Personal Financial Information Presentation and Consumer Spending

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Abstract

We study whether information design influences consumer behavior in a randomized field experiment with users of an online account aggregation app. Participants received a personalized index representing their net worth as a lifetime monthly cash flow. The presentation of this index varied across treatments in its framing and the salience of its display. Consumers exposed to a consumption-oriented frame and a salient comparison of the index with their past spending reduced discretionary spending. These findings show that minor variations in information presentation can significantly affect financial behavior, highlighting the power of design in promoting saving and informing policy and regulation.

JEL classification: D12, D14, D15, D91, G41, G51.

Keywords: Framing, Salience, Consumer Spending, Savings, Field Experiment.

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I. Introduction

Recent advancements in technology and the widespread use of online financial tools have transformed the way individuals interact with their finances. Today, almost all financial services are accessible through digital platforms, leading to a significant shift in how people manage their money.[1]

When individuals access their online financial accounts, they can keep track of their account balances and review recent transactions, which allows them to assess their financial standing and plan their future spending. In this paper, we test if consumers are influenced by the way in which their personal finances are presented. Changes in the presentation of information can affect consumers' sentiments, beliefs, or interpretation of the information and potentially lead to a change in behavior.

We conducted a field experiment on the users of an online account aggregation software. Account aggregation apps enable users to link various financial accounts such as checking, savings, retirement, investment, mortgage, loans, and more, through a single application. This aggregation provides users with a comprehensive and real-time overview of their finances, including details such as net worth, total expenditures, expenditure breakdown by categories, and income.[2]

[1]For instance, a considerable 71% of consumers in the U.S. with bank accounts utilize online banking services (Federal Reserve Board (2016)).

[2]Examples of research using account aggregation data include studies conducted in the US (Gelman, Kariv, Shapiro, Silverman, and Tadelis (2014), Baker (2018), D'Acunto, Rossi, and Weber (2023), Levi and Benartzi (2020)), Brazil (Medina (2021)), Germany (Becker (2017), Bräuer, Hackethal, and Hanspal (2022), UK (Chronopoulos, Lukas, and Wilson (2020), Hacıoğlu-Hoke, Känzig, and Surico (2021)) and Iceland

Users of the app were provided with a personalized index that represents their net worth as a monthly cash flow. That is, instead of presenting net worth as a lump sum (e.g., $650,000), it was presented as the equivalent inflation-protected lifetime monthly cash flow, which depends on the user's age and current market prices of life annuities (e.g., $2,000 per month for life). The index provides a relatively convenient reference for spending in comparison to the lump sum presentation, since consumers typically use monthly cash flows as a unit of measure for spending (e.g., rent, mortgage, utilities are typically billed monthly). We discuss the index in Section II.

Users of the app were randomly assigned into treatment groups that varied in the presentation of the index. The first variation in treatments was in the framing of the index. A significant body of research shows that consumers' perceived value and attractiveness of life annuities depends on the frame used to describe them (Agnew, Anderson, Gerlach, and Szykman (2008), Benartzi, Previtero, and Thaler (2011), Beshears, Choi, Laibson, Madrian, and Zeldes (2014), Brown, Kling, Mullainathan, and Wrobel (2008,0), Brown, Kapteyn, and Mitchell (2016), Goda, Manchester, and Sojourner (2014), Goedde-Menke, Lehmensiek-Starke, and Nolte (2014)).

Consumers place a higher value on annuities when the cash flow stream is described using a consumption frame (using words such as "spend" and "payment") than when described using an investment frame (using words such as "invest" and "earnings"). The consumption frame prompts individuals to reflect on a negative scenario in which they have to cut their spending due to a lack of resources, leading them to place a higher value on lifetime monthly income. Fear appeal messages have been widely studied and shown to influence attitude, intentions, and behaviors

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(Carlin, Olafsson, and Pagel (2017), Carvalho, Olafsson, and Silverman (2019), Gathergood and Olafsson (2024), Olafsson and Pagel (2018)). For a recent review of research utilizing transaction-level data, see Baker and Kueng (2022).

effectively (Peters, Ruiter, and Kok (2013), Tannenbaum, Hepler, Zimmerman, Saul, Jacobs, Wilson, and Albarracín (2015), Witte (1996)).

We test if using the consumption frame to describe the index can also drive consumers to adjust their spending levels. Accordingly, we use two different labels as the name of the index:

Financial Sustainability Index (FSI): This label prompts users to think of the index as a reference to their spending activities. This name induces users to reflect on a scenario in which their financial condition is no longer "sustainable" and are therefore forced to cut their spending.

Life Annuity Index (LAI): This label maintains a neutral tone and does not elicit any specific emotions from users. It simply describes the index for what it is - a life annuity quote.

The second variation in the treatments is the salience of the comparison between the index and the user's historical spending levels. Some of the treatment groups were presented with a time series plot that directly compares the index level with the user's historical monthly spending (hereafter "context plot"; see Figure 1). Users in treatments that did not receive the context plot had access to the same information content. A time series plot of the index was presented on the dashboard page, and a separate time series plot of historical spending was available on the app's Cash Flow page. However, without an explicit contrast between the index and spending, users are less likely to reflect on the difference between the two and adjust their spending.[3]

We find that users who were presented with the consumption frame (i.e., FSI) and a

[3]The experiment included a third variation in the treatments in which the personalized index represented a cash flow stream that starts at retirement rather than immediately. This variation did not have an impact on consumer behavior even though it is similar to reporting standards of fund performance required by the SECURE Act (2019) and common practices in the financial industry. This variation in treatments, the related treatment groups, and the tests are presented in Appendix B.

context plot decreased their discretionary spending by about 15% relative to users who received only the consumption frame with no plot or a context plot but with a neutral frame (i.e., LAI). The decrease in discretionary spending started immediately after the launch of the experiment and persisted throughout the eight months in which the experiment materials were presented on the app. These consumers increased their spending levels only gradually after the removal of the experiment content and converged to the spending levels of consumers in unaffected groups after an additional eight months.

The decrease in spending is most pronounced in relatively "tempting" spontaneous categories such as entertainment, restaurants, and clothing. This evidence is consistent with an improved ability to apply self-control due to an increased feeling of guilt and regret if they were to make the purchase (e.g., Hoch and Loewenstein (1991)). In contrast, we do not find a change in non-discretionary spending such as gas, groceries, and utilities, which are difficult to adjust, especially over a short time period.

Furthermore, we find a decrease in infrequent large-ticket transactions. This evidence is consistent with Karlan, McConnell, Mullainathan, and Zinman (2016) and Sussman and Alter (2012), showing that people tend to omit such "exceptional" transactions from their budget plan, and that salient reminders promote consumers to stay within their means.

Additionally, users in the affected treatments also decreased their cash withdrawals, representing an additional decrease in spending (i.e., not included in the discretionary spending variable). This decline in cash withdrawals is consistent with the notion that individuals assign a higher subjective value to cash transactions compared to non-cash transactions, leading them to prioritize cutting back on cash transactions first (Raghubir and Srivastava (2008)).

Existing research on consumer spending has predominantly relied on either aggregate consumption data or low-frequency consumer-level data. However, recent studies have begun to leverage high-frequency transaction-level data, providing a more granular understanding of consumer behavior. This body of literature demonstrates that consumers exhibit strong spending habits, typically making gradual adjustments over an extended period in response to changes in economic factors like interest rates, income, or credit availability (Baker and Kueng (2022), Havranek, Rusnak, and Sokolova (2017), Ravina (2019)). This paper shows that even in the presence of strong behavioral inertia, simple information design manipulations can prompt consumers to rapidly adjust their spending levels. Importantly, the response is caused by a change in consumers' sentiment or a perceived change in financial well-being and not by a change in any economic variable.

Consumers in the affected groups decreased their spending immediately after receiving the experimental treatments. However, their spending increased only gradually after the experiment content was removed. This pattern aligns with findings from prior studies documenting a non-linear adjustment in spending habits (Chen and Ludvigson (2009), Ferson and Constantinides (1991)1, Ganong and Noel (2019)). Specifically, these results are consistent with the predictions of the model proposed by Yogo (2008), which incorporates habit formation into a reference-dependent utility function with loss aversion. According to the model, a negative shock elicits a larger response than a positive economic shock.

Framing effects have been extensively explored in the social sciences, demonstrating their influence across various domains.[4] However, framing information to specifically influence

[4]Previous studies, such as those by Andreoni (1995), De Martino, Kumaran, Seymour, and Dolan (2006), Johnson, Hershey, Meszaros, and Kunreuther (1993), Payne, Sagara, Shu, Appelt, and Johnson (2013), Seibold (2021), and Shafir, Diamond, and Tversky (1997), have documented the impact of framing on decision-making.

consumer spending poses unique challenges. First, it requires consumers to deviate from their established spending habits, which are typically resistant to change. Second, there is a temporal gap between the exposure to the experimental treatments and actual spending activity. Lastly, the treatments employed in our study do not prescribe a specific course of action, leaving consumers to decide if and how to adjust their spending. Nonetheless, this study demonstrates that through online financial apps, where consumers are frequently exposed to the treatments, certain information designs can indeed influence consumer spending.

Studies that examine framing effects on decision-making have often produced mixed results. Maheswaran and Meyers-Levy (1990) showed that issue involvement, which refers to the personal relevance and salience of an issue to an individual, is a key determinant of framing effects. They further demonstrated that negatively framed messages are more influential when they contain a high level of involvement. Kühberger (1998) conducted a meta-analysis of framing experiments and concluded that salience manipulations are critical determinants of framing effects. Consistent with this existing evidence, our study demonstrates that the fear appeal message incorporated in the consumption frame has an impact on spending behavior, but only when accompanied by a salient context. In other words, information must include both a relevant framing and salient context for consumers to act upon it.

The paper contributes to the extensive body of research on tools aimed at increasing consumers' saving rates. Financial education programs have thus far proven to be costly and to have negligible effects on saving behavior (Campbell (2006), Fernandes, Lynch Jr, and Netemeyer (2014), Willis (2011)). Tax subsidies for retirement accounts tend to benefit wealthier individuals, who are already better prepared for retirement (Chetty, Friedman, Leth-Petersen, Nielsen, and Olsen (2014)). Employers' matching contributions to retirement accounts have had limited success in increasing saving rates (Choi, Laibson, Madrian, and Metrick (2002), Choi, Laibson, and Madrian (2011), Duflo, Gale, Liebman, Orszag, and Saez (2006)). Behavioral tools such as choice architecture, reminders, and information design have repeatedly been proven to be powerful in influencing savings and retirement account contributions. (Bai, Chi, Liu, Tang, and Xu (2021), Chetty et al. (2014), Choi et al. (2002), Choi, Laibson, Madrian, and Metrick (2004), Karlan et al. (2016), Madrian and Shea (2001), Thaler and Benartzi (2004)). However, these behavioral tools may not be applicable to a significant portion of nonretired households that have no access to retirement accounts.[5] In addition, the effect of an increase in retirement contributions on the overall saving rate is mitigated by early withdrawal from these accounts (Argento, Bryant, and Sabelhaus (2015), Beshears, Choi, Clayton, Harris, Laibson, and Madrian (2020a), Beshears, Choi, Iwry, John, Laibson, and Madrian (2020b)) and an increase in borrowing activity (Beshears, Choi, Laibson, Madrian, and Goda (2012)). This paper shows that information design can influence spending, which is the flip side of savings. Given the wide use of online financial services, information design tools can be easily implemented and distributed to a large mass of consumers at a low cost, including lower-income individuals who have no retirement accounts.[6]

[5] 26% of nonretired households in the U.S. have no retirement savings (Board of Governors of the Federal Reserve System (2021)).

[6] There is no formal data on the number of users of account aggregation apps globally. However, these apps are available in most countries, with an increasing number of third-party providers and banks offering them as a free service. The Open Banking regulation in Europe, particularly the Revised Payment Services Directive (PSD2), has significantly boosted their development and usage by requiring banks to provide standardized access to customer account information. Similar regulations are being adopted in many other countries, likely increasing the supply and usage of personal financial management tools with account aggregation technology.

II. Personalized Index

Account aggregation apps typically present the users' net worth as the first item on the first page users visit after logging in. In this study, all treatment groups received a personalized index that presented their net worth but with a change in the unit of measure. Instead of presenting net worth as a lump sum, it was presented as the equivalent inflation-protected lifetime monthly cash flow, which depends on the user's age, state of residence, and current market prices. This index reflects the market quote of a monthly cash flow from an immediate, inflation-protected life annuity. Life annuities are sold by large financial institutions (typically insurance companies) and provide a hedge for market, longevity, and inflation risks. By using the market prices and current net worth of the user (instead of a projected future next worth), the index does not require any assumptions.

Figure 2 illustrates the index dynamics in comparison to net worth as a lump sum in a simplified life cycle model with no uncertainty. An individual with a known end-of-life date receives a constant income flow every period until a known retirement age. Under any standard preferences, the individual will perfectly smooth their consumption over their lifetime. Net worth as a lump sum increases during the consumer's working years, peaks at retirement age, decreases over the retirement years, and depletes at the end of life. Net worth as a personalized index describes the constant cash flow level that the consumer can generate for the rest of their life, given their current net worth and time till the end of life. During the consumer's working years, like the lump sum, the index gradually increases. Two factors contribute to the rate of increase: wealth accumulation and the shortening of remaining life. The index peaks at retirement age, where it converges to the consumption level and remains constant until the end of life.

This index can potentially provide useful financial guidance for the individual. For a person in retirement, the index accurately shows the optimal level of consumption in the simplified framework described above. A person approaching retirement age can check whether the consumption level is close to the index level. If the difference between spending and the index levels is large, they can consider adjusting the consumption level, the income, or even the retirement age. For a younger person, the index is significantly lower than the optimal consumption level. That person can monitor whether the index level and the consumption level converge quickly enough.

The presentation of the personalized index can impact consumers' behavior through several non-exclusive channels. First, the index might reduce consumers' "illusion of wealth." Goldstein, Hershfield, and Benartzi (2016) show that, when net worth is sufficiently high, people tend to perceive it as having a higher value than the equivalent monthly cash flow. The presentation of net worth as a monthly cash flow instead of a lump sum might encourage users to feel less wealthy and change their spending behavior.

Second, monthly cash flow is the commonly used unit of measure for spending, such as monthly bills for rent, mortgage, and utilities. The presentation of net worth as a monthly cash flow provides a reference point for spending activity that encourages consumers to mentally simulate their lives under a different monthly budget. Reference-dependent utility consumers are predicted to be especially sensitive to potential changes in their standard of living and might therefore adjust their spending levels.

Third, the index might serve as an anchor for spending activity. Anchor effects occur when an initial salient value influences individuals' subsequent estimations or decisions. These effects are especially pronounced when there are no other competing reference points or information available (Kahneman (1992)). Given that consumers typically do not know their optimal level of spending nor does the app provide any other benchmark for spending, the index might have a strong impact as an anchor.

Note that none of these channels requires consumers to fully understand the economic interpretation of the index. In fact, it is highly plausible that many users do not fully grasp its meaning, since doing so would require relatively advanced financial and economic knowledge.

There are several reasons for using the index as the subject for information design manipulations. First, it is a new information content that is not already available on the app. This requirement ensures that all users have the same level of familiarity with the experimental content and are not biased toward the old information design. Second, the selection of the index is motivated by previous studies in behavioral economics, policy discussions, and practices in the financial industry. The academic research discussed in Section I examines the effects of information design manipulation on consumers' demand for life annuities, providing a foundation for exploring the impact of the personalized index on consumer spending in this study. Additionally, the recent SECUREwhite_Act (2019) requiring retirement account providers to display the account's worth as a projected lifetime monthly income and the offering of similar personalized indices by the financial industry, such as "CoRI" by BlackRock, demonstrate the applicability of the index to consumers' spending and savings decisions.

