Promoting Positive Financial Outcomes: The Role of Expense-Tracking as A Financial Self-Regulatory Behavior

By

Yiling Zhang

A dissertation submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

(Human Ecology)

at the

UNIVERSITY OF WISCONSIN-MADISON

2024

Date of final oral examination: 5/1/2024

The dissertation is approved by the following members of the Final Oral Committee:

Christina Yiwei Zhang, Assistant Professor, Consumer Science

Clifford A Robb, Lorna Jorgenson Wendt Professor in Money, Relationships & Equality, Consumer Science

Lydia M Ashton, Assistant Professor, Consumer Science

Evan Garrett Fraser Polman, Kuechenmeister-Bascom Professor in Business, Marketing

Acknowledgements

The journey of pursuing a doctoral degree and completing this dissertation has been an invaluable experience shaped by the tremendous support and guidance of many individuals. First and foremost, I would like to express my sincere gratitude to my advisor, Dr. Yiwei Zhang. It was her presentation on how consumers budget during my second year that sparked my curiosity and inspired me to explore expense tracking as my dissertation topic. Her invaluable guidance, unwavering support, and thought-provoking feedback have been instrumental in shaping my research and in nurturing my growth as an independent researcher. I am deeply appreciative of her mentorship style, which empowered me to find my own path while cultivating confidence in my research abilities.

I am deeply grateful to my exceptional dissertation committee members: Dr. Cliff Robb, Dr. Lydia Ashton, and Dr. Evan Polman. Dr. Robb's extensive experience in personal finance provided practical perspectives, such as suggesting that I clarify what I mean by better financial outcomes. Dr. Ashton's expertise in econometric modeling guided me in refining my analytical approach, leading to more robust findings. Dr. Polman's impressive responsiveness and insightful feedback helped me better frame my research questions, clarify the theoretical framework, and prepare me for successful publication efforts.

My heartfelt appreciation extends to the broader community of the School of Human

Ecology (SoHE). Dr. Melissa Bublitz not only provided valuable feedback on my dissertation chapters, but also shared practical advice on navigating the publication process, such as tailoring my work to specific journals. Dr. Katie Fitzpatrick's guidance on refining my job market paper and presentation slides was invaluable. Dr. Nancy Wong's expertise in theoretical frameworks helped me learn how to develop an appropriate conceptual foundation for my work. Dr. Gisella Kagy's meticulous review of my data description ensured clarity and comprehensibility. Dr. Michael Collins's mentorship in revising my job market materials was instrumental to my success in the academic job market. Dr. Megan Bea's practical suggestions on structuring my job market presentation helped me communicate my research effectively. I am also grateful to Dr. Judi Bartfeld for her efforts to foster a fair and nurturing environment for graduate students and to Patty Sigler, whose guidance in teaching helped me develop rich pedagogical skills as a student lecturer for four consecutive semesters.

The steadfast support of the SoHE staff – Michelle Holland, Michelle Hamilton, and Cadin Tonković-Ćapin – has been a constant source of strength. Their professionalism, knowledge, and willingness to help, whether I needed assistance in navigating administrative processes or a listening ear during stressful times, made a significant difference. I am also grateful for the wonderful events they organized, such as the International Student Coffee Chats and workshops, which provided opportunities for personal and professional growth.

My journey would not have been the same without the friendship and emotional support of my exceptional cohort – Xiangchen, Wanting, Felix, Trisha, and Madeline. We not only discussed our research and provided feedback to one another, but also explored Madison together, trying new foods and engaging in shared experiences that made the challenges of the doctoral program more manageable. Our friendship and the shared experiences full of both laughter and tears made this arduous journey truly memorable.

I am eternally indebted to my parents, whom I call Baba and Mama in Chinese, for their unconditional love, emotional encouragement, and financial support. Despite being professors themselves, they have never imposed expectations of achievement upon me. Instead, they taught me the importance of integrity and encouraged me to pursue a path that brought me genuine happiness and fulfillment. Their unwavering belief in my choices gave me the strength to stay true to my values and aspirations.

Finally, I would like to express my sincere gratitude to the tracking app company that shared the de-identified user data with me. Their support and willingness to collaborate with a young researcher like myself were invaluable in enabling this novel work on expense tracking behaviors.

Abstract

Many individuals set financial goals, yet encounter frequent consumption temptations in daily life. Failing to exercise self-control to resist these temptations can lead to overspending and negative financial outcomes. Such outcomes not only hinder financial well-being, but also have broader life implications, including increased stress, poorer personal health, and lower life satisfaction. Psychological self-regulation theories suggest that self-monitoring can help overcome self-control problems. Since expense tracking can be viewed as a form of financial self-monitoring, it may assist with enhancing financial self-control and promoting financial well-being. This dissertation conducted empirical analyses to examine real-world expense tracking behavior using data from a financial tracking app, supplemented with survey data collected from app users.

Building upon prior literature, this dissertation examines expense tracking as a self-regulatory behavior within the context of financial self-regulation, providing a comprehensive investigation into expense tracking behavior. Specifically, it offers suggestive evidence that: (a) expense tracking provides diagnostic information, facilitating spending control; (b) effective financial self-regulation hinges on accurate categorization, consistent recording patterns, and developing an expense tracking habit; and (c) fresh start effects aroused by temporal landmarks can promote the initiation and persistence of expense tracking behavior.

Collectively, these findings offer new insights to inform individual decision-makers, financial education, and financial service providers on leveraging expense tracking to promote financial well-being.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Individuals encounter numerous consumption temptations in their daily lives, which often conflict with their financial goals, such as savings goals or budgeting goals. Falling to execute self-control to resist these temptations can lead to negative financial outcomes, such as overspending, indebtedness, or non-adherence to budgets. Such outcomes not only hinder financial well-being, but also have broader implications for life and social aspects, including strained family relationships, stress, poor personal health, and lower life satisfaction (Bearden and Haws, 2012; Gutter and Copur, 2011; O'Neill et al., 2005; Xiao et al., 2006).

Psychological self-regulation theories suggest that self-monitoring as a self-regulatory behavior can help with self-control problems (Carver and Scheier, 2001). Financial self-regulation refers to the process by which people resist consumption temptations and align their spending and saving behaviors with their financial goals (Peetz and Davydenko, 2022). Since expense tracking can be considered a form of self-monitoring in the financial context, it can assist with financial self-control to promote financial well-being.

Despite the importance of expense tracking, there are significant gaps in the existing literature. First, expense tracking has mainly been studied in the mental budgeting and mental accounting literature to support budgeting (Heath and Soll, 1996; R. Thaler, 1985; R. H. Thaler, 1999; C. Y. Zhang and Sussman, 2018), instead of a self-regulatory behavior. Moreover, previous research in this domain has mainly focused on the challenges of recording expenditures (Barsalou, 1991; Gourville, 1998; Sussman and Alter, 2012; Sussman et al., 2015) and is often conducted in laboratory settings (C. Y. Zhang and Sussman, 2018) with limited exploration of how individuals track spending in real-world contexts.

Second, there is limited research that specifically addresses financial self-regulation. While financial goal setting is a common practice (Williamson and Wilkowski, 2020), research on self-regulation has predominantly focused on education (Duckworth et al., 2016, 2019), such as academic goals, and health (Burke et al., 2011; Mairs and Mullan, 2015; Thompson-Felty and Johnston, 2017; Todd and Mullan, 2014), such as weight loss and sleep. Moreover, existing studies on financial self-regulation have a narrow scope, primarily examining general self-regulation strategies (Peetz and Davydenko, 2022) and the factors associated with self-regulation in financial decision-making (Howlett et al., 2008; Palmer et al., 2021).

Third, there is a limited exploration of the motivations driving people to initiate expense tracking goals and their persistence in expense tracking activities (C. Y. Zhang and Sussman, 2018).

To fill these research gaps, this dissertation considers expense tracking as a self-regulatory behavior within the context of financial self-regulation, and aims to provide a comprehensive investigation into expense tracking behavior. Specifically, this three-paper dissertation addresses the following questions: Paper 1 examines how expense tracking, as a form of self-regulatory behavior, informs financial behaviors; Paper 2 explores expense tracking patterns that are associated with better financial self-regulation; Paper 3 examines the impact of fresh start effect on prompting expense tracking behavior.

1.1 Paper 1: Financial Self-regulation: How Does Expense Tracking Inform Financial Behaviors

Paper 1 examines how expense tracking informs financial behavior in terms of spending and budgeting. I obtained longitudinal administrative-level user data from a Chinese tracking app that facilitates expense tracking[1]. I focus on active tracking behavior wherein individuals manually record their transactions. Although app data are selective, they provide a means of measuring individuals' high-frequency tracking behavior.

Through empirical analysis (i.e., panel fixed effects models), I document that expense tracking provides diagnostic information, leading to spending control. In particular, I find evidence that persistent expense tracking is associated with a reduction in the share of discretionary spending over monthly spending. In other words, people decrease their self-reported spending, which is classified as discretionary spending, as a percentage of total spending the longer they track. However, persistent expense tracking does not necessarily lead to better adherence to monthly budgets.

This paper serves as the cornerstone of this dissertation, establishing that persistent expense tracking may be associated with positive financial behavior.

[1]Individuals can manually record their income and expenses, set spending limits, and perform basic spending analyses using this app.

1.2 Paper 2: Optimizing Expense Tracking for Financial Self-regulation: Insights from Individual Practices

Building upon the findings from Paper 1, Paper 2 explores expense tracking patterns conducive to effective financial self-regulation, aiming to offer practical insights for individual decision-makers and financial education initiatives striving to improve financial outcomes through the adoption of effective expense tracking practices. In particular, I investigate the accuracy, consistency, and temporal proximity of expense tracking, as these factors influence the quality of self-monitoring and, consequently, the success of self-regulation (Bandura, 1991).

Data were obtained from the same Chinese tracking app, with a survey administered to app users to collect self-reported tracking behavioral data[2] (subjective) and survey respondents' tracking data obtained from the tracking app company, serving as objective behavioral data. Through empirical analysis (i.e., OLS regressions), I document new descriptive evidence on the accuracy, temporal proximity, and consistency of expense tacking behavior and their association with reduced financial worries, assessing whether these aspects align with self-regulation theory (Bandura, 1991).

[2]This survey collects information including goals for tracking, tracking behavior, psychographic characteristics, and demographic information.

1.3 Paper 3: The Fresh Start Effect: How Temporal Landmarks Promote Expense Tracking Behavior

With the preceding studies establishing the connection between expense tracking and improved financial outcomes, Paper 3 focuses on exploring strategies to promote sustained expense tracking. Given the variability inherent in individuals' consumption patterns, which are closely tied to expense tracking, I leverage the fresh start effect, the tendency to pursue aspirational behaviors following temporal landmarks associated with new beginnings, and examine how such temporal landmarks can motivate and sustain expense tracking behavior.

I conducted empirical research (i.e., Cochrane–Orcutt regression and survival analysis) by examining aggregated app-level data and administrative user-level data obtained from the same tracking app.

Paper 3 provides evidence consistent with the fresh start effect in expense tracking, documenting that individuals are more likely to initiate expense tracking using the tracking app at the beginning of each week, month, and year. Moreover, individuals initiating expense tracking at the beginning of a month or year persist in tracking longer than those initiating at other times.

In summary, the findings from this dissertation document that expense tracking is a self-regulatory behavior within the context of financial self-regulation that may help with financial self-control. Expense tracking collects personal spending data that helps individuals align their financial behavior with their financial goals. Moreover, to optimize financial self-regulation, individuals should prioritize the accuracy in categorization, temporal proximity, and consistency of expense tracking. Additionally, individuals could leverage the fresh start effect to promote expense tracking behavior by initiating expense tracking at temporal landmarks signaling new starts.

Chapter 5 concludes this dissertation by offering a comprehensive overview of the research findings, their contributions to the literature, implications for practice, and acknowledging limitations and suggesting avenues for future research.

Chapter 2

Financial Self-regulation: How Does Expense Tracking Inform Financial Behaviors?

Abstract

Expense tracking is essential to money management, yet there is insufficient research on it. This paper examines expense tracking as a self-regulatory behavior within the context of financial self-regulation. Employing administrative-level user data from a Chinese tracking app, this paper finds that persistent expense tracking is associated with a reduction in the share of discretionary spending. However, it does not necessarily lead to better adherence to monthly budgets. These findings contribute to the literature on self-regulation and mental budgeting and provide implications for financial education and public policy by informing a way to promote prudent financial decisions.

2.1 Introduction

Individuals encounter numerous temptations in their daily lives, which often conflict with their financial goals, such as savings goals or budgeting goals. Falling to execute self-control to resist these temptations can lead to negative financial outcomes, such as overspending, indebtedness, or non-adherence to budgets. Such outcomes not only hinder financial well-being but also have broader implications for life and social aspects, including strained family relationships, stress, poor personal health, and lower life satisfaction(Bearden and Haws, 2012; Gutter and Copur, 2011; O'Neill et al., 2005; Xiao et al., 2006).

For individuals with financial goals, tracking their expenses can assist with financial self-control if it is treated as a self-regulatory behavior within the context of financial self-regulation. Self-regulation refers to a dynamic process of identifying a desired end state and working toward it while keeping track of progress along the way (Carver and Scheier, 2001). Despite the importance of expense tracking, there are significant gaps in the existing literature. First, expense tracking has mainly been studied within the mental budgeting domain as a means to support budgeting (Heath and Soll, 1996; R. Thaler, 1985; R. H. Thaler, 1999; C. Y. Zhang and Sussman, 2018), instead of a self-regulatory behavior. Moreover, previous research in this domain has mainly centered around the challenges of recording expenditures (Barsalou, 1991; Gourville, 1998; Su et al., 2021; Sussman et al., 2015), and often conducted in laboratory settings (C. Y. Zhang and Sussman, 2018) with limited exploration of how individuals track spending in real-world contexts. Second, while financial goal setting is a common practice (Fishbach and Hofmann, 2015; Williamson and Wilkowski, 2020), research on self-regulation has predominantly focused on education (Duckworth et al., 2016, 2019) and health goals (Burke et al., 2011; Mairs and Mullan, 2015; Thompson-Felty and Johnston, 2017; Todd and Mullan, 2014), such as academic achievement, weight loss, and sleep.

There is a lack of research specifically addressing financial self-regulation, and existing studies have a narrow scope, primarily examining general self-regulation strategies (Peetz and Davydenko, 2022) and factors associated with self-regulation in financial decision-making (Howlett et al., 2008; Palmer et al., 2021).

This paper examines expense tracking as a self-regulatory behavior within the financial self-regulation context and investigates how expense tracking informs financial behaviors. Drawing on self-regulation and mental budgeting theories, I hypothesize that expense tracking collects personal spending data, which provides critical feedback for evaluating whether one's spending is aligned with their financial goals.

This research analyzes administrative-level user data from a Chinese tracking app where users can manually record their income and expenses, set spending limits, and perform basic spending analyses. I find evidence that persistent expense tracking is significantly associated with a reduction in the share of discretionary spending (Analysis 1). However, it does not necessarily lead to better adherence to monthly budgets (Analysis 2).

Collectively, these findings contribute to the literature on mental budgeting by providing new empirical evidence on the relationship between expense tracking and budget adherence or budget adjustments. Furthermore, this research not only reconciles the findings with the established literature but also expands our understanding of expense tracking within the financial self-regulation context by highlighting it as a self-regulatory behavior that informs financial behaviors. Additionally, promoting positive financial behaviors through expense tracking may have important implications for financial education and public policy, offering insights into fostering prudent financial decision-making.

The remainder of this paper is structured as follows. First, I review the literature on self-regulation and mental budgeting upon which the hypotheses are developed. Next, I present the two analyses and their findings, respectively. Finally, I discuss the implications of this paper for theory and practice, limitations, and directions for future research.

2.2 Literature Review and Theoretical Framework

2.2.1 Financial Self-regulation

Self-regulation refers to a dynamic process of identifying a desired end state and working toward it while keeping track of progress along the way (Carver and Scheier, 2001). It involves individuals altering their responses or inner states in response to a given situation (Baumeister et al., 2007). For example, individuals aiming to lose weight might opt for a nutritious diet and track their daily calorie intake to ensure they don't overeat, even if they prefer junk food to healthy food.

There are rich self-regulation theories and models (for a review, read Inzlicht et al., 2021), and across different self-regulation models, goal setting and self-monitoring are considered essential (Karoly, 1993). Having a clear personal goal is essential for successful self-regulation, as personal standards are used to judge and guide one's actions in the exercise of self-directedness.

Self-monitoring is also integral to self-regulation as it helps improve self-regulation deficits (Todd and Mullan, 2014). Individuals must pay attention to their performance to stay the course or change (Bandura, 1991). For example, a student may have the goal of maintaining a GPA of 3.5 or higher throughout her academic career. This standard guides her actions, such as attending all classes and submitting assignments on time. She also needs to monitor her grades for each assignment to help her stay on track and make informed decisions regarding whether or not to complete the extra credit assignments. In doing so, she exercises self-directedness and regulates her behavior toward achieving her personal goal of academic success.

Self-monitoring has two functions: self-diagnostic and self-motivating (Bandura, 1991). It changes people's behavior to promote goal attainment by providing continuous information on achieving goal states. People can compare their current behavior with their goal standards and execute self-control if their behavior deviates from their goals. Prior research also shows that some people spontaneously set goals when engaging in self-monitoring and being periodically informed of their performance (Bandura and Cervone, 1983; Bandura and Simon, 1977). Moreover, success in self-regulation relies on the fidelity, consistency, and temporal proximity of self-monitoring (Bandura, 1991).

Self-regulation can be applied in the financial context and expense tracking can be treated as a self-monitoring behavior within this context. Financial self-regulation is defined as "the process by which people resist temptations and align their spending and saving behavior with their financial goals" (Peetz and Davydenko, 2022). It plays a central role in financial goal attainment, as financial problems are often associated with self-regulatory problems. Individuals who self-selected to engage in financial self-regulation aim to achieve their financial goals and ultimately attain financial well-being. In other words, they have implicit or explicit spending control goals. Some individuals may explicitly set goals to avoid overspending or increase savings. Effective financial self-regulation can align individuals' spending behavior with these financial goals. Some individuals may not set explicit financial goals but track spending to gain self-knowledge about their spending patterns (Heyen, 2020). However, prior research shows that self-monitoring has a self-motivating function (Bandura and Cervone, 1983; Bandura and Simon, 1977). With self-knowledge from expense tracking, individuals could identify areas for improvement and modify their behavior accordingly. This suggests that even for those who track spending without explicit financial goals, they may still have implicit financial goals.

2.2.2 Expense Tracking within Budgeting, Mental Budgeting, and Mental Accounting Domains

Expense tracking is a common feature established in the literature on budgeting (C. Y. Zhang et al., 2022), mental budgeting (Heath and Soll, 1996), and mental accounting (R. Thaler, 1985). These literatures have a similar definition of expense tracking and generally treat expense tracking as one fundamental step in budgeting (Heath and Soll, 1996). Budgeting is an important financial goal. How expense tracking supports budget adherence can supplement financial self-regulation literature by providing relevant evidence. Therefore, I review the literature on mental budgeting.

Research on mental budgeting indicates two fundamental budgeting processes: setting a budget and tracking ongoing expenses against the budget (Heath and Soll, 1996). Budgeting helps consumers achieve their financial goals as setting a budget increases the clarity of financial goals (Kan et al., 2018). expense tracking requires individuals to remember and assign various purchases to their appropriate accounts (Heath and Soll, 1996). Previous research has demonstrated that expense tracking supports budget adherence because it increases the pain of paying (Gourville, 1998; Kan et al., 2018). The pain of paying applies to purchases that have already happened and to planned purchases that do not occur. Webb and Spiller (2014) find that people feel that earmarked funds have already been spent. Therefore, tracking planned purchases can be similar to actually spending money, which increases the perception of financial constraint.

There are some challenges in tracking expenditures. For instance, people may overlook trivial costs, even frequent expenses (Gourville, 1998). Some expenses are easier to categorize, while others are hard to categorize. Tracking expenses of a category are more easily learned, classified, and remembered (Barsalou, 1991) and thus are easier to track. On the other hand, individuals may fail to record infrequent or unusual expenses because these expenses are hard to categorize and could lead to overspending (Sussman and Alter, 2012; Sussman et al., 2015).

2.2.3 Effect of Expense Tracking on Spending Control

Drawing on the two kinds of literature on self-regulation and mental budgeting, I next discuss the role of expense tracking by extending self-regulation theories to the personal finance domain.

I define expense tracking broadly as the practice of monitoring and evaluating one's expenses. This definition involves various approaches, such as manually recording expenses, categorizing them into relevant accounts, and monitoring expenses directly from bank or credit card statements. The key criterion is that individuals consistently review information related to the timing, amount, and nature of their expenses, such as expenditures on clothing in May. As long as such regular assessment occurs, the behavior can be classified as expense tracking.

I propose that expense tracking works the same way as self-monitoring in self-regulation. First, expense tracking collects personal spending data for evaluating one's progress toward financial goals. Particularly, when individuals set financial goals requiring spending control or adjustment, ongoing expense tracking becomes necessary in financial goal attainment. However, success in self-regulation also relies on the consistency of self-monitoring, as intermittent self-monitoring only provides partial information (Bandura, 1991). Therefore, individuals who persistently track their spending can better understand their spending patterns, which helps them monitor and align spending behavior with their financial goals.

H1*: ongoing expense tracking collects personal spending data, which helps individuals align their spending behavior with their financial goals.*

2.3 Sample Descriptions

Expense tracking could be a potential self-regulatory behavior within the financial context. Therefore, this paper aims to explore how expense tracking informs financial behaviors in terms of spending behaviors in a real-world context. Specifically, I examined the relationship between persistent expense tracking and two types of financial outcomes related to spending control: a decrease in the share of discretionary spending (Analysis 1) and an increase in budget adherence (Analysis 2).

I obtained administrative-level user data from a Chinese tracking app that facilitates expense tracking. In contrast to other budgeting tools such as Mint[3], which automatically pools all expenses and income from their users' bank accounts, this app relies on users' self-reported expenses and earnings. While self-reported data has limitations in terms of accuracy, as recording expenditures can be challenging (Sussman and Alter, 2012; Sussman et al., 2015), it can provide insights into expense tracking behaviors with efforts and attention. The primary functions of this app include recording the amount of earnings or spending on the selected category along with a time denoting when the transaction happens, adding notes to each transaction, setting spending limits (i.e., monthly budgets and categorical budgets), and performing basic spending analysis. Besides these self-reported app data, the app company collects limited demographic information. Only gender information is available.

This research involves two subsamples containing de-identified information. The first subsample includes person-record level data containing individuals' records from January 1st 2018, to December 31st 2019 (referred to as the Tracking Sample). These users were

[3]Mint is a registered trademark of Intuit Inc., https://www.mint.com/

randomly selected from all users who registered to use the app in 2018 (January 1^{st} 2018 - December 31^{st} 2018). To prepare for data analysis, I cleaned the raw data, and the final Tracking Sample includes 1,643 users. Appendix A describes how I cleaned the raw data in detail.

Since only 6% of users in the Tracking Sample set monthly budgets using the app and only these users' most recent budgetary spending limits as of the data collection date are available, another group of users was randomly selected from all users with budgetary spending limits and logged some records in June 2020 (referred to as the Budgeting Sample). The Budgeting Sample is also person-record level data containing individuals' records from July 1^{st} 2020 to December 31^{st} 2020[4]. Additionally, these users' budgetary spending limits were collected three times per month[5]. Appendix C describes how I cleaned the raw data in the Budgeting Sample in more detail. The final Budgeting Sample includes 1,388 users.

The original subsamples were collected at the person-record level. For my main analyses, I aggregated them to the person-month level. Although both the Tracking Sample and the Budgeting Sample are selective as they involve people using a specific Chinese tracking app, the Tracking Sample is more representative of general app users, while the Budgeting Sample is more selective. The Budgeting Sample only includes those who had set monthly spending limits as of June 2020. People with monthly spending limits may differ from the general population. For example, people with monthly spending limits may be more financially aware and goal-oriented when it comes to managing their money.

[4]The data in the Budgeting Sample was collected during the Covid pandemic. Therefore, there might be concerns regarding external validity, specifically the extent to which the findings can be applied to non-Covid times. Since the data was gathered after the Covid lockdown ended in all cities in China in April 2020, the experience of living through the Covid pandemic could potentially influence people's spending behavior.

[5]The amount of each user's monthly spending limit was collected three times a month (on day 1 of a month, on day 15 of a month, and on day 30 of a month).

TABLE 1
Summary Statistics for Two Subsamples

	(1) Tracking Sample	(2) Budgeting Sample
Panel A:User Level Characteristics		
Female	0.65	0.63
With monthly budgets	0.06	1.00
With records of income	0.65	0.78
Panel B: User-Month Level Characteristics		
Monthly income (in RMB)	4,207.15	10,131.52
	(16,489.85)	(19,266.93)
Monthly expenses (in RMB)	3,589.11	8,132.70
	(3,538.81)	(6,447.71)
Number of records per month	31.40	68.53
	(25.42)	(47.81)
Number of income records per month	4.88	5.46
	(14.46)	(12.24)
Number of expense records per month	28.92	64.14
	(22.40)	(44.70)
Number of Users	1,643	1,388

Note.—This table presents descriptive statistics for Tracking Sample (column (1)) and Budgeting Sample (column (2)). The table displays sample means and standard deviations (indicated in parentheses) with the number of users listed in the last row. RMB refers to the Chinese currency. One U.S. dollar is about 7 RMB. Average income and number of income per month are computed among users who ever reported income.

Table 1 presents the summary statistics for each subsample. I find some suggestive evidence that people in the Tracking Sample and Budgeting Sample are different. On average, users in the Tracking Sample reported spending 3,589.11 RMB (about \$513) and earning 4,207.15 RMB (about \$601) per month. Users in the Budgeting Sample reported spending 8,132.70 RMB (about \$1162) and earning 10,131.52 RMB (about \$1447) per month. Moreover, users in the Budgeting Sample are more inclined to report their income and have higher monthly income and expenses than users in the Tracking Sample. Additionally, users in the Budgeting Sample exhibit higher engagement in expense tracking activities, evident from the higher number of monthly records they created.

Financial goals relevant to spending control can be captured in two ways: the decrease of the share of discretionary expenses over total spending and budget adherence. Therefore, I used the Tracking Sample and Budgeting Sample to examine the effect of expense tracking on spending behavior.

2.4 Analysis 1: The Impact of Expense Tracking on Reducing Discretionary Spending

Analysis 1 examined if tracking expenses persistently reduces discretionary spending using the aggregated person-month level data in the Tracking Sample. I propose that persistent expense tracking is associated with more control in spending as expense tracking increases the pain of paying due to greater awareness (Kan et al., 2018) and provides information for self-reflection and self-improvement (Heyen, 2020; Lupton, 2014).

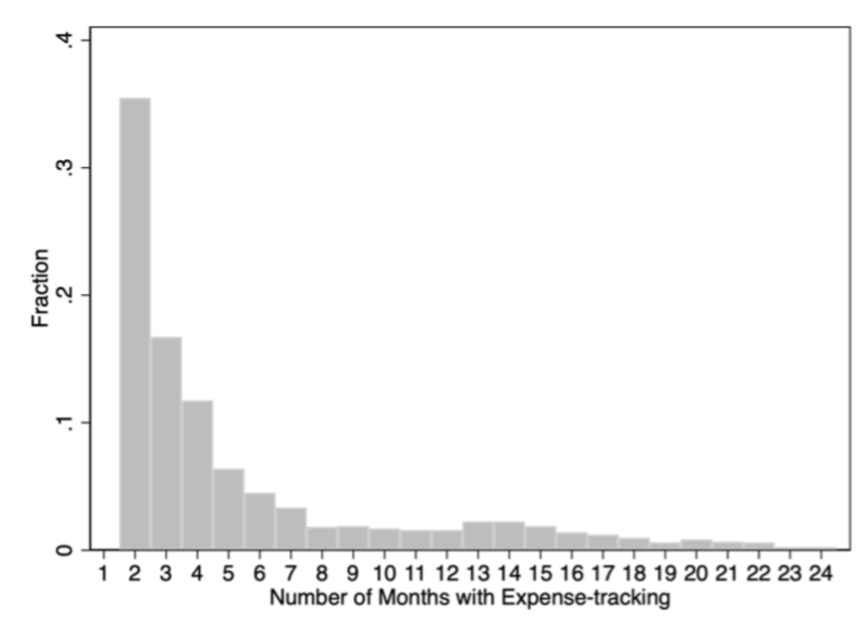
2.4.1 Data and Measures

The key predictor is tracking persistence. Since these data reveal active expense tracking behavior (i.e., manually record expenses) and the personal spending information is displayed on the app interface, individuals should notice their spending when they log a new record. Therefore, I defined tracking persistence ($TrackingPersistence_{im}$) as the number of months since the user started tracking to capture one's tracking experience and the amount of attention paid to personal spending information.

For people with financial goals that require monitoring spending, they should continue tracking until they achieve their goals. However, manually tracking spending requires effort and commitment. There are 42 users in the Tracking Sample who stop tracking for at least one month and then resume tracking later. Since it is unlikely that people have no spending in one month, these individuals have gaps in tracking. Having gaps in tracking when trying to regulate their financial behavior can suggest difficulties with self-regulation, situational barriers preventing tracking, motivation fluctuations, lack of reinforcement, or competing goals. However, due to data limitations, it is not possible to determine what occurred during the period when their spending data was missing. They may have given up tracking temporarily, or they may have continued to track their expenses using other methods during this time, but there is no way to confirm it. Taking a conservative approach, the count of months with expense tracking experience will not include this gap. For instance, suppose a user began tracking expenses in February 2018. In July 2019, she tracked for 18 months, and in August 2019, she tracked for 19 months. However, if the user stopped using the app in September 2019 and resumed in October 2019, the number of months they had tracked would be 20 in October 2019, despite the one-month gap.

The average tracking duration is 5.53 months with a standard deviation of 4.92 in the Tracking Sample. Figure 2 shows the distribution of tracking duration (in months) in the Tracking Sample. According to this figure, many users used the tracking app to track their expenses for a short period but discontinued tracking without resuming app usage until December 2019.

Fig. 2.—The Distribution of Expense Tracking Duration (in months) in the Tracking Sample



This figure displays a histogram representing the number of users with different durations of expense tracking experience. The x-axis is the number of months with expense tracking experience, while the y-axis represents the fraction. The Tracking Sample includes data from 2018 to 2019 from users who started tracking in 2018. The maximum number of months with expense tracking experience is 24.

