monthly total spending in column (1) and log monthly spending in the corespondent category in columns (2)-(4). The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. Sample X includes consumers who installed a mobile app during the 14 days after its release, and sample N includes users who installed the mobile app more 14 days after. Reported *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

B Matched Sample

We match consumers in our main sample with consumers that have been using the PC app over the same time period of 16 months (from t=-3 to t+12) but did not install the mobile during that window. For each of the samples (X, and N) and each calendar month, we calculate a propensity score by estimating a cross-sectional logistic regression of a mobile installation indicator variable on the mean levels of monthly income, spending, discretionary spending, and logins calculated over the three months before the installation of the mobile app. For each month and sample, we match the mobile adopters with non-adopters using a one-to-one matching with no replacement based on the propensity scores. Balance tests are presented in Table B1, and the analysis of our main results is in Table B2.

Table B1. Balance Tests

Panel A: Sample X

	mobile		match			
	mean	sd	mean	sd	diff	t-diff
Income	15,649.74	14,700.07	16,300.48	16,570.32	-650.74	-0.79
Spending	11,565.24	8,063.81	12,083.11	8,828.49	-517.87	-1.17
Discretionary Spending	3,668.02	3,021.51	3,876.96	3,229.10	-208.94	-1.28
Logins	4.41	10.17	4.91	10.21	-0.50	-0.94

Panel B: Sample N

	mobile		match			
	mean	sd	mean	sd	diff	t-diff
Income	13,273.52	15,268.12	13,008.09	16,102.11	265.43	0.99
Spending	10,420.69	8,719.13	10,263.23	9,014.29	157.47	1.04
Discretionary Spending	2,516.79	2,233.87	2,475.67	2,250.56	41.12	1.08
Logins	4.46	10.67	4.31	10.55	0.15	0.83

For each consumer in Sample X and Sample N, we calculate the monthly mean values of *Income*, *Spending*, *Discretionary Spending*, and *Logins* over the three months prior to the installation of the mobile app. Mean and standard deviations are reported in the first two columns. Columns three and four report the same variables for the matched sample of consumers that did not install the mobile app. The last two columns report the differences between the main sample and the matched sample.

Table B2. Matched Sample

Panel A: Logins

	Sample X			Sample N		
	(1)	(2)	(3)	(4)	(5)	(6)
sub-sample	mobile	match	mobile+match	mobile	match	mobile+match
Post	10.707***	-1.057**	-1.637***	7.331***	-0.658***	-0.338**
	(10.44)	(-2.21)	(-3.08)	(33.73)	(-5.01)	(-2.49)
*Post * Mobile*			12.925***			7.350***
			(13.84)			(33.82)
consumer FE	Y	Y	Y	Y	Y	Y
year-month FE	Y	Y	Y	Y	Y	Y
N	11,664	11,664	23,328	109,968	109,968	219,936
adj. R2	0.76	0.78	0.77	0.63	0.57	0.62

Panel B: Discretionary Spending

	Sample X			Sample N		
	(1)	(2)	(3)	(4)	(5)	(6)
sub-sample	mobile	match	mobile+match	mobile	match	mobile+match
Post	-0.116**	-0.006	-0.007	-0.076***	0.008	0.008
	(-2.44)	(-0.13)	(-0.17)	(-5.52)	(0.60)	(0.62)
*Post * Mobile*			-0.109**			-0.084***
			(-2.49)			(-4.75)
consumer FE	Y	Y	Y	Y	Y	Y
year-month FE	Y	Y	Y	Y	Y	Y
N	11,664	11,664	23,328	109,968	109,968	219,936
adj. R2	0.54	0.54	0.54	0.50	0.50	0.50

Logins is the count of monthly logins from all devices (PC and mobile). *Discretionary Spending* is the sum of monthly spending in all the categories listed in Table 1. The indicator variable *Post* equals zero for the three months before the mobile app installation and one for the mobile app installation month and the twelve following months. *Mobile* is a binary variable that equals one for consumers that installed a mobile app and zero for matched consumers that did not. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the consumer level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.