III. Experimental Design

The experiment was embedded in a financial management app that is offered to the general public at no cost. The first web page users view after logging into the app is the "dashboard" page, which provides a brief summary of the user's finances. The pre-experiment dashboard page is presented in Figure C1. Users were randomly assigned to seven groups.[7] Apart from the control group, all treated groups received a personalized index. The treatments differed in the name of the index and in the availability of a context plot. The treatments are summarized in Table 1 and illustrated in Figure 1. The treatment groups are defined as follows:

Control Group (Figure C1): The dashboard page was not changed for users in this group. The page includes time-series plots of net worth, total income, and total spending. This group serves as a baseline to detect any changes in financial activity that are not related to the experiment.

FSI-Plot Group (Figures C2, C3): Users received the Financial Sustainability Index, which contains a fear appeal message. They also received a context plot providing a salient comparison between the index level and historical monthly spending.

FSI-Plot-inf Group: Several studies have suggested that high annuities prices might explain the low demand for life annuities.[8] If annuities are overpriced, the consumers might respond to the index because it quotes an overly pessimistic cash flow. To address this concern, this group received the same treatment as the FSI-Plot group, except the quoted index was inflated by 20%. A differential response between these two groups would indicate that the change in behavior is sensitive to the exact quote used.

FSI-NoPlot Group (Figure C4): Users received the FSI and no context plot. By comparing the behavior of this group to that of users in the FSI-Plot group we can identify the impact of providing a salient comparison between the index and spending.

[7] Two of the seven groups are omitted from the main text and are described in Appendix **??**.

[8] See the discussion in Benartzi et al. (2011), Brown and Orszag (2006), and Brown (2007).

LAI-Plot Group (Figure C5): Users received the Life Annuity Index and no context plot. By comparing the behavior of this group to that of users in the FSI-Plot group, we can identify the impact of the framing effect embedded in the index names.

The experiment did not include a treatment that presents the index using neutral framing (LAI) with a context plot due to the limited number of users available for the experiment. As a result, we only test the impact of the context plot in the presence of consumption framing.

Goldstein et al. (2016) and Goda et al. (2014) showed that individuals respond to information about changes in their cash flow stream. Following their findings, users received information about the sensitivity of the index level to changes in their net worth ("At current market prices, an increase of $10,000 in your net worth will increase your [FSI/LAI] by $[X]").

The dashboard page of all the treated groups included a link to a FAQ page. The FAQ for each group was adjusted to reflect the corresponding index name. The FAQ page for the FSI-Plot group is presented in Figures C8 and C9.

Historical monthly income was removed from the dashboard page in all treatments but was available to all users on the Cash Flow page of the app. Kahneman (1992) shows that anchor effects are especially pronounced when no other competing reference points or information is available. The removal of monthly income from the landing page decreases the salience of this information and potentially increases the likelihood of using the index as the new benchmark for spending. In addition, historical monthly spending was not presented on the dashboard page for treatments that did not receive a context plot. All users could view their historical spending on the Cash Flow page of the app. The removal of monthly spending from the landing page reduces the salience of this information and the ability of users to directly compare it to the index level.

IV. Data

A. Annuity Price Quotes

We obtain life annuity prices from Hueler's Income Solutions® annuity quoting platform. This platform allows individuals to receive customized quotes of identical annuity contracts from large insurance companies in real time. All insurance companies that provide quotes are rated "A" or above by Moody's, S&P, and A.M. Best. The costs of investment management, distribution, administration, and other costs associated with annuity products are reflected in the annuity quotes. We use annuity quotes of inflation-protected life annuities for single, male buyers (reflecting the majority of the app users) with a nonqualified income of $100,000. We obtain the full annuities quotes grid for all ages between 35 and 85, all commencement dates between immediate and the age of 85, and all states.[9] Annuity quotes were updated once a week during the experiment. The personal index for each user was calculated as the average quote from all companies given the user's age, state of residence, and net worth.

B. Consumer Data

The sample consists of users of the financial management app who are not clients or prospective clients of the app provider's wealth management services. We restrict the sample to users above the age of 35, which is the minimum age of life annuity quotes. Additionally, retired users are excluded from the sample to accommodate the two treatment groups where the index

[9] Two of the treatment groups in this study received a personalized index representing a cash flow stream starting at retirement rather than immediately. Deferred annuities quotes were used for these two treatment groups. See details in Appendix **??**.

represents a deferred annuity quote with a commencement date at retirement. We keep users who had been using the app for at least five months before the experiment.

The sample includes only users who logged into the app at least once in the three months before the experiment, linked at least one credit or debit account, and had an average monthly income and spending above $1,000 in the five months before the experiment launch. These restrictions ensure that the sample includes only users who are actively using the app. We also exclude users with a net worth below $5,000 so that the level of the personal index is sufficiently positive.

Users of mobile financial apps log in to view their accounts more frequently than users who log in only from personal computers (Carlin, Olafsson, and Pagel (2023)). To ensure consistency in the level of exposure to the app and the experiment material, we include only users who have installed the mobile app prior to the start of the experiment and had logged in using a mobile device at least once in the three months before the experiment launch.

The final sample consists of 3,138 users. Data on users' transactions and login activity are collected for a period of 25 months, starting five months before the experiment launch and continuing for twenty months after.

Table 3 presents summary statistics of the sample as documented on March 17, 2014, the launch day of the experiment. The average age in the sample is 45. The average net worth is $1.1 million (median $0.6 million), and the average monthly income from all sources is $16.7K (median $12.6K). The personalized index in this table was calculated for all users, including the control group, as the average quote on an immediate inflation-protected life annuity. The average index level is $3,175, and the median is $1,561. The average number of monthly logins during the five months before the experiment's launch is 15.4 (median of 7.6), indicating that users in the sample are actively using the app. The average monthly spending is about $12K, and the median is $9.2K. The spending levels of users in this sample are well above their personalized index levels, as predicted for consumers relatively far from retirement age (see discussion in Section II and Figure 2).

The main variable of interest is discretionary spending, which refers to spending on items over which consumers have relatively more control and can adjust over a short period, such as entertainment and restaurants. We define discretionary spending as the sum of spending in categories that correspond to industries in the Consumer Discretionary sector according to the Global Industry Classification Standard (GIC code 25). The complete list of categories with example vendors for each category is presented in Table 2. The average level of discretionary spending in this sample is $3,689 (median $2,789), constituting about 30% of overall spending. We analyze expenditures on clothing, entertainment, restaurants, and travel, which are relatively large components of discretionary spending. We also analyze cash withdrawals, which reflect additional spending not included in the discretionary spending variable. The average monthly cash withdrawal in this sample is $925, and the median is $355.

Overall, the consumers in this sample are relatively wealthy and are similar to consumers in the 80th percentile of the income distribution based on their income level, overall spending, and spending on the categories studied in this paper.[10]

[10]Based on the Consumer Expenditures Survey of the BLS.

V. Empirical Specification

Experiment materials were available on the app for a period of eight months. The data cover the period from t=-5 to t=19, where the experiment launch month is t=0. We define two indicator variables:

$Intra$: equals 1 for event months in which experiment material was presented on the app, from t=0 to t=7.

$Post$: equals 1 for event months after the removal of experimental material from the app, from t=8 to t=19.

The main empirical specification is:

$$y_{i,t} = \sum_{j=2}^{j=5} \beta_j TG_{j,i} Intra_t + \sum_{j=2}^{j=5} \gamma_j TG_{j,i} Post_t + \delta_i + \theta_j + \epsilon_{i,t} \tag{1}$$

where $y_(i,t)$ is an outcome variable such as logins or log spending for consumer i in event month t. TG_j are treatment group indicator variables for each of the groups, where the omitted group serves as the reference level. δ_i is an individual fixed effect, and θ_j is an event-month fixed effect. Standard errors are clustered at the consumer level.[11]

β_j captures the average change in the outcome variable between the pre-experiment months (t=-5 to t=-1) and the experiment months (t=0 to t=7) of consumers in treatment group j, relative to the same change in the omitted treatment group. Similarly, γ_j captures the average change in the outcome variable between the pre-experiment months (t=-5 to t=-1) and the

[11] All tests are robust to double clustering of the standard errors by consumer and year-month.

post-experiment months (t=8 to t=19) of consumers in treatment group j, relative to the same change in the omitted treatment group.

In addition, we estimate the following specification for each of the treatment groups separately:

$$y_{i,t} = \sum_{t=-4}^{t=19} \beta_t I(t) + \delta_i + \epsilon_{i,t} \quad (2)$$

where $I(t)$ is an event-month indicator for month t. β_t captures the change in the outcome variable in event month t relative to event month t=-5. This within-group time-series analysis allows us to test the speed and duration of consumers' response to the treatments.

VI. Results

A. Attention

The experiment content was presented at the top of the dashboard page, which is the first page users see after logging into the app. Given this placement of the experiment content, login activity measures users' exposure to the experiment materials and level of attention to their personal finances.

Table 4 reports the effect of the treatments on the users' number of logins per month. The reference treatment group in the first column is the control group. The coefficients of all the interaction variables between the treatment indicators and $Intra$ reveal that the change in monthly logins between the the pre-experiment months and the experiment months is significantly larger for all the treatment groups relative to the same change in the control group. Users in each of the treatment groups increased their login frequency during the experiment months by about 1.3 logins per month relative to the control group. The coefficients of the interaction variables between the treatment indicators and $Post$ show that after the removal of the experiment material, the change in login frequency of users in all treatment groups relative to the pre-experiment months is still greater than the same change in the control group (about 0.6 more monthly logins), but the difference is not statistically significant. Columns 2 and 3 repeat the same regression with the FSI-Plot and FSI-Plot-inf groups as the baseline treatments. Although all groups increased their attention level during the experiment months relative to the control group, there are no notable differences in the login frequency across any of the other treatment groups during or after the experiment.

The results for the time series analysis for each of the treatment groups are presented in Figure 3 (formal results are in Table A1). Panel (a) displays the estimated coefficients in Equation 2, and panel (b) shows the average predicted values in each event month. The monthly login frequency of the treatment groups is similar and highly correlated between all the groups before the start of the experiment. At t=0 all the treated groups immediately diverge from the control group, and the predicted login frequency remains higher throughout the experiment months. The change in the login frequency of all the treated groups is still higher than that of the control group for about three months after the experiment, after which all the groups converge to the same login frequency.

Overall, the login analysis shows that users in all treated groups increased the level of attention to their finances throughout the experiment months. The change in login frequency is significant but small in magnitude, with only slightly more than one login per month relative to the control group. The change in login frequency started immediately after the launch of the experiment and can be attributed to interest in the new content on the app. The lack of difference in login frequency across the treated groups reveals that the increased attention cannot be attributed to any specific treatment feature, such as the index name or the presentation of a context plot. Therefore, any differences in spending behavior across the different treatments can not be attributed to a difference in consumers' login frequency.

B. Discretionary Spending

Table 5 presents the analysis of the treatment effects on the log of discretionary spending. The first column shows that both the FSI-Plot and the FSI-Plot-inf reduced their discretionary spending during the experiment period by about 15% relative to the change in the control group over the same period. None of the other groups had a significant change in their spending behavior. Columns 2 and 3 formally show that there were no significant differences between the FSI-Plot and the FSI-Plot-inf groups, and that the change in discretionary spending of these groups is significantly lower than that of the FSI-NoPlot and the LAI-Plot groups. Using the sample mean of monthly discretionary spending ($3,689), a 15% decline in discretionary spending corresponds to a drop of $553 per month, which is about 4.5% of overall monthly spending. The coefficients of the interaction variable between the treatment indicators and $Post$ show that after the removal of the experiment material from the app, there were no significant differences in discretionary spending between any of the groups.

This analysis confirms that information design can have a substantial impact on consumers' discretionary spending. However, the effect is sensitive to specific features in information presentation. Consumers only respond when the index is presented both under the consumption frame and contains a salient context. Presentation of either the consumption frame or a salient context by itself does not yield a partial response. The lack of difference in effect size between the FSI-Plot and FSI-Plot-inf groups indicates that the effect is robust to the exact quote used in the index.

Treatments that did not receive a context plot with a consumption framing of the index name did not show any differences in spending relative to the control group, suggesting that the omission of monthly income and spending from the dashboard page did not impact users' spending behavior. However, the decrease in spending in the FSI-Plot and the PSI-Plot-inf groups might have been smaller in magnitude if income was still presented on the dashboard page, providing a salient alternative benchmark for spending instead of the index.

Figure 4 shows the dynamics of the change in discretionary spending for each of the experiment groups relative to their spending at t=-5 (formal results are in Table A2). The changes in discretionary spending of all the groups are positively correlated and similar in magnitude before the experiment launch. The peak in discretionary spending at t=-3 and the sharp decline at t=-2 are driven by seasonal effects, with a high spending month in December followed by a low spending month in January. The change in discretionary spending of the FSI-Plot and FSI-Plot-inf groups diverge from all the other groups immediately at the launch of the experiment and remain lower throughout the experiment. The gap between these two groups and all the other groups remained large for three additional months after the experiment and gradually decreased afterwards. The changes in discretionary spending of all the groups converge only at t=16, nine months after the removal of the experimental content from the app.

The analysis in Figure 4 shows the within-group evolution of discretionary spending. To test the persistence of the effect after the experiment duration across groups, we conduct an additional analysis of discretionary spending over shorter periods than used in Equation 1. The results of this analysis are presented in Table 6. The dependent variable is the log of discretionary spending. The explanatory variables are the interactions of group indicators and a time period indicator where the time period in each regression is listed at the top of the column. The control group is the baseline group in all columns, and the reference time period is the five months before the experiment launch.[12] The first two columns show that the average change in discretionary spending is about 15% lower than the change in the control group during the experiment months. Column 3 shows that the decline in discretionary spending of the affected treatments during the following four months remained about 15% lower than the change in the control group. However, this effect is only significant at the 10% level. The magnitude of the change in these groups decays over time, and the point estimates of all the groups are similar to each other between t=16 and t=19.

Overall, the analysis in Figure 4 and Table 6 shows that the treatments had lasting effects beyond the period in which the experiment content was presented on the app. The FSI-Plot and FSI-Plot-inf treatments groups reduced their discretionary spending immediately at the start of the experiment but resumed their non-treatment levels of spending only after several months.

C. Spending Categories

In Table 7, we test the average spending response in different spending categories. Column 1 shows that both the FSI-Plot and FSI-Plot-inf reduced their restaurant expenditures by

[12]The sample in each regression includes the pre-experiment months (t=-5 to t=-1) and the four months listed at the top of each column.

about 14% relative to all the other groups during the experiment months. Restaurant spending is relatively easy to adjust by visiting less expensive restaurants or dining at home. Users in these groups also reduced their clothing expenditures by a significant 20% relative to the other groups (Column 2). Clothing expenses can be relatively easily adjusted as well by reducing purchase frequency or clothing price. Column 3 shows that users in the FSI-Plot and FSI-Plot-inf treatments decreased their expenditures on entertainment by about 14% percent relative to the change in other groups. Column 4 shows a decrease of about 24% in travel expenses for users in these two groups. Travel is likely to be a luxury item for many consumers that can be adjusted by choosing a more modest vacation or skipping it altogether.

Column 5 shows that consumers in the FSI-Plot and FSI-Plot-inf groups reduced their cash withdrawals by about 25% compared to other groups. Unlike the previous spending categories, cash withdrawals are not included in the discretionary spending variable. Therefore, this decrease in cash withdrawals reflects an additional decrease in spending. This evidence is consistent with consumers placing a higher subjective value on cash transactions and therefore being more likely to reduce these transactions first (Raghubir and Srivastava (2008)).

Sussman and Alter (2012) classified transactions into ordinary (i.e., common and frequent) transactions and exceptional (i.e., unusual or infrequent) transactions, with many of the largest expenses being the most exceptional.[13] They show that although consumers are fairly skillful at planning their ordinary spending, they systematically underestimate their future expenditures on exceptional items. Consumers tend to categorize each exceptional expense as a unique occurrence and consequently overspend after a series of exceptional expenses. Moreover,

[13] See additional discussion in Karlan et al. (2016).

changes in large and infrequent expenditures might be easier to implement, as the consumer will have to make a single (large) mental effort to apply self-control rather than exercise discipline and sacrifice every day.