The outcome variable used in Analysis 1 is the share of monthly expenses that are discretionary from the self-reported spending data. Spending can be broadly categorized as either discretionary[6] or mandatory. Peetz and Davydenko (2022) suggest that financial self-regulation can be applied to discretionary expenditures. Although this measure is not flawless and may not apply universally, it addresses certain limitations inherent in the subsamples, such as incomplete income reporting and the absence of information on wealth accumulation. Moreover, reducing such expenses can be a practical strategy for avoiding overspending for people with[7] or without monthly budgets. Generally, a lower level of discretionary spending

[6]Discretionary spending differs from discretionary income, which typically refers to the money remaining after covering taxes and essential cost-of-living expenses. Individuals may not allocate their entire income for spending and the leftover money may be saved or invested.

[7]C. Y. Zhang and Sussman (2018) document that nearly 75% of individuals who currently budget aim to

is a proxy for positive spending behaviors[8] as it increases available funds for savings or investments for future needs. Therefore, the decrease in the share of discretionary expenses may be a reasonable financial goal. The share of discretionary expenses (SDE) is a percentage that is computed as total expenses in the discretionary categories (for user i in month m) divided by the total expenses (for the same user in the same month) times 100.

$$SDE_{im} = DiscretionaryExpenses_{im}/MonthlyExpenses_{im} \times 100 \tag{2.1}$$

The app contains 33 preset expense categories (summary statistics are listed in Table A1 in Appendix A). These categories are not mutually exclusive and could be interpreted differently by individuals. People do not explicitly indicate whether they view an expense category as discretionary or non-discretionary in the app. Therefore, I construct an artificial measure to identify discretionary expenditures. To ensure a conservative approach in estimating the share of discretionary spending, I selected eight expense categories that are more likely to be considered discretionary spending[9]. Next, I ordered these eight categories by

prevent overspending, and this motivation appears consistent regardless of income or wealth using a nationally representative survey in the U.S.A.

[8]The share of discretionary spending may rise with higher income, allowing individuals to allocate more funds to discretionary items without overspending. Nevertheless, positive financial behavior often means reducing overall expenditure to increase savings or investments for handling unexpected needs or retirement. Since mandatory spending is fixed, cutting discretionary spending becomes a practical way to improve one's financial position. Thus, even if the share of discretionary spending increases with income, it may not necessarily indicate positive financial behavior if it does not lead to higher savings.

[9]The definitions of some categories may be debatable. For example, the meals category includes spending on food provided by others, such as dining in restaurants, food take-out, or food delivery. Cultural differences can make purchasing food from others cheaper and more convenient in China. Thus, this trend keeps increasing (Cheng, 2022), especially for students or workers who purchase food at canteens. The meals category has the highest number of reported records, and the average expenses per record in the meals category are around 36.75 RMB ($5.25), indicating that people tend to report having simple and light meals rather than formal sit-down meals in this category that may cost over 100 RMB ($14). Therefore, I considered expenses in the meals category as nondiscretionary, as they are used to fulfill the basic need for food. The cash gifts category is another one that may be controversial. Unlike traditional

the number of records in each category, which indicates how frequently the expense occurs. Categories with higher numbers of reported records may signal expenses that are more likely to occur every month, making it more meaningful to track changes in spending for those categories across months. Conversely, categories with lower numbers of reported records may signal expenses that occur only in some months. Not having such expenses in other months does not necessarily imply that people intentionally decrease this type of spending. For example, not spending on gifts in a month could be because there were no celebrations or life events. Additionally, individuals may regulate their spending by taking a holistic approach. For example, suppose they spend more in one discretionary category, such as purchasing a birthday gift for a friend. In that case, they may reduce expenses in other discretionary categories to avoid overspending. Therefore, I examined the changes in three sets of discretionary expense categories, rather than changes in each discretionary expense category individually.

I calculated the share of discretionary expenditures based on three definitions of discretionary expense categories with varying frequencies. The first measure, SDE 1, includes only frequently occurring discretionary expenses such as snacks, clothing, and entertainment. The second measure, SDE 2, consists of all expense categories in SDE 1, plus less frequent discretionary expenses such as travel, social interaction, and gifts. Finally, the third measure, SDE 3, includes all expense categories in SDE 2, plus infrequent discretionary expenses such as lottery and donations. Of the three measures of discretionary expense categories, SDE 1 is the most conservative measure, while SDE 3 is the least stringent measure. SDE 3 encompasses more expense categories, some of which are infrequent expenses. Therefore,

gifts, cash gifts are nondiscretionary because the amount given to others should follow a general norm in China. Regardless of their income level, people are expected to send a certain amount of money as cash gifts to others, such as relatives or friends.

the likelihood of inadvertently including a category that may not be considered discretionary rises in SDE 3. Table 3 shows the summary statistics of the three measures of SDEs for all users in the Tracking Sample. The share of monthly discretionary expenses only accounts for a small amount over the average monthly expenses (average SDE 1=9.92%, SDE 2=14.32%, SDE 3=14.57%), which makes sense as individuals should spend more on nondiscretionary categories. Therefore, the low percentage of SDEs may mean that the three sets of discretionary expense categories chosen are reasonable.

TABLE 3
SUMMARY STATISTICS FOR SDES

	Median	Mean	S.D.	Min	Max
SDE 1	2.87	9.92	16.06	0	100
SDE 2	5.76	14.32	20.24	0	100
SDE 3	6.05	14.57	20.46	0	100
Number of Observations			9,083		

NOTE.—This table presents descriptive statistics for the three measures of the share of monthly expenses that are discretionary (SDEs) for all users in the Tracking Sample. The table displays sample medians, means, standard deviations (indicated as S.D.), minimum and maximum numbers with the number of observations in the last row.

2.4.2 Empirical Strategy

In this section, I examined the relationship between tracking persistence and discretionary spending. I regressed SDEs on tracking persistence, the amount of monthly income, and month fixed effects with robust standard errors[10] (Equation 2.2). A decreasing trend in this variable (i.e., a negative coefficient of $TrackingPersistence_{im}$) would signify a reduction in

[10]Expense tracking may become less effective as people gain sufficient knowledge about their financial conditions, which suggests that the relationship between tracking persistence and the reduction in the share of discretionary spending could be nonlinear. Therefore, I ran non-parametric regressions with each number of months since starting tracking using the app (to capture the amount of tracking experience) and controlled for monthly income, month fixed effects with panel fixed effects. The coefficient plots of each number of months since starting tracking using the app are in Figure B2 in Appendix B. The coefficients decrease as people get more tracking experience, which suggests a linear trend over the data collection period.

the discretionary spending categories and progress toward financial goal attainment. I ran the following specification with panel fixed effects:

$$SDE_{im} = \beta_0 + \beta_1 TrackingPersistence_{im} + \beta_2 Income_{im} + \beta_3^{'}\Gamma_m + \beta_4^{'}P_i + \upsilon_{im} \tag{2.2}$$

where the dependent variable SDE_{im} is the share of total expenses that are discretionary made by user i in month m; $TrackingPersistence_{im}$ is the number of months since the user i started tracking in month m; $Income_{im}$ is the amount of earnings reported by user i in month m; Γ_m is the month fixed effects; P_i is the individual fixed effects.

Three variables are included as controls. First, I included a continuous variable ($Income_{im}$) as the total amount of income entries (e.g., investment, rental, or pocket money) each month. Table 1 displays the summary statistics of monthly income. Approximately 65% of the users in the Tracking Sample reported income at least once during the data collection period. Regardless of the type of income, earning money in a particular month may indicate that individuals have more financial resources during that period, enabling them to spend more. However, it is also likely that some people who earned money did not report it, leading to the absence of income data on the app interface[11]. Consequently, when adding a new record, individuals were solely reminded of their expenses. This imbalanced information could cause them to focus more on how much they have spent, making users more likely to limit their subsequent spending. Therefore, for those users who did not report any income in a specific month, I consider their person-month level income as zero[12].

[11] Tracking income may be more manageable, especially for individuals who receive a regular salary, which could potentially result in selective underreporting. To address this issue, I have tested two models, with and without income as a control variable. The results are similar (see Table B3 in Appendix B). Therefore, I decided to include income as a control variable since this adds precision to the estimates.

[12] I have tested two models to handle observations without reported income: treating them as zero or

Second, I included month fixed effects (Γ_m) to control for any seasonal variation that may influence the dependent variable. National holidays or big sales events happen in certain months, and individuals' consumption may increase during these special periods. For example, November 11$^{\text{th}}$ is a popular online sales day in China, similar to the Black Friday sales in the U.S.A. The online daily sales of Taobao, an online C2C market in China, reached about 38 billion U.S. dollars on November 11$^{\text{th}}$, 2019.

Third, I included individual fixed effects (P_i) to control for any individual factors that may influence the dependent variable, such as socioeconomic status, education, and wealth.

2.4.3 Results

Results in Table 4 show that all SDEs decrease significantly over time when controlling for any time-invariant factors influencing the dependent variable. This suggests that people decrease their self-reported spending, which is classified as discretionary spending, as a percentage of total spending the longer they track. Specifically, for each additional month of expense tracking, there is a corresponding decrease of 0.12 percentage points in SDE 1, 0.17 percentage points in SDE 2, and 0.18 percentage points in SDE 3. This translates to an approximate reduction of 4.31 RMB to 6.46 RMB in discretionary spending for every additional month of expense tracking experience. Although the effect sizes are small, the coefficients of interest are significant. Moreover, the small effect sizes make sense as the percentage of discretionary spending is a relatively small portion of overall expenditure.

treating them as missing values. While the significance levels decrease in the latter case (potentially due to the significantly reduced number of observations), the coefficient estimates of interest remain negative (shown in Table B4 in Appendix B). When income is not reported, the absence of income information on the app interface suggests that individuals cannot enhance their financial self-awareness regarding income when accessing personal financial information in the app. Considering that the availability of income information is linked to individuals' financial self-awareness regarding their income, I decided to treat observations without reported income as zero.

TABLE 4
Spending Reduction Based on the Share of Discretionary Expenses (Tracking Sample)

	SDE1	SDE2	SDE3
Tracking Persistence	-0.12**	-0.17**	-0.18**
	-0.04	-0.06	-0.06
Constant	10.37***	15.50***	15.50***
	-0.59	-0.8	-0.8
Number of Observations	9,083	9,083	9,083

Note.—robust standard error in parentheses. SDE 1= the share of monthly discretionary expenses belonging to the snacks, clothing, and entertainment category over monthly expenses; SDE 2= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, and gifts category over monthly expenses; SDE 3= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, gifts, lottery, and donation category over monthly expenses. I regressed SDEs on tracking persistence, the amount of monthly income, and month fixed effects with panel fixed effects and robust standard errors. Each column represents one regression with a different measure of the share of monthly discretionary expenses over monthly income as the dependent variable. Only the key predictor variable and constant term are reported in this table. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

I conducted five sets of robustness checks. First, tracking persistence is defined as the number of months since a user initiates expense tracking, without accounting for any gaps. While I assume expense tracking is cumulative, some users who discontinued tracking for longer period (i.e., 5 months) may have forgotten their prior experiences, potentially requiring a reset. Nevertheless, most users in the Tracking Sample maintained continuous tracking, with only 47 instances (involving 42 users) of temporary discontinuation for at least one month and then resumed later. To assess whether the regression results are influenced by these tracking gaps, I reran the regressions outlined in Equation 2.2, excluding these 42 users. The results remained consistent (see Table B5 in Appendix B).

Second, some users stopped tracking and never restarted tracking during the data collection period. Since these users can stop tracking at any point during their last month, the self-reported spending in their last month may be less than the actual amount of monthly spending. It is possible that the less monthly spending reported in the last month may drive the effect detected previously. Thus, I ran the same regressions without the last month for each user. Again, the coefficients of interest are negative and significant (see Table B6 in Appendix B).

Third, users who track their expenses for shorter durations may be primarily those who are merely trying the tracking app, rather than actively engaging in serious expense tracking activities. To address this issue, I excluded such users by setting a minimum tracking duration of three months[13]. Therefore, I restricted the sample to users who had tracked their expenses for at least three months, and then ran the same regression analyses using the specifications outlined in Equation 2.2. The coefficients of interest are still significant and negative (see Table B6 in Appendix B), suggesting that users who track their expenses for more than three months also experience a reduction in their discretionary spending as a percentage of total spending, the longer they track. Moreover, the magnitude of the coefficients remains consistent, suggesting that these results are robust.

Fourth, users start expense tracking on any day in their first month. The self-reported spending in their first month may be less than the actual amount of monthly spending, despite the fact that users could report expenses that happened before they started using the app. Moreover, some users had no expense tracking experience before using the app. To address these issues, I re-ran the same regressions for each user without the first month and coded their second month as the first month with tracking experience. Despite the changes, the coefficients of interest are still negative and significant (see Table B6 in Appendix B), suggesting a decrease in the share of discretionary spending over time.

Fifth, the Tracking Sample underwent certain sample restrictions, such as excluding users with extremely high or low monthly spending. To assess the sensitivity of the results

[13]Prior research documents that it takes about 66 days for people to establish a habit through repeated behaviors (Lally et al., 2010). Therefore, a three-month time frame is reasonable to exclude users who only tried the app briefly, while allowing others to establish a routine and consistently use the tracking app.

to these restrictions, I reran the same sets of regressions using an unrestricted sample and found consistent and robust results (see Table B7 in Appendix B).

Moreover, the original process of sample restriction aims to create a representative sample of app users. However, this method provides limited insight into the broader spectrum of households in China. To address this, I adopted an alternative method by referencing the China Statistical Yearbook 2019 (presenting data for 2018), published by the National Bureau of Statistics of China[14]. Given the limited available information, typically limited to means, I used the per capita disposable income of households categorized by income quintiles to establish inferred cutoff points[15]. Subsequently, I reanalyzed the regression using this refined sample (N=1,113) and observed consistent and robust outcomes (refer to Table B8 in Appendix B).

Additionally, I examined the heterogeneity of the effect of tracking persistence on discretionary spending for users with monthly budgets (i.e., monthly spending limits) and users without monthly budgets. This examines whether the effect is driven by users with monthly budgets, as they may be more likely to limit their spending. Thus, I ran the same regressions for users with monthly budgets (N=115) and users without budgets in the app (N=1,528), respectively. The regression results suggest that the impact of expense tracking on the reduction in the share of discretionary expenses is not driven by users who budget (refer to Table B9 in Appendix B). The coefficients of interest become insignificant for users with

[14]This report is available online at https://www.stats.gov.cn/sj/ndsj/2019/indexeh.htm.

[15]This report categorizes households nationwide, both rural and urban, into five quintiles: low-income, lower-middle-income, middle-income, upper-middle-income, and high-income households. The lower cutoff point was determined based on the disposable income of low-income rural households, which stands at 3,666.2 RMB annually. To obtain monthly data, I divided this by 12, resulting in a monthly disposable income of 305.52 RMB. The upper cutoff point was derived from the disposable income of high-income urban households, reported at 84,907.1 RMB annually. Following the same conversion, this translates to a monthly disposable income of 7,075.59 RMB. As this represents per capita disposable income and individuals may manage household-level expenditures, I adjusted it by multiplying it with the average household size (3 persons), yielding an upper cutoff point of 21,226.775 RMB.

monthly budgets. There are two possible explanations. First, there are limited observations associated with users who budget, as only 115 users set budgets in the app in the Tracking Sample. Therefore, the insignificant results may be due to power issues. Second, users with monthly budgets may be more financially constrained, with little room to cut expenses.

2.4.4 Discussion

Analysis 1 documents that expense tracking provides critical personal spending information that helps promote spending control in terms of the share of discretionary expenses. Although robustness checks yield consistent results, two important points should be noted. First, individuals may have subjective definitions of discretionary expenses. To avoid misclassification, Analysis 1 includes only discretionary expense categories that may apply broadly.

Second, many users only used the app for less than one month. As the analysis focuses on spending pattern changes over months, these users were automatically excluded from the regressions. Table B10 in Appendix B presents summary statistics and t-test results comparing users with tracking durations of more than one month and within one month[16]. Typically, users tracking expenses for one month or less have higher monthly incomes and lower monthly spending. Their reduced inclination to set monthly spending limits further highlights their affluence. While the regression analyses excluded these users, their financial situation may not warrant as much concern about money matters, potentially limiting the benefits of expense tracking for them.

[16] As users might use the app for just a day or a week, users with one month or less of expense tracking experience may not capture their entire month's spending/income accurately. Therefore, summary statistics for these users could be biased. User-level characteristics and information typically available at the beginning of each month, such as income, may be less prone to bias.

2.5 Analysis 2: The Impact of Expense Tracking on Budget Adherence

In Analysis 2, I focused on budget adherence as a different type of financial goal. I examined the role of expense tracking in budget adherence. Specifically, I explored whether persistent expense tracking is associated with an increase in people's likelihood of adhering to their preset monthly budgets. As discussed earlier, expense tracking is a fundamental step in budgeting. Individuals should monitor their spending behavior against their budgets. Therefore, I propose that tracking persistence could promote budget adherence by spending within one's monthly budget.

2.5.1 Data and Measures

Monthly budgets set in the app represent self-imposed financial goals. Analysis 2 examines budget adherence among users with budgeting goals over six months (July 2020 - December 2020). On average, individuals tracked their spending against their budgets for 5.11 months during this timeframe.

Two outcome variables could be used to measure spending control toward a budgeting goal. First, I created dummy variables indicating whether a user's self-reported spending is within the self-imposed monthly budget each month ($BudgetAdherence_{im}$). I define budget adherence as accumulated monthly expenses less than or equal to the monthly budgets.

Second, I defined a continuous measure of the gap between monthly budgets and monthly expenses ($BudgetSlack_{im}$), which is computed as self-imposed monthly budgets minus the self-reported monthly expenses. A positive amount signals spending within monthly budgets, while a negative amount signals spending exceeding monthly budgets. Budget slack offers more information than budget adherence. For instance, someone overspending \$1000 in the first month and \$500 in the second month shows progress in spending control. Using a binary variable would label them as failing to adhere in both months, obscuring their improvement over time. Increasing budget slack is a good thing because (a) it generally reflects effective spending control toward self-imposed financial goals, and (b) it can also prompt individuals to reconsider their budget appropriateness and make adjustments.

Users can adjust their monthly budgets at any time within a month, and the amount of each user's monthly spending limit was collected three times a month (on day 1 of a month, on day 15 of a month, and on day 30 of a month). It is not clear which of the budget snapshots best represents the monthly budgets that users are trying to adhere to. Therefore, I included two sets of outcomes in a particular month: one is based on the budgeting data collected at the beginning of each month, and the other is based on the budgeting data collected at the end of each month[17].

Table 5 displays the summary statistics for budgeting data used in Analysis 2. On average, users adhere to their budgets about 33%-34% of the months over the six-month observation period. The average monthly budget collected at the end of each month is smaller, suggesting a general trend of users reducing their budgets more frequently than increasing them. This trend is further highlighted by the decrease in budget slack from the beginning of each month to month end. Such reductions may lead to the decline in the likelihood of budget adherence. For instance, the average budget adherence decreases from 0.34 to 0.33. Additionally, the difference in the number of observations between the month-beginning and month-end data suggests that some users deleted their monthly budget

[17]Monthly budgets collected at the beginning of each month reflect users' initial planning. Nonetheless, various factors can lead to budget adjustments—these may stem from internal factors like accommodating unforeseen expenses or external factors such as changes in employment status. Therefore, the monthly budgets collected at the end of each month might reflect users' planning with accommodations.

information in the app and never established a new budget afterward.

TABLE 5
Summary Statistics for Monthly Budgets, Budget Adherence, and Budget Slack

	(1) Month-beginning Data	(2) Month-end Data
Monthly Budget (RMB)	5,783.92	5,762.49
	(4,521.84)	(4,485.39)
Budget Adherence	0.34	0.33
Budget Slack (RMB)	(2,348.78)	(2,365.98)
	(6,361.73)	(6,213.16)
Number of Users	1,388	1,388
Number of Observations	7,089	7,060

Note.—This table presents descriptive statistics for budgeting data collected at the beginning of each month (column (1)) and at the end of each month (column (2)). The table displays sample means and standard deviations (indicated in parentheses) with the number of users listed in the last row. Budget adherence is a dummy variable indicating whether accumulated monthly spending is less than or equal to the monthly budget. Budget slack is computed as monthly budgets minus the monthly expenses. RMB refers to the Chinese currency. One U.S. dollar is about 7 RMB.

Similar to Analysis 1, I measured the tracking persistence variable ($TrackingPersistence_{im}$) using the number of months since the user started tracking to capture one's tracking experience and the amount of attention paid on spending information. The start of tracking is indicated by the date the user created her first record using the app.

2.5.2 Empirical Strategy

In this section, I examined the relationship between tracking persistence and budget adherence. First, I regressed budget adherence on tracking persistence, the amount of monthly income, and month fixed effects with robust standard errors (Equation 2.3). Second, I regressed budget slack on tracking persistence, the amount of monthly income, and month fixed effects with robust standard errors (Equation 2.4). I ran the following specifications with panel fixed effects[18]:

[18]To assess whether the relationship between tracking persistence and budget adherence or budget slack is nonlinear, I ran non-parametric regressions with each number of months since starting tracking using the

$$BudgetAdherence_{im} = \beta_0 + \beta_1 TrackingPersistence_{im} + \beta_2 Income_{im} + +\beta_3^{'}\Gamma_m + \beta_4^{'}P_i + \upsilon_{im} \tag{2.3}$$

$$BudgetSlack_{im} = \beta_0 + \beta_1 TrackingPersistence_{im} + \beta_2 Income_{im} + +\beta_3^{'}\Gamma_m + \beta_4^{'}P_i + \upsilon_{im} \tag{2.4}$$

where the dependent variable $BudgetAdherence_{im}$ indicating whether user i spends within the monthly budget in month m; $BudgetSlack_{im}$ indicating the difference between user i's monthly budgets in month m and user i's monthly expenses in month m; $TrackingPersistence_{im}$ is the number of months since the user i started tracking in month m; $Income_{im}$ is the amount of earnings reported by user i in month m; Γ_m is the month fixed effects; P_i is the individual fixed effects.

Similar to Analysis 1, I also included a continuous variable ($Income_{im}$) indicating the amount of income in a month (Table 1 displays the summary statistics of monthly income) to control for the available resources, month fixed effect (Γ_m) to control for any seasonal variation influencing budget adherence and individual fixed effect (P_i) to control for any individual factors affecting budget adherence.

app (to capture the amount of tracking experience). The coefficient plots are in Figure D11 in Appendix D. The coefficients increase as people get more tracking experience, suggesting a linear trend over the data collection period. None of the coefficients are significant when budget adherence is the dependent variable, while some are significant when budget slack is the dependent variable. Moreover, the confidence intervals get larger as the number of months since starting using the app increases. One possible explanation is that there were fewer observations for larger number of months since starting tracking using the app. In particular, fewer people in the Budgeting Sample tracked for an extended period. For example, about 6.61% of the users have used this app to track their spending for more than three years.

2.5.3 Results

TABLE 6
Spending Reduction Based on Monthly Budget Adherence and Budget Slack

	Budget Adherence		Budget Slack	
	(1)	(2)	(3)	(4)
	Month-beginning Data	Month-end Data	Month-beginning Data	Month-end Data
Tracking Persistence	0.01	0.01	469.07+	357.48
	(0.02)	(0.02)	(271.67)	(266.82)
Constant	0.15	0.13	-8,410.71*	-6,969.23+
	(0.33)	(0.32)	(3,856.61)	(3,789.16)
Number of Observations	7,089	7,089	7,089	7,060

Note.—Robust standard error in parentheses. Budget adherence is a dummy variable indicating whether accumulated monthly expenses is less than or equal to the monthly budget. Budget slack is computed as monthly budgets minus the monthly expenses. I regressed budget adherence and budget slack on tracking persistence, monthly income, and month fixed effects with panel fixed effects and robust standard errors, respectively. Since users can change their monthly budgets, I ran regressions with dependent variables measured based on budgeting data collected at the beginning and end of each month. Each column represents one regression with a different measure of budget adherence/budget slack as the dependent variable. Only the key predictor variable and constant term are reported in this table. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

The regression results are displayed in Table 6. Two findings emerge from the regression results. First, when comparing the two outcome variables on each budgetary data collection point (column (1) vs. (3), column (2) vs. (4)), the coefficients of budget slack become significant within a 90% confidence interval when using the month-beginning data. This may be due to the fact that there are more variations in budget slack than budget adherence. While, on average, people's self-reported monthly spending tends to exceed their self-imposed monthly budgets, the observed upward trend may suggest an improvement in spending control over time (with less overspending from the self-reported data). However, the nonsignificant coefficients of budget adherence further suggest that the quantitative changes in budget slack (reduced overspending) are not substantial enough to bring about a qualitative change in budget adherence (shifting from overspending to spending within budget) over the six-month data collection period.

Second, when comparing the two budgetary information collection points for each outcome variable (column (1) vs. (2), column (3) vs. (4)), the coefficients of budget slack become insignificant when using the month-end data. However, this does not conclude that persistent expense tracking does not affect budget adherence. The insignificant result may be attributed to the general decreases in self-imposed monthly budget amounts (as indicated in the summary statistics in Table 5) at the month-end.

As a robustness check, I conducted the same set of regressions on an unrestricted sample, including users who reported extreme spending or set extreme budgets. None of the coefficients of interest were found to be significant, as detailed in Table D12 in Appendix D. This lack of significance can be attributed to the inclusion of extreme values, such as monthly budgets of 999,999,999 RMB, which inflate the coefficients and muddle the effects.

Moreover, similar to Analysis 1, the original process of sample restriction in Analysis 2 aims to create a representative sample of app users. As another robustness check, I applied the same cutoff points based on statistics from the China Statistical Yearbook 2019. I reanalyzed the regression using this refined sample (N=1,045) and observed consistent outcomes (refer to Table D13 in Appendix D). However, none of the coefficients of interest were significant. This lack of significance may potentially stem from a loss of power resulting from dropping additional users.

2.5.4 Discussion

The regression results in Analysis 2 are mixed, which could potentially stem from the dynamic nature of budgeting behavior. For instance, individuals may initially adhere to their monthly budgets but later decide to decrease them, leading to subsequent overspending, or vice versa.

Alternatively, the mixed results might be attributed to the limited observation period. As previously discussed, the quantitative changes in budget slack (reduced overspending) may not be significant enough to induce a qualitative shift in budget adherence (moving from overspending to spending within budget) over the six-month data collection period. It might require a longer observation period than six months to detect such a qualitative change in budget adherence.

Since monthly budgets are self-imposed financial goals, people could freely adjust these goals. Prior literature documents the difficulty for people to accurately predict future consumption (Min and Ulkumen, 2014). Therefore, setting monthly budgets can be challenging. About 42% of users in the Budgeting Sample adjusted their monthly budgets. Some people adjust their budgets because they fail to predict their future consumption accurately. Others may ”cheat” by inflating their monthly budgets to create a sense of achievement in reaching their financial goals, even if they haven't altered their spending behaviors. It is unclear whether these budget adjustments are due to learning or cheating behavior. However, evidence suggests that users are not likely to be merely inflating their budgets to achieve their financial goals. Approximately 64.38% of budget adjustments are downward adjustments. Moreover, some of these downward adjustments significantly impact budget adherence. For instance, the Budgeting Sample includes 260 instances where budget adherence based on the initial budget amount differs from budget adherence based on the adjusted amount at the end of the month. In 58.85% of these cases, users decreased their budgets to the point where they stayed within their monthly budget based on the initial amount but exceeded it based on the adjusted amount. Taken together, these findings suggest that people may be less likely to cheat by decreasing their monthly budgets. Moreover, even if some users strategically increase their budgets to ensure adherence to their goals, this behavior could be viewed positively as a means of striving towards inhibitional goals. Tracking negative behaviors that one wants to decrease is more prone to the ”what-the-hell effect” (Cochran and Tesser, 2014). Therefore, strategically increasing monthly budgets to maintain motivation and continue tracking progress could be more effective than giving up tracking altogether.

Another issue to note is that as the analysis focuses on spending pattern changes over months, users who only track spending against their budgets for one month were automatically excluded from the regressions. Table D14 in Appendix D presents summary statistics and t-test results comparing users who track spending against their budgets for more than one month and within one month. These two groups of users differ in many dimensions. Typically, although users who track longer are more likely to report income, there are no significant differences in monthly income. Moreover, users who discontinue tracking their spending against budgets tend to have lower monthly spending and thus are more likely to adhere to their budgets. This makes sense as tracking spending against budgets adds limited value for individuals who can easily adhere to their budgets.

2.6 General Discussion

This paper examines how expense tracking, as a self-regulatory behavior, informs financial behavior within the financial self-regulation context using novel administrative-level user data from a Chinese tracking app and survey data from the United States. It provides suggestive evidence supporting that expense tracking provides critical personal spending information that helps promote spending control in terms of the decrease in the share of discretionary expenses.

This paper contributes to several streams of literature. First, this paper demonstrates that persistent expense tracking is associated with better financial outcomes, highlighting the importance of expense tracking as a self-regulatory tool for achieving financial goals. This finding not only contributes to the existing literature on self-regulation, which has limited research specifically focused on financial goals, but also adds to the growing body of knowledge on financial self-regulation. Second, although the analysis between tracking persistence and budget adherence yields mixed results, this paper still adds to the literature on budgeting (C. Y. Zhang et al., 2022), mental budgeting (Heath and Soll, 1996), and mental accounting (R. Thaler, 1985) by examining how expense tracking informs individuals' spending behavior to their budgetary constraints using naturally occurring data.

Third, this research contributes to public policy and financial education by informing an emerging avenue to promote consumer financial well-being. With the increased availability of tracking apps, tracking and reflecting on personal spending information has become more accessible and convenient. By integrating expense tracking into financial education, individuals can make informed spending decisions and improve their financial outcomes. Moreover, findings in Analysis 1 suggest that the effect of expense tracking on the share of discretionary expenses is not driven by having spending limits. Even without explicit spending limits, promoting expense tracking alone may still effectively facilitate spending control as the personal spending information could help identify areas for improvement in the process of financial self-regulation. This finding may be more informative given people's difficulty in predicting their future consumption and setting spending limits (Sussman and Alter, 2012).