We test if the decrease in spending is a result of a reduction in spending on exceptional expenses. We use the sum of the five largest transactions of each user in a given month as a proxy for large and infrequent transactions.[14] Note that the consumers' largest transactions are typically rent, mortgage, and loan payments. However, these expenses are typically constant over time and are therefore absorbed by the consumer fixed effects. Column 6 shows that both the FSI-Plot and FSI-Plot-inf groups significantly reduced their large transactions during the experiment months, suggesting that these users avoided or reduced spending on infrequent large-ticket transactions. Overall, the reduction in spending is driven by a decrease in both common and exceptional transactions.

D. Additional Tests

In the first column of Table 8, we test the effect of the different treatments on the users' overall spending level. We find a decline of about 6% in overall spending in the FSI-Plot and FSI-Plot-inf groups relative to the change in any of the other treatment groups. However, this decline is only significant at the 10% level. Given the average monthly mean of overall spending of \$12,364, a decrease of 6% in overall spending translates to a reduction of approximately \$742 per month. This decrease roughly corresponds to the combined decrease in monthly discretionary

[14] Results are robust to the selected number of extreme transactions.

spending and cash withdrawals.[15] In addition, we test the effect of the different treatments on overall monthly spending minus discretionary spending and cash withdrawals and find no significant differences between any of the groups. This evidence confirms that consumers did in fact decrease their spending levels and did not shift their expenses from discretionary spending and cash transactions to other spending categories.

As a falsification test, we check if there is a change in spending categories that are relatively difficult to adjust, especially in the short run. We find no significant differences in spending on gas, groceries, telephone, or utilities between any of the treatment groups (columns 2 to 5).

VII. Conclusion

This paper documents the critical impact of information design on consumers' spending behavior. The frame in which the information is presented and the salience of the context can have a significant impact on consumers' spending, despite strong behavioral inertia in spending and the temporal distance between exposure to treatment and the spending activity. Furthermore, the effects on spending behavior start immediately after the exposure to the treatment and last for several months beyond the experiment duration, showing that the impact of the information design lasts beyond the exposure to the treatment and supports an asymmetrical adjustment of spending habits.

Information tools that influence spending behavior offer several advantages over the

[15]The decrease in monthly discretionary spending = 15% * $3,689 = $553. The decrease in monthly cash withdrawals = 25% * $925 = $231.

existing tools aimed at influencing saving behavior. First, information design tools are easy to implement at low cost relative to financial education, tax subsidies, and employer matching contribution. Second, unlike choice architecture interventions, information design tools can be applied to all consumers rather than only to individuals with retirement plans. Third, a decrease in spending reflects an equal size increase in consumer savings. An increase in retirement plan contributions might not reflect an increase in savings due to early withdrawals and an increase in borrowing.

The sensitivity of individuals' responses to subtle details in information presentation can be leveraged by firms. For instance, wealth management companies can utilize information design tools that enhance their clients' saving rates. On the other hand, loan providers can strategically design information to encourage consumers to increase their spending and borrowing levels.

Given the potential impact of information design on consumer behavior, policymakers may need to consider regulations to protect consumers in this context. Current regulations on information presentation already exist in various industries such as food, tobacco, alcohol, and cosmetics, where warning labels are regulated in terms of content, size, location, and color. However, in the realm of consumer finance, information design regulations are primarily limited to areas such as interest rate quotes, credit card statements, and fee disclosure. By specifying guidelines and standards for the presentation of personal financial information, policymakers can mitigate deceptive practices by firms.

A common limitation of all research using transaction level data is the potential incompleteness of the data. Data obtained from account aggregation apps, banks, or credit card companies might not include all the consumers' accounts. It is possible that the change in spending behavior in the observed accounts is offset by an increase in spending in unobserved accounts. Similar concerns existed in the retirement contribution literature for more than two decades until Chetty et al. (2014) showed that an increase in retirement contributions does not crowd out savings in other accounts. We mitigate this concern by selecting relatively active users who are more likely to have linked all their accounts to the app.[16]

Another limitation caused by potential data incompleteness is the inaccurate estimation of users' net worth and personalized index. The omission of retirement or debt accounts will bias the net worth presented on the app. Additionally, real assets such as real estate are not included in the app. It is possible that consumers respond to the index they observe on the app even if it does not reflect their real net worth. Alternatively, they might ignore the index if they feel that it does not represent their current financial situation accurately.

This paper demonstrates the significant impact of information design on the spending behavior of consumers who are relatively far from retirement and whose spending levels are significantly above their index levels. Future research should explore the effects of providing annuitized values to consumers at or near retirement. These consumers may have spending levels below their annuitized net worth, and examining whether they increase their spending after being exposed to the index could offer valuable insights into the retirement decumulation puzzle.[17]

Future research can explore the exact mechanisms through which the index influences consumer behavior. One possibility is that the index provides new information that was not previously available to consumers, expanding their information set and leading to improved spending decisions. Another potential channel is that the index establishes a new reference point

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[16] See Baker and Kueng (2022) for a full discussion on the limitations of research using transaction-level data.

[17] See Battistin, Brugiavini, Rettore, and Weber (2009) for a comprehensive review of the retirement decumulation puzzle.

for spending, distinct from the reference point consumers previously used, such as monthly income. Finally, it is possible that the index serves as an anchor for spending behavior, meaning consumers might adjust their spending levels based on any random salient reference point provided.

This study shows that the presentation of the index has a critical role in influencing consumer behavior. The consumption frame used to describe the index potentially induces a feeling of guilt and regret, leading to an improvement in consumers' self-control through a decrease in the temptation value of unnecessary spending (e.g., Baumeister (2002), Fudenberg and Levine (2012), Hoch and Loewenstein (1991)). The context plot comparing the index to the consumer spending primes users to take a specific action of cutting their spending and increasing their savings (e.g., Gollwitzer and Sheeran (2006)). Future research can explore if similar information designs can influence other consumers' decisions, such as stock market participation, debt repayment, and the claiming age of social security benefits.

Consumers use a variety of benchmarks for their spending behavior, such as their monthly income or spending in the previous month. Recent studies have shown that providing consumers with information about their peers' income, debt, or spending levels can influence their own spending behavior (D'Acunto et al. (2023), van Rooij, Coibion, Georgarakos, Candia, and Gorodnichenko (2024)). This study demonstrates that consumers adjust their spending when presented with the annuitized value of their net worth. Future research should explore which of these benchmarks consumers perceive as most important and whether the presentation of single or multiple benchmarks has a stronger impact on consumer spending.

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FIGURE 1

Top of Dashboard Page for the FSI-Plot Treatment

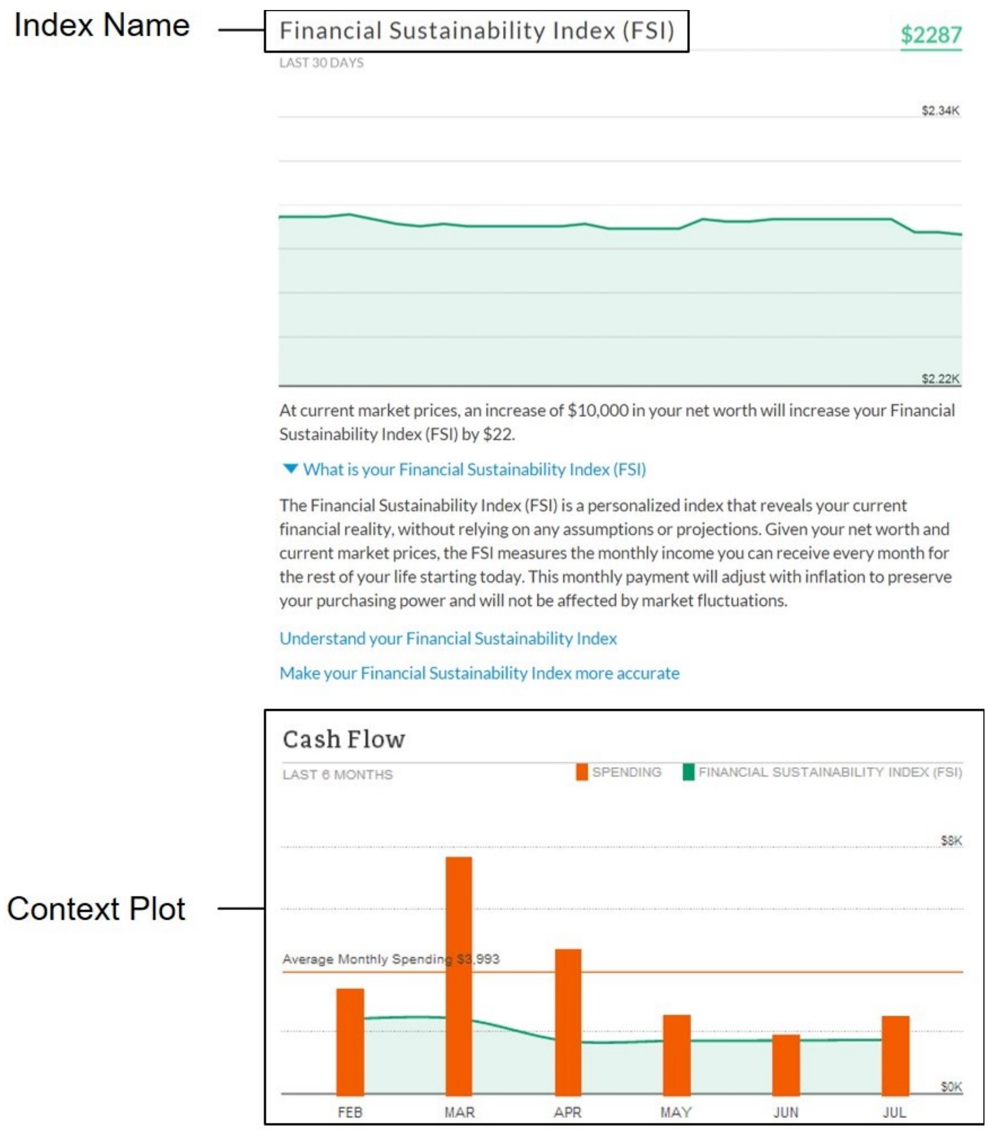


FIGURE 2

Net Worth and Index Levels Over the Consumer's Life Cycle

The figure illustrates the index and net worth level of a life cycle of a consumer with a constant income level during their working years and no income after retirement. Given no uncertainty, the consumer can smooth their consumption perfectly. Net worth as a lump sum is the accumulated wealth from income savings. Net worth as an index is the constant consumption level that the person can afford until the end of their life given their level of accumulated wealth and time till the end of life. For simplicity, the real return on savings is set to zero. The plot of Net Worth as a lump sum is scaled down by a factor of 6.

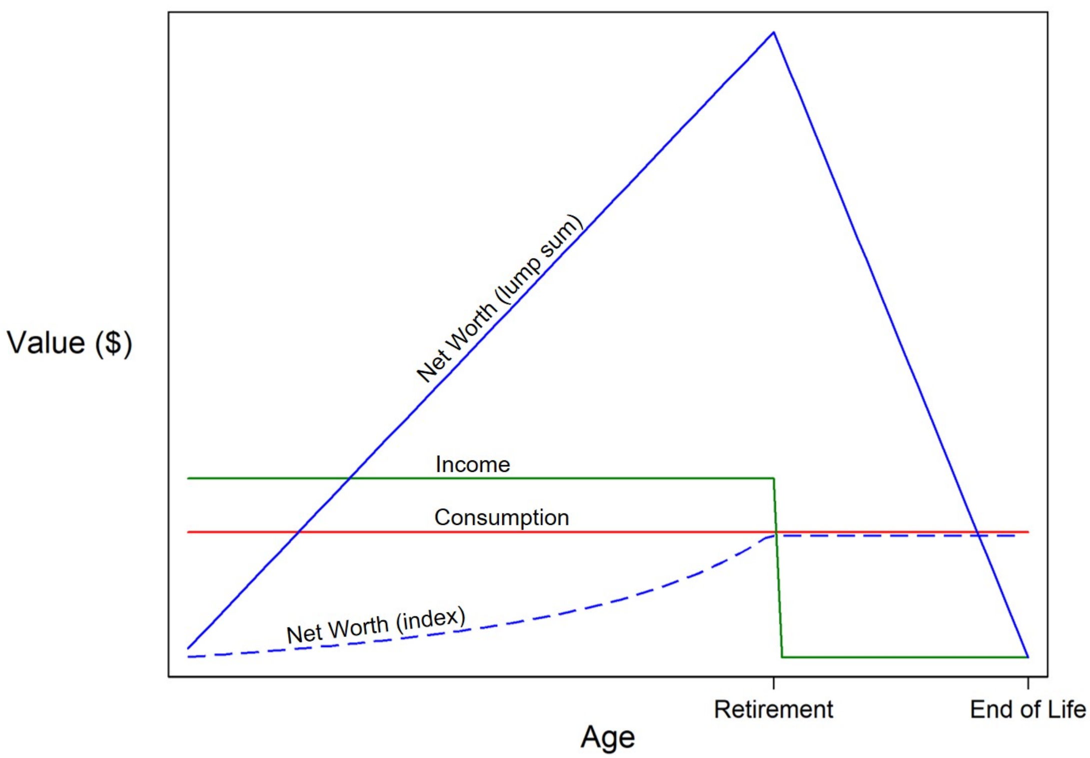
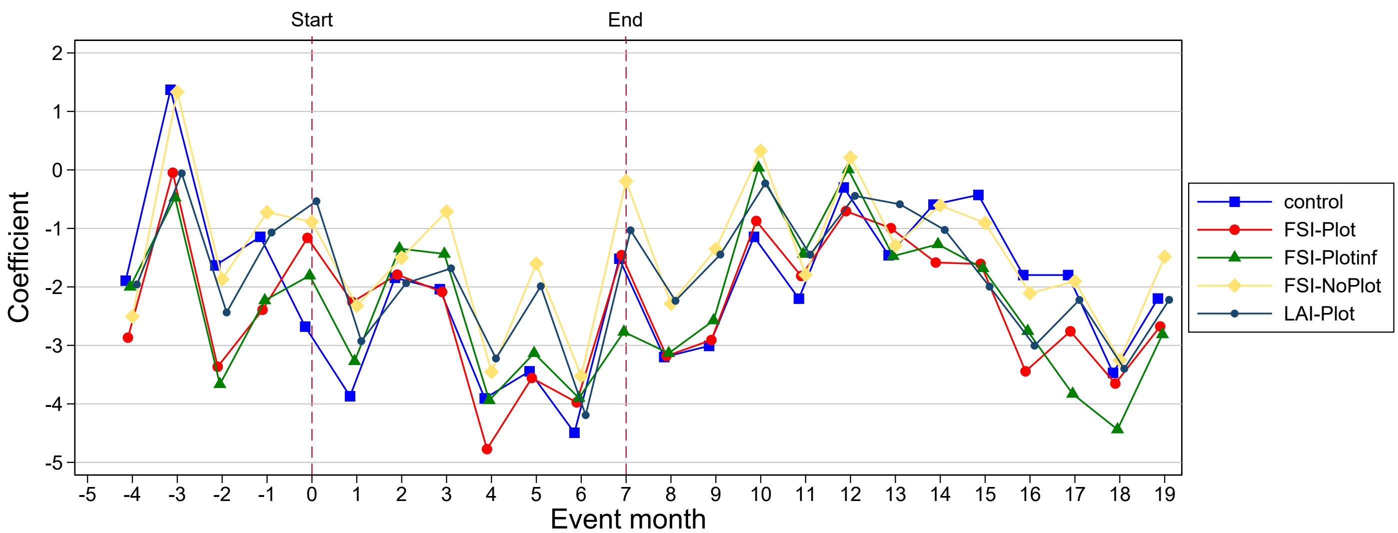


FIGURE 3

Monthly Logins by Treatment Group

Panel (a) shows the estimated coefficients in a regression of monthly login count on event month indicator variables with consumer fixed effects for each treatment group. Panel (b) shows the average predicted values for that regression. Detailed regression results are in Table A1.