There are limitations to this research, which suggest some opportunities for future research. First, the samples used are selective. This non-representativeness may stem from issues related to selection (i.e., who is using the tracking app) and attrition (i.e., who remains using the tracking app). For example, individuals who voluntarily track their expenses may be more financially sophisticated. However, obtaining a representative sample is challenging for this research topic. The tradeoff I encountered is that, although the app data is selective, it provides a means to measure individual high-frequency tracking behaviors. Moreover, the findings might be specific to the country context, as cultural norms and financial behaviors can differ significantly between countries (M. L. Zhang et al., 2018). Therefore, caution is warranted when generalizing these results to the broader population, especially to those who do not currently track their expenses.

Second, while having real-world data offers the benefit of providing external validity to aid our understanding of theoretical constructs, there are some limitations of the data that may affect the validity of the measures and the findings. All the data are self-reported, raising questions about potential misreporting that could bias the measurements. For example, in Analysis 1, since there is no information on whether users view an expense category as discretionary or non-discretionary in the app, I defined three sets of discretionary spending categories that may apply to a broader population. However, people may have their own definition of discretionary spending categories, making the share of discretionary expenditures measures less valid. Therefore, it is unclear whether people actually decrease the share of discretionary spending or decrease the likelihood of reporting expenses belonging to the defined discretionary spending categories the longer they track. Moreover, people could underreport some expenses, as prior literature finds that individuals tend to overlook trivial costs (Gourville, 1998). In Analysis 2, the monthly budgets are self-imposed, and monthly spending relies on self-reporting. If any misreporting causes the actual monthly spending to be higher than the reported monthly spending, the measures of budget slack or budget adherence may be incorrect. Additionally, while users in the Budgeting Sample all had monthly budget information stored in the app, it cannot be confirmed that they genuinely pursued a budgeting goal during the data collection period[19]. It is possible that a user may initially set up monthly budgets but subsequently abandon budgeting, neglecting to update

[19]Typically, when users set a spending limit, this information is stored in the app's database until updated. However, the budgeting details are not displayed in the main interface. If users wish to assess spending against monthly budgets or update their budgeting information, they must navigate to a different interface within the app.

the information. Together, future research could examine the impact of persistent expense tracking and spending behaviors using alternative data sources.

Third, while this research demonstrates associations between expense tracking and financial behaviors, it does not establish causality. However, a large-scale experiment conducted in the U.S. found that the effect of expense tracking on spending habits may extend beyond individuals who voluntarily partake in such activities. Approximately 10 percent of participants in this experiment tasked with tracking their expenditures over a relatively brief period (two consecutive weeks) reported noticeable changes in their consumption patterns because of the increased awareness of spending facilitated by the act of maintaining a spending diary (Daniel Dorfman et al., 2021). Further investigations, such as controlled lab experiments, are needed to establish causal relationships.

Fourth, the awareness of income and wealth may also be necessary to form an understanding of one's financial situation. However, some users from the tracking app did not track and report their income, and there is no information regarding their net wealth. Future research should explore income tracking and its implications.

There are more avenues to explore in future studies. There may be cultural distinctions in how budgeting and expense tracking are perceived in Western and Chinese contexts. In English, budgeting involves tracking expenses against a predetermined budget, which entails setting budgets for various categories of expenses (Heath and Soll, 1996). However, in Chinese, expense tracking is primarily about recording spending and categorizing it into accounts, which may not necessarily involve setting budgets for different expense categories. As indicated in the Tracking Sample, only about 6% of users set monthly budgets using the app. The app company conducted phone interviews among its users to understand why they underutilized the function of setting spending limits. Some users stated that they tracked spending to gain self-knowledge about their spending patterns. However, as discussed earlier, even for these individuals who track spending for self-knowledge, they may still have implicit financial goals if they identify areas for improvement and modify their behavior accordingly through the self-knowledge gained from expense tracking. Therefore, it is still unclear whether Chinese people have implicit spending goals or can track spending without any financial goals. Future research could examine these cultural distinctions in more depth.

Moreover, exploring the interplay between adhering to financial goals and setting financial goals can provide valuable insights. Psychological self-regulation literature documents that self-monitoring has a self-motivating function (Bandura, 1991). Therefore, it would be interesting to investigate whether exposure to expense tracking can motivate individuals to set additional financial goals. For instance, individuals who engage in expense tracking to gain self-knowledge about their spending patterns may also be motivated to reduce unnecessary expenses. This line of inquiry can shed light on the potential motivating factors of expense tracking and its impact on goal-setting processes. Moreover, while this research broadly supports the notion that expense tracking promotes better financial decision-making, there are different tracking methods (i.e., active tracking vs. automated tracking), individual differences, and cultural differences in expense tracking behaviors. Future studies could delve deeper into these aspects and identify the most effective form of expense tracking that facilitates positive financial behaviors.

Chapter 3

Optimizing Expense Tracking for Financial Self-regulation: Insights from Individual Practices

Abstract

Expense tracking is a self-monitoring behavior within the context of financial self-regulation. Therefore, expense tracking patterns and their impact on the quality of self-monitoring are essential for facilitating financial goal attainment. Despite its importance, empirical evidence of expense tracking remains limited. This research presents new descriptive evidence by investigating the accuracy, consistency, and temporal proximity of expense tracking using survey data coupled with real-world tracking data obtained from a tracking app company. The findings not only enrich self-regulation theory by shedding light on expense tracking quality but also offer valuable insights into effective strategies for enhancing financial self-regulation. Furthermore, this research contributes to the literature on personal finance

and mental budgeting, providing practical implications for individual decision-makers and financial education initiatives seeking to improve financial outcomes through the adoption of effective expense tracking practices.

3.1 Introduction

Findings in Chapter 2 suggest that expense tracking can be viewed as a form of self-monitoring behavior within the context of financial self-regulation. By actively monitoring their spending, individuals gain valuable insights into their spending habits, enabling better control over their expenditures. Therefore, understanding expense tracking behavior patterns can play a crucial role in promoting financial goal attainment and overall financial wellbeing. However, despite the importance of expense tracking, empirical evidence on its patterns remains limited (for a review, see C. Y. Zhang and Sussman, 2018). While prior research in mental accounting mainly focuses on how individuals categorize their mental accounts and their impact on financial behaviors (Barsalou, 1991; Sussman and Alter, 2012; R. Thaler, 1985; C. Y. Zhang et al., 2022), self-regulation theory posits that the effectiveness of self-regulation hinges on the accuracy, consistency, and temporal proximity of self-monitoring behaviors (Bandura, 1991). Therefore, examining these aspects can provide insights into effective strategies for promoting financial self-regulation.

This research presents new descriptive evidence on the accuracy, temporal proximity, and consistency of expense tacking behavior and their association with financial worries, assessing whether empirical analyses on these aspects align with the self-regulation theory (Bandura, 1991). I focus on active tracking behavior wherein individuals manually record their transactions. Data were obtained from a Chinese tracking app, with a survey administered to app users to collect self-reported tracking behavioral data (subjective) and survey respondents' tracking data obtained from the tracking app company, serving as objective behavioral data.

Several findings emerge from the empirical analysis. First, I examine individuals' tendency to record expenses with an accurate category and date of purchase as proxies for expense tracking accuracy. I find that a significant portion of respondents reported accuracy in expense tracking, particularly in categorization and transaction date indications. Approximately 85.50% of respondents indicated always ensuring an accurate category while tracking, while approximately 93.47% ensured accurate transaction date indication. Accuracy in category selection is significantly associated with reduced financial worries, in line with the self-regulation theory (Bandura, 1991). However, the association with date accuracy yielded mixed results and the findings are inconsistent in the subsample analysis. Moreover, when comparing the two accuracy dimensions, I find a moderate correlation coefficient of 0.5 between accuracy in category selection and date selection, suggesting that individuals may prioritize one dimension over the other.

Second, I explore the timing of individuals' expense tracking activities as an indicator of temporal proximity. Individuals generally prioritize promptness in expenses-tracking, as approximately 85.26% of the respondents indicated either tracking immediately after the purchase or on the same date when the purchase happens. Moreover, the findings suggest that adhering to a clear transaction recording pattern, whether it involves tracking immediately, on the same day, regularly, or flexibly, is associated with fewer financial worries than not adhering to a clear transaction recording pattern. Although immediate recording may require more effort, it emerges as a method associated with the least financial worries. There are no significant differences in financial worries among the other three alternative recording patterns (tracking on the same day, regularly, or flexibly).

Third, I examine habit strength in expense tracking as a proxy for consistency in expense tracking, as individuals should consistently record their expenses as they occur. I find a significant association between habit strength in expense tracking and expense tracking duration. This suggests that individuals could develop a habit of expense tracking through repeated behaviors. Moreover, in line with the self-regulation theory (Bandura, 1991), consistency in expense tracking is significantly associated with fewer financial worries. Additionally, I identified five common barriers that affect expense tracking consistency: being too busy, not having a phone, overspending, forgetfulness, and difficulty in categorizing expenses. Forgetting emerges as a prevalent barrier, with over half of the respondents (53.72%) indicating it as the reason for not logging transactions.

Together, these findings on expense tracking patterns have several contributions. First, the alignment between subjective survey responses and objective app usage data strengthens the validity of certain research findings, enabling a more robust assessment of survey measures through app data analysis.

Second, this research enriches psychological self-regulation theory (Bandura, 1991) by examining the quality of expense tracking, including accuracy, consistency, and temporal proximity, within the framework of financial self-regulation. I also assess their alignment with self-regulation theory by examining their association with financial worries. For example, while self-regulation theory emphasizes the importance of accurate self-monitoring, this research reveals that individuals may prioritize only one aspect of accuracy when tracking expenses, and only accuracy in categorization is significantly linked to lower financial worries.

Third, this research contributes to the literature on personal finance and mental budgeting by identifying expense tracking patterns and features that are associated with lower financial worries. Understanding these nuances can guide future research on personal finance and mental budgeting. For instance, this study finds that individuals can develop a habit of expense tracking, which is associated with reduced financial worries. Since expense tracking is often viewed as a means to support budgeting, this prompts further exploration of whether budgeting itself can evolve into habitual behavior and whether it is more effective to cultivate budgeting as a long-term or short-term objective.

Despite the descriptive nature of the findings and the unknown direction of the relationships, this research has practical implications for individual decision-makers, financial education initiatives, and tracking app developers. By acknowledging the features that are associated with reduced financial worries, adhering to these tracking patterns suggested by the self-regulation theory could potentially maximize the benefits of expense tracking.

Moreover, these findings have significant implications for financial education initiatives aimed at enhancing financial management skills as well as for tracking app developers seeking to improve tracking engagement. For example, the identification of common barriers hindering consistent expense tracking suggests that tracking app developers can integrate reminders to prompt users to track their expenses regularly, thereby addressing forgetfulness as a barrier.

The remainder of this paper is organized as follows. First, I review the literature on the quality of self-monitoring within the self-regulation framework. Next, I present analyses pertaining to the accuracy, consistency, and temporal proximity of expense tracking. Finally, I discuss the implications of this paper for theory and practice, limitations, and directions for future research.

3.2 Theoretical Framework

Findings in Chapter 2 suggest that expense tracking can be viewed as a form of self-monitoring behavior wherein individuals gather essential personal spending data to enhance their financial self-awareness, ultimately leading to improved financial outcomes within the framework of financial self-regulation. Because self-monitoring serves as a mechanism for detecting discrepancies, the quality of this process becomes crucial (Bandura, 1991). Several factors influence the probability of activating self-reactive mechanisms upon observing one's behavior. According to the self-regulation theory, the accuracy, consistency, and temporal proximity of self-monitoring contribute significantly to its effectiveness (Bandura, 1991).

Expense tracking involves remembering and assigning various purchases to appropriate accounts (Heath and Soll, 1996). Therefore, the accuracy of an individual's expense tracking can be assessed in two dimensions: the alignment of records with appropriate categories, and their association with the correct purchase dates. Previous research in the domain of mental accounting underscores considerable variability among individuals in how they classify their expenditures in terms of their level of detail (C. Y. Zhang et al., 2022). Moreover, the categorization process influences subsequent consumption decisions, as individuals often do not perceive funds as entirely fungible across categories (R. Thaler, 1985). Thus, the categorization of expenses can significantly impact subsequent spending behavior within the corresponding category and may even predispose individuals to overspending. For example, consumers tend to overspend when they narrowly categorize exceptional expenses, rather than incorporating them into a broader set of purchases (Sussman and Alter, 2012). Additionally, categorization poses challenges, with certain expenses being easier to classify than others. Representative expenses within a category are more readily learned, categorized, and recalled (Bandura, 1991), and are thus easier to track.

Accurate recording of purchase dates is equally important for providing precise personal spending data, which influences subsequent spending decisions. Individuals often evaluate their financial standing within specific temporal frames (Choe and Kan, 2021; Liu and Chou, 2016), such as weekly or monthly periods. Therefore, inaccurately dated transactions may cause individuals to form biased perceptions of their financial status, potentially resulting in erroneous spending decisions. For instance, misdating a recent purchase as occurring in the preceding or subsequent month can distort individuals' perceptions of their current month's expenditures, potentially resulting in overspending in the current month.

In addition to aligning transactions with the correct categories and dates, the timely recording of expenses ensures the availability of accurate personal financial information for reflection, which further allows individuals to form an accurate financial self-awareness of their current financial situation. In this regard, timely expense tracking surpasses regular tracking in efficacy. For example, people who track their weekly expenses, but only do so at the end of the week, may risk neglecting some spending that occurred earlier. This delay can lead to an inaccurate perception of available funds and overspending later in the week, as unrecorded expenses distort their financial awareness when making purchase decisions.

Success in self-regulation also relies on the consistency of self-monitoring, as intermittent self-monitoring provides only partial information (Bandura, 1991). Stopping goal pursuit prematurely is a major self-regulatory failure (Karoly, 1993), indicating a lack of ability to persist in taking actions related to achieving a goal or overcoming obstacles that hinder goal pursuit (Heckhausen and Heckhausen, 2018). Given the pervasive nature of consumption opportunities in daily life, consistency reflects an individual's propensity to record transactions upon occurrence. However, expense tracking, as an ongoing process, poses challenges due to its effortful and demanding nature. Previous literature has highlighted numerous obstacles to maintaining accurate expenditure records, including overlooking trivial costs and failing to record infrequent or atypical expenses, which can lead to overspending (Barsalou, 1991; Gourville, 1998; Sussman and Alter, 2012; Sussman et al., 2015).

3.3 Data and Measures

To explore expense tracking patterns regarding accuracy, temporal proximity, and consistency, I obtained data from a Chinese tracking app. This app enables users to manually record their earnings and spending across various categories, add transaction notes, set spending limits (monthly and categorical budgets), and conduct a basic spending analysis.

A central contribution of this research is the combination of self-reported tracking behavioral data from a survey with respondents' actual app usage data. This not only allows me to investigate the relationship between the accuracy, consistency, and temporal proximity of expense tracking and financial worries but also enables the validation of survey data against actual app usage.

In this section, I detail the survey administration process, the data cleaning procedures, and describe the information collected among survey respondents.

3.3.1 Tracking Behavior Data

To gather more information regarding tracking behavior, a survey was administered to app users between November 30$^{\text{th}}$, 2021, and December 31$^{\text{st}}$, 2021 (For the complete list of survey questions, please refer to Appendix G). The survey link was distributed to all active users through app messages throughout the survey period. Participation in the survey was voluntary, and only users aged 18 years or older were eligible to respond.

The survey collected detailed information on expense tracking behavior, including their perceived accuracy of logged transactions, the timing of recording transactions, barriers to tracking, and habit strength related to tracking. This information serves as subjective behavioral data. Demographic information and financial worries were also gathered from the survey participants.

Additionally, I acquired survey respondents' app usage data from the tracking app company. This dataset includes every transaction record logged by respondents from their initial use of the app to the end of 2021. Each transaction entry contains the amount, date, categorization, and any associated notes. These transaction-level data serve as objective behavioral data.

In total, 4,853 respondents completed the survey. To ensure data integrity, four respondents who completed the survey twice and 106 respondents who failed the attention check question were excluded from the analysis.

Among the remaining respondents, 97 indicated using the app for business management and 449 reported tracking both personal and others' income and expenses. The majority (4,197) tracked their personal income and expenses. As this study focuses on individual expense tracking behavior, respondents engaged in business tracking were excluded from the sample. I further excluded seven respondents who only recorded their income.

The provision of demographic information is voluntary, and I incorporated an "prefer not to disclose" option for each demographic question to avoid forced responses. Among the remaining sample, approximately 25.01% chose not to disclose certain demographic information. Rather than excluding individuals who selected "prefer not to disclose," I opted to keep the category labeled as "prefer not to disclose" for each demographic variable.

After all the exclusions and adjustments, the final sample comprises 4,639 respondents (referred to as the Survey Sample). This includes individuals aged 18 and above who used the app for non-business-related expense tracking behavior, passed the attention check, and did not report extremely low or high monthly spending. Figure E15 in Appendix E provides an overview of the data cleaning process.

Among the Survey Sample, monthly expenses ranged from 0 RMB to 10,778,970 RMB (approximately \$1.5 million), with a standard deviation of 68,751.65. Despite a median value of 4,014.9 RMB (around \$574), the mean stands considerably higher at 11,788.37 RMB (approximately \$1,684), suggesting a skewed distribution of the expense data. Extremely low expenses may occur due to unreported transactions, whereas unusually high expenses could stem from affluent individuals.

To mitigate potential bias, the same cutoffs were applied as in Chapter 2, excluding respondents who ever reported monthly expenses $\geq$ 32,407.14 RMB (around \$4,630) and those who ever reported monthly expenses $\leq$106.6 RMB (approximately \$15). These cutoffs help identify and remove data points that likely reflect inaccurate reporting or unrepresentative high-spending behaviors, ensuring that the remaining data are representative of the broader user base. After this exclusion, I created a Restricted Sample including 1,894 respondents.

Table 7 presents summary statistics for the demographic characteristics and app usage of respondents, both in aggregate and disaggregated by whether respondents reported extreme monthly spending according to app data. The results in column (1) suggest that respondents in the Survey Sample tend to be younger (about 82% aged below 35), educated (63% have a bachelor's degree or higher), employed (63%), have a monthly income between 1000-8000 RMB (52%), and are predominantly female (approximately 68%). Moreover, the t-test analysis in column (4) suggests that respondents who ever reported extremely high or low monthly spending did not differ statistically in education level and gender compared to those who did not report extreme spending. However, individuals who ever reported extremely high or low spending tended to be younger, employed full-time, had lower reported incomes, and were single.

TABLE 7

Survey Data Descriptive Statistic (Demographic Characteristics)

	(1) All Users	(2) w/o Extreme Spending	(3) w/ Extreme Spending	(4) Difference
Panel A: Survey Data				
Age Brackets				
18-25 yrs	0.41	0.37	0.47	0.10***
26-35 yrs	0.41	0.41	0.41	0
36-45 yrs	0.12	0.15	0.08	-0.06***
46-55 yrs	0.04	0.05	0.03	-0.03***
56-65 yrs	0.01	0.01	0.01	-0.01*
66+ yrs	0	0	0	0
Prefer not to disclose	0	0.01	0	0
Education				
Junior high school or less	0.03	0.03	0.02	-0.01
High school or equivalent	0.08	0.07	0.08	0.01
Associate degree	0.23	0.23	0.22	-0.01
Bachelor's degree	0.54	0.54	0.53	-0.01
Graduate degree	0.08	0.07	0.09	0.01
Ph.D. or more	0.01	0	0.01	0
Prefer not to disclose	0.05	0.04	0.05	0.01
Employment Status				
Full-time	0.57	0.55	0.59	0.04**
Part-time	0.02	0.02	0.02	-0.01
Self-employed	0.04	0.05	0.02	-0.03***
Not currently employed	0.07	0.07	0.06	-0.01
Retired	0.01	0.02	0.01	-0.01*
Student	0.17	0.17	0.18	0.01
Other	0.03	0.03	0.03	0
Prefer not to disclose	0.09	0.09	0.09	0
Monthly Income (in RMB)				
No income	0.04	0.04	0.03	0
<1000	0.04	0.04	0.03	-0.01
1,001-3,000	0.19	0.18	0.21	0.03**
3,001-5,000	0.17	0.17	0.19	0.02
5,001-8,000	0.16	0.15	0.18	0.03**
8,001-10,000	0.09	0.09	0.08	-0.01
10,001-20,000	0.09	0.1	0.08	-0.02*
>20,000	0.04	0.06	0.01	-0.04***
Prefer not to disclose	0.17	0.17	0.18	0.01
Female	0.68	0.67	0.68	0.01
Marital Status				
Single	0.32	0.3	0.37	0.07***
With Partner	0.18	0.16	0.21	0.04***
Married without kids	0.11	0.12	0.09	-0.03***
Married with kids	0.22	0.25	0.18	-0.08***
Other	0.01	0.01	0.01	0
Prefer not to disclose	0.15	0.15	0.15	0
Panel B: App Usage Data				
Report Income	0.95	0.96	0.93	-0.04***
Monthly Income (RMB)	18,346.16	25,791.66	6,626.72	19,164.93***
Monthly Expenses (RMB)	33,166.17	51,189.06	4,797.59	46,391.47***
Number of Records per Month	63.76	59	71.25	-12.25***
Tracking Duration in Months	29.16	30.15	27.73	-2.41***
Number of Respondents	4,639	2,745	1,894	

Note.—This table presents descriptive statistics for survey respondents in the Survey Sample both in aggregated and disaggregated by whether respondents ever report monthly expenses $\geq$ 32,407.14 RMB or monthly expenses $\leq$ 106.6 RMB from the app data. All table entries in the first three columns represent sample means, with the number of respondents listed in the last row. The fourth column represents the difference(s) between the respondents who reported extreme monthly spending and those who did not. RMB refers to Chinese currency. One U.S. dollar is approximately 7 RMB. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

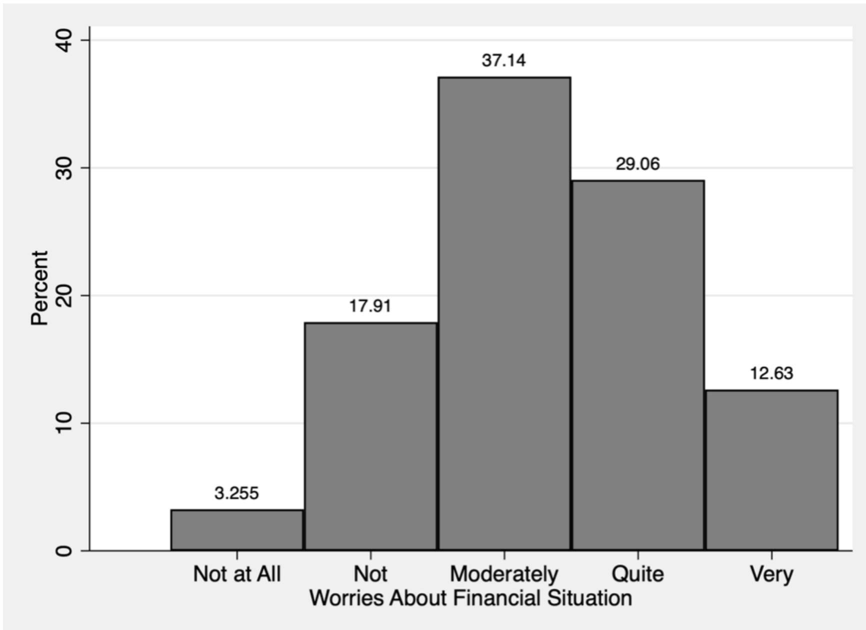
3.3.2 Measuring Financial Worries

Because expense tracking is a self-monitoring behavior in financial self-regulation, the main outcome of interest is people's financial worries. Given the potential biases in self-reported spending data, such as underreporting or inaccurate transaction recording, I directly measured respondents' level of worries about their financial situation. In the survey, respondents were asked, "How much do you worry about your current financial situation?" with respondents able to indicate one of five possible answers: "Not at all," "Not", "Moderately", "Quite", and "Very." I then coded these responses to a range from 1 (Not at all) to 5 (Very).

On average, individuals in the Survey Sample tend to express concerns about their financial situation. The average score is 3.3 with a standard deviation of 1. However, there is no statistically significant difference between the respondents who reported extreme monthly spending and those who did not.

Figure 8 shows the distribution of financial worry in the Survey Sample. A larger proportion of respondents (41.69%) indicated either quite or very worried about their financial situation compared to those who indicated that they were not at all worried (21.17%). Slightly more than one-third of the respondents (37.14%) indicated that they were moderately worried about their financial situation.

FIG. 8.—Distribution of Financial Worry Among Survey Respondents



This figure shows the distribution of responses to the survey question "How much do you worry about your current financial situation?" with five possible answers: "Not at all," "Not", "Moderately", "Quite", and "Very." The bars represent the percentage of respondents in the full Survey Sample (N=4,639) who selected each level of financial worry.

3.4 Empirical Approaches

This study aims to examine individuals' expense tracking patterns, focusing on accuracy, temporal proximity, and consistency. First, I examine the unconditional distribution of each pattern among all respondents in the Survey Sample. Subsequently, I analyze the distribution of these patterns based on worries about the financial situation to explore the unconditional relationship between specific expense tracking patterns and financial worries.

After presenting evidence on these relationships, I report regression-adjusted results investigating the association between specific expense tracking patterns and financial worries with or without covariates. Specifically, I employ the following specification with robust standard errors:

$$Y_i = \beta_0 + \beta_1 TrackingPattern_i + \beta_2^{'} X_i + \upsilon_{im} \tag{3.1}$$

where the dependent variable Y_i is financial worries for individual i; $TrackingPattern_i$ is the specific expense tracking pattern of interest for individual i; X_i is a vector of individual-level demographics, including age, gender, education, employment status, income, and marital status for individual i. The coefficient of interest is β_1, which measures the relationship between a specific expense tracking pattern and financial worries.

Additionally, when possible, I evaluate whether the objective measures of these tracking patterns from the survey align with the subjective measures derived from app usage data.

3.5 Results

3.5.1 Accuracy of Expense Tracking Behavior

Accurate expense tracking is crucial for effective financial management as it provides reliable personal spending information that assists individuals in making well-informed spending decisions based on their prior expenditures. Inaccuracies in expense records can lead to misunderstandings about actual costs and consumption levels, potentially resulting in poor financial outcomes, such as overspending. Therefore, I examine the accuracy of expense tracking behavior and its association with respondents' financial worries.

Survey respondents manually recorded their transactions using a tracking app. When making an entry, app users must select the category and date of the transaction. Therefore, the accuracy of individuals' expense tracking can be assessed across two dimensions: whether a record is linked to the correct category, and whether it is associated with an accurate purchase date. In this subsection, I first examine each dimension and then explore the relationship between these two aspects of accuracy.

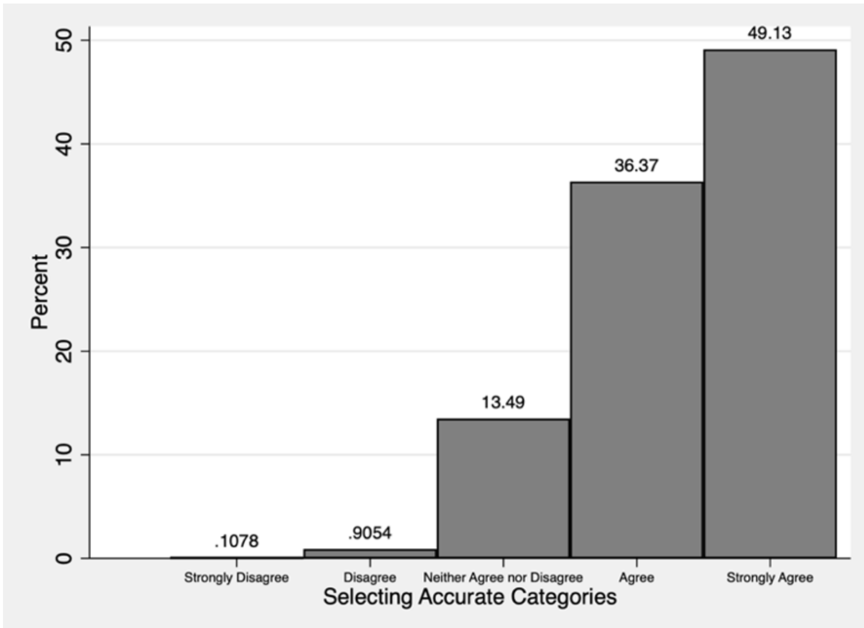
3.5.1.1 Accuracy of Categorization

To assess the perceived accuracy of categorization and its relationship with financial worries, I asked respondents, "I always make sure I select the accurate category while tracking," with responses ranging from Strongly Disagree (=1) to Strongly Agree (=5). The average score is 4.33 with a standard deviation of 0.75, indicating a general inclination towards agreement among respondents in selecting accurate categories. There is no statistically significant difference in categorization accuracy between respondents who reported extreme monthly spending and those who did not.

Figure 9 presents the distribution of the propensity to select accurate categories among the respondents in the Survey Sample. The majority agreed with the statement, with 49.13% strongly agreeing and 36.37% agreeing. Only a small proportion (approximately 1.01%) disagreed with this statement.

Next, I examine the relationship between category selection accuracy and levels of worry about financial situations. Given that there are very few respondents indicate strongly disagree, disagree, and neither agree nor disagree with selecting accurate categories, I group these three options together and label them as "Disagree/Uncertainty". The aggregated option consists of 14.50% of the responses, making the sample sizes more comparable. On average, respondents who indicate "Disagree/Uncertainty" in selecting accurate categories have an average score of 3.45 in the levels of worries about financial situations, respondents who indicate "Agree" have an average score of 3.32, and respondents who indicate "Strongly Agree" have an average score of 3.24.