(a) Coefficients



(b) Predicted Values

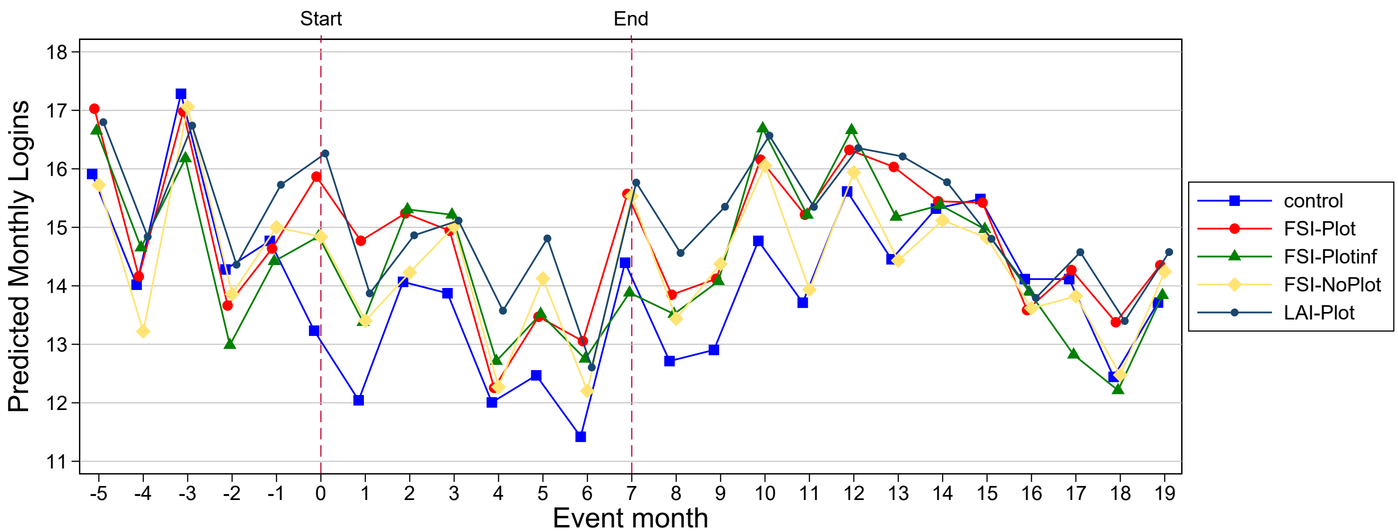


FIGURE 4

Monthly Discretionary Spending by Treatment Group

The figure shows the estimated coefficients in a regression of log monthly discretionary spending on event month indicator variables with consumer fixed effects for each treatment group. Detailed regression results are in Table A2.

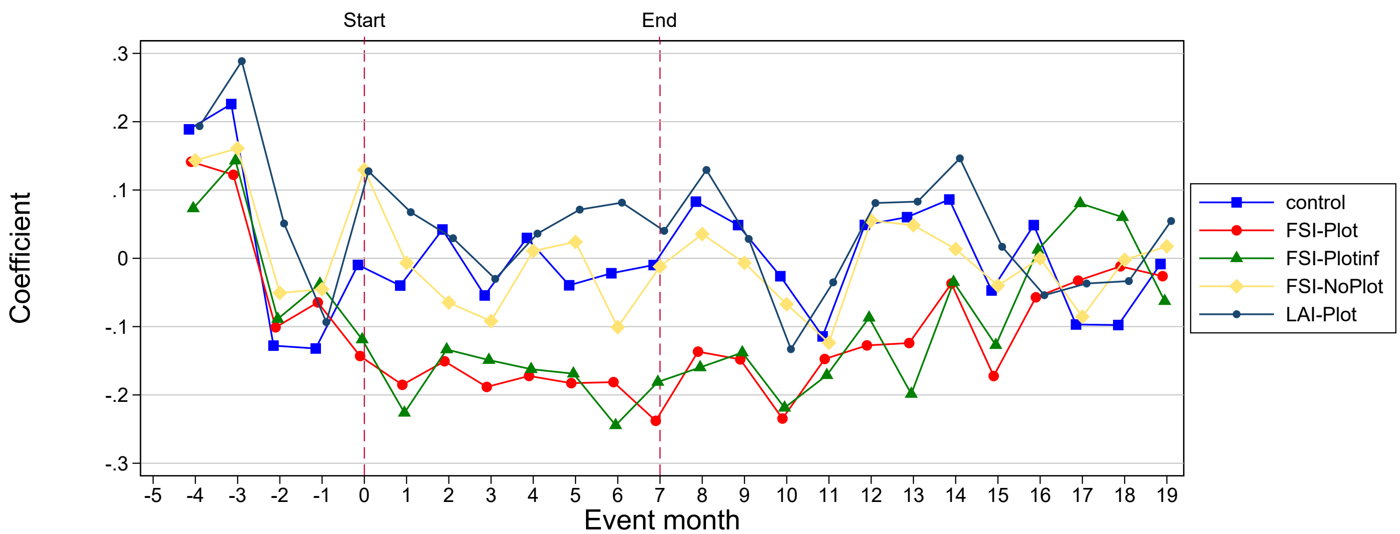


TABLE 1

Treatment Groups

#	group name	index name	index and spending plot	comments
1	Control	-	-	
2	FSI-Plot	Financial Sustainability Index	yes	
3	FSI-Plot-inf	Financial Sustainability Index	yes	index inflated by 20%
4	FSI-NoPlot	Financial Sustainability Index	no	
5	LAI-Plot	Life Annuity Index	yes	

TABLE 2

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 3

Summary Statistics

Age, *Net Worth*, and *Personalized Index* were documented on the experiment launch day. *Personalized Index* was calculated for all users, including the control group, as the average monthly cash flow quote on an immediate life annuity. The remaining variables describe monthly averages over the five months preceding the experiment launch.

Variable	N	Mean	Std. Dev.	10%	Median	90%
Age	3,138	44.6	7.9	36.0	43.0	56.0
Net Worth	3,138	1,128,106	1,493,896	72,558	637,308	2,623,589
Personalized Index	3,138	3,178	5,211	168	1,561	7,462
Logins	3,138	15.4	20.5	1.2	7.6	41.0
Income	3,138	16,784	13,162	4,564	12,570	35,137
Spending	3,138	12,364	9,887	3,341	9,200	25,913
Discretionary Spending	3,138	3,689	3,449	553	2,789	7,930
Clothing	3,138	374	495	12	205	929
Entertainment	3,138	168	217	1	97	421
Restaurants	3,138	504	480	40	386	1,076
Travel	3,138	693	1,034	0	304	1,891
Cash Withdrawal	3,138	925	1,326	0	355	2,638

TABLE 4

Treatment Effects on Login Behavior

The dependent variable in all columns is the count of monthly logins. *Control*, *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, and *LAI-Plot* are treatment group indicator variables (see Table 1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1). *Intra* is an indicator variable for the eight months during which experiment materials were presented in the app (t=0 to t=7), and *Post* is an indicator for the following twelve months (t=8 to t=19). 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.

Variables	(1)	(2)	(3)
*Control * Intra*		-1.417**	-1.288**
		(-2.03)	(-2.11)
*FSI-Plot * Intra*	1.417**		0.129
	(2.03)		(0.17)
*FSI-Plot-inf * Intra*	1.288**	-0.129	
	(2.11)	(-0.17)	
*FSI-NoPlot * Intra*	1.293**	-0.123	0.005
	(2.05)	(-0.16)	(0.01)
*LAI-Plot * Intra*	1.229**	-0.187	-0.058
	(2.05)	(-0.25)	(-0.09)
*Control * Post*		-0.691	-0.700
		(-0.75)	(-0.80)
*FSI-Plot * Post*	0.691		-0.009
	(0.75)		(-0.01)
*FSI-Plot-inf * Post*	0.700	0.009	
	(0.80)	(0.01)	
*FSI-NoPlot * Post*	0.522	-0.169	-0.177
	(0.57)	(-0.16)	(-0.17)
*LAI-Plot * Post*	0.556	-0.135	-0.144
	(0.61)	(-0.13)	(-0.14)
reference group	Control	FSI-Plot	FSI-Plot-inf
consumer FE	Y	Y	Y
event month FE	Y	Y	Y
N	54,750	54,750	54,750
adj. R2	0.74	0.74	0.74

TABLE 5

Treatment Effects on Discretionary Spending

The dependent variable in all columns is the log of monthly discretionary spending. *Control*, *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, and *LAI-Plot* are treatment group indicator variables (see Table 1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1). *Intra* is an indicator variable for the eight months during which experiment materials were presented in the app (t=0 to t=7), and *Post* is an indicator for the following twelve months (t=8 to t=19). 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.

Variables	(1)	(2)	(3)
*Control * Intra*		0.156**	0.147**
		(2.22)	(2.25)
*FSI-Plot * Intra*	-0.156**		-0.009
	(-2.22)		(-0.13)
*FSI-Plot-inf * Intra*	-0.147**	0.009	
	(-2.25)	(0.13)	
*FSI-NoPlot * Intra*	-0.012	0.144**	0.135**
	(-0.18)	(2.00)	(2.01)
*LAI-Plot * Intra*	0.009	0.165**	0.156**
	(0.13)	(2.24)	(2.26)
*Control * Post*		0.092	0.073
		(0.98)	(0.77)
*FSI-Plot * Post*	-0.092		-0.019
	(-0.98)		(-0.19)
*FSI-Plot-inf * Post*	-0.073	0.019	
	(-0.77)	(0.19)	
*FSI-NoPlot * Post*	-0.022	0.070	0.050
	(-0.25)	(0.73)	(0.52)
*LAI-Plot * Post*	-0.035	0.057	0.038
	(-0.37)	(0.57)	(0.37)
reference group	Control	FSI-Plot	FSI-Plot-inf
consumer FE	Y	Y	Y
event month FE	Y	Y	Y
N	54,750	54,750	54,750
adj. R2	0.64	0.64	0.64

TABLE 6

Treatment Effects on Discretionary Spending Over Four Months Intervals

The dependent variable in all columns is the log of monthly discretionary spending. *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, and *LAI-Plot* are treatment group indicator variables (see Table 1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1) and the reference group is the *Control* group. Treatment group indicators are interacted with a time period indicator for the four months listed at the top of each column. Experiment materials were presented on the app from $t = 0$ to $t = 7$. 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.

Variables	(1)	(2)	(3)	(4)	(5)
Interaction:	$I(0 \leq t \leq 3)$	$I(4 \leq t \leq 7)$	$I(8 \leq t \leq 11)$	$I(12 \leq t \leq 15)$	$I(16 \leq t \leq 19)$
FSI-Plot * $I(a \leq t \leq b)$	-0.140**	-0.172**	-0.153*	-0.141	0.018
	(-2.02)	(-1.97)	(-1.69)	(-1.31)	(0.16)
FSI-Plot-inf * $I(a \leq t \leq b)$	-0.128**	-0.166**	-0.157*	-0.136	0.074
	(-2.03)	(-2.00)	(-1.70)	(-1.28)	(0.63)
FSI-NoPlot * $I(a \leq t \leq b)$	-0.004	-0.020	-0.049	-0.028	0.010
	(-0.06)	(-0.23)	(-0.55)	(-0.28)	(0.09)
LAI-Plot * $I(a \leq t \leq b)$	0.007	0.011	-0.057	-0.012	-0.036
	(0.10)	(0.13)	(-0.63)	(-0.12)	(-0.30)
consumer FE	Y	Y	Y	Y	Y
event month FE	Y	Y	Y	Y	Y
N	19,710	19,710	19,710	19,710	19,710
adj. R2	0.72	0.69	0.67	0.63	0.59

TABLE 7

Treatment Effects on Spending Categories

The dependent variables in columns (1)-(4) are the log of monthly spending in the corresponding category, and the log of monthly cash withdrawal is in column (5). The dependent variable in column (6) is the log sum of the five largest spending transactions for a given consumer-month. *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, and *LAI-Plot* are treatment group indicator variables (see Table 1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1) and the reference group is the *Control* group. *Intra* is an indicator variable for the eight months during which experiment materials were presented in the app (t=0 to t=7), and *Post* is an indicator for the following twelve months (t=8 to t=19). 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.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Dependent:	Restaurants	Clothing	Entertainment	Travel	Cash Withdrawal	5 Largest Transactions
*FSI-Plot * Intra*	-0.140**	-0.219**	-0.155**	-0.222**	-0.265**	-0.127***
	(-1.96)	(-2.37)	(-2.23)	(-2.12)	(-2.23)	(-2.94)
*FSI-Plot-inf * Intra*	-0.137**	-0.184**	-0.132**	-0.257**	-0.237**	-0.141***
	(-1.99)	(-2.07)	(-2.03)	(-2.45)	(-2.19)	(-3.92)
*FSI-NoPlot * Intra*	0.052	0.010	0.014	0.015	-0.009	-0.037
	(0.75)	(0.10)	(0.21)	(0.14)	(-0.07)	(-0.98)
*LAI-Plot * Intra*	0.020	-0.004	0.002	0.082	0.007	-0.038
	(0.29)	(-0.05)	(0.03)	(0.74)	(0.06)	(-1.03)
*FSI-Plot * Post*	0.004	0.089	-0.018	0.035	0.006	-0.042
	(0.05)	(0.81)	(-0.20)	(0.27)	(0.04)	(-0.88)
*FSI-Plot-inf * Post*	0.008	0.030	0.023	-0.017	0.021	0.000
	(0.09)	(0.29)	(0.28)	(-0.13)	(0.15)	(0.00)
*FSI-NoPlot * Post*	-0.021	-0.010	0.016	0.027	-0.030	-0.011
	(-0.23)	(-0.09)	(0.18)	(0.21)	(-0.21)	(-0.25)
*LAI-Plot * Post*	-0.037	-0.041	-0.048	0.011	0.025	0.033
	(-0.40)	(-0.39)	(-0.56)	(0.08)	(0.17)	(0.71)
consumer FE	Y	Y	Y	Y	Y	Y
event month FE	Y	Y	Y	Y	Y	Y
N	54,750	54,750	54,750	54,750	54,750	54,750
adj. R2	0.70	0.48	0.56	0.48	0.49	0.49

TABLE 8

Treatment Effects on Additional Spending Categories

The dependent variables are the log of monthly total spending in column (1) and log monthly spending in the corresponding category in columns (2)-(5). *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, and *LAI-Plot* are treatment group indicator variables (see Table 1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1) and the reference group is the *Control* group. *Intra* is an indicator variable for the eight months during which experiment materials were presented in the app (t=0 to t=7), and *Post* is an indicator for the following twelve months (t=8 to t=19). 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.

Variables	(1)	(2)	(3)	(4)	(5)
Dependent:	Spending	Gas	Groceries	Telephone	Utilities
*FSI-Plot * Intra*	-0.065*	0.026	0.010	-0.046	-0.086
	(-1.95)	(0.39)	(0.15)	(-0.65)	(-0.95)
*FSI-Plot-inf * Intra*	-0.053*	0.090	0.069	-0.001	-0.080
	(-1.74)	(1.24)	(1.00)	(-0.01)	(-0.91)
*FSI-NoPlot * Intra*	0.007	0.008	0.024	0.007	-0.107
	(0.22)	(0.14)	(0.35)	(0.09)	(-1.22)
*LAI-Plot * Intra*	0.006	0.093	0.025	-0.030	-0.021
	(0.19)	(1.43)	(0.37)	(-0.41)	(-0.22)
*FSI-Plot * Post*	-0.003	-0.024	-0.041	-0.012	-0.126
	(-0.06)	(-0.31)	(-0.42)	(-0.14)	(-1.06)
*FSI-Plot-inf * Post*	-0.012	0.010	0.063	0.051	-0.073
	(-0.30)	(0.11)	(0.65)	(0.58)	(-0.66)
*FSI-NoPlot * Post*	0.021	0.023	-0.005	0.071	-0.162
	(0.52)	(0.34)	(-0.06)	(0.82)	(-1.46)
*LAI-Plot * Post*	0.017	-0.098	0.013	-0.082	-0.167
	(0.40)	(-1.25)	(0.14)	(-0.95)	(-1.44)
consumer FE	Y	Y	Y	Y	Y
event month FE	Y	Y	Y	Y	Y
N	54,750	35,450	43,625	34,650	33,550
adj. R2	0.60	0.37	0.42	0.28	0.24

Internet Appendix

A. Detailed Analysis

TABLE A1

Monthly Logins by Treatment Group (7 Groups)

The dependent variable in all columns is the count of monthly logins. $I(t = x)$ are event month indicator variables. Event month $t = -5$ is the baseline level in all columns. Each column presents the regression results for a given treatment group. The treatment groups in columns (6) and (7) are described in Appendix B. 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.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment:	Control	FSI-Plot	FSI-Plot-inf	FSI-NoPlot	LAI-Plot	FSI-NoPlot-retire	LAI-NoPlot-retire
I(t=-4)	-1.893***	-2.867***	-1.998***	-2.505***	-1.958***	-1.906***	-3.304***
	(-3.65)	(-4.11)	(-2.80)	(-3.67)	(-3.12)	(-3.07)	(-5.36)
I(t=-3)	1.371**	-0.047	-0.473	1.334	-0.059	1.294*	-0.036
	(2.05)	(-0.06)	(-0.59)	(1.55)	(-0.07)	(1.71)	(-0.04)
I(t=-2)	-1.633**	-3.365***	-3.664***	-1.869**	-2.437***	-2.046***	-3.246***
	(-2.40)	(-3.92)	(-4.07)	(-2.37)	(-2.86)	(-2.60)	(-4.21)
I(t=-1)	-1.144*	-2.391***	-2.231**	-0.724	-1.070	-1.078	-2.261***
	(-1.71)	(-2.72)	(-2.31)	(-0.88)	(-1.22)	(-1.34)	(-2.72)
I(t=0)	-2.679***	-1.161	-1.807**	-0.887	-0.535	-0.809	-1.834**
	(-3.95)	(-1.28)	(-1.97)	(-1.04)	(-0.59)	(-0.95)	(-2.30)
I(t=1)	-3.869***	-2.258**	-3.271***	-2.323***	-2.927***	-1.753**	-3.837***
	(-5.94)	(-2.21)	(-3.51)	(-2.71)	(-3.20)	(-2.21)	(-5.08)
I(t=2)	-1.845***	-1.789*	-1.344	-1.500*	-1.934**	-1.226	-2.537***
	(-2.83)	(-1.80)	(-1.44)	(-1.69)	(-2.08)	(-1.52)	(-2.82)
I(t=3)	-2.039***	-2.085**	-1.436	-0.710	-1.683*	-1.136	-2.788***
	(-2.99)	(-2.04)	(-1.47)	(-0.81)	(-1.80)	(-1.36)	(-3.06)
I(t=4)	-3.906***	-4.773***	-3.938***	-3.454***	-3.223***	-3.646***	-2.911***
	(-5.68)	(-4.65)	(-4.03)	(-4.10)	(-3.55)	(-4.55)	(-3.18)
I(t=5)	-3.443***	-3.557***	-3.133***	-1.601*	-1.988**	-2.174**	-2.028**
	(-5.08)	(-3.36)	(-3.14)	(-1.86)	(-2.14)	(-2.51)	(-2.24)
I(t=6)	-4.493***	-3.974***	-3.900***	-3.523***	-4.192***	-3.178***	-3.537***
	(-6.15)	(-3.51)	(-3.52)	(-3.67)	(-4.62)	(-3.87)	(-3.92)
I(t=7)	-1.517**	-1.457	-2.769**	-0.191	-1.033	-0.350	-2.272**
	(-2.05)	(-1.28)	(-2.55)	(-0.20)	(-1.05)	(-0.38)	(-2.38)
I(t=8)	-3.199***	-3.180***	-3.133***	-2.288***	-2.237**	-2.166**	-3.628***
	(-4.42)	(-2.84)	(-2.87)	(-2.59)	(-2.15)	(-2.46)	(-3.58)
I(t=9)	-3.009***	-2.908***	-2.573**	-1.350	-1.446	-1.413	-2.985***
	(-4.03)	(-2.74)	(-2.44)	(-1.40)	(-1.38)	(-1.51)	(-3.01)
I(t=10)	-1.144	-0.872	0.038	0.329	-0.230	0.589	-1.720*
	(-1.50)	(-0.80)	(0.03)	(0.32)	(-0.22)	(0.59)	(-1.76)
I(t=11)	-2.201***	-1.813*	-1.438	-1.793*	-1.448	-0.509	-2.637***
	(-2.85)	(-1.67)	(-1.29)	(-1.76)	(-1.44)	(-0.52)	(-2.63)
I(t=12)	-0.299	-0.704	0.009	0.214	-0.444	0.713	-0.367
	(-0.37)	(-0.63)	(0.01)	(0.19)	(-0.42)	(0.70)	(-0.31)
I(t=13)	-1.459*	-0.995	-1.473	-1.293	-0.587	-0.379	-2.263**
	(-1.82)	(-0.89)	(-1.34)	(-1.18)	(-0.52)	(-0.38)	(-2.07)
I(t=14)	-0.592	-1.583	-1.271	-0.606	-1.026	-0.312	-1.845*
	(-0.75)	(-1.45)	(-1.17)	(-0.58)	(-0.93)	(-0.34)	(-1.77)
I(t=15)	-0.428	-1.607	-1.682	-0.906	-1.995*	-0.656	-2.546**
	(-0.57)	(-1.44)	(-1.48)	(-0.86)	(-1.79)	(-0.72)	(-2.39)
I(t=16)	-1.797**	-3.443***	-2.756**	-2.108**	-3.005***	-2.080**	-3.178***
	(-2.27)	(-3.04)	(-2.39)	(-2.01)	(-2.89)	(-2.34)	(-3.20)
I(t=17)	-1.797**	-2.758**	-3.829***	-1.903*	-2.223**	-1.591	-1.414
	(-2.11)	(-2.34)	(-3.33)	(-1.68)	(-2.02)	(-1.60)	(-1.36)
I(t=18)	-3.469***	-3.652***	-4.438***	-3.249***	-3.399***	-3.042***	-2.752***
	(-4.19)	(-3.23)	(-4.10)	(-3.01)	(-3.16)	(-3.23)	(-2.63)
I(t=19)	-2.199***	-2.675**	-2.811**	-1.484	-2.221**	-1.413	-1.643
	(-2.68)	(-2.48)	(-2.47)	(-1.32)	(-2.00)	(-1.48)	(-1.56)
consumer FE	Y	Y	Y	Y	Y	Y	Y
N	11,450	10,550	11,250	10,850	10,650	11,925	11,775
adj. R2	0.77	0.75	0.73	0.74	0.72	0.76	0.74

TABLE A2

Monthly Discretionary Spending by Treatment Group (7 Groups)

The dependent variable in all columns is the log of monthly discretionary spending. $I(t = x)$ are event month indicator variables. Event month $t = -5$ is the baseline level in all columns. Each column presents the regression results for a given treatment group. The treatment groups in columns (6) and (7) are described in Appendix B. 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.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment:	Control	FSI-Plot	FSI-Plot-inf	FSI-NoPlot	LAI-Plot	FSI-NoPlot-retire	LAI-NoPlot-retire
I(t=-4)	0.189***	0.141***	0.073	0.143**	0.194***	0.089**	0.144**
	(3.15)	(2.96)	(1.21)	(2.29)	(3.34)	(2.57)	(2.46)
I(t=-3)	0.226***	0.122*	0.143*	0.161**	0.289***	0.061	0.099
	(3.26)	(1.94)	(1.83)	(2.53)	(4.03)	(1.61)	(1.53)
I(t=-2)	-0.128*	-0.101	-0.089	-0.051	0.051	-0.118***	-0.132*
	(-1.77)	(-1.38)	(-1.10)	(-0.65)	(0.66)	(-2.68)	(-1.71)
I(t=-1)	-0.132*	-0.065	-0.037	-0.045	-0.093	-0.140***	-0.151*
	(-1.82)	(-0.88)	(-0.47)	(-0.55)	(-1.12)	(-3.19)	(-1.96)
I(t=0)	-0.010	-0.143*	-0.119	0.130*	0.127*	-0.058	0.104
	(-0.14)	(-1.73)	(-1.32)	(1.70)	(1.69)	(-1.28)	(1.29)
I(t=1)	-0.040	-0.185**	-0.226**	-0.007	0.068	-0.138***	0.018
	(-0.52)	(-2.06)	(-2.52)	(-0.08)	(0.85)	(-2.88)	(0.21)
I(t=2)	0.042	-0.151*	-0.133*	-0.065	0.029	-0.125**	0.018
	(0.56)	(-1.84)	(-1.71)	(-0.70)	(0.36)	(-2.46)	(0.22)
I(t=3)	-0.054	-0.188**	-0.149*	-0.092	-0.030	-0.143***	-0.089
	(-0.68)	(-2.06)	(-1.74)	(-1.04)	(-0.35)	(-2.72)	(-1.00)
I(t=4)	0.030	-0.172**	-0.162**	0.011	0.036	-0.074	-0.095
	(0.37)	(-1.98)	(-2.00)	(0.12)	(0.40)	(-1.52)	(-1.00)
I(t=5)	-0.040	-0.183**	-0.169**	0.024	0.071	-0.065	-0.099
	(-0.46)	(-2.06)	(-1.98)	(0.27)	(0.81)	(-1.34)	(-1.13)
I(t=6)	-0.022	-0.181**	-0.244***	-0.101	0.082	-0.118**	-0.132
	(-0.26)	(-2.02)	(-2.66)	(-1.05)	(0.93)	(-2.44)	(-1.41)
I(t=7)	-0.010	-0.238***	-0.181*	-0.012	0.040	-0.089*	-0.087
	(-0.11)	(-2.63)	(-1.91)	(-0.14)	(0.44)	(-1.75)	(-0.91)
I(t=8)	0.083	-0.137	-0.160	0.035	0.129	-0.014	-0.024
	(0.90)	(-1.47)	(-1.62)	(0.39)	(1.45)	(-0.27)	(-0.27)
I(t=9)	0.049	-0.148	-0.138	-0.007	0.028	-0.095*	-0.035
	(0.51)	(-1.46)	(-1.40)	(-0.07)	(0.29)	(-1.80)	(-0.39)
I(t=10)	-0.026	-0.235**	-0.219**	-0.067	-0.133	-0.175***	-0.157*
	(-0.29)	(-2.41)	(-2.33)	(-0.70)	(-1.30)	(-3.33)	(-1.76)
I(t=11)	-0.114	-0.147	-0.171*	-0.124	-0.035	-0.203***	-0.127
	(-1.32)	(-1.63)	(-1.66)	(-1.28)	(-0.39)	(-3.72)	(-1.48)
I(t=12)	0.049	-0.127	-0.087	0.055	0.081	-0.069	0.043
	(0.55)	(-1.20)	(-0.87)	(0.54)	(0.77)	(-1.25)	(0.45)
I(t=13)	0.060	-0.124	-0.199*	0.048	0.083	-0.061	-0.009
	(0.60)	(-1.16)	(-1.91)	(0.48)	(0.81)	(-1.08)	(-0.10)
I(t=14)	0.086	-0.037	-0.035	0.014	0.146	-0.068	0.007
	(0.90)	(-0.34)	(-0.35)	(0.13)	(1.48)	(-1.18)	(0.07)
I(t=15)	-0.047	-0.172	-0.127	-0.040	0.017	-0.020	-0.032
	(-0.49)	(-1.53)	(-1.21)	(-0.37)	(0.17)	(-0.35)	(-0.32)
I(t=16)	0.049	-0.057	0.013	0.000	-0.054	-0.044	-0.093
	(0.47)	(-0.53)	(0.12)	(0.00)	(-0.49)	(-0.74)	(-0.86)
I(t=17)	-0.097	-0.033	0.080	-0.085	-0.037	0.010	-0.130
	(-0.96)	(-0.30)	(0.78)	(-0.76)	(-0.33)	(0.15)	(-1.18)
I(t=18)	-0.098	-0.012	0.060	-0.002	-0.033	-0.192***	-0.201*
	(-0.94)	(-0.10)	(0.54)	(-0.02)	(-0.29)	(-3.03)	(-1.77)
I(t=19)	-0.008	-0.026	-0.063	0.018	0.055	-0.024	-0.136
	(-0.08)	(-0.23)	(-0.56)	(0.15)	(0.47)	(-0.40)	(-1.18)
consumer FE	Y	Y	Y	Y	Y	Y	Y
N	11,450	10,550	11,250	10,850	10,650	11,925	11,775
adj. R2	0.64	0.68	0.61	0.61	0.65	0.64	0.67

B. Additional Treatment Groups

A third variation in information design (in addition to framing and salience of context) was a current- versus future-self framing. An individual can be viewed as two conflicted agents: a current self and a future self (Strotz (1955), Thaler and Shefrin (1981)). Previous studies confirm that individuals tend to make decisions that favor their current selves and often treat their future selves as they would treat a stranger.[18] In this study, we examine the effect of presenting the intertemporal choice dilemma in either a current-self frame or a future-self frame.

In the current-self framing, users received the annuitized value of their net worth represented by a cash flow stream that starts immediately (using immediate annuities quote). In this frame, users are primed to reflect on questions that place the current self in the center, such as "Can I retire today?" or "How far away am I from sustainably retiring, based on my current net worth?" In the future-self framing, users received the annuitized values of their net worth as a cash flow stream starting at retirement (calculated using the deferred annuities quote). Under this frame, users are primed to reflect on questions that place their future self in the center such as "Will I have enough money to spend when I retire?" To the extent that people identify with their current selves more than their future selves, we can expect that users receiving current-self framing would alter their saving behavior more than users receiving the future-self framing.

Unlike the other variations in treatments, the current-self/future-self variation is not a pure information design test, as the users are exposed to somewhat different information content. Nevertheless, it is important to test because most financial planners, retirement account providers, and the Social Security Administration offer some projection of wealth or income at a future date.

[18] Examples include Pronin and Ross (2006), Pronin, Olivola, and Kennedy (2008), and Wakslak, Nussbaum, Liberman, and Trope (2008). Researchers have been exploring tools to mitigate this conflict by creating commitments to the future self (e.g., Choi, Laibson, Madrian, Metrick et al. (2005), Thaler and Benartzi (2004)) or by improving the vividness or connectedness with the future self (Hershfield, Goldstein, Sharpe, Fox, Yeykelis, Carstensen, and Bailenson (2011)).

Yet it is difficult to argue that the exposure to the new information content might drive a differential response between the treatments, as immediate and deferred annuity quotes are equally available to the public.[19]

In addition to the five experiment groups described in the main text, two additional experiment groups were included to test the current-/future-self framing effect. The groups are described below and in Table B1.

FSI-NoPlot-retire Group (Figure C6): Users in this treatment group received a personalized index named FSI, which represents a potential cash flow that will start at retirement and no context plot. By comparing the behavior of this group to that of the FSI-NoPlot group, we can identify the effect of the current-self or future-self framing under the consumption frame, but without the salience of the spending context.

LAI-NoPlot-retire Group (Figure C7): Users in this treatment group received a personalized index named LAI, which represents a potential cash flow that will start at retirement, and no context plot. By comparing the consumption behavior of this group with that of the LAI-Plot group, we can identify the effect of the current-self or future-self framing combined with the context effect.

As noted in the main text, framing effects are sensitive to the salience of the context in which they are presented. In this study, it was not possible to design a treatment group with high salience of context and future-self framing. Presentation of current spending levels with future potential monthly income in the same plot was likely to confuse users and therefore was not included in the experiment.