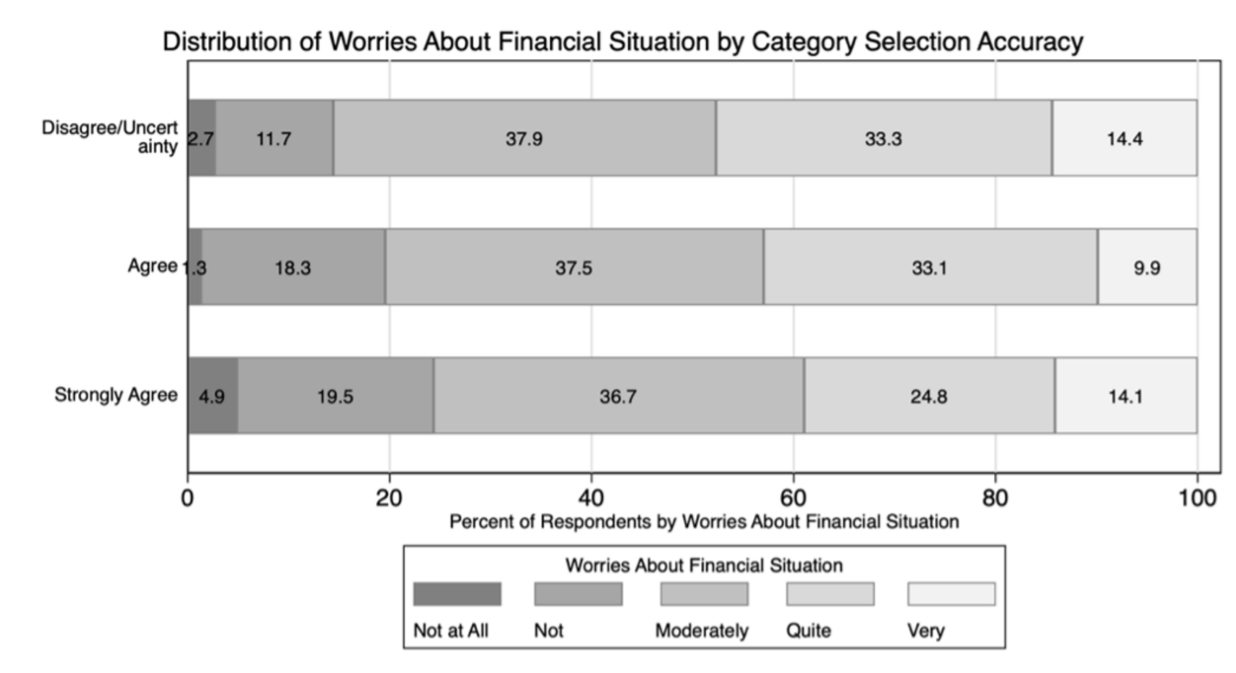
FIG. 9.—Distribution of Propensity to Select Accurate Categories



This figure shows the distribution of responses to the survey question, I always make sure I select the accurate category while tracking," on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The bars represent the percentage of respondents in the full Survey Sample (N=4,639) who selected each scale point.

Examining the unconditional distribution of the levels of worries about financial situations based on category selection accuracy (Figure 10) yields a consistent finding. Specifically, approximately 47.7% of respondents who indicate "Disagree/Uncertainty" when questioned about selecting accurate categories express either quite or very high levels of worries about their financial situation. Similarly, about 43% of respondents who indicate "Agree" report either quite or very high levels of worry, while approximately 38.9% of those who indicate "Strongly Agree" express similar worries about their financial situation.

FIG. 10.—Distribution of Worries About Financial Situation by Category Selection Accuracy



This figure shows the unconditional distribution of the levels of worry about financial situations based on category selection accuracy in the full Survey Sample (N=4,639).

These observed patterns persisted, even after controlling for demographic and economic variables. Table 11 presents the regression results without covariates (column (1)) and with covariates (column (2)). Worries about the financial situation were regressed on each level of category selection accuracy ("Disagree/Uncertainty", "Agree", "Strongly Agree"). The results remain consistent with and without controls, suggesting that individuals who report a higher tendency to select accurate categories while tracking their expenses are significantly less likely to report worries about their financial situations.

For example, the results in column (1) demonstrate that compared with individuals who disagree or are uncertain about selecting accurate categories while tracking, those who agree that they select accurate categories are associated with a decrease of 0.13 in financial worries. However, the magnitude of this effect is relatively small. Given that the overall range of financial worries is four, this effect corresponds to a change of approximately 3%.

TABLE 11
REGRESSION RESULTS (ACCURACY IN CATEGORIZATION)

	(1)	(2)
Category Selection Accuracy		
(Baseline: Disagree/Uncertainty)		
Agree	-0.13**	-0.12**
	-0.04	-0.04
Stronger Agree	-0.21***	-0.20***
	-0.04	-0.04
Constant	3.45***	4.22***
	-0.04	-0.13
Controls	No	Yes
Number of Respondents	4639	4639

NOTE.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and each level of category selection accuracy as a set of predictors using the Survey Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

I conduct a set of robustness checks to assess the robustness of this effect. First, I ran the same set of regressions on the Restricted Sample to assess whether the significant effect is driven by people reporting extremely low or high monthly spending. This significant association holds when analyzing the Restricted Sample (Table F16, F).

Second, to avoid force responses, individuals can select “prefer not to disclose” for each demographic question. However, individuals who choose this option may have varying demographic characteristics, and cannot be treated as a homogeneous group. For instance, those who select ”prefer not to disclose” for age may have different ages, making it inappropriate to group them together as a single age category in the regression analysis. To address this concern, I conducted the same set of regression analyses, treating the 1,163 individuals who ever selected ”prefer not to disclose” as missing in the Survey Sample. The results, as shown in Table F17 in Appendix F, show that the association remains robust and significant.

Third, in the previous analysis, financial worries were treated as a continuous measure in the regression models. However, its original measurement is categorical, ranging from 1 (Not at all) to 5 (Very). To better capture its categorical nature, I conducted a multinomial logistic regression[20] with demographic controls. In this analysis, the base group for the dependent variable was individuals who indicated "Very" on the financial worry question, while the base group for the independent variable was "Disagree/Uncertainty" in the category selection accuracy question.

The results (refer to Table F18 in Appendix F) show that the association remains robust and significant. For instance, the results in column (1) show that, compared to individuals who disagree or are uncertain about selecting accurate categories while tracking, those who strongly agree that they select accurate categories are associated with a 0.60 increase in the relative log odds of being in the "Not at All" worried category regarding their financial situation compared to the "Very" worried category. While not all coefficients of interest are statistically significant, the overall association between financial worries and category selection accuracy is statistically significant.

Fourth, in the previous analysis, the perceived accuracy of category selection was treated as a categorical variable and I grouped three options together and labeled them as "Disagree/Uncertainty" to ensure an adequate sample size for comparison. However, to directly examine the association between category selection accuracy and financial worries, I conducted another regression, treating category selection accuracy as a continuous variable, ranging from 1 (Strongly disagree) to 5 (Strongly agree). This approach yielded robust and significant results, suggesting that the inclination to select categories accurately during

[20] Although ordered logistic regression is more parsimonious, this model may violate the proportional odds assumption. Therefore, a multinomial logistic regression is considered more appropriate in this scenario.

tracking is linked to fewer financial worries (Table F19 Appendix F).

Across all analyses, the findings consistently show that individuals who are more inclined to select accurate categories have lower levels of financial worry. Although the findings are descriptive, they align with predictions from self-regulation theories (Bandura, 1991), which suggests that expense tracking accuracy plays a pivotal role in effective financial self-regulation. By providing accurate personal spending information, expense tracking enables individuals to make well-informed spending decisions based on their prior expenditures.

The prior findings are based on survey data, yet the prior literature highlights potential misreporting issues in such data (Ansolabehere and Hersh, 2012; Meyer et al., 2015). To assess the validity of this measure in reflecting respondents' propensity to select an accurate category, I delved into the app usage data for further insight. Although the app provides 33 preset expense categories, they may not entirely align with the users' tracking needs. Therefore, the app allows users to create customized categories. Within the Survey Sample, I identified 8,016 customized expense categories. The adoption of customized categories may signal an individual's inclination to accurately categorize expenses. Therefore, I examined both the extensive margin (propensity to use customized expense categories) and the intensive margin (the number of customized expense categories used) by each respondent to explore whether these measures are significantly associated with the tendency to select accurate categories while tracking.

Table 12 presents summary statistics regarding the propensity to use expense categories and the number of customized categories used per respondent. On average, about 87% of the respondents had set customized expense categories and employed 5.54 customized expense categories.

Next, I regressed the extensive margin (propensity to use customized expense categories)

TABLE 12
Descriptive Statistic (Customized Expense Categories)

	Survey Sample
Using Customized Expense Categories (1=Yes, 0=No)	0.87
Number of Customized Expense Categories	5.54
	-6.55
Number of Respondents	4,639

Note.—This table provides descriptive statistics for the respondents included in the Survey Sample. All values in the table indicate the sample means, with the standard deviations shown in parentheses. The final row shows the total number of respondents.

and the intensive margin (number of customized categories used) per respondent on the tendency to select accurate categories while tracking, with a set of control variables (age, gender, education, employment status, income, and marital status). The results in column (1) of Table F20 in Appendix F suggest that the perceived tendency to select accurate categories is not significantly associated with the propensity to use customized expense categories. The insignificant results in column (1) may be due to the limited variation in the propensity to use customized expense categories, as the summary statistic in Table 12 documents that approximately 87% of the respondents created customized expense categories in the survey sample.

In contrast, the results in column (2) suggest that people who strongly agree to select accurate categories are significantly associated with a 0.58 increase in the number of customized expense categories used compared to people who disagree or are uncertain about selecting accurate categories. Since the intensive margin is a better proxy for people's actual usage of customized expense categories, these results provide suggestive evidence of the consistency between the survey measure and the measures derived from the app tracking data. This alignment further supports the validity of the survey measure as an indicator of an individual's propensity to select expense categories accurately.

3.5.1.2 Accuracy of Date of the Purchase

As mentioned earlier, the accuracy of expense tracking includes both the accuracy of category selection and date selection. I discussed the accuracy of category selection in the previous subsection. Therefore, in this subsection, I investigate the perceived accuracy of purchase dates and their association with financial worries.

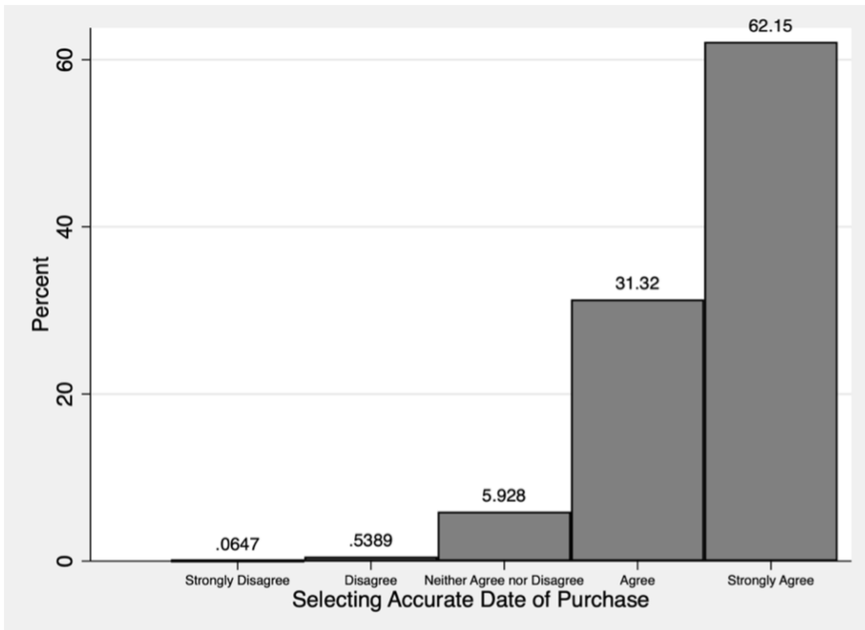
App users are prompted to select the date on which any transaction is recorded. If the transaction date is not selected, the default date is the date on which the transaction is entered into the app. The app interface displays expenses and income by day of the month, with default settings showing the accumulated expenses and income for the current month. Therefore, inaccurate date may lead to incorrect information access and biased financial self-awareness. For instance, recording a recent large purchase as occurring in the previous month may not be reflected in the app's accumulated monthly spending, potentially leading individuals to believe they are within the budget for the current month and, consequently, overspend.

To measure the perceived accuracy of the purchase date, respondents were asked to rate their agreement with the statement "I always make sure I select the date when the transaction happens while tracking" on a scale ranging from Strongly Disagree (=1) to Strongly Agree (=5). The average score is 4.55 with a standard deviation of 0.64, indicating a general tendency towards agreement among respondents in selecting an accurate date of purchase while tracking. There is no statistically significant difference in the accuracy of the date of purchase between the respondents who reported extreme monthly spending and those who did not.

Figure 13 presents the distribution of the propensity to select an accurate purchase date among respondents in the Survey Sample. The majority agreed with the statement, with

62.15% strongly agreeing and 31.32% agreeing. Only a small proportion (approximately 0.6%) either disagreed or strongly disagreed with this statement.

FIG. 13.—Distribution of Propensity to Select Accurate Date of Purchase

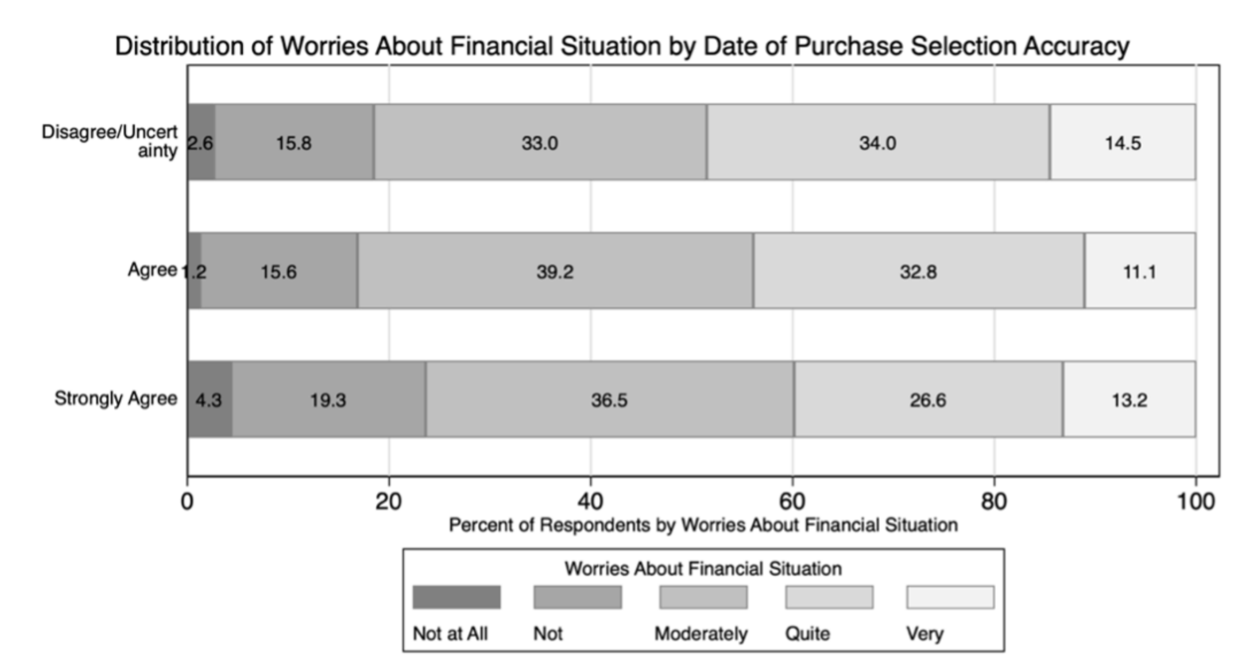


This figure shows the distribution of responses to the survey question "I always make sure I select the date when the transaction happens while tracking" on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The bars represent the percentage of respondents in the full Survey Sample (N=4,639) who selected each scale point.

Next, I examine the relationship between perceived date selection accuracy and levels of worry about financial situations. Similar to the analysis of categorization accuracy, given that there are very few respondents who indicate strongly disagree, disagree and neither agree nor disagree with selecting accurate date of purchase, I group these three options together and label them as "Disagree/Uncertainty". On average, respondents who indicate "Disagree/Uncertainty" in selecting accurate dates have an average score of 3.42 in the levels of worries about financial situations, respondents who indicate "Agree" have an average score of 3.37, and respondents who indicate "Strongly Agree" have an average score of 3.25.

Examining the unconditional distribution of the levels of worries about financial situations based on date selection accuracy (Figure 14) also yields a consistent finding. Specifically, as shown in Figure 14, approximately 48.5% of respondents who indicate "Disagree/Uncertainty" when questioned about selecting accurate categories express either quite or very high levels of worries about their financial situation. About 43.9% of respondents who indicate "Agree" report either quite or very high levels of worry, and approximately 39.8% of those who indicate "Strongly Agree" express similar worries about their financial situation.

FIG. 14.—Distribution of Worries About Financial Situation by Date Selection Accuracy



This figure shows the unconditional distribution of the levels of worries about financial situations based on date selection accuracy in the full Survey Sample (N=4,639).

These observed patterns remained consistent after adjusting for the demographic and economic variables. Table 15 presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about financial situations as the outcome of interest and each level of agreement on date selection accuracy (1=Strongly Disagree to 5=Strongly Agree) as a set of predictors. The regression results in both columns are consistent. Although there is no significant difference between individuals who agree and those who disagree or are uncertain about date selection accuracy, individuals who strongly agree that they select the correct date are significantly associated with a decrease in financial worries ranging from 0.17 to 0.15 compared to those who disagree or are uncertain. However, the magnitude of this effect is relatively small. Given that the overall range of financial worries spans four, this effect accounts for a change of 3.75% to 4.25%.

TABLE 15
Regression Results (Date Selection Accuracy)

	(1)	(2)
Date Selection Accuracy		
(Baseline: Disagree/Uncertainty)		
Agree	-0.05	-0.04
	(0.06)	(0.06)
Stronger Agree	-0.17**	-0.15*
	(0.06)	(0.06)
Constant	3.42***	4.16***
	(0.06)	(0.14)
Controls	No	Yes
Number of Respondents	4,639	4,639

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and each level of agreement on date selection accuracy as a set of predictors using the Survey Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

I also conducted a set of robustness checks. First, this pattern persists when excluding respondents who ever reported "Prefer not to disclose" in any demographic questions (refer to Table F21 in Appendix F). However, in column (2) of Table F21 in Appendix F, the significance decreases and is only significant with a 90% confidence interval.

Second, when examining the effect using the Restricted Sample (refer to Table F22 in Appendix F), the coefficients of interest become insignificant both with and without the covariates. This suggests that while there is a significant difference in financial worries between people who strongly agree and those who disagree or are uncertain about the tendency to select accurate dates while tracking, this significance may be driven by individuals who have ever reported extreme monthly spending.

Similar to the analysis of category selection accuracy, I turned to the app data to assess the validity of the survey measure. Each record in the app is associated with two dates: Date 1 (when the record was logged into the app system) and Date 2 (when the record occurred). However, there are some limitations in the app data that make it impossible to find an appropriate proxy for assessing date selection accuracy. Although users can enter transactions either in advance (prospective expense tracking) or later (retrospective expense tracking) than the date of the purchase and specify Date 2 accordingly, only individuals who record retrospective or prospective expenses need to select a specific Date 2 due to accuracy concerns. Moreover, because Date 2 defaults to the same date as Date 1, I lack sufficient information to distinguish whether the records reported on the same date as the purchase are, in fact, prospective or retrospective expense records, as individuals may simply neglect to indicate the actual purchase date. Therefore, I cannot directly measure the propensity to record expenses with accurate dates.

3.5.1.3 Additional Analysis Regarding Accuracy in Expense Tracking

One important question of interest is whether individuals tend to prioritize both dimensions of accuracy in expense tracking or focus on one over the other. Conducting a pairwise correlation between individuals' tendencies for accuracy in categorization and accuracy on the date of purchase, I found a significant correlation between these two aspects, $r(4637) = 0.50, p < 0.001$. The correlation coefficient of 0.50, although significant, suggests a moderate relationship. Individuals who value one aspect of accuracy are only moderately likely to value the other.

This finding has important implications for our understanding of the effectiveness of expense tracking patterns. Given the moderate association between the two accuracy measures, people could prioritize one accuracy dimension over the other when tracking. This may further suggest that given the effort required to record accurate expenses, people could prioritize category selection accuracy if people face limitations in their ability to record all available information.

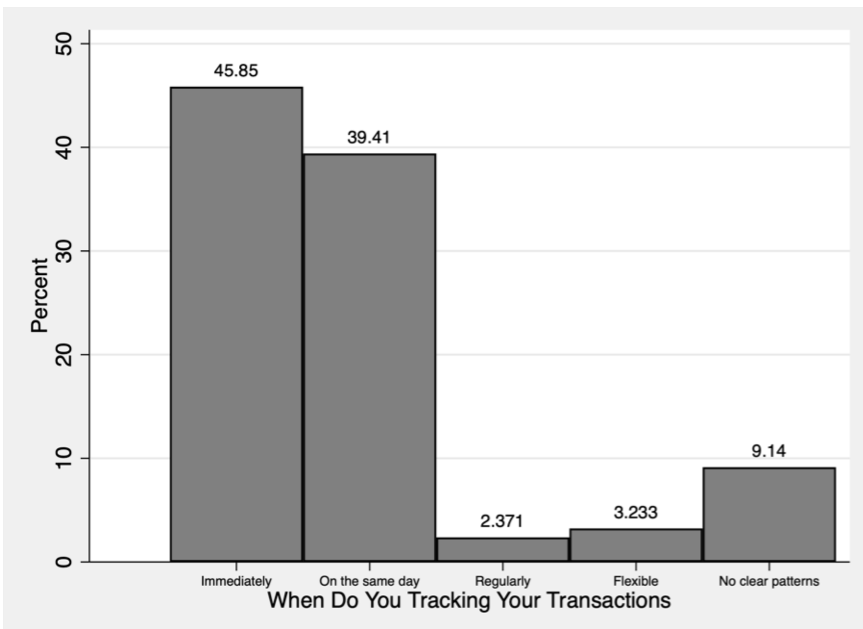
However, while I find that perceived category selection accuracy is more significantly associated with fewer financial worries than perceived date selection accuracy in this research, I do not conclude that date selection accuracy is completely useless in terms of financial self-regulation. There are limitations (e.g., misreporting in survey measures) in this study that prevent making such a conclusion. Therefore, comparing and contrasting both dimensions of accuracy in expense tracking in terms of the effectiveness of financial self-regulation is likely to offer a fruitful path for future research.

3.5.2 Temporal Proximity in Expense Tracking Behavior

In addition to accurately categorizing and dating transactions, promptly recording them is essential for individuals to maintain precise financial self-awareness. Timely expense tracking ensures that individuals can reflect on accurate personal spending information, thus forming the basis for effective financial management.

To better understand the temporal aspect of expense tracking behavior, I investigated when respondents typically record their transactions. I assessed it in the survey by asking respondents about their typical transaction-recording habits. Respondents are given options such as (a) record transactions immediately after it happens, (b) record the transaction on the same date when it happens, (c) record the transaction regularly, such as once a week, (d) the timing depends on the nature of the transaction (being flexible), such as recording large purchases immediately and recording small purchases regularly, and (e) there is no clear pattern.

FIG. 16.—Distribution of Propensity to Select Accurate Date of Purchase



This figure shows the distribution of responses to the survey questions regarding their typical transaction-recording habits. The bars represent the percentage of respondents in the full Survey Sample (N=4,639) who selected each scale point.

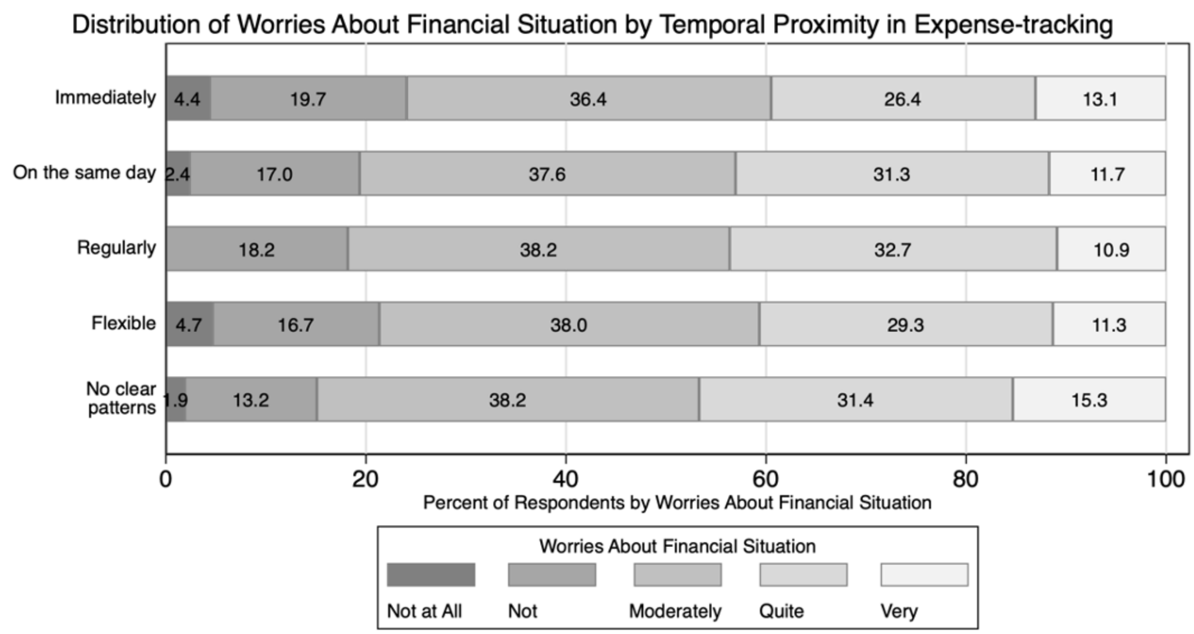
Figure 16 presents the distribution of each response option in the Survey Sample. Approximately 45.85% recorded transactions immediately after purchase, whereas 39.41% recorded them on the same day. Approximately 2.37% reported recording transactions regularly, and 3.23% indicated flexibility in their recording habits based on the nature of the transaction. In addition, 9.14% reported no clear patterns for recording transactions. Grouping the first two options together, nearly 85.26% of the respondents recorded transactions on the same date they occurred. This reveals a general tendency among individuals to prioritize promptness in expense tracking. Such behavior appears rational because delayed recording may lead to forgotten or overlooked transactions, resulting in inaccurate spending information.

Next, I present the unconditional distribution of levels of worries about financial situations by perceived temporal proximity in expense tracking (Figure 17). As shown in Figure 17, approximately 39.5% of respondents who indicate "record the transaction immediately after it happens" report either quite or very high levels of worries about their financial situation. About 43% of those who indicate "record the transaction on the same date when it happens" express similar worries about their financial situation. Approximately 43.6% of those who indicate "record the transaction regularly" report similar worries about their financial situation. About 40.6% of those who indicate "the timing depends on the nature of the transaction" express similar worries about their financial situation. About 46.7% of those who indicate "there is no clear pattern" report similar worries about their financial situation. This finding suggests that individuals who indicate recording transactions immediately are associated with fewer financial worries.

Lastly, I investigated whether the observed patterns in Figure 17 persist even after adjusting for demographic and economic variables. Table 18 displays the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest, and a set of dummy variables capturing each option from the survey question regarding when individuals tend to log their transactions as predictors. For comparison, I treated those who reported recording on the same day as the baseline[21].

[21] I selected tracking expenses on the same day as the baseline for comparison because I believe it strikes an appropriate balance between commitment and the risk of forgetting. This approach requires less commitment than recording expenses immediately after they occur, while also being associated with a

FIG. 17.—Distribution of Worries About Financial Situation by Temporal Proximity in Expense Tracking



This figure shows the unconditional distribution of the levels of worries about financial situations based on typical transaction-recording habits in the full Survey Sample (N=4,639).

The regression results in column (2) with covariates suggest that individuals who report immediately recording transactions when they happen are significantly associated with being less worried about their financial situation than those who record transactions on the same day. Moreover, individuals who report no clear patterns are significantly associated with being more worried about their financial situation than those who record transactions on the same day. These findings align with self-regulation theory, as temporal proximity, a key aspect of quality in self-monitoring, matters in terms of financial self-regulation outcomes.

However, there is no significant difference between people who report recording transactions on the same day and those who report recording transactions regularly or flexibly.

lower risk of missing records compared to tracking less frequently, such as once a week.

This finding seems to contradict what is predicted by self-regulation theory. However, it is possible that fewer people reported recording transactions regularly or flexibly, which may bias the results.

TABLE 18
Regression Results (Temporal Proximity in Expense Tracking)

	(1)	(2)
Temporal Proximity (Baseline=On the same day)		
Immediately	-0.09**	-0.06*
	(0.03)	(0.03)
Regularly	0.03	0.02
	(0.09)	(0.09)
Flexible	-0.07	-0.03
	(0.09)	(0.08)
No clear patterns	0.12*	0.11*
	(0.05)	(0.05)
Constant	3.33***	4.10***
	(0.02)	(0.13)
Controls	No	Yes
Number of Respondents	4639	4639

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and a set of dummy variables capturing each option from the survey question regarding when individuals tend to log their transactions as predictors using the Survey Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

As robustness checks, I conducted the same set of regressions using the Restricted Sample (refer to Table F23 in Appendix F) or excluding the respondents who ever selected “Prefer not to disclose” for any demographic questions (refer to Table F24 in Appendix F). Only some of these patterns persist as some coefficients of interest become less significant. For example, the coefficient of recording immediately becomes insignificant in column (2) with covariates from Table F23 and the coefficient of having no clear patterns becomes insignificant in Table F24.

Although the findings are mixed, the analysis still provides some implications. First, in general, it may be better to plan when to record transactions, as individuals following some expense tracking patterns on when to record their transactions are better off than individuals without clear patterns when recording transactions. Second, among these recording patterns, recording immediately is the best. This may be attributed to the fact that immediate recording is the only method that minimizes the risk of overlooking expenses and consequently failing to report some expenditures.

Similar to the analysis of the date selection accuracy, there are some limitations in the app data that make it impossible to find an appropriate proxy for assessing the temporal proximity of expenses-tracking. Because Date 2 defaults to the same date as Date 1, individuals may simply neglect to indicate the actual purchase date. Therefore, I could not directly measure lapses in recording expenses to assess the validity of answers regarding the timing of expense tracking from the survey.

3.5.3 Consistency in Expense Tracking Behavior

Stopping self-monitoring prematurely is a significant self-regulatory failure (Karoly, 1993), indicating an inability to persist in actions related to goal achievement or overcome obstacles in goal pursuit (Heckhausen and Heckhausen, 2018). Therefore, in addition to the accuracy and temporal proximity of self-monitoring, consistency in self-monitoring is another important aspect that affects the quality of self-monitoring and, thus, impacts self-regulation effectiveness (Bandura, 1991). In this subsection, I move to examine the consistency of expense tracking and assess its association with financial worries.