Table B2 presents the effect of all the treatments on login behavior. Both the FSI-NoPlot-retire and the LAI-NoPlot-retire groups show a similar increase in login activity as the other treatment groups. This confirms the previous conclusion that the increase in login activity can be attributed to an interest in the new features of the app. Also, as the increase in

[19]Numerous websites provide free quotes for both immediate and deferred annuities. Inflation-protected life annuities used in this study are relatively difficult to obtain for both immediate and deferred annuities.

login activity is similar across all treated groups, we reconfirm that none of the experiment features were more engaging than the rest (e.g., differed annuity quotes did not draw more attention than the immediate annuity quotes).

The remaining tables and figures in this appendix present the full set of tests for all seven treatment groups in the experiment. Neither the FSI-NoPlot-retire nor the LAI-NoPlot-retire treatments had an impact on user spending behavior relative to the control, FSI-NoPlot, or LAI-Plot groups. The lack of impact of retirement treatments reconfirms the previous conclusion that framing effects are sensitive to the presence of a salient context. Current or future framing had no differential impact on financial behavior in the absence of a salient context. The lack of response to future-self framing is concerning and merits additional research, as it is a common method of presenting retirement income used by retirement account providers.

TABLE B1

Treatment Groups (7 Groups)

#	group name	index name	index and spending plot	comments
1	control	-	-	
2	FSI-Plot	Financial Sustainability Index	yes	
3	FSI-Plot-inf	Financial Sustainability Index	yes	index inflated by 20%
4	FSI-NoPlot	Financial Sustainability Index	no	
5	LAI-Plot	Life Annuity Index	yes	
6	FSI-NoPlot-retire	Financial Sustainability Index	no	cash flow starts at retirement
7	LAI-NoPlot-retire	Life Annuity Index	no	cash flow starts at retirement

TABLE B2

Treatment Effects on Login Behavior (7 Groups)

The dependent variable in all columns is the count of monthly logins. *Control*, *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, *FSI-NoPlot-retire*, *LAI-Plot*, and *LAI-NoPlot-retire* are treatment group indicator variables (see Table B1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1). *Intra* is an indicator variable for the eight months during which experiment materials were presented in the app (t=0 to t=7), and *Post* is an indicator for the following twelve months (t=8 to t=19). 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.

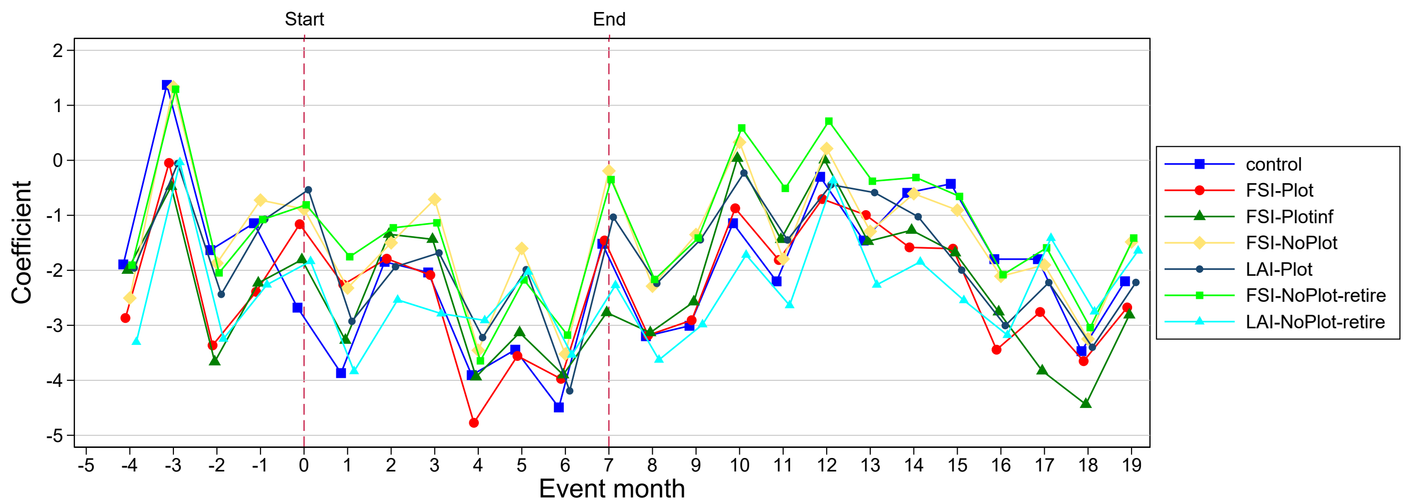
Variables	(1)	(2)	(3)
*Control * Intra*		-1.417**	-1.288**
		(-2.03)	(-2.11)
*FSI-Plot * Intra*	1.417**		0.129
	(2.03)		(0.17)
*FSI-Plot-inf * Intra*	1.288**	-0.129	
	(2.11)	(-0.17)	
*FSI-NoPlot * Intra*	1.293**	-0.123	0.005
	(2.05)	(-0.16)	(0.01)
*LAI-Plot * Intra*	1.229**	-0.187	-0.058
	(2.05)	(-0.25)	(-0.09)
*FSI-NoPlot-retire * Intra*	1.277**	-0.139	-0.011
	(2.13)	(-0.18)	(-0.02)
*LAI-NoPlot-retire * Intra*	1.366**	-0.051	0.078
	(2.12)	(-0.06)	(0.11)
*Control * Post*		-0.691	-0.700
		(-0.75)	(-0.80)
*FSI-Plot * Post*	0.691		-0.009
	(0.75)		(-0.01)
*FSI-Plot-inf * Post*	0.700	0.009	
	(0.80)	(0.01)	
*FSI-NoPlot * Post*	0.522	-0.169	-0.177
	(0.57)	(-0.16)	(-0.17)
*LAI-Plot * Post*	0.556	-0.135	-0.144
	(0.61)	(-0.13)	(-0.14)
*FSI-NoPlot-retire * Post*	0.865	0.174	0.165
	(0.95)	(0.16)	(0.16)
*LAI-NoPlot-retire * Post*	0.661	-0.030	-0.039
	(0.76)	(-0.03)	(-0.04)
reference group	Control	FSI-Plot	FSI-Plot-inf
consumer FE	Y	Y	Y
event month FE	Y	Y	Y
N	78,450	78,450	78,450
adj. R2	0.74	0.74	0.74

FIGURE B1

Monthly Logins by Treatment Group (7 Groups)

Panel (a) shows the estimated coefficients in a regression of monthly login count on event month indicator variables with consumer fixed effects for each treatment group. Panel (b) shows the average predicted values for that regression. Detailed regression results are in Table A1.

(a) Coefficients



(b) Predicted Values

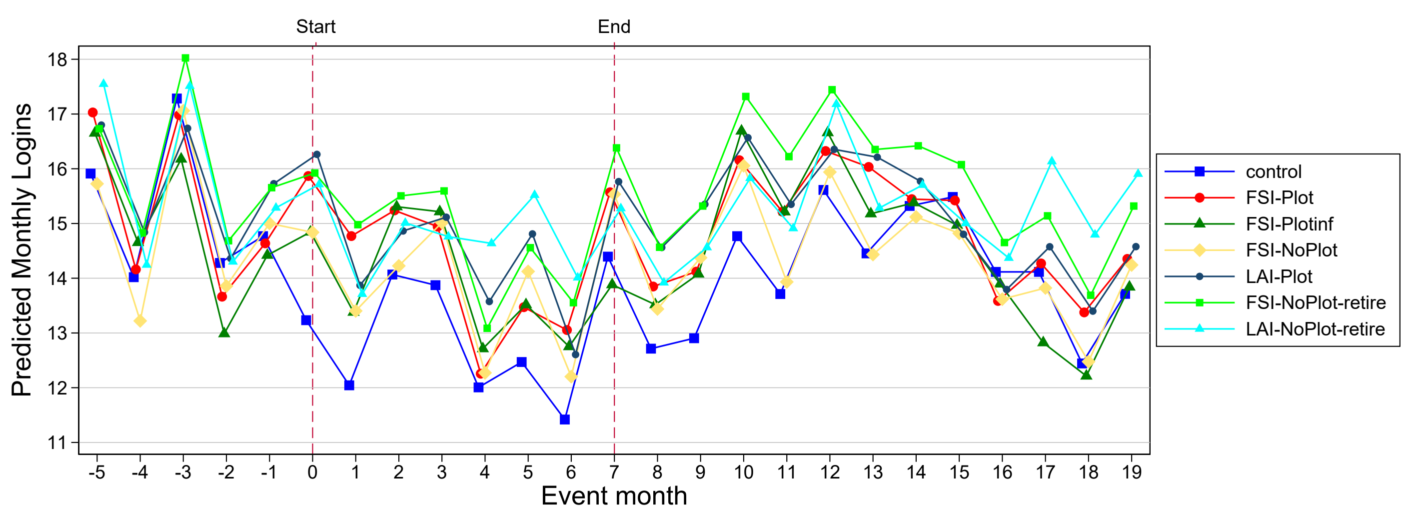


TABLE B3

Treatment Effects on Discretionary Spending (7 Groups)

The dependent variable in all columns is the log of monthly discretionary spending. *Control*, *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, *FSI-NoPlot-retire*, *LAI-Plot*, and *LAI-NoPlot-retire* are treatment group indicator variables (see Table B1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1). *Intra* is an indicator variable for the eight months during which experiment materials were presented in the app (t=0 to t=7), and *Post* is an indicator for the following twelve months (t=8 to t=19). 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.

Variables	(1)	(2)	(3)
*Control * Intra*		0.156**	0.147**
		(2.22)	(2.25)
*FSI-Plot * Intra*	-0.156**		-0.009
	(-2.22)		(-0.13)
*FSI-Plot-inf * Intra*	-0.147**	0.009	
	(-2.25)	(0.13)	
*FSI-NoPlot * Intra*	-0.012	0.144**	0.135**
	(-0.18)	(2.00)	(2.01)
*LAI-Plot * Intra*	0.009	0.165**	0.156**
	(0.13)	(2.24)	(2.26)
*FSI-NoPlot-retire * Intra*	-0.036	0.120**	0.111**
	(-0.66)	(1.99)	(2.04)
*LAI-NoPlot-retire * Intra*	0.006	0.162**	0.154**
	(0.09)	(2.11)	(2.12)
*Control * Post*		0.092	0.073
		(0.98)	(0.77)
*FSI-Plot * Post*	-0.092		-0.019
	(-0.98)		(-0.19)
*FSI-Plot-inf * Post*	-0.073	0.019	
	(-0.77)	(0.19)	
*FSI-NoPlot * Post*	-0.022	0.070	0.050
	(-0.25)	(0.73)	(0.52)
*LAI-Plot * Post*	-0.035	0.057	0.038
	(-0.37)	(0.57)	(0.37)
*FSI-NoPlot-retire * Post*	-0.026	0.066	0.047
	(-0.34)	(0.82)	(0.58)
*LAI-NoPlot-retire * Post*	-0.034	0.057	0.038
	(-0.38)	(0.59)	(0.39)
reference group	Control	FSI-Plot	FSI-Plot-inf
consumer FE	Y	Y	Y
event month FE	Y	Y	Y
N	78,450	78,450	78,450
adj. R2	0.65	0.65	0.65

FIGURE B2

Monthly Discretionary Spending by Treatment Group (7 Groups)

The figure shows the estimated coefficients in a regression of log monthly discretionary spending on event month indicator variables with consumer fixed effects for each treatment group. Detailed regression results are in Table A2.

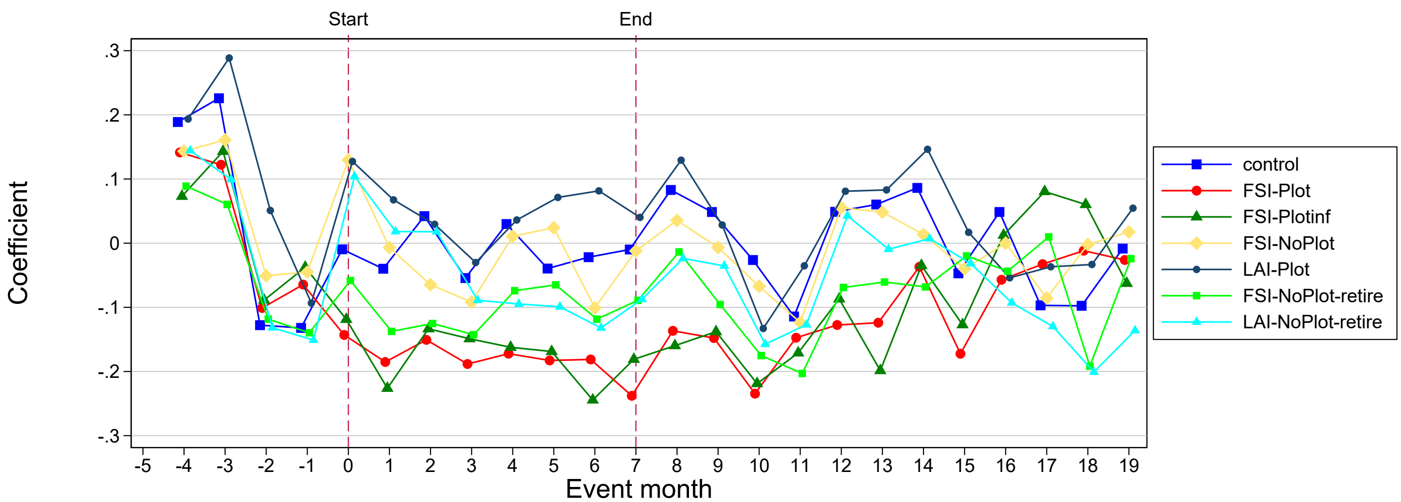


TABLE B4

Treatment Effects on Discretionary Spending Over Four Months Intervals (7 Groups)

The dependent variable in all columns is the log of monthly discretionary spending. *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, *FSI-NoPlot-retire*, *LAI-Plot*, and *LAI-NoPlot-retire* are treatment group indicator variables (see Table B1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1) and the reference group is the *Control* group. Treatment group indicators are interacted with a time period indicator for the four months listed at the top of each column. Experiment materials were presented on the app from $t = 0$ to $t = 7$. 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.

Variables	(1)	(2)	(3)	(4)	(5)
Interaction:	$I(0 \leq t \leq 3)$	$I(4 \leq t \leq 7)$	$I(8 \leq t \leq 11)$	$I(12 \leq t \leq 15)$	$I(16 \leq t \leq 19)$
FSI-Plot * $I(a \leq t \leq b)$	-0.140**	-0.172**	-0.153*	-0.141	0.018
	(-2.02)	(-1.97)	(-1.69)	(-1.31)	(0.16)
FSI-Plot-inf * $I(a \leq t \leq b)$	-0.128**	-0.166**	-0.157*	-0.136	0.074
	(-2.03)	(-2.00)	(-1.70)	(-1.28)	(0.63)
FSI-NoPlot * $I(a \leq t \leq b)$	-0.004	-0.020	-0.049	-0.028	0.010
	(-0.06)	(-0.23)	(-0.55)	(-0.28)	(0.09)
LAI-Plot * $I(a \leq t \leq b)$	0.007	0.011	-0.057	-0.012	-0.036
	(0.10)	(0.13)	(-0.63)	(-0.12)	(-0.30)
FSI-NoPlot-retire * $I(a \leq t \leq b)$	-0.048	-0.024	-0.067	-0.039	0.029
	(-0.88)	(-0.35)	(-0.91)	(-0.47)	(0.31)
LAI-NoPlot-retire * $I(a \leq t \leq b)$	0.067	-0.054	-0.045	0.004	-0.063
	(0.98)	(-0.61)	(-0.52)	(0.04)	(-0.53)
consumer FE	Y	Y	Y	Y	Y
event month FE	Y	Y	Y	Y	Y
N	28,242	28,242	28,242	28,242	28,242
adj. R2	0.73	0.70	0.68	0.64	0.60

TABLE B5

Treatment Effects on Spending Categories (7 Groups)

The dependent variables in columns (1)-(4) are the log of monthly spending in the corresponding category, and the log of monthly cash withdrawal is in column (5). The dependent variable in column (6) is the log sum of the five largest spending transactions for a given consumer-month. *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, *FSI-NoPlot-retire*, *LAI-Plot*, and *LAI-NoPlot-retire* are treatment group indicator variables (see Table B1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1) and the reference group is the *Control* group. *Intra* is an indicator variable for the eight months during which experiment materials were presented in the app (t=0 to t=7), and *Post* is an indicator for the following twelve months (t=8 to t=19). 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.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Dependent:	Restaurants	Clothing	Entertainment	Travel	Cash Withdrawal	5 Largest Transactions
*FSI-Plot * Intra*	-0.140**	-0.219**	-0.155**	-0.222**	-0.265**	-0.127***
	(-1.96)	(-2.37)	(-2.23)	(-2.12)	(-2.23)	(-2.94)
*FSI-Plot-inf * Intra*	-0.137**	-0.184**	-0.132**	-0.257**	-0.237**	-0.141***
	(-1.99)	(-2.07)	(-2.03)	(-2.45)	(-2.19)	(-3.92)
*FSI-NoPlot * Intra*	0.052	0.010	0.014	0.015	-0.009	-0.037
	(0.75)	(0.10)	(0.21)	(0.14)	(-0.07)	(-0.98)
*LAI-Plot * Intra*	0.020	-0.004	0.002	0.082	0.007	-0.038
	(0.29)	(-0.05)	(0.03)	(0.74)	(0.06)	(-1.03)
*FSI-NoPlot-retire * Intra*	-0.005	-0.005	0.006	-0.005	-0.023	-0.002
	(-0.09)	(-0.08)	(0.09)	(-0.05)	(-0.20)	(-0.08)
*LAI-NoPlot-retire * Intra*	0.023	-0.041	-0.007	0.021	-0.025	-0.000
	(0.33)	(-0.47)	(-0.10)	(0.20)	(-0.27)	(-0.01)
*FSI-Plot * Post*	0.004	0.089	-0.018	0.035	0.006	-0.042
	(0.05)	(0.81)	(-0.20)	(0.27)	(0.04)	(-0.88)
*FSI-Plot-inf * Post*	0.008	0.030	0.023	-0.017	0.021	0.000
	(0.09)	(0.29)	(0.28)	(-0.13)	(0.15)	(0.00)
*FSI-NoPlot * Post*	-0.021	-0.010	0.016	0.027	-0.030	-0.011
	(-0.23)	(-0.09)	(0.18)	(0.21)	(-0.21)	(-0.25)
*LAI-Plot * Post*	-0.037	-0.041	-0.048	0.011	0.025	0.033
	(-0.40)	(-0.39)	(-0.56)	(0.08)	(0.17)	(0.71)
*FSI-NoPlot-retire * Post*	0.021	0.066	0.002	0.018	0.003	0.021
	(0.29)	(0.79)	(0.02)	(0.14)	(0.02)	(0.52)
*LAI-NoPlot-retire * Post*	-0.017	0.011	-0.009	-0.014	0.013	0.017
	(-0.19)	(0.11)	(-0.11)	(-0.11)	(0.11)	(0.40)
consumer FE	Y	Y	Y	Y	Y	Y
event month FE	Y	Y	Y	Y	Y	Y
N	78,450	78,450	78,450	78,450	78,450	78,450
adj. R2	0.71	0.50	0.57	0.48	0.49	0.49

TABLE B6

Treatment Effects on Additional Spending Categories (7 Groups)

The dependent variables are the log of monthly total spending in column (1) and log monthly spending in the corresponding category in columns (2)-(5). *FSI-Plot*, *FSI-Plot-inf*, *FSI-NoPlot*, and *LAI-Plot* are treatment group indicator variables (see Table B1 for details). The baseline period in all regressions is the five months before the experiment launch (t=-5 to t=-1) and the reference group is the *Control* group. *Intra* is an indicator variable for the eight months during which experiment materials were presented in the app (t=0 to t=7), and *Post* is an indicator for the following twelve months (t=8 to t=19). 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.

Variables	(1)	(2)	(3)	(4)	(5)
Dependent:	Spending	Gas	Groceries	Telephone	Utilities
*FSI-Plot * Intra*	-0.065*	0.026	0.010	-0.046	-0.086
	(-1.95)	(0.39)	(0.15)	(-0.65)	(-0.95)
*FSI-Plot-inf * Intra*	-0.053*	0.090	0.069	-0.001	-0.080
	(-1.74)	(1.24)	(1.00)	(-0.01)	(-0.91)
*FSI-NoPlot * Intra*	0.007	0.008	0.024	0.007	-0.107
	(0.22)	(0.14)	(0.35)	(0.09)	(-1.22)
*LAI-Plot * Intra*	0.006	0.093	0.025	-0.030	-0.021
	(0.19)	(1.43)	(0.37)	(-0.41)	(-0.22)
*FSI-NoPlot-retire * Intra*	-0.001	0.033	0.024	-0.047	0.002
	(-0.02)	(0.64)	(0.37)	(-0.65)	(0.03)
*LAI-NoPlot-retire * Intra*	0.001	0.100	0.076	-0.000	0.015
	(0.04)	(1.53)	(1.11)	(-0.00)	(0.17)
*FSI-Plot * Post*	-0.003	-0.024	-0.041	-0.012	-0.126
	(-0.06)	(-0.31)	(-0.42)	(-0.14)	(-1.06)
*FSI-Plot-inf * Post*	-0.012	0.010	0.063	0.051	-0.073
	(-0.30)	(0.11)	(0.65)	(0.58)	(-0.66)
*FSI-NoPlot * Post*	0.021	0.023	-0.005	0.071	-0.162
	(0.52)	(0.34)	(-0.06)	(0.82)	(-1.46)
*LAI-Plot * Post*	0.017	-0.098	0.013	-0.082	-0.167
	(0.40)	(-1.25)	(0.14)	(-0.95)	(-1.44)
*FSI-NoPlot-retire * Post*	-0.018	-0.001	0.057	0.024	0.042
	(-0.45)	(-0.02)	(0.63)	(0.31)	(0.36)
*LAI-NoPlot-retire * Post*	-0.005	-0.027	0.044	0.034	0.012
	(-0.12)	(-0.33)	(0.48)	(0.39)	(0.10)
consumer FE	Y	Y	Y	Y	Y
event month FE	Y	Y	Y	Y	Y
N	78,450	51,375	62,350	49,675	48,150
adj. R2	0.61	0.37	0.42	0.27	0.24

TABLE B7

Balance Tests

Variables are defined in Table 3.

Panel A.

Treatment	N	Age mean	Age sd	Net Worth mean	Net Worth sd	Personalized Index mean	Personalized Index sd	Logins mean	Logins sd
Control	458	44.48	7.78	1,146,247	1,583,688	3,274	5,562	15.25	17.52
FSI-Plot	422	44.4	7.93	1,184,688	1,645,099	3,310	4,854	15.29	22.21
FSI-Plot-inf	450	44.23	7.96	1,086,211	1,357,686	2,953	4,791	14.98	21.03
FSI-NoPlot	434	44.67	7.77	1,114,032	1,391,693	2,990	4,603	14.97	20.20
LAI-Plot	426	44.78	7.9	1,126,652	1,600,438	3,367	6,766	15.69	19.15
FSI-NoPlot-retire	477	44.48	7.91	1,097,916	1,302,980	3,037	4,713	15.98	21.60
LAI-NoPlot-retire	471	44.84	8.08	1,144,653	1,563,826	3,328	4,940	15.78	21.27

Panel B.

Treatment	N	Income mean	Income sd	Spending mean	Spending sd	Discretionary Spending mean	Discretionary Spending sd	Clothing mean	Clothing sd
Control	458	16,863	12,683	12,323	9,826	3,610	3,290	371	492
FSI-Plot	422	16,721	13,405	12,748	10,396	3,694	3,547	406	577
FSI-Plot-inf	450	16,446	12,753	12,459	10,062	3,836	3,709	384	552
FSI-NoPlot	434	16,692	13,110	12,047	9,841	3,669	3,549	370	484
LAI-Plot	426	17,284	13,525	12,678	10,434	3,621	3,206	369	467
FSI-NoPlot-retire	477	16,972	13,370	12,022	8,656	3,690	3,168	362	396
LAI-NoPlot-retire	471	16,531	13,355	12,323	9,971	3,701	3,654	359	485

Panel C.

Treatment	N	Entertainment mean	Entertainment sd	Restaurants mean	Restaurants sd	Travel mean	Travel sd	Cash Withdrawal mean	Cash Withdrawal sd
Control	458	170	224	508	494	667	1,050	913	1,281
FSI-Plot	422	172	238	531	547	677	1,038	946	1,458
FSI-Plot-inf	450	177	213	495	450	742	1,123	969	1,292
FSI-NoPlot	434	163	201	499	434	686	1,014	934	1,331
LAI-Plot	426	168	225	509	460	749	1,156	942	1,320
FSI-NoPlot-retire	477	163	197	490	445	682	830	903	1,344
LAI-NoPlot-retire	471	161	224	499	525	656	1,018	871	1,264

C. Experiment Material

FIGURE C1

Full Dashboard Page for the Control Group

This dashboard page was presented to all treatment groups before the experiment launch $(t < 0)$ and after the removal of the experiment material from the app $(t > 7)$.