3.5.3.1 Habit Strength in Expense Tracking Behavior

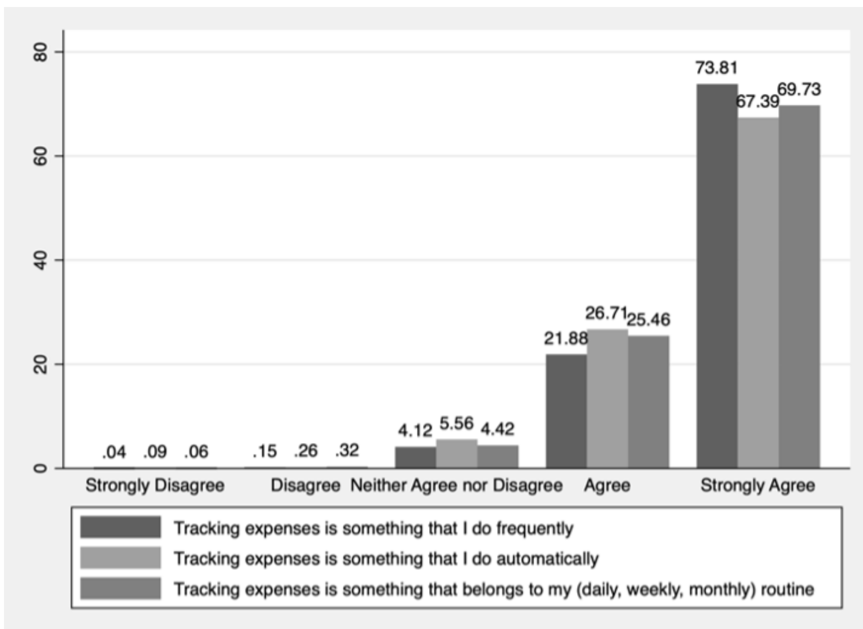
Given the multitude of daily consumption opportunities, expense tracking consistency refers to whether people consistently record a transaction when it occurs. However, expense tracking, as a self-monitoring behavior, demands effort, and can be challenging. Not all goal-oriented movements require conscious and deliberate action, and some can become automatic. Indeed, developing a habit of expense tracking might be the optimal strategy for achieving consistency in this behavior. As habits form, regulatory behaviors can shift from conscious and deliberate processes to impulsive and association-driven systems, facilitating quick and efficient actions (Strack and Deutsch, 2004).

Conceptually, habit formation is straightforward: consistent context-behavior associations develop through repeating the behavior in a consistent context (Gardner and Lally, 2018). Therefore, through repeated expense tracking behavior, individuals may form the habit of monitoring their transactions and reflecting on spending data, making financial self-regulation less effortful. In this context, developing a habit of tracking spending may signal greater consistency in expense tracking.

To test whether tracking can become habitualized with practice, I assessed respondents' habit strength in tracking using a simplified version of the Self-Report Habit Index (SRHI) developed by Verplanken and Orbell (2003). Because expense tracking frequently occurs, I focused on assessing habit strength in expense tracking. Respondents rated their agreement with three statements: (a) "Tracking expenses is something that I do frequently"; (b) "Tracking expenses is something that I do automatically"; and (c) "Tracking expenses is something that belongs to my (daily, weekly, monthly) routine." Responses ranged from Strongly Disagree (=1) to Strongly Agree (=5).

Figure 19 presents the distribution of the answers to each habit strength question. On average, people tend to agree with these three statements. For example, approximately 73.81% of respondents indicate "Strongly Agree" with the statement "Tracking expenses is something that I do frequently," about 67.39% of respondents indicate "Strongly Agree" with the statement "Tracking expenses is something that I do automatically," and approximately 69.73% of respondents indicate "Strongly Agree" with the statement "Tracking expenses is something that belongs to my (daily, weekly, monthly) routine."

FIG. 19.—Distribution of Answers to Each Habit Strength Question



This figure shows the distribution of responses to the survey question on habit strength in expense tracking. The bars represent the percentage of respondents in the full Survey Sample (N=4,639) who selected each scale point.

Since I measured habit strength using three statements, I assessed internal consistency by computing Cronbach's alpha. The alpha coefficient is 0.89, indicating high internal consistency. I then constructed a variable named habit strength in expense tracking as the average of all three items. I treated this variable as a continuous variable, ranging from weak habit

(=1) to strong habit (=5). The average rating was 4.65 with a standard deviation of 0.53, indicating a fairly strong expense tracking habit among the respondents on average. However, one caveat is that this does not imply that all tracking app users have a strong habit of expensive tracking. Since the survey was administered to active tracking app users, it is possible that those who actively tracked their spending were more likely to participate in the survey.

Since self-regulation theory documents that consistency of self-monitoring matters in terms of effective financial self-regulation, I investigated whether habit strength in expense tracking, as a proxy for consistency of expense tracking, is associated with fewer financial worries. First, I assess the unconditional relationship between habit strength in expense tracking and worries about financial situations. I find a significant correlation, $r(4637) = -0.06, p < 0.001$, which means that having a stronger habit of expense tracking is associated with fewer financial worries. However, the correlation coefficient of -0.06 suggests that this relationship is very weak.

Second, I regressed worries about the financial situation on habit strength in expense tracking, both with and without adjusting for demographic and economic variables. Table 20 displays the regression results, both without covariates (column (1)) and with covariates (column (2)). The analysis in both columns reveals a significant association between habit strength and fewer worries about the financial situation. For example, the results in column (2) document that a one-unit increase in habit strength was associated with a 0.07-unit decrease (on a 5-point scale) in worries about the financial situation.

TABLE 20
REGRESSION RESULTS (CONSISTENCY IN EXPENSE TRACKING)

	(1)	(2)
Habit Strength in Expense Tracking	-0.12***	-0.07**
(Weak Habit=1, Strong Habit=5)	(0.03)	(0.03)
Constant	3.87***	4.41***
	(0.12)	(0.17)
Controls	No	Yes
Number of Respondents	4,639	4,639

NOTE.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and habit strength in expense tracking as a predictor using the Survey Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

As robustness checks, I conducted the same set of regressions using the Restricted Sample (refer to Table F25 in Appendix F) or excluding the respondents who ever selected "Prefer not to disclose" for any demographic questions (refer to Table F26 in Appendix F). In general, the results are significant and robust. However, in column (2) of Table F26, the significance of the coefficient of interest decreases but remains significant within the 90% confidence interval.

Additionally, I regress financial worries on each individual habit strength measure with controls (Table F27 in Appendix F). Column (1) shows the results when the agreement level on "Tracking expenses is something that I do frequently" is the independent variable. Column (2) shows the results when the agreement level on "Tracking expenses is something that I do automatically" is the independent variable. Column (3) shows the results when the agreement level on "Tracking expenses is something that belongs to my (daily, weekly, monthly) routine" as the independent variable. The coefficients of interest are all significant, with the expected signs (negative). This finding suggests that the significant association between habit strength in expense tracking and financial worries in Table 20 is not driven by the agreement level in a single item. Instead, people who are less financially worried are associated with better agreement with all three statements.

Together, the previous findings suggest that consistent expense tracking is associated with fewer financial worries. This finding aligns with the self-regulation theory (Bandura, 1991). One implication of these findings is to underscore the significance of consistent expense tracking for effective financial self-regulation. Since the findings are descriptive in nature, future research could investigate this relationship in a causal manner. Additionally, these findings shed light on how to promote expense tracking for future research. While expense tracking may initially require effort, it can become less effortful with repeated behaviors. Therefore, promoting the development of expense tracking may be more beneficial in the long run.

Similar to prior analyses, I examine app data to assess the validity of the habit strength measure from the survey data. Since habit in general is developed through repeated behaviors, I examine the relationship between respondents' duration of expense tracking experience and habit strength measures.

I decide to use the number of weeks with records of expenses to capture the duration of expense tracking behavior. This choice is based on the rationale that the weekly cycle, with its shorter timeframe including both workdays and weekends, can provide a more accurate measure of duration than the monthly cycle.

The app data provide an estimate of respondents' tracking experience, but many may have engaged in tracking behavior before using the tracking app. To estimate the overall duration of the tracking experience, respondents were asked whether they had any tracking experience before using the app, and if so, how long they had engaged in tracking using other methods in the past. The self-reported tracking duration ranges from less than 1 month to more than 60 months. A total of 1,913 respondents indicated having expense tracking experience before starting to use the tracking app. Among them, 600 individuals reported less than one month of tracking experience, whereas 95 respondents indicated tracking for over 60 months in the survey.

To ensure consistency and facilitate later analysis, I constructed a variable capturing non-app tracking duration in weeks. Employing a consecutive approach, I categorized individuals reporting less than one month as having one week of expense tracking experience and those reporting over 60 months as having 261 weeks of expense tracking experience before starting to use the tracking app. Additionally, for respondents who indicated no prior expense tracking behavior before using the app, I assigned a value of zero to the variable.

I also constructed a variable capturing the app tracking duration, measured as the number of weeks with tracking records for each user in the app. I then added the app tracking duration and non-app tracking duration together to create a new variable capturing the total number of weeks with an expense tracking experience.

Moreover, I constructed a variable capturing the number of consecutive weeks with expense records as a proxy for the longest streak. While it is common for individuals to not spend in a week, it is less likely for them to not spend in a month. Therefore, I define the number of consecutive weeks as the number of weeks with expense tracking behavior since individuals started using the app until they had more than four consecutive weeks without any reported expenses.

Table 21 presents the summary statistics of the tracking duration measures. On average, respondents engaged in tracking for approximately 19.65 weeks before using the app and continued to use the app for approximately 113.92 weeks, resulting in a cumulative expense tracking experience of approximately 133.57 weeks. The average number of consecutive weeks with expenses is 82.73.

TABLE 21
DESCRIPTIVE STATISTIC (CONSISTENCY IN EXPENSE TRACKING)

	Survey Data
Number of Weeks with Non-app Tracking Experience	19.65
	(50.12)
Number of Weeks with App Tracking Experience	113.92
	(55.53)
Total Number of Weeks with Expenses	133.57
	(77.19)
Number of Consecutive Weeks with Expenses	82.73
	(70.70)
Number of Respondents	4,639

NOTE.—This table provides descriptive statistics for the respondents included in the Survey Sample. All values in the table indicate the sample means, with the standard deviations shown in parentheses. The final row shows the total number of respondents.

To assess the validity of the habit strength measure from the survey, I examine whether the total number of weeks with expenses and the number of consecutive weeks with expenses are associated with habit strength. I regress them on the habit strength measure with the controls (Table F28 in Appendix F). Results show that habit strength is greater when people track for a longer duration in terms of the total number of weeks with expenses and the number of consecutive weeks with expenses. These findings further suggest that the habit strength measure from the survey is valid, as both the survey and app data are consistent.

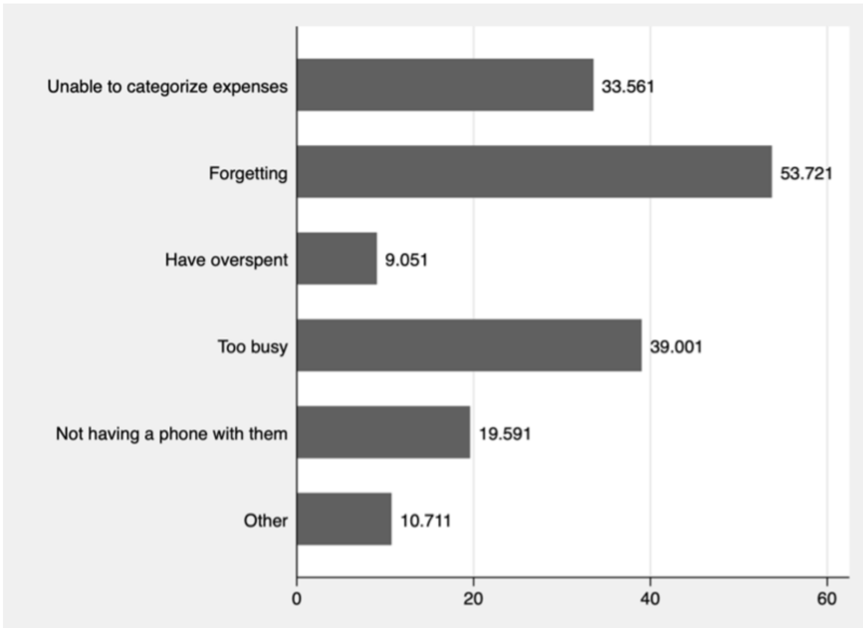
3.5.3.2 Barriers to Consistency

Prior findings suggest that consistent expense tracking is associated with fewer financial worries. Ideally, individuals who hope to use expense tracking to regulate their financial behavior should consistently log their expenses for each time they spend money. However, barriers can prevent people from tracking expenses, potentially affecting expense tracking consistency. Therefore, in this subsection, I examine the barriers to consistent expense tracking.

Since the app tracking data lacks information on whether an individual failed to track a specific record at a specific time, I directly asked respondents about the obstacles that prevent them from tracking expenses in the survey. Respondents were given multiple options to select, including (a) I am not sure about how to categorize spending, (b) I forget about the expenses, (c) I realize that I have already overspent, (d) I am too busy, (e) my phone is not with me, and (f) others.

Figure 22 shows the distribution of each barrier. The most commonly chosen obstacle is forgetting, with 53.72% of respondents indicating that they did not log a transaction because they forgot. Additionally, being too busy (39.00%), being unable to categorize expenses (33.56%), and not having a phone with them (19.59%) were frequently chosen reasons for not making an entry. About 10.71% of respondents selected "others," while only 9.05% indicated that they avoided expense tracking if they realized that they had already overspent. Avoiding expense tracking due to overspending could be seen as behavior aligned with the "ostrich effect" (Karlsson et al., 2009; Olafsson and Pagel, 2017), which suggests that individuals with limited financial resources may pay less attention to their personal finances. Upon further analysis, I find that people who avoid expense tracking if they overspend are indeed more likely to have low incomes compared to those who indicate otherwise, $t(4163.4) = -2.35, p < 0.01$. Despite this difference, it is encouraging to note that only a few people avoided expense tracking due to overspending.

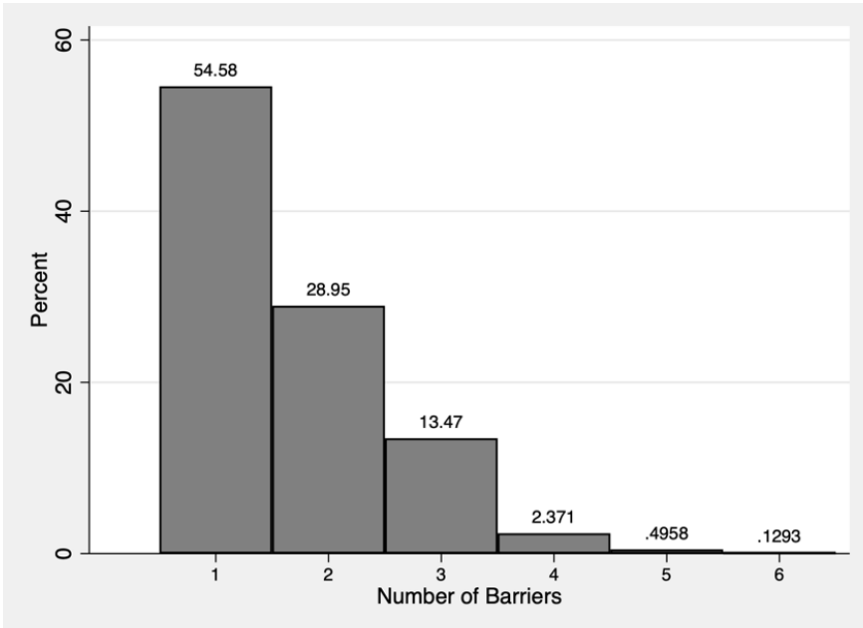
Fig. 22.—Distribution of Each Barrier



This figure shows the distribution for each barrier. The bars represent the percentage of respondents in the full Survey Sample (N=4,639) who selected each barrier.

As respondents could face varying numbers of obstacles and were allowed to select multiple obstacles in the survey, I constructed a variable indicating the total number of obstacles faced by each respondent. This approach accounts for the possibility that individuals may encounter multiple challenges in expense tracking. On average, respondents reported encountering 1.66 types of obstacles, with a standard deviation of 0.85. The range varied from a minimum of one to a maximum of six obstacles. Figure 23 shows the distribution of the number of barriers selected by each respondent. Generally, the percentage decreases as the number of barriers increases. More than half of the respondents (about 54.58%) only indicate one barrier.

FIG. 23.—Distribution of the Number of Barriers



This figure shows the distribution of the number of barriers. The bars represent the percentage of respondents in the full Survey Sample (N=4,639) who selected a different number of barriers.

As barriers may prevent people from consistently tracking their expenses, I examine whether individuals facing obstacles are associated with different expense tracking durations. While it is unclear whether specific types of obstacles affect tracking behavior, a general assumption is that the more obstacles a respondent faces, the more likely they are to avoid tracking, leading to a reduction in the tracking duration. To test this assumption, I regressed the total number of weeks with expense tracking experience and the number of consecutive weeks with expenses on the number of obstacles to expense tracking, controlling for demographic and economic variables.

The regression results presented in column (1) of Table 24 show that facing more obstacles is not significantly associated with the total number of weeks of expense tracking experience. This insignificance may stem from the fact that the barrier question is specifically tailored to app tracking and should not be associated with expense tracking before using the app. Moreover, individuals may encounter obstacles and temporarily discontinue tracking but later resume the practice. Therefore, the insignificant association between the total number of weeks spent expense tracking and the number of barriers does not refute the assumption that barriers may impede consistent expense tracking.

TABLE 24
Regression Results

	(1) # Total Weeks	(2) # Consecutive Weeks
# Barriers	0.74	-2.40*
	(1.30)	(1.16)
Constant	81.45***	55.14***
	(9.56)	(8.85)
Controls	Yes	Yes
Number of Respondents	4639	4639

Note.—Robust standard error in parentheses. This table presents the regression results with the number of barriers as the independent variable. Column (1) shows the results when the total number of weeks with expense tracking experience is the dependent variable. Column (2) shows the results when the number of consecutive weeks with expenses is the dependent variable. The control variables include age, gender, education, employment status, income, marital status, whether having kid(s). Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

Conversely, the results in column (2) of Table 24 demonstrate that facing more obstacles is significantly associated with the number of consecutive weeks with expenses and greater habit strength in expense tracking. However, the magnitude of this effect is relatively small. Given that the average number of consecutive weeks with expenses is 82.73, this change represents a 2.90% decrease in the tracking duration.

As these common barriers impede tracking duration and consistency in expense tracking matters in terms of financial self-regulation, one implication is that future research investigating ways to overcome these obstacles may be fruitful for individual trackers, financial educators, and tracking app developers. For example, tracking app developers can implement reminders to prompt users to regularly track their expenses, helping them avoid forgetting and maintain consistency. Additionally, financial educators could provide guidance on strategies to overcome common barriers, empowering individuals to maintain effective expense tracking habits.

3.6 General Discussion

In this study, I investigated expense tracking patterns pertaining to accuracy, consistency, and temporal proximity, and their association with individuals' financial worries. Several findings emerged from the empirical analysis. First, individuals generally report that they tend to be accurate in their expense tracking. Approximately 85.50% of respondents strongly agreed or agreed that they always indicated the accurate category (e.g., "snack"), and about 93.47% of the respondents strongly agreed or agreed that they always indicated the accurate transaction date when recording an expenditure. Moreover, accuracy in categorization is significantly linked to lower financial worries, aligning with the self-regulation theory. However, the association between accuracy in selecting dates of purchase and financial worries yielded mixed results, possibly influenced by individuals reporting extreme monthly spending.

Second, when examining both dimensions of expense tracking accuracy simultaneously, the correlation coefficient between these two dimensions is 0.5, suggesting a moderate correlation. Therefore, individuals may prioritize one dimension over the other.

Third, individuals generally report prioritizing promptness in expenses-tracking, as approximately 85.26% of the respondents indicated either tracking immediately after the purchase or on the same date when the purchase happens. However, the analysis of the temporal proximity of expense tracking revealed mixed results. Adhering to a pattern for recording transactions seems more beneficial than having no clear recording pattern as individuals without a clear recording pattern are significantly associated with higher financial worries. Moreover, recording immediately emerges as the method associated with the fewest financial worries, likely due to its effectiveness in minimizing the risk of overlooking expenses compared to other tracking patterns. Concerning the remaining tracking patterns, there are no significant differences in financial worries observed among the three alternative tracking patterns.

Fourth, I find a significant association between habit strength in expense tracking and expense tracking duration. This suggests that individuals could develop a habit of expense tracking through repeated behaviors to ensure consistency in expense tracking. Moreover, consistency in expense tracking is significantly associated with fewer financial worries, aligning with the self-regulation theory (Bandura, 1991). Additionally, I identified five common barriers that may impede consistent tracking. Forgetting emerged as the most frequently cited obstacle, with more than half of the respondents (53.72%) indicating that they did not log a transaction because they had forgotten to do so. Furthermore, my analysis reveals a significant association between reporting more of these barriers and fewer consecutive weeks of expense tracking.

3.6.1 Contributions and Implications

This research presents novel descriptive evidence of expense tracking patterns using data from a survey paired with respondents' expense tracking data. One contribution of this research is the unique alignment between subjective survey data and objective app usage data, which enhances the validity of certain research findings. This alignment allows for a more robust evaluation of survey measures by leveraging the objective app data, thereby strengthening the assessment.

Second, the findings enrich psychological self-regulation theory by examining the quality of expense tracking, including accuracy, consistency, and temporal proximity within the self-regulation framework. Moreover, I assess whether the findings align with the self-regulation theory (Bandura, 1991) and discuss their implications on promoting positive financial outcomes. For example, I find that while self-regulation theory documents that accurate self-monitoring matters in self-regulation, individuals may only prioritize one aspect of accuracy when tracking expenses, and only accuracy in categorization is significantly associated with lower financial worries.

Third, it contributes to the literature on personal finance and mental budgeting by identifying the patterns and features of expense tracking that may facilitate improved financial outcomes. Although the findings are descriptive, understanding these nuances can guide future research on personal finance and mental budgeting, providing avenues for deeper exploration of the mechanisms that may influence financial behavior. For instance, I find that individuals can develop a habit of expense tracking, which is associated with fewer financial worries. This finding opens up avenues for further research. Since expense tracking is often viewed as a means to support budgeting, several questions arise: Can expense tracking indeed become a habitual behavior, thereby better supporting budgeting efforts? Can budgeting itself evolve into a habitual behavior? Is it more effective to cultivate budgeting as a long-term goal, or does it serve better as a short-term objective?

Although previous findings are descriptive and the direction of the relationship is unknown, they still have some practical implications for individual decision-makers, financial education initiatives, and tracking tool developers. By recognizing the tracking features that are significantly associated with reduced financial worries, individuals should be mindful of their tracking patterns and focus on accuracy, temporal proximity, and consistency. Adhering to suggestions from the self-regulation theory could potentially help maximize the benefits of expense tracking.

These findings also hold significant implications for financial education initiatives aimed at improving financial management skills as well as for tracking app developers seeking to enhance tracking engagement. For instance, identifying common barriers that hinder consistent expense tracking implies that app developers could integrate reminder features in their app to encourage users to track their expenses regularly, effectively addressing forgetfulness as a barrier.

3.6.2 Limitations and Future Research

There are several limitations to consider in this research. First, the findings are descriptive, limiting my ability to discern whether accuracy, temporal proximity, or consistency in expense tracking directly contributes to reduced financial worries, or whether individuals who are already financially well are simply more inclined to prioritize these aspects of tracking. Future research could address this gap by conducting experiments to investigate the causal relationship between expense tracking behavior and financial outcomes.

Second, the sample used in this analysis comprises users of a specific tracking app rather than a random sample representing the broader population of individuals who engage in tracking practices. Therefore, caution is warranted when generalizing the findings to a broader population of individuals who engage in tracking practices. Future research could examine expensive tracking behavior using a representative sample.

Third, there are certain limitations inherent in the data that may bias the findings. The survey solely captures self-reported tracking patterns. For instance, respondents report their perceived accuracy in expense tracking rather than the actual accuracy in expense tracking. While the survey measures generally align with similar measures derived from the tracking app, suggesting the validity of self-reported measures, they still limit the ability to conclusively establish the connection between actual expense tracking behavior and financial outcomes. Additionally, the app usage data, although reflective of people's actual tracking behavior, could still be subject to bias. For instance, it is challenging to ascertain whether certain expenses are overlooked and not tracked at all. The tracking data only show that conditioning on making an entry, how likely this expense tracking behavior is accurate and consistent. Future research could aim to obtain additional data by incorporating actual spending, such as by linking with bank payments, to assess instances where individuals fail to track a record and identify which types of expenses are more likely to be missed.

Chapter 4

The Fresh Start Effect: How Temporal Landmarks Promote Expense Tracking Behavior

Abstract

Expense tracking is an important behavior that helps financial goal attainment, yet what motivates this behavior is not well understood. This paper explores the role of the "fresh start effect," the tendency to pursue aspirational behaviors following temporal landmarks associated with new beginnings among people with a fresh start mindset, in motivating expense tracking. Using administrative data from a Chinese tracking app, this research provides evidence consistent with a fresh start effect in expense tracking, documenting that individuals are more likely to initiate expense tracking using the tracking app at the beginning of each week, month, and year. Moreover, individuals initiating expense tracking at the beginning of a month or year persist in tracking longer than those initiating at other times.

These findings highlight the importance of the fresh start effect in motivating and sustaining expense tracking behavior, and support the robustness of this effect across cultural contexts.

4.1 Introduction

Expense tracking, which refers to the practice of monitoring and evaluating one's expenses, is a financial behavior with significant implications for individuals' financial well-being. It has been viewed as a fundamental step to support budgeting (Heath and Soll, 1996; R. Thaler, 1985; R. H. Thaler, 1999). Moreover, prior literature document it as a prevalent positive financial behavior for managing finances (Furrebøe et al., 2023; Hernandez et al., 2017; Robson and Peetz, 2020), even in the absence of traditional budgeting (Sinnewe and Nicholson, 2023). Therefore, understanding what motivates people to track their expenses and sustain such tracking behavior is crucial because it directly affects their financial well-being. However, the existing literature on expense tracking primarily focuses on the challenges associated with accurately recording expenditures (Gourville, 1998; O'Curry, 2002; Sussman and Alter, 2012; Sussman et al., 2015), with limited exploration of the possible nudges that drive people to initiate expense tracking behavior and persistence in expense tracking activities (C. Y. Zhang and Sussman, 2018).

Prompting expense tracking behavior can be challenging because it is linked to individuals' consumption patterns, which exhibit considerable variability. Nevertheless, certain situational factors, such as the fresh start effect, may exert a more consistent and widespread influence on expense tracking behavior. Price et al. (2018) introduced the concept of the fresh start mindset, defined as the belief in the possibility of initiating a new beginning and navigating a different life path, irrespective of one's past or current circumstances. Individuals with a stronger fresh start mindset tend to invest in transformative changes (Price et al., 2018). This mindset, rooted in neoliberalism and the Protestant self-reliant history in the United States, shares connections with individualism (Price et al., 2018). However, the globalization of neoliberal principles has transcended traditional Protestant or neoliberal traditions, evident in its presence in countries such as Mexico and Russia (Strizhakova et al., 2021). While Strizhakova et al. (2021) contend that the fresh start mindset is a prevalent belief due to globalization, its applicability in other countries, such as China, remains underexplored.

Different types of fresh starts exist, including major life transitions (Su et al., 2021), performance resets (Dai, 2018), and temporal landmarks associated with new beginnings[22] (Beshears et al., 2021; Dai et al., 2014, 2015; Davydenko and Peetz, 2019; Hennecke and Converse, 2017). This paper focuses on temporal landmarks as signals for new beginnings (referred to as temporal landmarks for simplicity in this paper). For example, the New Year serves as a significant temporal landmark, and the tradition of creating New Year resolutions is well documented (Marlatt and Kaplan, 1972; Norcross et al., 2002). A growing body of literature on the fresh start effect, either correlational (Dai et al., 2014) or laboratory evidence (Beshears et al., 2021; Dai et al., 2015; Davydenko and Peetz, 2019; Hennecke and Converse, 2017), suggests that temporal landmarks serving as fresh starts are opportune moments for promoting self-improvement behaviors. However, research on how the fresh start effect applies to financial behaviors is limited, with the exception of one paper focusing on retirement savings (Beshears et al., 2021). Moreover, previous studies on the fresh start effect mainly examine its influence on the initiation of transformative goals, such as weight

[22] Prior research has identified the following temporal landmarks as signaling the start of a new phase (Dai et al., 2014; Soster et al., 2010): beginning of a calendar cycle (e.g., the start of a week, month, or year); the beginning of a fresh period on an academic or work calendar (e.g., the first month of a semester, the first workday after a holiday); and the beginning of a new chapter in one's personal history (e.g., immediately following a birthday).

loss or smoking cessation, with limited exploration of whether goal initiation prompted by the fresh start affects goal persistence. Dai et al. (2017) touched upon goal persistence by sending a reminder mailer with fresh-start–based framing to promote prescription medication adherence. This experiment yielded null results, possibly because of the challenges in running the field experiment. For example, they could not control the timing of reminder receipt, leading to delays between the target fresh-start date and the actual reminder delivery. This delay likely reduced the effectiveness of the reminders in prompting goal setting. Moreover, potential contamination from a separate study is possible, as participants in the control group may have received medication adherence reminders or had prior exposure to reminders in another randomized clinical trial.

The present research explores the impact of the fresh start effect on initiating and sustaining expense tracking behavior in China. It uses both aggregated and disaggregated user data from a Chinese mobile application designed for expense tracking. Through empirical analysis, the research documents that individuals are more likely to initiate expense tracking behavior at the beginning of each week, month, and year (Study 1). Moreover, individuals initiating expense tracking at the start of each month or year tend to maintain this practice longer than those who start at other times (Study 2).

This research contributes to various streams of literature. First, it fills a gap in the literature on personal finances, budgeting, and mental budgeting by documenting the fresh start effect as a potential nudge driving people to initiate expense tracking behavior. Second, this research extends the understanding of the fresh start effect by examining its impact on goal persistence, an aspect that has received limited attention previously. Third, this research extends the scope of the fresh start mindset from prior literature (Price et al., 2018; Strizhakova et al., 2021) by providing evidence of the fresh start effect in China. This strengthens the argument that the fresh start mindset may transcend cultural distinctions in the era of globalization (Strizhakova et al., 2021). Moreover, it adds robustness to the literature on the fresh start effect by employing Chinese solar calendar-based temporal landmarks, such as Chinese holidays. While prior studies predominantly center on temporal landmarks rooted in the Gregorian calendar, such as U.S. federal holidays (Beshears et al., 2021; Dai et al., 2014, 2015; Davydenko and Peetz, 2019; Hennecke and Converse, 2017), the findings with Chinese temporal landmarks suggest that temporal landmarks, rather than factors specific to the Gregorian calendar, serve as motivating factors for expense tracking behavior.

The findings have implications for individual decision-makers, financial service providers, and policymakers. Individual decision-makers can leverage fresh start feelings at temporal landmarks to reinforce intentions for improving financial behaviors and strategically map out plans for goal persistence. Financial service providers can also incorporate these insights into their offerings and marketing strategies to boost customer engagement and enhance their financial well-being. Moreover, policymakers can design education programs and policies to inform individuals about the impact of temporal landmarks on financial decisions and collaborate with institutions to incentivize positive financial behaviors.

The remainder of this paper is organized as follows. First, I present a comprehensive review of the relevant theories and evidence to lay the foundation for developing my hypotheses. Next, I present two studies examining the initiation and persistence of expense tracking behavior, respectively. Finally, I discuss the contributions and policy implications of these findings for both theoretical understanding and practical applications for individual decision-makers, financial service providers, and policymakers, along with suggestions for future research.

4.2 Theoretical Framework

4.2.1 Fresh start mindset and fresh start effect (temporal landmarks) in the Chinese culture

Price et al. (2018) defined the fresh start mindset as the belief that "people can make a new start, get a new beginning, and chart a new course in life, regardless of their past or present circumstances." The fresh start mindset is rooted in neoliberalism with the Protestant self-reliant history in the United States, which is related to individualism (Price et al., 2018). However, globalization has facilitated the dissemination of neoliberal principles worldwide, allowing a fresh start mindset to transcend traditional Protestant or neoliberal traditions and manifest in other countries, as evidenced by its presence in Mexico and Russia (Strizhakova et al., 2021).

While, to my knowledge, the fresh start mindset in China remains unexplored, the fresh start metaphor aligns with some fundamental concepts rooted in Chinese culture. Numerous Chinese idioms reflect the historical belief that individuals continue to transform over time and under various circumstances. For example, the Chinese phrase "一元复始万象更新" translates to "A new beginning, everything refreshed" in English. This phrase conveys that with the start of something new or the beginning of a new cycle, everything can be rejuvenated, renewed, and transformed for the better. Another Chinese phrase "士别三日当刮目相待" translates to "When friends have been apart for three days, they should look at each other with new eyes" in English. This phrase conveys that even a short separation can lead to a fresh perspective and renewed appreciation of each other's company or quality. These two examples emphasize the concept of a fresh start and the potential for positive change and renewal in various aspects of life. Such belief enables the Chinese to separate their future selves from their past self, thus motivating them to transform their futures.

Individuals with a stronger fresh start mindset tend to invest in transformative changes when they experience a sense of renewal (Price et al., 2018). Various factors can evoke this feeling of a fresh start, including major life transitions (Su et al., 2021), performance resets (Dai, 2018), and temporal landmarks associated with new beginnings (Beshears et al., 2021; Dai et al., 2014, 2015; Davydenko and Peetz, 2019; Hennecke and Converse, 2017).

This research specifically focuses on temporal landmarks as signals for new beginnings, building on the prior identification of specific temporal landmarks (Dai et al., 2014; Soster et al., 2010), including the beginning of a calendar cycle (e.g., the start of a week, month, or year), the beginning of a fresh period on an academic or work calendar (e.g., the first month of a semester, the first workday after a holiday), and the beginning of a new chapter in one's personal history (e.g., immediately following a birthday). Dai et al. (2014, 2015) introduced the fresh start effect, in which temporal landmarks motivate individuals to initiate aspirational behaviors, such as health-related goals, by establishing new mental accounting periods that disconnect them from past imperfections. A growing body of literature reinforces the fresh start effect, suggesting that temporal landmarks, as fresh starts, are opportune moments for promoting self-improvement behaviors (Beshears et al., 2021; Davydenko and Peetz, 2019; Hennecke and Converse, 2017).

Given the prevalence of the fresh start metaphor among the Chinese and the strong evidence from the fresh start effect literature on the impact of temporal landmarks on self-improvement behaviors, temporal landmarks as nudges for engaging in self-improvement behaviors should be applicable in the Chinese context.

4.2.2 Fresh start effect (temporal landmarks) and its application in expense tracking behavior

Although no research has directly examined the fresh start effect on expense tracking behavior, existing literature has explored the impact of the fresh start effect on some other financial behaviors. For example, previous research documents that individuals who embrace a fresh start mindset tend to invest more effort in activities related to budgeting behavior, including better budgeting on spending, increased savings, reduced unplanned expenditures, and more effective management of credit card balances (Price et al., 2018). The influence of the fresh start mindset on budgeting efforts surpasses its impact on health-related and possession disposition efforts (Price et al., 2018). Additionally, Beshears et al. (2021) find that the fresh start effect prompts individuals to take one-time action to increase contributions to their retirement savings.

Expense tracking is an aspirational behavior linked with financial well-being. It is a common feature established in the literature on budgeting (C. Y. Zhang et al., 2022), mental budgeting (Heath and Soll, 1996), and mental accounting (R. Thaler, 1985) as a means to support budget adherence. Moreover, it is a prevalent positive financial behavior for managing finances (Furrebøe et al., 2023; Hernandez et al., 2017; Robson and Peetz, 2020), even in the absence of traditional budgeting (Sinnewe and Nicholson, 2023). Findings in Chapter 2 suggest that expense tracking helps people better understand their financial situation, resulting in better spending control. These findings suggest that understanding what motivates people to engage in expense tracking activities may yield valuable insights. While the timing of expense tracking behavior is primarily driven by individuals' consumption patterns, as there is no need to track expenses when there are no expenditures, prior research on the fresh start literature indicates that the feeling of a fresh start at temporal landmarks may exert a more consistent and widespread influence on expense tracking behavior.

The Fresh Start Effect Motivates Individuals to Start Expense Tracking Behavior at Temporal Landmarks. The beginning of a new cycle prompted by the incidence of temporal landmarks signals a fresh start. Chinese people with a fresh start mindset (Price et al., 2018; Strizhakova et al., 2021) are more likely to feel detached from their past imperfections and adopt a broader perspective of life at temporal landmarks (Dai et al., 2014, 2015). Therefore, I propose that individuals are more likely to start expense tracking behavior at temporal landmarks.

H1*: Individuals are more likely to start expense tracking behavior at temporal landmarks.*

Individuals Motivated to Initiate Expense Tracking Because of the Fresh Start Effect Tend to Keep Track of Their Expenses for A Longer Time. Goal persistence is characterized by the ability to resist temptation to give up during a single phase of pursuing a goal and repeatedly resume goal-directed actions (Brandstätter and Bernecker, 2022). Goals with varying levels of abstraction may be associated with different timeframes. Typically, self-improvement goals tend to be more abstract and not time-bound, which can lead to long-term commitment. By contrast, specific goals (e.g., moving to a new apartment or buying a laptop) are concrete and typically sustain individuals' commitment until the goal is successfully achieved.

The initiation of expense tracking behavior can occur under various circumstances. For instance, some individuals may start expense tracking with a specific savings goal, whereas others may begin with more abstract self-improvement goals, such as enhancing their financial situation. If temporal landmarks evoke a sense of detachment from individuals' past financial imperfections and inspire a more holistic perspective on their lives, then those who start expense tracking at temporal landmarks prompted by the fresh start effect may be more inclined to set abstract self-improvement goals, enhancing the likelihood of goal persistence compared to those who do so at other times.

Moreover, maintaining persistent expense tracking requires ongoing effort, and many individuals may struggle to sustain this practice. The frequent recurrence of temporal landmarks throughout the year offers numerous opportunities for individuals to rekindle their motivation for expense tracking (Dai et al., 2014). In other words, individuals who initially begin expense tracking at temporal landmarks driven by the fresh start effect may find themselves motivated to continue this practice on similar occasions (i.e., similar temporal landmarks that mark renewal), increasing their persistence in their expense tracking behavior over an extended period.

Although all temporal landmarks signal the commencement of a period that may prompt self-improvement goals, not all of these goals are set within the optimal timeframe, potentially affecting goal persistence. When the chosen timeframe aligns with the natural cycle of the target behavior, it provides the best opportunity to initiate self-improvement goals. For example, starting dieting in the morning before breakfast might yield better results than beginning it in the afternoon. In the context of the current research, initiating expense tracking at the beginning of a month may help prevent overspending more effectively than starting in the middle of a month when one might have already spent close to their monthly earnings, increasing the risk of failing to improve their financial situation. Such a failure can trigger the "what-the-hell" effect[23] (Cochran and Tesser, 2014), which causes individuals to abandon their expense tracking behavior. Taking these pieces of literature together, I propose that individuals who start expense tracking at temporal landmarks prompted by the fresh start effect, aligning with the initiation of a financial cycle, are more likely to

[23] "What-the-hell" effect refers to the tendency for indidviudals to give up self-control behaviors after a small lapse.

maintain this practice longer than those who start at other times.

H2: *Individuals who start expense tracking at temporal landmarks prompted by the fresh start effect, aligning with the initiation of a financial cycle, are more likely to keep track of their expenses longer than those who start at other times.*

4.3 Study 1: Expense Tracking Initiation at Temporal Landmarks

Study 1 aims to test H1, investigating the impact of the fresh start effect on the initiation of expense tracking behavior. Previous research has found that the feeling of a fresh start can motivate people to start transformative behaviors at temporal landmarks (Beshears et al., 2021; Dai et al., 2014, 2015). Therefore, Study 1 adopts an approach similar to that of Dai et al. (2014) to examine whether there is a greater propensity for starting expense tracking behavior at temporal landmarks.

4.3.1 Data and measures

In Study 1, I used administrative data from a popular Chinese tracking app (referred to as the Tracking App Sample), which facilitates expense tracking behavior, to capture actions to start expense tracking behavior. This app is freely available for download and use in both the Apple app store and the Android app stores. With millions of ratings on the Apple App Store and several hundred million downloads across popular Android app platforms in China like Huawei, Xiaomi, and VIVO, this app is likely to be representative of expense tracking apps in China, as evidenced by its popularity.

In China, individuals commonly use multiple payment methods, including cash or digital payments, with the latter being increasingly prevalent. Digital payment methods includeWeChat Pay, Alipay, Apple Pay, Android Pay, and various bank-developed digital apps linked to credit card payments. However, spending data from these payment sources cannot be seamlessly integrated to provide a comprehensive summary of expenses. Many individuals likely rely on manual reporting of their total spending. Therefore, unlike other financial tools like Mint[24], which automatically pool expenses and income from users' bank accounts, this tracking app relies on users' self-reported expenses and income.

The app data help understand how individuals track spending manually. The primary functions of this app include tracking the amount of earnings and spending within specific categories and dates, adding notes to each transaction, and performing basic spending analysis.

The Tracking App Sample is time series data containing aggregated information, including the number of daily app downloads and the number of daily account registrations[25] from January 1st 2018 to December 31st 2019[26]. I conducted tests for data stationarity using the Augmented Dickey-Fuller test for daily downloads and daily registrations. Both tests yield a p-value of zero, indicating stationary time series.

Table 25 displays the summary statistics of the data from the Tracking App Sample. On average, there are more daily downloads than registrations. However, this difference in numbers may not necessarily imply that users abandon expense tracking after downloading the app, as the app does not mandate registration for usage.

[24] Mint are registered trademark of Intuit Inc., https://www.mint.com/

[25] Daily account registrations may differ from daily app downloads because this app doesn't mandate user registration for its basic usage. Account registration is necessitated solely for users intending to synchronize their tracking data.

[26] I stopped collecting data in early 2020 due to the effects of the COVID-19 crisis on people's spending decisions.

TABLE 25
Descriptive Statistics for Data from the Tracking App Sample

	Mean	S.D.
Daily downloads	25,134.76	9,554.74
Daily registrations	17,238.56	6,620.33
Number of Observations	730	

Note.—This table presents the descriptive statistics for the data from the Tracking App Sample. The table displays the sample means and standard deviations, with the number of observations listed in the last row.

4.3.2 Empirical strategy

This section outlines the empirical approach used to test the impact of the fresh start effect on the start of expense tracking behavior (H1). Specifically, I examine whether individuals are more likely to start expense tracking using the tracking app at temporal landmarks.

The Durbin-Watson statistic suggests positive autocorrelation in the error term when employing OLS regressions. This implies the potential omission of key variables, such as economic well-being, affecting financial management. Daily level measures of these variables are not feasible. Therefore, I use the Cochrane–Orcutt regression to adjust for positive serial correlation in the error term. The model is expressed as follows:

$$Y_t = \beta_0 + \beta_1 Time_t + \beta_2^{'} Controls_t + \beta_3 Trend_t + v_t \tag{4.1}$$

where the dependent variables are the number of daily downloads and the number of daily registrations at time t; $Time_t$ is a vector of time-varying covariates indicating temporal landmarks at time t; $Controls_t$ is a vector of time-varying dummies indicating whether the date is a Chinese holiday, whether the date is associated with an online sales event, and whether the data is the first workday following an online sales event at time t; $Trend_t$

captures the linear trend.

The dependent variables for Study 1 (Y_t) are the number of daily downloads and the number of daily registrations from the Tracking App Sample at time t, respectively.

The key independent variables are a set of time indicators signaling temporal landmarks ($Time_t$) adapted from Dai et al. (2014), which are relevant to current research on expense tracking behavior within the Chinese cultural context.

Days since the start of the week is a continuous variable indicating the days elapsed since the beginning of the current week. Since Chinese people tend to think that Monday, instead of Sunday, is the start of a week, Monday is coded as 1, and Sunday is coded as 7.

Days since the start of the month is a continuous variable indicating the days elapsed since the beginning of the month. The minimum value is 1, and the maximum value is 31.

Months since the start of the year is a continuous variable indicating the number of months elapsed since the beginning of the current year. January is coded as 1, and December is coded as 12.

A dummy variable indicates whether the date is the *first workday after a national holiday* in China. I focus solely on Chinese holidays for which individuals are legally entitled to take days off because individuals typically have more opportunities for consumption during their days off. These holidays include the New Year, Chinese New Year, Qingming Festival, Labor Day, Dragon Boat Festival, Mid-Autumn Festival, and National Day.

Expense tracking, inherently linked to expenditures, becomes particularly relevant when significant spending or multiple purchases occur. In such instances, individuals may feel the need to monitor their spending to ensure they do not overspend. Therefore, dates associated with increased consumption opportunities, although not serving as temporal landmarks signaling a fresh start, should be incorporated as control variables ($Controls_t$). I include a dummy variable indicating whether the date is a Chinese holiday mentioned above or not. Moreover, significant sales events can also impact expense tracking behavior. While most sales events coincide with holidays, which have been accounted for, there are specific dates in China marked by major online sales events akin to the Black Friday in the United States. Online shopping is popular[27] in China, especially among tracking app users with internet access and smartphones. There are three major online sales days in China: June 18^{th}, November 11^{th}, and December 12^{th}. Therefore, I include a dummy variable indicating whether a date is associated with an online sales event.

Additionally, individuals might engage in retrospective expense tracking, preferring to record purchases later to avoid the increased pain of paying while shopping (Kan et al., 2018). Alternatively, individuals may seek to compensate for their overindulgence during online sales events by commencing expense tracking. Considering these possibilities, I include a dummy variable representing the first workday following an online sales event as a covariate.

A linear trend ($Trend_t$) is also included. Ongoing growth in the user population of this tracking app enhances its visibility to potential users. The increased downloads contribute to a higher ranking in the App Store search results, attracting more attention. Moreover, a growing user base can increase word-of-mouth referrals, making it more appealing to new users.

4.3.3 Results

Table 26 presents the Cochrane–Orcutt Regression results examining the impact of the fresh start effect on the number of daily downloads and daily registrations. The temporal landmarks that significantly motivate the initiation of expense tracking are the days since the

[27]For example, the online daily sales of Taobao, an online C2C market, reached about 38 billion U.S. dollars on November 11^{th} 2019.

start of a week, days since the start of a month, and month since the start of a year. Specifically, each day passed in the "days since the start of a week" variable is associated with a decrease of 480.87 in daily downloads and 323.16 in daily registration of the expense tracking app. Each day passed in the "days since the start of a month" variable is associated with a decrease of 580.68 in daily downloads and 397.14 in daily registration of the expense tracking app. Each month passed in the "months since the start of a year" variable is associated with a decrease of 589.49 in daily downloads and 408.21 in daily registration of the expense tracking app.

These regression results can imply the difference in expense tracking behavior motivated by the fresh start effect between any two dates. For instance, the difference in downloads attributed to the fresh start effect between January 1st, 2018 (a Monday) and March 7th, 2018 (a Wednesday) can be calculated as follows: 3 (days difference in the week) $\times$ -480.87 + 7 (days difference in the days since the start of a month) $\times$ -580.68 + 3 (month differences since the start of the year) $\times$ -589.49=-7275.84.

To discuss the magnitude of these effects, I compared them with an event when the app's paid features in the Apple App Store were temporarily free[28] (January 3rd to January 10th, 2018), which significantly increased the daily downloads and registrations of the app ($p < 0.001$). The figure below illustrates the varying magnitudes of these effects:

[28] The app's paid features are priced at approximately 30 RMB in the Chinese Apple App Store. One RMB equates to approximately 7 U.S. dollars.

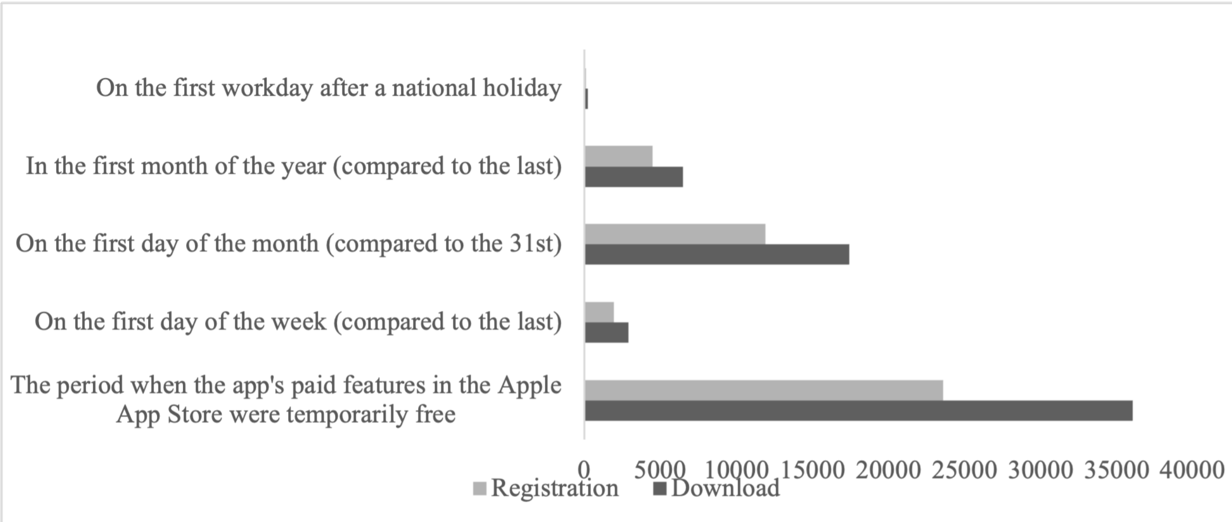
TABLE 26

Estimates of the Changes in the Daily Downloads, and Registrations Over Time

	# Downloads	# Registrations
Temporal Landmarks		
Days since the start of the week (Monday)	-480.87***	-323.16***
	(75.86)	(51.21)
Days since the start of the month	-580.68***	-397.14***
	(33.95)	(22.97)
Months since the start of the year	-589.49*	-408.21*
	(252.64)	(173.16)
First workday after a national holiday	-244.14	-100.15
	(1,105.92)	(746.99)
Control Variables		
National holidays in China	-3,665.39***	-2,417.17**
	(1,094.37)	(739.98)
Online sales event	2,005	1,408.79
	(1,661.14)	(1,121.59)
First workday after an online sales event	1,940.49	1,345.04
	(1,667.28)	(1,125.74)
Constant	2,9170.76***	1,9705.48***
	(2,873.71)	(1,974.08)
Linear time trend	Yes	Yes
Control for special periods	Yes	Yes
R-squared	0.41	0.41
DW-statistic(transformed)	1.84	1.83
N	729	729

Note.—Standard errors in parentheses. "Downloads refers to the number of downloads of the tracking app per day; Registrations refers to the number of registrations in the tracking app per day. I regressed these dependent variables on temporal landmarks, a linear time trend, and a set of control variables (dummies indicating whether the date is a Chinese holiday, whether the date is associated with an online sales event, and whether the data is the first workday following an online sales event) with robust standard errors, respectively. Additionally, I accounted for special periods when downloads and registrations were likely to be affected. There are three special time periods: January 3rd 2018 to January 10th 2018, and January 19th 2018 to July 5th. From January 3rd, 2018, to January 10th, 2018, the app's paid features in the Apple App Store were temporarily free, and thus, there was a spike in the number of downloads and registrations on that day. For some reason, individuals were unable to use "expense tracking" as a keyword to search for this tracking app in the Apple App Store from January 3rd 2018 to January 10th 2018 and January 19th 2018 to July 5th. Each column represents a regression with different dependent variables. Only the key predictor variables and constant terms are presented in this table. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

FIG. 27.—Changes in the Fitted Daily Download and Registration as a Function of the Date and Its Proximity to a Variety of Temporal Landmarks



This figure presents the changes in the fitted daily downloads and registrations as a function of the date and its proximity to various temporal landmarks. These effects are compared with the effect of the app's paid features being temporarily free in the Apple App Store.

The number of days since the beginning of the month has the largest effect, followed by the number of months since the beginning of the year, and finally, the days since the beginning of each week. The first workday after a national holiday has no significant effect. Only some effects are meaningful in an economic sense. For example, the increase in daily downloads associated with the start of the week (compared to the end of the week) is approximately 8% as large as the increase in daily downloads caused by this free offer, suggesting a small effect. Similarly, the increase in daily downloads associated with the start of the year (compared to the end of the year) is approximately 18%, as large as the increase caused by the free offer. However, the increase in daily downloads associated with the start of the month (versus the end of the month) is approximately 48% as large as the increase caused by the free offer, indicating a moderate effect.

Although prior literature find that the first day after a national holiday serves as a valid temporal landmark (Dai et al., 2014), results from the Cochrane–Orcutt Regression document that individuals are not inclined to initiate expense tracking after such holidays. This could be attributed to the fact that not all holidays signal a fresh start. There are seven national holidays in China. Some holidays, such as the New Year, may symbolize a fresh beginning, but others, such as Labor Day, may not. To account for this, I regressed the number of daily downloads and the number of daily registrations on the first workday after each holiday dummy (as temporal landmarks) and each holiday dummy (as control variables), respectively. Despite the opportunity for individuals to take a break during holidays, the regression results in Table H36 in Appendix H, align with expectations, revealing that not all holidays signal a fresh start. The insignificant coefficient of the first workday after a national holiday may be attributed to the fact that only the first workday after New Year is significant, whereas the first workdays after all other national holidays are insignificant.

I conducted two robustness checks. First, I ran Cochrane–Orcutt Regressions without control variables to assess whether the fresh start effect still holds. I find very similar results, as detailed in Table H37 in Appendix H. Temporal landmarks, including days since the start of the week, days since the start of the month, and months since the start of the year, remain significant with negative signs. However, the coefficients for the first workday after a national holiday become slightly significant without covariates. These findings collectively suggest that the effect persists, even without covariates.

Second, I examined the robustness of the fresh start effect by testing alternative starting dates. These alternative starting dates include the number of months since the start of spring, summer, autumn and winter. The onsets of spring, summer, autumn, and winter are temporal landmarks only when they are made salient (Dai et al., 2015). In the current context, people are less aware of a specific month as the start of spring, summer, autumn or winter. Therefore, the number of months since the start of spring, summer, autumn, and winter should not have a significant effect.

In China, the start of spring, summer, autumn, and winter is determined by the Chinese Twenty-Four Solar Terms. Spring typically commences in February, summer starts in May, autumn begins in August, and winter starts in November. For example, the number of months since the start of spring would be one in February, two in March, and so forth. Subsequently, January of the following year was counted as 12 months since the beginning of spring.

I conducted Cochrane–Orcutt Regression using the start of spring, summer, autumn, and winter, along with other temporal landmarks (i.e., days since the start of the week and month, as well as the first workday after a national holiday) and controls. The results in Table H38 Appendix H suggest that none of these alternative starting dates are significant within a 95% confidence interval.

4.3.4 Discussion

The regression results from Study 1 suggest that, within the context of Chinese culture, the fresh start effect can serve as a motivating factor for initiating expense tracking behavior. Individuals are more likely to start expense tracking using a tracking app at temporal landmarks that signal a fresh start. However, an alternative explanation exists. Instead of the fresh start effect, the tendency to start expense tracking may simply be a psychological response to compensate for overindulgence or goal rebound, the tendency to become even more motivated to achieve the goal after the initial setback (Laran and Janiszewski, 2009). Individuals may overspend on specific temporal landmarks, such as weekends and holidays, and thus, want to control spending after weekends or holidays. Consequently, people are more likely to record their spending after holidays or weekends to manage their limited resources.

Distinguishing this alternative explanation from the fresh start effect is challenging, as individuals encounter increased consumption opportunities during weekends or Chinese national holidays. However, while not constituting a temporal landmark, an online sales event aligns with the general trend of increased spending. This suggests that it may be influenced not by the fresh start effect but by the aforementioned alternative explanation. However, the number of downloads and registrations in Table 26 are not significant on the first workday after an online sales event, despite the general tendency for increased spending during online sales events. These findings help to rule out the aforementioned alternative explanation.

Study 1 used data from a specific tracking app, which may raise questions about the generalizability of the findings to a broader population. To address this concern, I conducted additional analysis. Specifically, I explore the impact of the fresh start effect on daily search volume for "expense tracking" ("记账" in Chinese) using data from the "Baidu Search Index"[29] from January 1st, 2018, to December 31st, 2019. Search volume could serve as an indicator of an individual's intention to begin expense tracking, with higher daily search index values reflecting increased online searches for a specific term. Baidu, similar to Google in the United States, is a popular search engine in China, implying that this data is representative of a larger population of Chinese individuals with internet access.

Given that the Durbin-Watson statistic indicates autocorrelation in the error term, I ran Cochrane–Orcutt Regression with the same set of temporal landmarks and covariates used in Study 1. The results, presented in Table H39 in Appendix H, mirror those of Study 1, with all temporal landmarks exhibiting significant coefficient estimates in line with expected signs, except for the first workday after a national holiday. Individuals are significantly more

[29]For more information about "Baidu Search Index", visit the following link: http://zhishu.baidu.com/v2/index.html#/

likely to search for "expense tracking" at the beginning of each week, month, and year. This suggests their increased interest in and intention to initiate a fresh start by tracking their spending at these temporal landmarks.

4.4 Study 2: Persistent expense tracking Initiated at Temporal Landmarks

Study 2 aims to test the impact of the fresh start effect on the persistence of expense tracking behavior (H2) measured as continuous tracking over a period of time. As discussed earlier, behaviors motivated by the fresh start effect are inclined to be self-improvement goals that are not time bound. Individuals striving towards such behaviors can experience extended expense tracking durations through frequent reminders at temporal landmarks. Moreover, specific temporal landmarks aligned with financial cycles present an optimal opportunity for initiating self-improvement goals. Therefore, individuals who begin expense tracking prompted by the fresh start effect, synchronized with the financial cycle, are more likely to keep track of their expenses longer than those who start at other times.

4.4.1 Data and measures

In Study 1, I have already documented that the increased download and registration of a tracking app at the start of each week, month, and year is attributed to the fresh start effect, which motivates individuals to initiate expense tracking. This serves as a basis for Study 2, where I examine the impact of the fresh start effect on goal persistence by comparing the duration of expense tracking between app users who commence tracking at temporal landmarks and those who do not. To accomplish this, I acquired administrative user-level data from the same tracking app company.

To obtain a representative sample of app users and examine their tracking persistence, approximately 8,000 users were randomly selected from all users registered to use the tracking app in 2018. I acquired de-identified data on their tracking behavior from the time of registration until March 2020 (longitudinal tracking data). I exclude tracking data from 2020 to eliminate potential COVID-related effects, focusing on the timeframe between 2018 and 2019. Considering that randomly selected users might have started expense tracking in December 2018, this timeframe allows me to observe their tracking duration for at least one year.

Figure I40 in Appendix I illustrates the sample cleaning process. Approximately 94 users had no tracking data and were excluded, leaving 7,906 users with complete information. There are two potential reasons for users not having tracking data: first, users may have registered but never logged any transactions; and second, users may have registered, recorded transactions, and subsequently deleted these records. Users may report expenses that occur before they start tracking (i.e., retrospective tracking). Therefore, to focus on persistence in expense tracking since users initiated expense tracking behavior, I excluded records that occurred before the month when the user started tracking using the app.

Next, these users were categorized into three groups: those who only recorded income (N=271), those who only recorded expenses (N=2,662), and those who recorded both expenses and income (N=4,890). I excluded 271 users who only recorded their income because this research focuses on expense tracking behavior. To avoid potential bias, I further excluded three users who participated in a promotion that promoted tracking persistence in 2018[30].

[30] On November 11th 2018, the tracking app company held a promotion that offered to reimburse app users their yearly subscription if they consistently recorded their income or expenses at least once a week for an entire year. Users can voluntarily choose to participate in this promotion.

There are 1,617,816 records (income or expenses) generated by 7,549 users from January 1st 2018 to December 31st 2019. Approximately 89% of the records are records of expenses. While there might be concerns about the potential underreporting of income, this dataset remains suitable for examining expense tracking behavior. On average, users create 3.18 records of expenses per day with a standard deviation of 3.45.

To prepare for the analysis of expense tracking persistence, I aggregated the longitudinal data to the person level, constructing a new cross-sectional dataset (N=7,549). This cross-sectional dataset includes user-specific information regarding the duration of their expense tracking behavior, date of initial app usage, and other user-level characteristics (referred to as the Tracking Profile Sample).