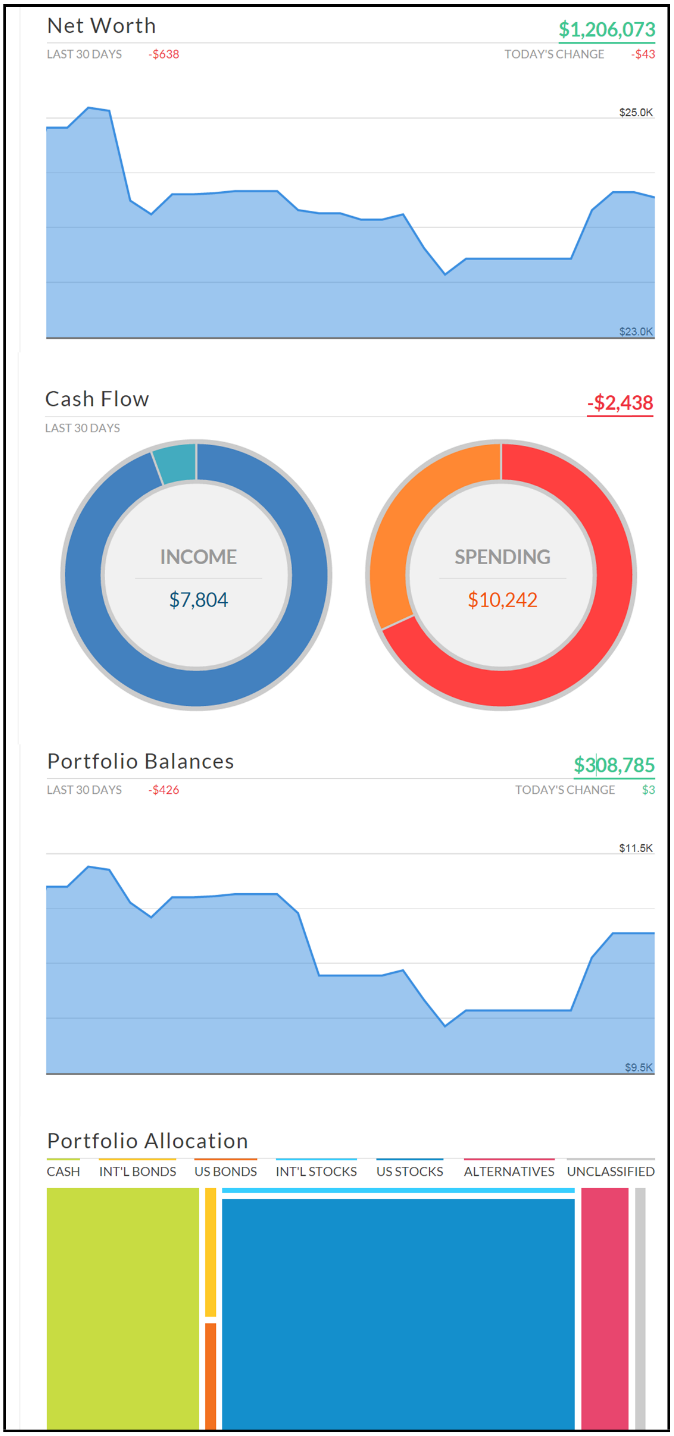


FIGURE C2

Full Dashboard Page for the FSI-Plot Treatment

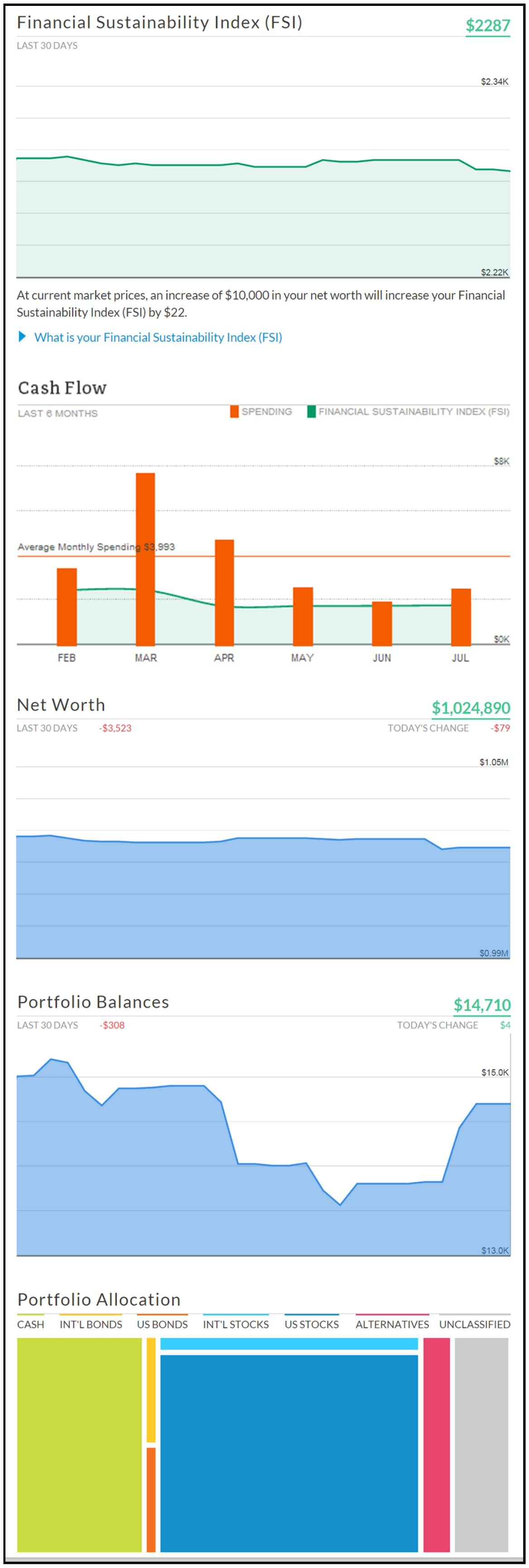


FIGURE C3

Top of the Dashboard Page for the FSI-Plot Treatment

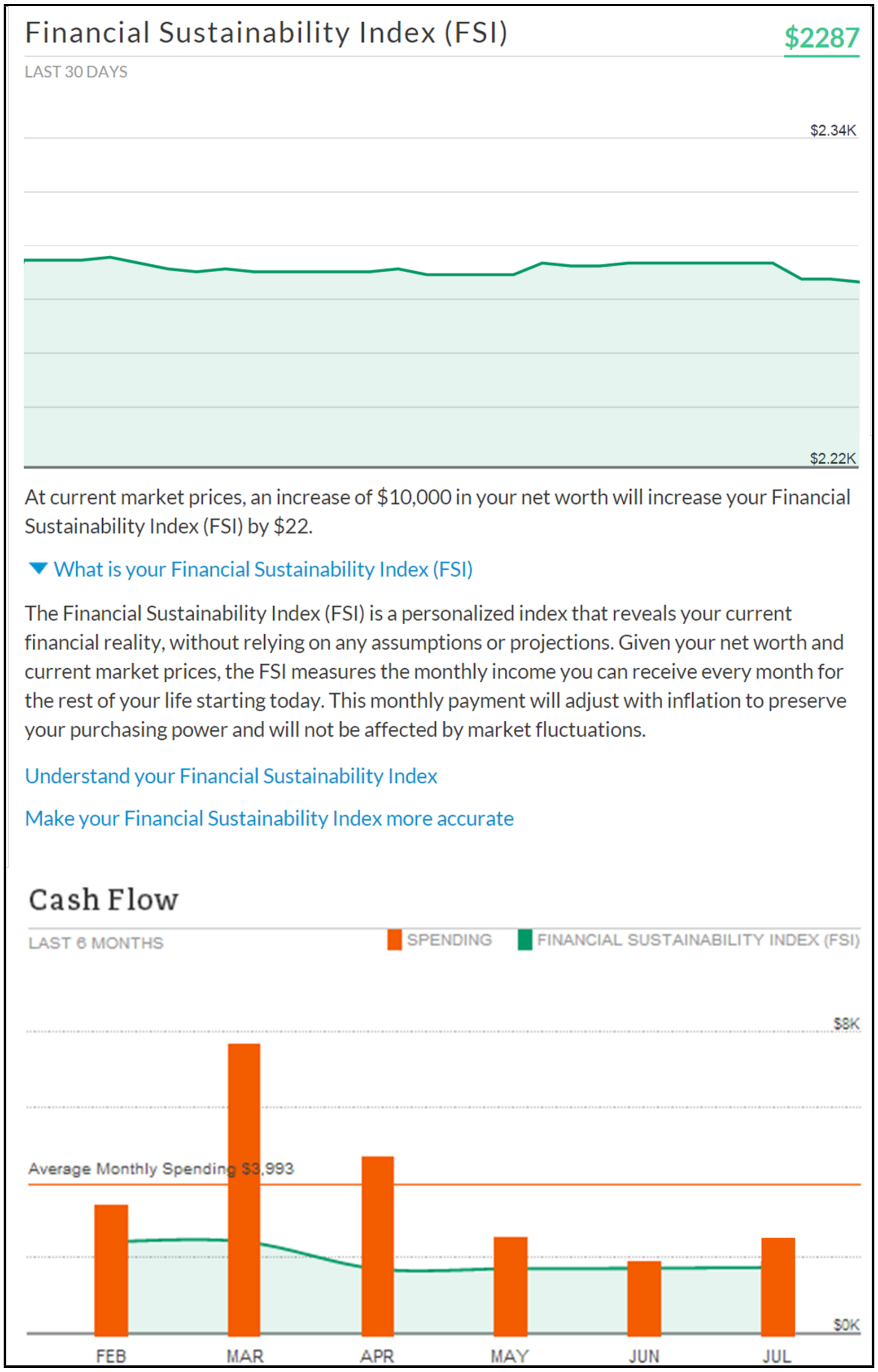
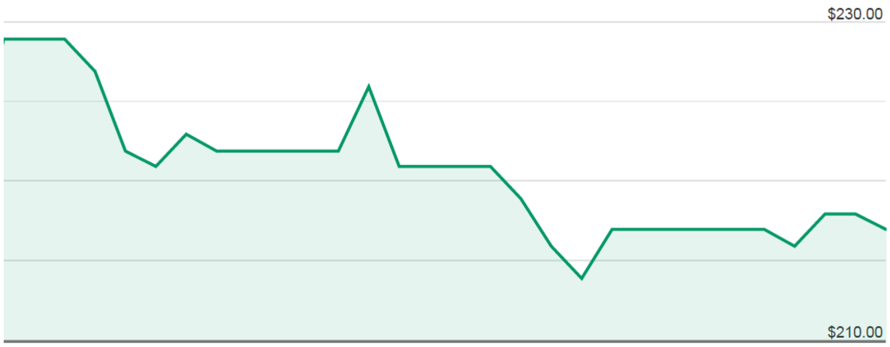


FIGURE C4

Top of the Dashboard Page for the FSI-NoPlot Treatment

Financial Sustainability Index (FSI) $217

LAST 30 DAYS



At current market prices, an increase of $10,000 in your net worth will increase your Financial Sustainability Index (FSI) by $31.

▼ What is your Financial Sustainability Index (FSI)

The Financial Sustainability Index (FSI) is a personalized index that reveals your current financial reality, without relying on any assumptions or projections. Given your net worth and current market prices, the FSI measures the monthly income you can receive every month for the rest of your life starting today. This monthly payment will adjust with inflation to preserve your purchasing power and will not be affected by market fluctuations.

Understand your Financial Sustainability Index

Make your Financial Sustainability Index more accurate

FIGURE C5

Top of the Dashboard Page for the LAI-Plot Treatment

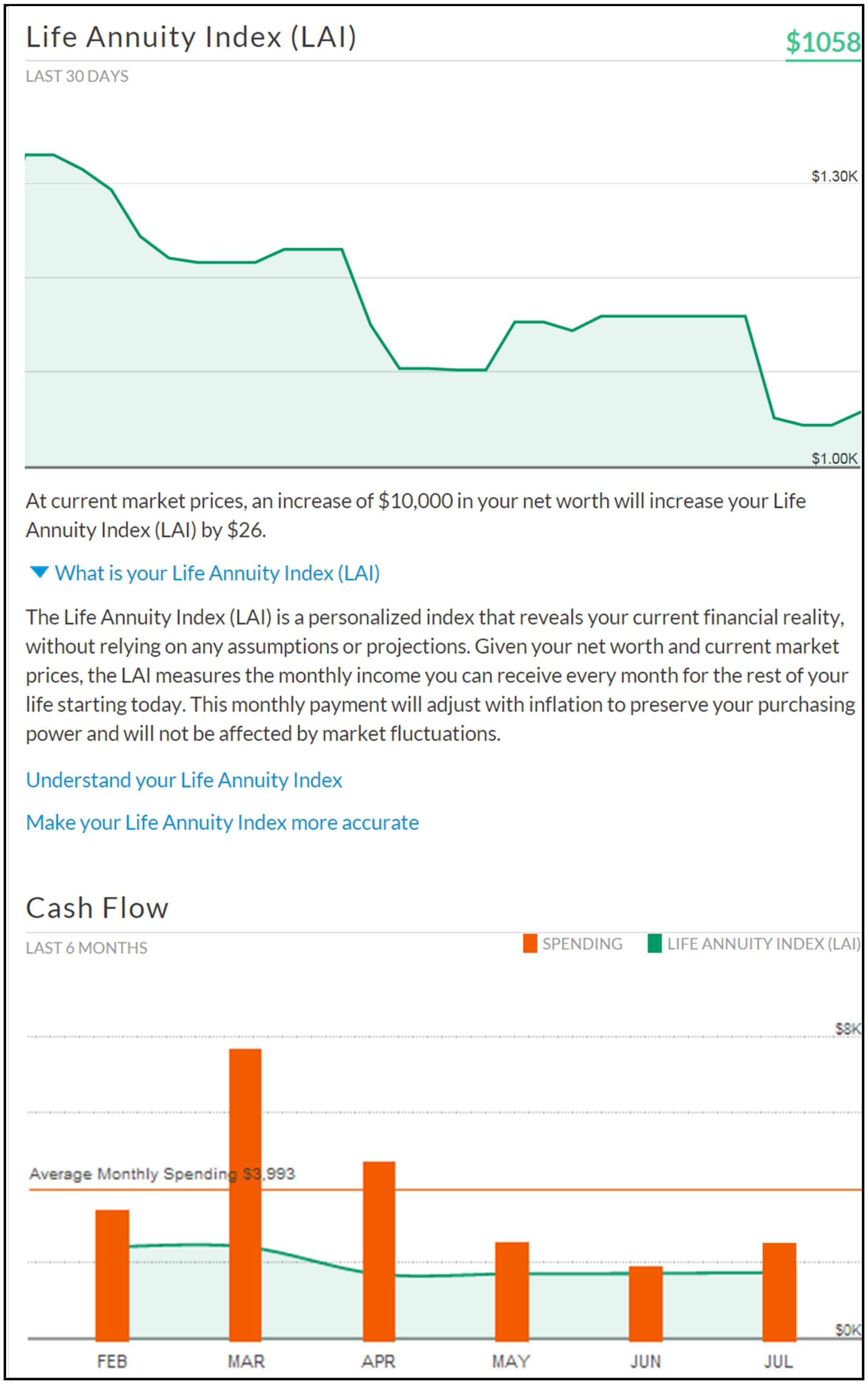
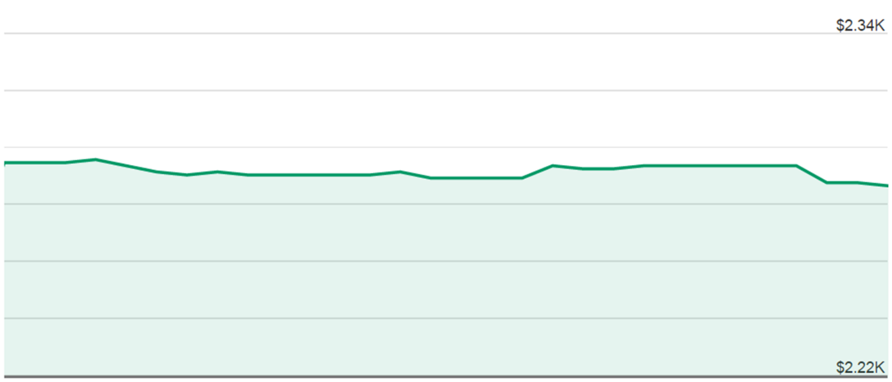


FIGURE C6

Top of the Dashboard Page for the FSI-NoPlot-retire Treatment

Financial Sustainability Index (FSI) **$2287**

LAST 30 DAYS



At current market prices, an increase of $10,000 in your net worth will increase your Financial Sustainability Index (FSI) by $58.

▼ What is your Financial Sustainability Index (FSI)

The Financial Sustainability Index (FSI) is a personalized index that reveals your current financial reality, without relying on any assumptions or projections. Given your net worth and current market prices, the FSI measures the monthly income you can receive every month for the rest of your life starting at your retirement. This monthly payment will adjust with inflation to preserve your purchasing power and will not be affected by market fluctuations.

Understand your Financial Sustainability Index

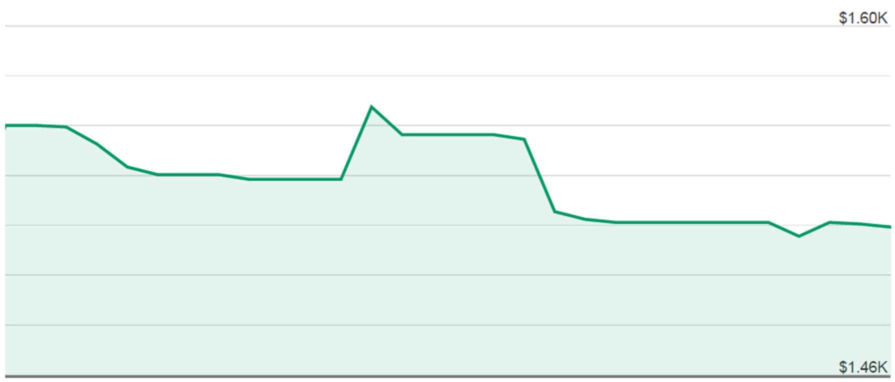
Make your Financial Sustainability Index more accurate

FIGURE C7

Top of the Dashboard Page for the LAI-NoPlot-retire Treatment

Life Annuity Index (LAI) $1520

LAST 30 DAYS



At current market prices, an increase of $10,000 in your net worth will increase your Life Annuity Index (LAI) by $122.

▼ What is your Life Annuity Index (LAI)

The Life Annuity Index (LAI) is a personalized index that reveals your current financial reality, without relying on any assumptions or projections. Given your net worth and current market prices, the LAI measures the monthly income you can receive every month for the rest of your life starting at your retirement. This monthly payment will adjust with inflation to preserve your purchasing power and will not be affected by market fluctuations.

Understand your Life Annuity Index

Make your Life Annuity Index more accurate

FIGURE C8

FAQ page for the FSI-Plot Treatment (part 1)

What is your Financial Sustainability Index?

The Financial Sustainability Index (FSI) is a personalized index that reveals your current financial reality, without relying on any assumptions or projections. Given your net wealth and current market prices, the FSI measures the monthly income you can receive every month for the rest of your life starting today. This monthly payment will adjust with inflation to preserve your purchasing power and will not be affected by market fluctuations.

What can I learn from the Financial Sustainability Index?

Having all of your financial information in a single location is a great first step. The next step is to understand what this information actually means. Do you have enough money? Should you be saving more? Can you afford to increase your spending? The goal of the FSI is to give you reliable answers to these hard questions.

What are the problems with current solutions?

Unfortunately, people often struggle to come up with the correct answers to personal finance questions. Instead of using reliable numbers, they tend to rely on short-cuts, such as whether or not the amount of money in an investment account *seems* like a lot, or if it's more than our peers have saved. However, these shortcuts often lead to the wrong conclusions when it comes to financial planning.

Another approach involves using financial calculators to come up with a multi-decade financial plan. While these plans can be useful, they are highly dependent on many assumptions about the distant future, such as years of remaining work, market returns, inflation rates and other variables. Alas, history demonstrates that these assumptions are often very inaccurate, which means that our detailed financial plans can be misleading. Life is full of unexpected events, especially over long time horizons.

How is the Financial Sustainability Index different?

The Financial Sustainability Index takes a new approach to financial planning. Instead of making assumptions about the distant future, it simply tells you what you can purchase in the financial markets at current market prices.

The monthly income stream eliminates all the major risk factors that are relevant to your financial future:

- *Market risk* - The FSI income stream will not be affected by any market fluctuation.
- *Inflation risk* – Over the last 20 years, cash lost 37% of its value. The FSI presents possible real monthly income that preserves your purchasing power.
- *Longevity risk* – The FSI represent the income you can receive for the rest of your life.

The FSI is simple, fast and intuitive. The Index is based upon extensive field studies in the areas of household finance, behavioral economics and psychology to help you make the best financial decisions. It does not require you to read through lengthy financial reports. It adjusts instantly to your financial information and market conditions. All information is described in terms of monthly income (rather than a lump sum) so that you can think more clearly about your financial future.

FIGURE C9

FAQ page for the FSI-Plot Treatment (part 2)

What should I do with this information?

The FSI does *not* tell you how much you should be spending, or how to divide your savings between bonds and stock. Rather, it is simply a useful piece of information that helps you understand where you stand.

Using this index you can measure how far are you from a sustainable level of spending. For example, if your average monthly spending is far above your FSI level, then your current spending levels are not sustainable. Perhaps you should cut back, or even postpone your retirement. On the other hand, if your FSI is above your spending levels, then you might consider increasing your spending and enjoying higher living standards.

From your dashboard, you can see how additional savings or spending affect your FSI. You might want to consult the dashboard or speak to one of our dedicated financial advisors about the potential impact of additional spending or saving.

This data are for informational purposes only and does not constitute a recommendation to buy or sell securities. You should not rely on this information as the primary basis of your investment, financial, or tax planning decisions. Third party data is obtained from sources believed to be reliable. However, we cannot guarantee that data's currency, accuracy, timeliness, completeness or fitness for any particular purpose.

How is the index calculated?

The index is calculated daily using your net worth, personal information and current market prices of many asset classes including government bonds, fixed income securities, inflation swaps and annuities. The index is sensitive to changes in your net worth, as well as to shifts in market conditions such as inflation and interest rates.