I decided to use the number of weeks with records of expenses to capture the persistence of expense tracking behavior[31]. Two key considerations primarily influenced this decision. First, due to variations in how users document their expenses, some may prefer to report aggregate spending for a day, while others may detail each specific purchase, relying on the total number of expense records generated by each user, or the overall count of days with expense records may not accurately signify their persistence in tracking expenses. Second, as a shorter timeframe with workdays and weekends, the weekly cycle can provide a more accurate measure of goal persistence than the monthly cycle. For example, individuals initiating an expense tracking goal at the end of one month and those starting at the beginning of the next month may fall into the same week. However, when measuring persistence in months, those initiated at the end of the month would track one month more than those starting at the beginning of the next month. Therefore, week serves as a more conservative

[31] Users may not incur expenses every week, leading to instances where they do not report any expenses during a given week. Alternatively, users might cease expense tracking temporarily and later resume, creating gaps in their expense tracking activities. Therefore, I did not rely on the duration since users initiated expense tracking activities using the app to capture persistence.

estimate, as it measures the continuity of tracking at a more granular level.

Table 28 contains summary statistics for the Tracking Profile Sample. The demographic information collected is limited, with only gender information available. More females use this tracking app.

TABLE 28
Descriptive Statistics in the Tracking Profile Sample

	All Users
Female	0.63
Tracking Duration	16.08
	(22.17)
Record Expenses Only	0.35
With Monthly Spending Limits	0.07
Number of Users	7,549

Note.—This table presents the descriptive statistics for the Tracking Profile Sample. The table displays the sample means and standard deviations in parentheses with the number of users listed in the last row.

The dependent variable (Y_i) is the number of weeks with records of expenses for each user in the Tracking Profile Sample, starting from their first week (i.e., the week when they initiated expense tracking) until December 2019[32]. The distribution of the total number of weeks with expense records is provided in Appendix I Figure I41 On average, users in the Tracking Profile Sample keep track of their expenses for 16.08 weeks with a standard deviation of 22.17. The considerable standard deviation indicates a highly left-skewed distribution, with a significant portion of users trying the tracking app for only one week before abandoning it.

[32]The person-record data reveals that not every user maintains a consistent record of expenses every week since they began expense tracking. Individuals may encounter gaps in their expense tracking for various reasons, including instances where they did not make any expenditures, forgot to record expenses, or faced challenges due to lack of willpower. If an individual initiates expense tracking motivated by the fresh start effect, they may experience a similar motivation boost at other temporal landmarks, serving as reminders to restart their expense tracking. Therefore, I do not consider having gaps in expense tracking as a complete failure. Consequently, I used the total number of weeks with expense records, rather than the number of consecutive weeks with records, to capture goal persistence.

The key independent variables in Study 2 are the same as those in Study 1, except that all time indicators are generated based on the date when a user created the first record ($RTime_i$). This adjustment is made because registration dates may not precisely signify the start of expense tracking behavior. Approximately 76.41% of the users in the Tracking Profile Sample created their first records on their registration dates. Some users may delay using the app for various reasons, such as planning to start expense tracking in the future (e.g., "I will start expense tracking next Monday"). Appendix I includes the distributions of users' first record months and first record days of the month in the Tracking Profile Sample, as illustrated in Figures I42 and I43, respectively.

Moreover, I controlled for seven variables ($Control_i$) that may affect goal persistence. First, I created a dummy variable indicating whether user i only recorded expenses because this variable may signal different user profiles. Approximately 35.25% of the users in the Tracking Profile Sample recorded expenses only. There may be many reasons for not tracking income. Some users may not have an income, such as students or the unemployed. Moreover, monitoring income may be more manageable, especially for individuals who receive a regular salary, which could potentially result in selective underreporting.

Second, to assess users' commitment to expense tracking behavior, I added one dummy variable to indicate users with paid subscriptions[33]. The distinction between these user groups may reflect their willingness to invest in the app and commit to expense tracking. Approximately 5.78% of users in the Tracking Profile Sample have paid subscriptions.

Third, I included a categorical variable indicating which type of smartphone (Android vs. iPhone) the user used. Prior studies document that individuals' smartphone types can infer

[33] Users are not obligated to pay a subscription fee to use this tracking app. However, individuals with a paid subscription can enjoy an ad-free experience and gain access to a wider range of analytical tools for reviewing their reported spending.

their personality and spending habits (Reinfelder et al., 2014; Schmall, 2018). On average, iPhone users may be more affluent than Android users. Since the Tracking Profile Sample has limited demographic information, I used phone type to signal wealth. About 70.04% of the users use iPhones. Moreover, I also included a dummy variable indicating whether the user switched phone types within the measuring period. Changing phone types may signal a greater commitment to expense tracking, as users who do not track spending often may not bother reinstalling the tracking app on their new smartphones. Only 4.97% of the users switched their phone types.

Fourth, I included gender as a control variable, as it may influence financial sensitivity and stress (Bondy, 2019). About 63.23% of the users in the Tracking Profile Sample are females.

Finally, I added a dummy variable indicating whether a user sets monthly spending limits, such as monthly or categorical budgets. Only 7.30% of the users in the Tracking Profile Sample set monthly spending limits in the app. The creation of spending limits matters because it could signal higher engagement in expense tracking. For example, setting spending limits may signal financial stress, and these people need to carefully record all expenses to ensure that their accumulated expenditures do not exceed the spending limits.

4.4.2 Empirical strategy

In this section, I outline the empirical approach used to investigate whether individuals who start tracking at the fresh start temporal landmarks prompted by the fresh start effect are more likely to keep track of their expenses for a longer time (H2). This analysis employs OLS regressions, both with and without controlling for specific individual characteristics, and the equation is as follows:

$$Y_i = \beta_0 + \beta_1 RTime_t + \beta_2^{'} Controls_t + \upsilon_{it} \tag{4.2}$$

where the dependent variables are the total number of weeks with expense records for user i; $RTime_i$ is a vector of time indicators created based on the date when user i created their first record; $Controls_t$ is a vector of control variables, including dummy variables indicating whether user i only records expenses, whether user i has a paid subscription, whether user i uses an iPhone, whether user i switched phone type within the data collection period, whether user i is a female, and whether user i set a monthly spending limit.

4.4.3 Results

Table 29 shows the regression results without (column (1)) and with controls (column (2)). There are no significant differences between regressions with or without covariates. The temporal landmarks that significantly affect the persistence of expense tracking are the days since the start of a month and the months since the start of a year. Specifically, in column (2) of Table 29, for each day that passes in the "days since the start of a month" variable, there is a decrease of 0.09 weeks (equivalent to 0.63 days) in tracking persistence. This suggests that an individual who initiates expense tracking on the first day of the month, on average, continues monitoring spending for approximately 18.9 days longer than someone who starts tracking at the end of the month (on the 31st). Similarly, for each month that passes in the "months since the start of a year" variable, there is a decrease of 0.48 weeks (equivalent to 3.36 days) in tracking persistence. On average, a person who begins expense tracking in January keeps tabs on spending for approximately 36.96 days longer than someone who starts tracking in December. Notably, the impact of the months since the start of the year is greater than that of the days since the start of the month.

TABLE 29
ESTIMATES OF THE IMPACT OF FRESH START EFFECT ON PERSISTENT EXPENSE TRACKING BEHAVIOR (OLS REGRESSION)

	Number of Weeks with Expenses	
	(1)	(2)
Temporal Landmarks		
Days since the start of the week (Monday)	0.1	0.18
	(0.13)	(0.12)
Days since the start of the month	-0.10***	-0.09**
	(0.03)	(0.03)
Months since the start of the year	-0.59***	-0.48***
	(0.08)	(0.08)
First workday after the national holiday	0.91	0.79
	(1.78)	(1.66)
Control Variables		
National holidays in China		1.74+
		(0.95)
Online sales day		-0.89
		(2.09)
First workday after an online sales day		4.19
		(2.99)
Record expenses only		-10.58***
		(0.45)
With paid subscription		1.93+
		(1.14)
Female		2.15***
		(0.49)
With spending limits		14.83***
		(1.25)
iPhone users		-1.05+
		(0.54)
Switch phone types		14.56***
		(1.49)
Constant	21.22***	20.99***
	(0.98)	(1.11)
Controls	No	Yes
R-squared	0.0096	0.1363
N	7,549	7,549

NOTE.—Standard errors in parentheses. "Number of Weeks with Expense Records" captures the duration of expense tracking. I regressed it on temporal landmarks based on the user's first record and a set of control variables with robust standard errors. These controls include dummy variables indicating whether the user only records expenses, has a paid subscription, uses an iPhone, switched phone types during the data collection period, is identified as female, and sets any monthly spending limits. Regressions were conducted using Ordinary Least Squares (OLS) without controls and with controls. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

These regression results can imply the difference in expense tracking persistence motivated by the fresh start effect between any two dates. For example, considering the regression results with covariates, the difference in the number of weeks with expense records attributed to the fresh start effect between January 1st, 2018 (a Monday) and March 7th, 2018 (a Wednesday) can be calculated as follows: 7 (days difference in the days since the start of a month) $\times$ -0.09 + 3 (month differences since the start of the year)$\times$ -0.48 = -2.07.

In terms of the magnitude of the effect, given that previous studies suggest that it typically takes about 66 days to form a habit (Lally et al., 2010), the observed effect sizes are significant, explaining 29% to 56% of the time required to establish a habit.

Conversely, the days since the start of the week and the first workday after a national holiday do not significantly impact users' expense tracking duration. The app interface is purposefully tailored to enable users to assess their spending and earnings on a monthly basis by displaying the spending and earnings in a particular month. Mondays may fall towards the end of a month, a period when individuals may have already exceeded their budget or are nearing their limit. In such instances, initiating expense tracking at the start of a week could be susceptible to the "what-the-hell" effect, which undermines tracking persistence, as app users typically do not assess their financial situation on a weekly basis.

Moreover, the first workday after a national holiday is not significant. When examining each holiday individually, only app users registered on the first workday following the New Year are significantly more likely to track expenses for an extended period (refer to Appendix I Table I44 for regression results). This could be attributed to the fact that only the first day after New Year is perceived as a fresh start that promotes expense tracking behavior, as shown in Study 1 (refer to Appendix H Table H36 for regression results). Alternatively, this finding provides suggestive evidence that further supports the argument that temporal landmarks aligned with the natural cycle of self-improvement goals are crucial for goal persistence, given that only the New Year aligns with yearly financial cycles among the seven national holidays considered.

Some user characteristics influence the expense tracking persistence. Specifically, females, users who set up spending limits, users who recorded both expenses and income, users who used Android phones, and users who switched phone types during the data collection period are more likely to keep tabs on spending longer. Due to data limitations, I am unable to account for all the factors. Some omitted variables may influence control variables and users' persistent expense tracking behavior. For example, individuals' income may influence both the setup rate of spending limits and their tendency for persistent tracking.

I also conducted several additional analyses to test the robustness of these effects. First, following the methodology of Study 1, I conducted OLS regression using alternative temporal landmarks, including the start of spring, summer, autumn, and winter, instead of the start of the year, while controlling for other variables (see Table I45 in Appendix I). None of these alternative starting dates yielded significant results, except for the number of months since the start of summer. However, contrary to the fresh start effect, although the number of months since the start of summer is significant, the sign is positive.

Second, I conducted the analysis using the days with expenses to indicate tracking duration (Table I46 in Appendix I). While I obtained consistent results, the estimates may be biased. This bias can occur because of variations in people's shopping frequency, rendering the overall count of days with expense records an inaccurate indicator of their persistence in tracking expenses.

Third, although I controlled for some variables that might capture user characteristics, the sample may be influenced by users with extremely low monthly expenses, which might indicate unreported transactions, and users with unusually high monthly expenses, which might indicate affluent individuals or small business owners using the app for business purposes[34]. To mitigate potential biases, I trimmed the data by excluding users who ever had monthly expenses that fell within the top 5% ($\geq$ 32,407.14 RMB) and bottom 5% ($\leq$ 106.6 RMB) ranges, resulting in a refined sample of 5,297 users. As a robustness check, I ran the same set of regressions using this refined sample, and the results are consistent (refer to Appendix I Table I47 for the regression results).

Fourth, there are 94 users without tracking information in the initial sample. While I have no tracking information for these 94 users, it is still possible that some of them started expense tracking and later abandoned it, deleting their tracking data from the app. To address this, I conducted a robustness check by including these 94 users in the regression analysis, treating their tracking duration as zero and the date of registration as the date when they initiated expense tracking. Since I lack information about their tracking behavior, I could not include covariates related to their tracking behavior. The results in Table I48 in Appendix I show no significant differences in the outcome, as the days since the start of a month and months since the start of a year remain significant, and the signs do not change.

Fifth, I examined the impact of the fresh start effect on expense tracking persistence using time-to-event analysis with and without covariates. I excluded data from 2020 to avoid bias introduced by the COVID-19 outbreak in China[35]. In the time-to-event analysis, the event is stopping expense tracking. Individuals with records in 2020 were right-censored because they did not stop expense tracking by the end of the sample period (December 2019). Time-to-event analysis (see Table I49 in Appendix I) results also show that temporal landmarks

[34] Monthly expenses range from 0.1 RMB to 1,079,351,906 RMB, with a standard deviation of 8,911,737.26. One RMB equates to approximately 7 U.S. dollars.

[35] All cities in China experienced lockdowns starting from the Chinese New Year in January 2020, leading to decreased consumption opportunities and affecting the occurrence of expenses recorded in the app.

that significantly affect the persistence of expense tracking are the days since the start of a month and the month since the start of a week. Specifically, for each day that passes in the "days since the start of a month" variable, the rate of stopping expense tracking using the tracking app increases by 0.6%. This suggests that individuals starting on the last day of the month have an 18% higher rate of stopping compared to those starting on the first day. Similarly, for each month in the "months since the start of a year" variable, the rate of stopping increases by 2.1%. This suggests a 25.2% higher rate of cessation for individuals starting in December than in January. Although the impact of the months since the start of the year is greater than that of the days since the start of the month, both effects remain substantial.

Sixth, individuals started tracking at various time points within the data collection period, resulting in different observation periods. For instance, I observed individuals who commenced expense tracking in December 2018 for 12 months, whereas others began in January 2018 and were observed for 24 months. To address these varying observation periods, I conducted the same regression analysis, focusing solely on individuals within a one-year window from the onset of tracking. The results of this analysis (refer to Table I50 in Appendix I) remained consistent.

4.4.4 Discussion

The findings from Study 2 support H2, suggesting that individuals who initiate expense tracking at the start of each month and year tend to maintain their expense tracking behavior for a longer duration than those at other times in the month or year. This further suggests that temporal landmarks that are aligned with the natural cycle of self-improvement goals play a crucial role in goal persistence.

The findings in Study 2 are built upon those in Study 1, where it establishes that expense tracking initiated at temporal landmarks is attributed to the fresh start effect. However, there are alternative explanations for this finding. For example, the start of a month often aligns with individuals receiving paychecks or paying bills, making it a natural point for initiating expense tracking. Moreover, certain times of the year may prompt changes in income or expenses that necessitate closer monitoring of finances.

Study 1 relies on aggregated app-level data to examine goal initiation, which lacks detailed individual-level information. However, the samples used in Study 2 are randomly selected among all users who registered to use the app in 2018, which could be considered representative of app users. Therefore, I explored individual-level data to provide suggestive evidence that while these alternative explanations may influence goal initiation, they may not fully negate the fresh start effect.

First, I examined the occurrence of earnings. I created a histogram showing income occurrence distribution by day of a month, days of a week, and months of a year among users who ever reported income. Figure I51 in Appendix I shows that although there are more income reports at the beginning of each month, people actually report income throughout the month. Moreover, the reported income is distributed more evenly across a week. Additionally, there are fewer reports on income at the beginning of each year. These findings suggest that app users can receive daily, weekly, biweekly, or monthly pay, not just at the start of each month. Together, this provides suggestive evidence that the app sample used in Study 1 should not be dominated by people who only report income at temporal landmarks, which helps rule out the explanation that the initiation of expense tracking is prompted by receiving salary at temporal landmarks.

Second, I explored the spending data. While I do not have information about people's reactions to each spending, I assume that larger spending may be more likely to bring challenges to people's financial conditions, necessitating closer monitoring of personal finances. Therefore, I examined the date when the largest expenses for each user occurred. I created a histogram showing the distribution of the occurrence of the largest expenses by days of a month, days of a week, and months of a year. Similarly, Figure I52 in Appendix I shows that although the largest expenses are more likely to occur at the beginning of each month, they could occur throughout the month. Moreover, the distribution of the largest expenses is more evenly spread across the week. Additionally, there are fewer reports on the largest expenses at the beginning of each year. Together, this provides suggestive evidence that the app sample used in Study 1 should not be dominated by people who experience large spending at temporal landmarks, which helps rule out the explanation that the initiation of expense tracking is prompted by facing challenges or significant changes in financial conditions.

Additionally, I explored whether the fresh start effect influences how people engage in expense tracking. The app allows its users to create customized categories. There are 33 preset expense categories and 4,245 user-generated expense categories in the sample. The use of more expense categories may signal greater engagement in expense tracking, and the use of customized expense categories may signal a higher level of attention to detail in expense tracking. Therefore, I regressed the number of expense categories used by each user, distinguishing between preset and user-generated categories, on a set of temporal landmarks and covariates used in Study 2.

The findings in Table I53 Appendix I document that individuals who commenced expense tracking at the beginning of each month significantly used more expense categories to track their spending, primarily driven by the increased usage of preset expense categories. Furthermore, those who initiated expense tracking at the start of each year also employed significantly more expense categories, including both preset and customized expense categories, to track their spending. These results suggest that individuals who start expense tracking because of the fresh start effect tend to track for longer durations and exhibit higher engagement in expense tracking activities.

4.5 General Discussion

This research explores the fresh start effect as a motivating factor for initiating and maintaining expense tracking behavior. In Study 1, consistent with prior literature on the fresh start effect (Beshears et al., 2021; Dai et al., 2014, 2015; Price et al., 2018), I document that certain temporal landmarks (i.e., the days since the start of a week, the days since the start of a month, and the month since the beginning of a year) significantly prompt the initiation of expense tracking behavior. Study 1 is not merely a replication of the literature for two key reasons. First, while financial behaviors examined in prior fresh start literature (Beshears et al., 2021; Price et al., 2018) are related, they are not identical to expense tracking. Second, the finding that goal initiation at temporal landmarks among app users is due to the fresh start effect provides crucial support for Study 2, which investigates the persistence of expense tracking motivated by temporal landmarks.

Conversely, in Study 2, I find contrasting results compared to the prior literature, documenting that temporal landmarks aligned with the financial cycle significantly impact the persistence of expense tracking. Previous literature exploring the effect of the fresh start effect on prescription medication adherence yielded null results (Dai et al., 2017). However, these divergent findings do not necessarily suggest a mixed impact of the fresh start effect on goal persistence. Instead, issues with the field experiment setting in the prior literature may have muddled the results.

4.5.1 Contributions and implications

This research contributes to the existing literature on personal finances, budgeting, mental budgeting, and the fresh start effect. First, the findings advance research on personal finances, budgeting, and mental budgeting by providing empirical support for the fresh start effect as a possible driver prompting individuals to initiate expense tracking behavior, thus augmenting understanding in this domain.

Second, this research extends previous literature on the fresh start effect by demonstrating its impact on goal persistence, suggesting that promoting financial behaviors in sync with the financial cycle can lead individuals to sustain these behaviors for longer durations. To the best of my knowledge, this is the first study to establish a significant association between the fresh start effect and goal persistence. While this paper does not establish a general link between the fresh start effect and goal persistence, it sheds some light that can help inform future research.

Third, this research adds robustness to the literature on the fresh start mindset, as the observed fresh start effect suggests that Chinese individuals also exhibit a fresh start mindset. The inferred fresh start mindset can be attributed to two distinct factors. On one hand, it strengthens the argument that the fresh start mindset may transcend cultural distinctions due to the global dissemination of neoliberal principles (Strizhakova et al., 2021). Chinese people could embrace these principles without abandoning their collectivist culture. On the other hand, this could signify that the Chinese have developed more individualistic tendencies over time, given the link between individualism and neoliberalism. The idea of self-reliance, which amplifies the fresh start mindset among Chinese people, could be rooted in a special form of individualism. Despite the common perception of Chinese society as collectivist, classical Chinese thought also embraces elements of individualism. This form of individualism differs from the modern Western concept, as it emphasizes one's inner strength within the context of one's connection and unity with external authority and power (Brindley, 2010; Munro, 1985). For example, an enduring concept in Chinese philosophy is self-cultivation, a type of integrated individualism existing in the foundational texts of early Chinese Confucianism (Ivanhoe, 2000). According to figures such as Mencius, each individual is seen as their own moral agent by virtue of living a life that aligns with proper and healthy human values. Furthermore, influenced by the one-child policy, the Chinese moved towards smaller families, contributing to the development of some elements of individualism within the country.

Fourth, this research examines temporal landmarks based on the Chinese solar calendar, specifically Chinese holidays. As prior research has mainly focused on temporal landmarks associated with the Gregorian calendar (Beshears et al., 2021; Dai et al., 2014, 2015; Davydenko and Peetz, 2019; Hennecke and Converse, 2017), such as U.S. federal holidays, this approach contributes to the robustness of the fresh start literature. This finding suggests that the motivating factors for expense tracking behavior are primarily attributed to temporal landmarks rather than factors exclusive to the Gregorian calendar.

These findings have practical implications for individual decision-makers, financial service providers, and policymakers. For individual decision-makers, the findings emphasize the opportunity to use fresh start feelings at temporal landmarks to reinforce intentions for improving financial behaviors. Furthermore, this study suggests that the selection of an appropriate temporal landmark is crucial for goal persistence, highlighting the importance of strategic planning in initiating financial goals.

These findings also suggest ways to effectively nudge people to pursue financial goals that foster long-term persistence and ensure their lasting commitment and dedication. Financial service providers, such as banks or tracking app developers, can integrate these insights into their offerings and marketing strategies to enhance user engagement and promote financial well-being. For example, a bank app can send push notifications to its users at temporal landmarks, reminding them to assess their financial situation and make self-improvement changes.

For policymakers, this research suggests avenues for designing financial education programs and policies that foster responsible financial behavior. For example, educational campaigns (e.g., financial education in school curricula) could be launched to inform individuals about the influence of temporal landmarks on financial behavior. These campaigns could include practical tips on how to leverage fresh start feelings at strategic times to initiate and persist with financial goals. Additionally, policymakers could collaborate with financial institutions to develop incentives or reward programs that encourage individuals to engage in positive financial behavior aligned with temporal landmarks.

4.5.2 Limitations and future research

Although this research has many contributions and implications, it has certain limitations, and future research could attempt to address them. First, this paper exclusively examines the impact of the fresh start effect on the persistence of expense tracking. Future research could explore the broader connection between the fresh start effect and sustained goal pursuit, as well as investigate potential moderators and mediator influencing this relationship. For instance, factors such as goal complexity or goal clarity could moderate the impact of the fresh start effect on goal persistence.

Moreover, while Dai et al. (2015) demonstrates a causal link between temporal landmarks and increased intentions for goal pursuit, the descriptive nature of this research limits the establishment of a causal connection between the fresh start effect and expense tracking behavior. Future studies could examine this in a tightly controlled setting.

Second, the analyses of goal persistence rely on data from specific groups of Chinese individuals, leaving an open question about the generalizability of the findings to a broader population. Future research could use more representative samples.

Third, this paper documents the fresh start effect among the Chinese to infer that Chinese individuals may possess a fresh start mindset. Additional research could directly test this mindset among Chinese people by using the validated scale developed by Price et al. (2018).

Fourth, due to limitations in the dataset used, this research, focusing on routinely shared landmarks, such as the first day of a month and holidays, cannot capture individuals' sentiments about personally meaningful temporal landmarks, such as the first day after a birthday. Moreover, the findings in Tables H36 and I44 suggest that not all temporal landmarks are equally significant. Future research could explore the variations among all types of temporal landmarks and identify those that consistently and significantly influence self-improvement behaviors.

Chapter 5

Conclusion

In this dissertation, I conducted three studies examining expense tracking as a self-regulatory behavior within the context of financial self-regulation using unique data from a Chinese tracking app that facilitates expense tracking.

In the second chapter (Paper 1), I conduct empirical analyses using longitudinal administrative-level user data from the tracking app. I document that expense tracking provides diagnostic spending information, leading to spending control. In particular, I find evidence that persistent expense tracking is associated with a reduction in the share of discretionary spending over monthly spending.

In the third chapter (Paper 2), I examine survey data coupled with respondents' app usage data from the financial app, and document three descriptive pieces of evidence that could inform future research on expense tracking and effective financial self-regulation. First, expense tracking accuracy includes two dimensions: accurate categorization of expenses and accurate recording of purchase dates. I find that a considerable majority of respondents reported being accurate in categorizing expenses and indicating transaction dates. Accuracy in categorization was linked to reduced financial worries, aligning with the self-regulation theory (Bandura, 1991). However, the association with date accuracy was inconsistent with mixed results in the subsample analysis. There was a moderate correlation between accuracy in category selection and date selection, suggesting that individuals may prioritize one dimension over the other.

Second, regarding the temporal proximity of expense tracking, most individuals prioritize promptness, as the majority indicate tracking expenses immediately after purchase or on the same day. Having transaction recording patterns, regardless of the tracking frequency—be it immediate after spending, daily, weekly, or otherwise— are associated with fewer financial worries than not having a recording pattern. Moreover, immediate recording after spending is linked to the least financial worries and there are no significant differences in financial worries among people who record expenses on the same date, regularly and flexibly.

Third, regarding the consistency in expense tracking, there is a significant association between habit strength and expense tracking duration, suggesting that individuals can develop a habit of expense tracking through repetition. Consistency in expense tracking is associated with fewer financial worries, consistent with the self-regulation theory (Bandura, 1991). Additionally, common barriers to expense tracking consistency included busyness, not having a phone to record transactions, overspending, forgetfulness, and difficulty categorizing expenses, with forgetting being the most prevalent barrier, reported by over half of the respondents.

In the fourth chapter (Paper 3), I analyze both aggregated and disaggregated user data from the same tracking app. Through empirical analysis, I document that individuals are more likely to initiate their expense tracking behavior and persist in such behaviors, following temporal landmarks that signal the start of a new phase.

5.1 Contribution and Implications

Together, these three papers suggest that expense tracking could be treated as a self-regulatory behavior that aids in financial self-control. The findings present a comprehensive understanding of expense tracking behavior within the context of financial self-regulation and contribute to various streams of literature.

First, it contributes to the literature on self-regulation by identifying expense tracking as a self-regulatory behavior and the features of expense tracking behavior that facilitate improved financial outcomes. These findings expand our understanding of expense tracking behavior in the context of financial self-regulation.

Second, this dissertation contributes to the personal finance, mental accounting and mental accounting literature by illustrating how expense tracking informs individuals' spending behavior regarding budgetary constraints. Although the findings in Paper 1 do not reveal a significant association between persistent expense tracking and budget adherence, possibly due to the dynamic nature of budgeting behavior, this dissertation uses naturally occurring data, enriching our understanding of how individuals categorize and manage their financial resources.

Third, this dissertation adds to the literature on the fresh start effect by providing empirical support for its role in promoting goal initiation. Moreover, the findings extend past research on the fresh start effect by demonstrating its impact on goal persistence, suggesting that promoting financial behaviors in sync with the financial cycle can lead individuals to sustain these behaviors for longer durations. Additionally, by examining its applicability in Chinese culture and its connection to temporal landmarks based on the Chinese solar calendar, the findings extend past research primarily centered on Western contexts.

The implications of this dissertation extend to individual decision-makers, financial education initiatives and financial service providers. For individual decision-makers, this research emphasizes the importance of persistent expense tracking for achieving better financial outcomes. It suggests that individuals should incorporate expense tracking as a long-term financial self-regulatory practice, even without explicit financial goals in mind. By paying adequate attention to personal spending information collected via expense tracking, individuals can make more informed spending decisions and identify areas for improvement.

For financial education initiatives, this research recognizes expense tracking as a crucial component of financial behavior and advocates its integration into financial education curricula. Emphasis could shift towards promoting expense tracking as a fundamental financial self-regulatory practice. For example, initiatives could motivate individuals to start expense tracking as a preliminary step towards establishing suitable financial goals based on personal spending insights. By providing individuals with the necessary knowledge and skills to monitor and manage their expenses, financial education programs can significantly enhance their financial self-awareness and facilitate better financial outcomes.

For financial service providers, financial interventions leveraging the fresh start effect could effectively modify individuals' financial behavior. For example, financial service providers can encourage individuals to initiate budgeting or saving behaviors by evoking a fresh start feeling at certain temporal landmarks. They can also design marketing campaigns or incentives that coincide with temporal landmarks, such as the beginning of a new month or a significant personal event. By leveraging these moments, providers can inspire individuals to initiate and sustain efforts to achieve financial goals that require ongoing commitment and persistence.

5.2 Limitations and Future Research

There are limitations to this dissertation, which suggest opportunities for future research. First, the data on expense tracking behavior were derived from a specific Chinese tracking app, potentially limiting the external validity of the findings due to a lack of representativeness. This limitation arises from the potential issues related to selection bias (i.e., who is using the tracking app) and attrition (i.e., who remains using the tracking app). Therefore, caution is advised when extrapolating these results to broader populations, particularly for individuals not currently engaged in expense tracking. Moreover, the findings may be influenced by country context, given the significant variations in cultural norms and financial behaviors across different nations. Therefore, future research could explore expense tracking behavior using representative samples across various cultural contexts.

Second, certain limitations are inherent in the data that may bias the findings. The tracking app relies on self-reported spending and earnings, meaning that the spending data in Paper 1 may not accurately reflect actual spending. Furthermore, the survey data used in Paper 2 is also self-reported. This means that the survey solely measures the perceived tracking patterns, not the actual behaviors. For example, it measures perceived accuracy in tracking, rather than the actual accuracy in tracking. While the survey measures generally align with similar metrics derived from the tracking app usage data, suggesting the validity of self-reported measures, they still constrain the ability to conclusively establish the connection between actual expense tracking behavior and financial worries. Future research could aim to obtain additional data by integrating actual spending, such as by linking with bank payments, to help validate the self-reported measures.

Third, the findings of this dissertation are descriptive, not causal. This limits some implications. For example, in Paper 2, I am unable to discern whether accuracy, temporal proximity, or consistency in expense tracking directly contributes to reduced financial worries, or whether individuals who are already financially well are simply more inclined to prioritize these aspects of tracking. Therefore, further investigations, such as controlled lab experiments, are needed to establish causal relationships.

Fourth, this dissertation primarily focuses on active tracking behavior, where individuals manually record their expenses. However, alternative automated tracking methods exist, where spending is automatically pooled from individuals' bank accounts. Future research could explore various tracking methods and assess how differences in tracking methods affect financial self-regulation outcomes.

Fifth, this dissertation focuses on expense tracking behavior, which does not mean that income tracking is not useful. The awareness of income is necessary to form an understanding of one's financial conditions. However, some users of the tracking app did not track and report their income. Although these users may still be aware of their available financial resources, I cannot test this assumption. Furthermore, the gig economy has experienced substantial growth in recent years, particularly in the United States. This has led to the emergence of fragmented income sources, such as Uber drivers earning income per ride and the advent of non-traditional payroll methods that enable frequent payments to employees. In light of these developments, income-tracking may hold even greater importance in today's context. Therefore, future research could explore income-tracking and delve into different focuses (income focus, expense focus, or both) and their impacts.

Chapter 6

Appendices

A Chapter 2: Data Cleaning for The Tracking Sample

Initially, 8000 users were randomly selected from all users registered in 2018. About 94 users were excluded due to missing tracking information in 2018[36].

Each record in my sample is associated with two dates: Date 1 (when the record was logged into the app system) and Date 2 (when the record occurred). By default, Date 2 is the same as Date 1. However, users can enter transactions either in advance or later. Users may report expenses before they started tracking (retrospective tracking). Since this study analyzes the trends of spending behavior as users gain more tracking experience, records that occurred before the month when the user started tracking using the app were excluded. Additionally, to eliminate COVID-specific effects, records from 2020 were dropped, resulting in the removal of 83 users.

Next, users were categorized into three groups: those who only recorded income (N=271),

[36]There are two potential reasons. First, users may have registered but never logged any activity. Second, users may have registered, recorded transactions, and subsequently deleted these recorded transactions.

those who only recorded expenses (N=2,662), and those who recorded both expenses and income (N=4,890). The 271 users who only recorded incomes were excluded since this study focuses on expense tracking behavior.

Monthly expenses range from 0.1 RMB to 1,079,351,906 RMB[37] with a standard deviation of 8,911,737.26. Despite a median value of 2,887.27 RMB, the mean stands considerably higher at 151,048.49 RMB, suggesting a skewed distribution of the expense data. To address outliers, I further refined the data by excluding users who ever had monthly expenses that fell within the top 5% ($\geq$ 32,407.14 RMB) and bottom 5% ($\leq$ 106.6 RMB) ranges. About 2,252 users were dropped. This adjustment allowed me to mitigate biases introduced by extremely low expenses, which might indicate unreported transactions, as well as unusually high expenses from affluent individuals or small business owners using the app for business purposes. This exclusion method employed helps ensure that the remaining data remains representative of the broader user base.

For Analysis 1, the reduction in the share of discretionary expenses (SDE) in a month was used to measure financial goal attainment. The app offers 33 preset spending categories (refer to Table A1) and 4,248 user-generated categories in the sample. As there is insufficient information to determine if a user-generated category is discretionary or non-discretionary, the analysis focused solely on the users who exclusively used preset expense categories to track spending from the first month of app usage until the end of 2019. Moreover, I excluded users with only one month of expense tracking experience as the analysis examines changes in spending patterns over multiple months[38]. As a result, the final sample consisted of expense records from 1,643 users (referred to as Tracking Sample).

[37]RMB refers to the Chinese currency. One U.S. dollar is about 7 RMB.

[38]Users with only one month of expense tracking experience will be automatically dropped in the empirical analysis using panel fixed effects.

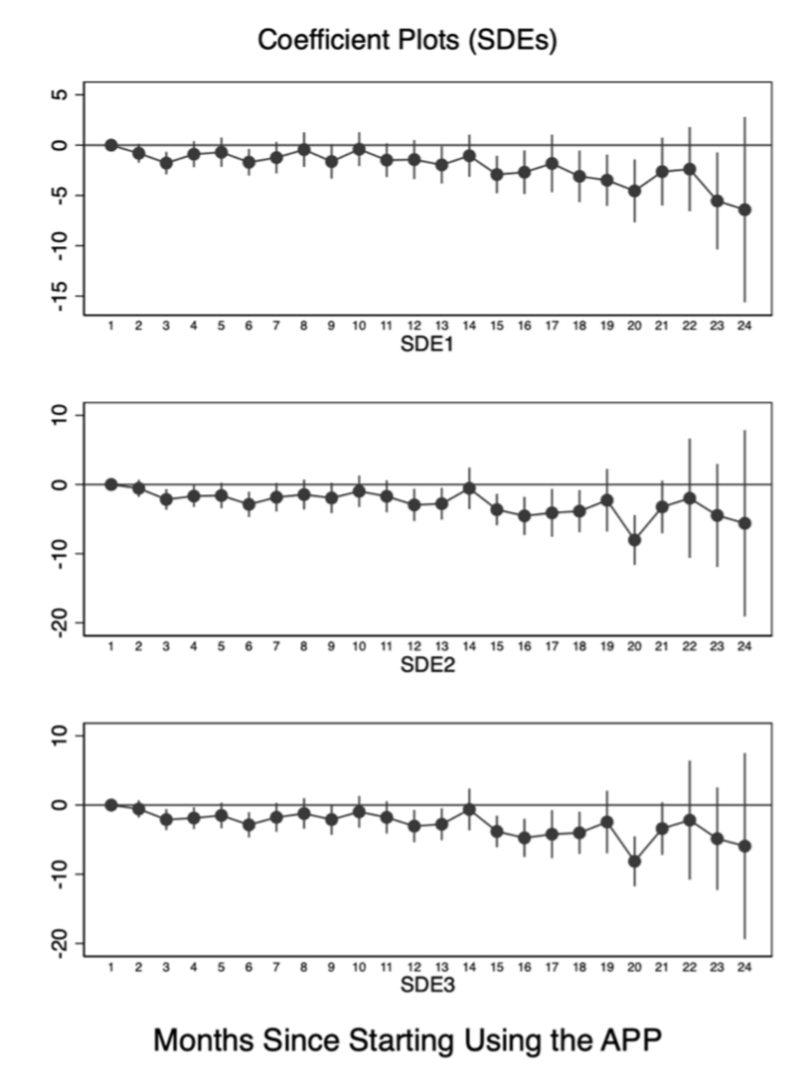
TABLE A1
SUMMARY STATISTICS FOR PRESET SPENDING CATEGORIES IN TRACKING SAMPLE

Preset expense categories	Num. of Records	Avg. Expenses per Record (RMB)	Avg. Expenses per Record ($)
Meals	143,577	36.75	5.25
Transportation	28,909	62.62	8.95
Shopping	28,583	178.03	25.43
Goods for Daily Use	23,168	149.13	21.30
Snacks	18,156	26.33	3.76
Fruit	8,775	29.88	4.27
Clothing	7,944	227.43	32.49
Vegetables	7,723	38.57	5.51
Children	6,374	314.51	44.93
Beauty	5,859	230.48	32.93
Entertainment	5,840	146.10	20.87
Cell Phone (Bills)	4,230	102.23	14.60
Health Care	3,676	329.06	47.01
Education	3,350	282.54	40.36
Vehicle	3,280	321.01	45.86
Home Goods	3,088	337.04	48.15
Housing	2,862	931.79	133.11
Travel	2,262	559.82	79.97
Alcohol and Tobacco	2,165	70.36	10.05
Social Interaction	2,020	321.44	45.92
Office	1,649	435.66	62.24
Elder	1,516	644.99	92.14
Cash Gift	1,464	553.51	79.07
Parcel-delivery Service	1,324	49.06	7.01
Gifts	1,282	284.37	40.62
Consumer Electronics	1,076	414.87	59.27
Books	998	71.33	10.19
Sport	892	337.62	48.23
Dependents	793	606.94	86.71
Pets	610	227.49	32.50
Maintenance	422	493.23	70.46
Lottery	395	144.41	20.63
Donation	298	194.46	27.78

NOTE.—This table provides descriptive statistics for 33 preset spending categories in the Tracking Sample. It presents the total number of records in each expense category and the average expense per record in both Chinese currency (RMB) and U.S. dollars ($). One U.S. dollar is equivalent to about 7 RMB.

B Chapter 2: Additional Analyses for Analysis 1

Fig. B2.—Coefficient Plots of The Estimates for Each Month Since Starting Using the App



I ran non-parametric regressions, considering each number of months since initiating app usage as independent variables while controlling for monthly income and month fixed effects with panel fixed effects. This figure presents the coefficient plots of the estimates for each number of months since starting tracking using the app. The top scatter plot represents the coefficient plots when the share of spending on snacks, clothing, and entertainment (SDE 1) is the dependent variable. The middle scatter plot represents the coefficient plots when the share of spending on snacks, clothing, entertainment, travel, social interaction, and gifts (SDE 2) is the dependent variable. The bottom scatter plot represents the coefficient plots when the share of spending on snacks, clothing, entertainment, travel, social interaction, gifts, lottery and donations (SDE 3) is the dependent variable. The vertical lines indicate the width of the 95% confidence interval for the parameters, while the dots represent the estimated values.

TABLE B3

Analysis 1 without Income as a Control

	SDE1	SDE2	SDE3
Tracking Persistence	-0.12**	-0.17**	-0.18**
	(0.04)	(0.06)	(0.06)
Constant	10.40***	15.55***	15.53***
	(0.59)	(0.79)	(0.80)
Number of Observations	9,083	9,083	9,083

Note.—Robust standard error in parentheses. SDE 1= the share of monthly discretionary expenses belonging to the snacks, clothing, and entertainment category over monthly expenses; SDE 2= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, and gifts category over monthly expenses; SDE 3= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, gifts, lottery, and donation category over monthly expenses. I regressed SDEs on tracking persistence and month fixed effects with panel-fixed effects and robust standard errors. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE B4

Analysis 1 Treating Underreported Income as Missing

	SDE1	SDE2	SDE3
Tracking Persistence	-0.09	-0.12	-0.12
	(0.06)	(0.08)	(0.08)
Constant	11.41***	15.93***	16.02***
	(0.97)	(1.42)	(1.44)
N	3,683	3,683	3,683

Note.—Robust standard error in parentheses. SDE 1= the share of monthly discretionary expenses belonging to the snacks, clothing, and entertainment category over monthly expenses; SDE 2= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, and gifts category over monthly expenses; SDE 3= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, gifts, lottery, and donation category over monthly expenses. I regressed SDEs on tracking persistence, the amount of monthly income, and month fixed effects with panel fixed effects and robust standard errors and excluded any observations with missing income. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE B5
Robustness Checks for Analysis 1 (No Tracking Gaps)

	SDE1	SDE2	SDE3
Tracking Persistence	-0.12**	-0.17**	-0.18**
	(0.04)	(0.06)	(0.06)
Constant	10.58***	15.66***	15.60***
	(0.61)	(0.81)	(0.82)
N	8,822	8,822	8,822

Note.—Robust standard error in parentheses. SDE 1= the share of monthly discretionary expenses belonging to the snacks, clothing, and entertainment category over monthly expenses; SDE 2= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, and gifts category over monthly expenses; SDE 3= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, gifts, lottery, and donation category over monthly expenses. I regressed SDEs on tracking persistence, the amount of monthly income, and month fixed effects with panel fixed effects and robust standard errors and excluded any observations with tracking gaps. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE B6
Robustness Checks for Analysis 1 (Tracking Duration)

	(1) Track for ≥3 Months			(2) w/o Last Month			(3) w/o First Month		
	SDE1	SDE2	SDE3	SDE1	SDE2	SDE3	SDE1	SDE2	SDE3
Tracking Persistence	-0.11**	-0.17**	-0.17**	-0.14**	-0.20**	-0.20**	-0.10*	-0.13*	-0.14*
	(0.04)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)
Constant	10.27***	15.53***	15.56***	10.99***	15.99***	16.19***	10.23***	15.40***	15.48***
	(0.61)	(0.83)	(0.84)	(0.66)	(0.87)	(0.87)	(0.63)	(0.87)	(0.88)
N	7,917	7,917	7,917	7,440	7,440	7,440	7,440	7,440	7,440

Note.—Robust standard error in parentheses. SDE 1= the share of monthly discretionary expenses belonging to the snacks, clothing, and entertainment category over monthly expenses; SDE 2= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, and gifts category over monthly expenses; SDE 3= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, gifts, lottery, and donation category over monthly expenses. I regressed SDEs on tracking persistence, the amount of monthly income, and month fixed effects with panel fixed effects and robust standard errors. Group (1) restricted Tracking Sample to users who track expenses for at least three months. Group (2) included monthly tracking data without the last month for each user. Group (3) included monthly tracking data without the first month for each user. Each column represents one regression with a different measure of the share of monthly discretionary expenses over monthly income as the dependent variable. Only the key predictor variable and constant term are reported in this table. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE B7

Robustness Checks for Analysis 1 (Different Sample Restrictions)

	(1)			(2)		
	Users with Expense Records			Users w/o Extreme Monthly Spending		
	SDE1	SDE2	SDE3	SDE1	SDE2	SDE3
Tracking Persistence	-0.05**	-0.09***	-0.10***	-0.06**	-0.08*	-0.09**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Constant	9.58***	13.97***	14.34***	10.32***	14.63***	14.93***
	(0.29)	(0.38)	(0.38)	(0.35)	(0.44)	(0.45)
No. Obs.	37,543	37,543	37,543	24,691	24,691	24,691
No. Users.	7,552	7,552	7,552	5,300	5,300	5,300

Note.—Robust standard error in parentheses. SDE 1= the share of monthly discretionary expenses belonging to the snacks, clothing, and entertainment category over monthly expenses; SDE 2= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, and gifts category over monthly expenses; SDE 3= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, gifts, lottery, and donation category over monthly expenses. I regressed SDEs on tracking persistence, the amount of monthly income, and month fixed effects with panel fixed effects and robust standard errors. Group (1) presents the regression results for all users who recorded expenses in the original sample. Group (2) displays the regression results for users who recorded expenses after excluding those who reported extremely high ($\geq$ 32,407.14 RMB) and low ($\leq$ 106.6 RMB) monthly spending in the original sample. Each column represents one regression with a different measure of the share of monthly discretionary expenses over monthly income as the dependent variable. Only the key predictor variable and constant term are reported in this table. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE B8

Robustness Checks for Analysis 1 (Alternative Sample Restrictions)

	SDE1	SDE2	SDE3
Tracking Persistence	-0.13**	-0.13*	-0.13*
	(0.05)	(0.06)	(0.06)
Constant	10.43***	15.80***	15.86***
	(0.70)	(0.98)	(1.00)
No. Obs.	5,988	5,988	5,988
No. Users	1,113	1,113	1,113

Note.—Robust standard error in parentheses. SDE 1= the share of monthly discretionary expenses belonging to the snacks, clothing, and entertainment category over monthly expenses; SDE 2= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, and gifts category over monthly expenses; SDE 3= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, gifts, lottery, and donation category over monthly expenses. I regressed SDEs on tracking persistence, the amount of monthly income, and month fixed effects with panel fixed effects and robust standard errors after excluding those who reported extremely high ($\geq$ 21226.775 RMB) and low ($\leq$ 305.52 RMB) monthly spending in the original sample. Each column represents one regression with a different measure of the share of monthly discretionary expenses over monthly income as the dependent variable. Only the key predictor variable and constant term are reported in this table. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE B9

HETEROGENEITY ANALYSIS FOR ANALYSIS 1

	(1) Users w/o Monthly Budgets			(2) Users w Monthly Budgets		
	SDE1	SDE2	SDE3	SDE1	SDE2	SDE3
Tracking Persistence	-0.12**	-0.15*	-0.16**	-0.03	-0.25+	-0.24
	(0.05)	(0.06)	(0.06)	(0.11)	(0.15)	(0.15)
Constant	10.01***	14.98***	14.98***	13.45***	19.59***	19.32***
	(0.62)	(0.83)	(0.84)	(1.88)	(2.64)	(2.68)
No. Obs.	8,177	8,177	8,177	906	906	906
No. Users	1,528	1,528	1,528	115	115	115

NOTE.—Robust standard error in parentheses. SDE 1= the share of monthly discretionary expenses belonging to the snacks, clothing, and entertainment category over monthly expenses; SDE 2= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, and gifts category over monthly expenses; SDE 3= the share of discretionary expenses belonging to the snacks, clothing, entertainment, travel, social interaction, gifts, lottery, and donation category over monthly expenses. I regressed SDEs on tracking persistence, the amount of monthly income, and month fixed effects with panel fixed effects and robust standard errors for users with monthly budgets (Group 2) and users without monthly budgets (Group 1), respectively. Each column represents one regression with a different measure of the share of monthly discretionary expenses over monthly income as the dependent variable. Only the key predictor variable and constant term are reported in this table. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE B10
Summary Statistics by Expense Tracking Duration

	Users Track > 1 Month	Users Track⩽ 1 Month	Differences
Panel A: User Level Characteristics			
Female	0.65	0.61	0.03*
With monthly budgets	0.07	0.03	0.04***
With records of income	0.65	0.42	0.23***
Panel B: User-Month Level Characteristics			
Monthly income (in RMB)	3895.82	6787.23	-2891.40***
	(16420.35)	(31385.99)	
Monthly expenses (in RMB)	4051.31	2524.17	1527.14***
	(4771.90)	(4151.40)	
Number of records per month	45.76	19.86	25.90***
	(39.54)	(28.26)	
Number of income records per month	7.55	7.66	-0.11
	(24.66)	(28.07)	
Number of expense records per month	35.73	13.54	22.19***
	(30.75)	(15.74)	
Share of Discretionary Expenses			
SDE 1	9.92	10.28	-0.36
	(0.17)	(19.92)	
SDE 2	14.32	15.48	-1.16
	(0.21)	(0.68)	
SDE 3	14.57	16.17	-1.61*
	(20.46)	(25.78)	
Number of Users	1,643	1,356	

Note.—This table presents descriptive statistics for users who used the app to track their expenses for more than one month or less than one months in the Tracking Sample. The table displays sample means and standard deviations (indicated in parentheses) with the number of users listed in the last row. RMB refers to the Chinese currency. One U.S. dollar is about 7 RMB. Average income and number of income per month are computed among users who ever reported income. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

C Chapter 2: Data Cleaning for Budgeting Sample

Initially, a random selection was made from the pool of users with information regarding monthly budgets and logged records in June 2020, resulting in 3000 users. To track changes in their monthly budgets, the budgeting status of these users was manually collected three times a month: on the first, fifteenth, and thirtieth day of each month. Concurrently, their tracking activities were also recorded during this period. About 492 users were excluded due to missing tracking information during the six-month data collection period (July-December 2020)[39].

Users' monthly expenses ranged from 0 RMB to 2,182,526,022 RMB, with a standard deviation of 20,181,893.84. Extremely low monthly expenses may signal that users fail to report all expenses in a given month, while very high monthly expenses may be attributed to wealthy individuals or small business owners using the app for business purposes. Since Tracking Sample is a more representative sample of app users, while Budgeting Sample is more selective, I used the same cutoffs as in Tracking Sample to exclude users with extremely large monthly expenses (monthly expenses $\geq$ 32,407.14 RMB) and users with extremely low monthly expenses (monthly expenses $\leq$ 106.6 RMB). This step resulted in the exclusion of 822 users. Furthermore, users exhibited significant variation in their monthly budgets, ranging from 1 RMB to 999,999,999 RMB. The average is 348,329.20 RMB with a standard deviation of 18,470,095.48. It is possible that some users did not set up their monthly budgets seriously. To avoid biases introduced by these outliers, I further excluded users who ever had monthly expenses that fell within the top 1% of monthly budgets (monthly budget $\geq$ 31,000 RMB) and the bottom 1% of monthly budgets (monthly budget $\leq$ 800 RMB). This

[39] There are two potential reasons. First, users never logged any activity from July 2020 to December 2020. Second, users recorded transactions, and subsequently deleted these recorded transactions from July 2020 to December 2020.

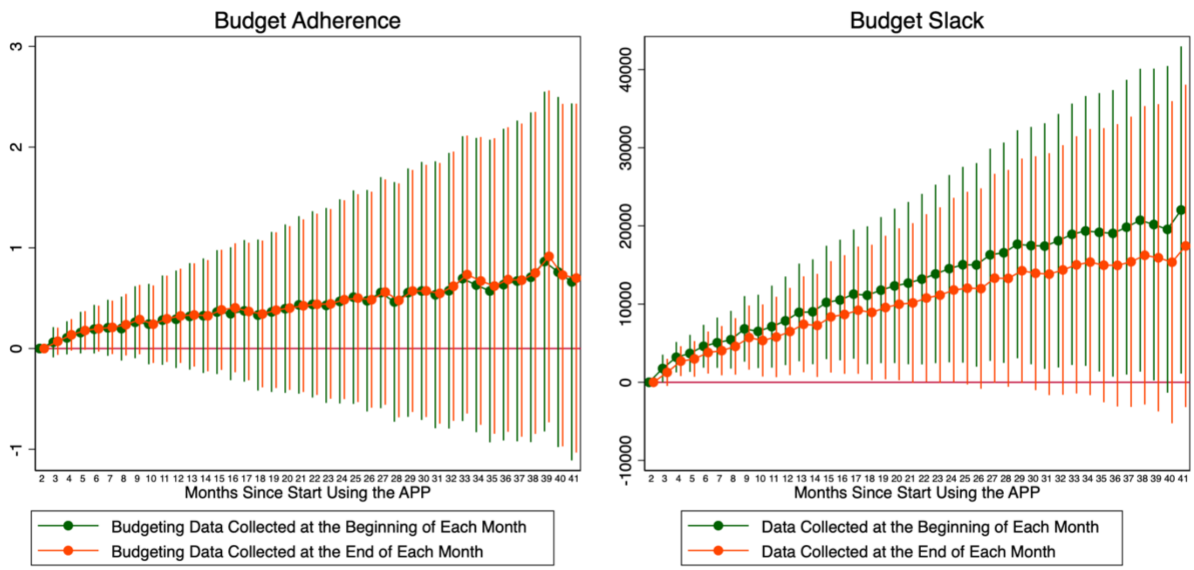
step dropped 59 users.

Following that, I excluded one users who did not provide spending information while having a budget, as the assessment of budget adherence depends on comparing spending against budgeted amounts. Lastly, I excluded 210 users who had only one month of data containing both spending and budgeting information. This was necessary as the analysis focuses on tracking changes in spending patterns across multiple months[40]. The final sample consisted of expense records and budgeting information from these 1,388 users (referred to as the Budgeting Sample).

[40]Users with only one month of data with both spending and budgeting information will be automatically dropped in the empirical analysis using panel fixed effects.

D Chapter 2: Additional Analyses for Analysis 2

Fig. D11.—Coefficient Plots of The Estimates for Each Month Since Starting Using the App



I ran non-parametric regressions, considering each number of months since initiating app usage as independent variables while controlling for monthly income and month fixed effects with panel fixed effects. This figure presents the coefficient plots of the estimates for each number of months since starting tracking using the app. The left scatter plot represents the coefficient plots when budget adherence is the dependent variable, and the right scatter plot represents the coefficient plots when budget slack is the dependent variable. The vertical lines indicate the width of the 95% confidence interval for the parameters, while the dots represent the estimated values.

TABLE D12

Robustness Checks for Analysis 2 (Full Sample)

	Budget Adherence		Budget Slack	
	(1)	(2)	(3)	(4)
	Month-beginning	Month-end	Month-beginning	Month-end
Tracking Persistence	0	0	-5,359,857	-4,461,891
	(0.02)	(0.02)	(6,395,680.20)	(6,889,063.67)
Constant	0.29	0.26	75,982,587.53	63,314,451.97
	(0.25)	(0.24)	(89,993,311.39)	(96,911,780.68)
Number of Observations	11,226	11,226	11,226	11,184

Note.—Robust standard error in parentheses. Budget adherence is a dummy variable indicating whether accumulated monthly expenses is less than or equal to the monthly budget. Budget slack is computed as monthly budgets minus the monthly expenses. I regressed budget adherence and budget slack on tracking persistence, monthly income, and month fixed effects with panel fixed effects and robust standard errors, respectively. Since users can change their monthly budgets, I ran regressions with dependent variables measured based on budgeting data collected at the beginning and end of each month. Each column represents one regression with a different measure of budget adherence/budget slack as the dependent variable. Only the key predictor variable and constant term are reported in this table. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE D13

Robustness Checks for Analysis 2 (Alternative Cutoff Points)

	Budget Adherence		Budget Slack	
	(1)	(2)	(3)	(4)
	Month-beginning	Month-end	Month-beginning	Month-end
Tracking Persistence	0.03	0.03	435.98	304.67
	(0.03)	(0.03)	(272.68)	(265.16)
Constant	-0.01	-0.06	-7,367.06+	-5,607.21
	(0.38)	(0.37)	(3,918.24)	(3,810.90)
Number of Observations	5,339	5,339	5,339	5,315

Note.—Robust standard error in parentheses. Budget adherence is a dummy variable indicating whether accumulated monthly expenses is less than or equal to the monthly budget. Budget slack is computed as monthly budgets minus the monthly expenses. I regressed budget adherence and budget slack on tracking persistence, monthly income, and month fixed effects with panel fixed effects and robust standard errors, respectively. Since users can change their monthly budgets, I ran regressions with dependent variables measured based on budgeting data collected at the beginning and end of each month. Each column represents one regression with a different measure of budget adherence/budget slack as the dependent variable. Only the key predictor variable and constant term are reported in this table. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

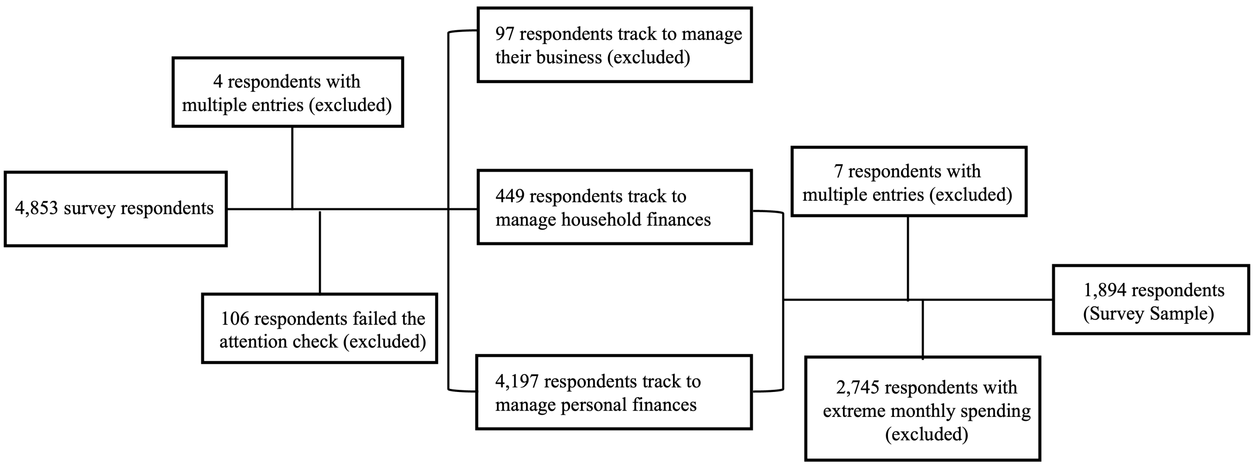
TABLE D14
Summary Statistics by Expense Tracking Duration

	Track > 1 Month	Track ⩽ 1 Month	Differences
Panel A: User Level Characteristics			
Female	0.63	0.57	0.06*
With records of income	0.78	0.46	0.32***
Panel B: User-Month Level Characteristics			
Monthly income (in RMB)	10,131.52	8,624.42	1,507.10
	(19,266.93)	(11,535.34)	
Monthly expenses (in RMB)	8,132.70	4,965.00	3,167.70***
	(6,447.71)	(5,804.14)	
Number of records per month	68.53	30.81	37.72***
	(47.81)	(36.28)	
Number of income records per month	5.46	4.41	1.06
	(12.24)	(6.43)	
Number of expense records per month	64.14	28.8	35.34***
	(44.70)	(34.26)	
Budgetary Information			
Monthly Budget (Month-beginning)	5,783.92	6,262.99	-479.07
	(4,521.84)	(5,606.11)	
Monthly Budget (Month-end)	5,762.49	6,441.26	-678.78
	(4,485.39)	(5,736.61)	
Budget Adherence (Month-beginning)	0.34	0.67	-0.34***
Budget Adherence (Month-end)	0.33	0.72	-0.39***
Budget Slack (Month-beginning)	-2,348.78	1,298	-3,646.77 ***
	(6,361.73)	(6,921.16)	
Budget Slack (Month-end)	-2,365.98	1,643.18	-4,009.16***
	(6,213.16)	(6,681.33)	
Number of Users	1,388	210	

Note.—This table presents descriptive statistics for users who used the app to track their expenses for more than one month or less than one months in the Budgeting Sample. The table displays sample means and standard deviations (indicated in parentheses) with the number of users listed in the last row. RMB refers to the Chinese currency. One U.S. dollar is about 7 RMB. Average income and number of income per month are computed among users who ever reported income. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

E Chapter 3: Sample Cleaning

Fig. E15.—Sample Cleaning Process



This figure illustrates the process of cleaning the Survey Sample from all respondents who completed all questions.

F Chapter 3: Additional Analyses

TABLE F16
Regression Results (Restricted Sample)

	(1)	(2)
Category Selection Accuracy (Baseline: Disagree/Uncertainty)		
Agree	-0.21***	-0.18***
	(0.06)	(0.05)
Stronger Agree	-0.27***	-0.22***
	(0.06)	(0.05)
Constant	3.49***	4.32***
	(0.05)	(0.17)
Controls	No	Yes
Number of Respondents	2,745	2,745

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and each level of category selection accuracy as a set of predictors using the Restricted Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 * *p < .01 * * * p < .001$

TABLE F17
Regression Results (Excluded Missing Demographic Info))

	(1)	(2)
Category Selection Accuracy (Baseline: Disagree/Uncertainty)		
Agree	-0.15**	-0.14**
	(0.05)	(0.05)
Stronger Agree	-0.22***	-0.20***
	(0.05)	(0.05)
Constant	3.47***	4.18***
	(0.05)	(0.15)
Controls	No	Yes
Number of Respondents	3,476	3,476

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and each level of category selection accuracy as a set of predictors using the Survey Sample, excluding individuals who ever select "prefer not to disclose" in demographic questions. The control variables include age, gender, education, employment status, income, and marital status Significance levels $+p < .1, *p < .05 * *p < .01 * * * p < .001$

TABLE F18
MULTINOMINAL LOGISTIC REGRESSION RESULTS (ACCURACY IN CATEGORIZATION)

	(1) "Not at All"	(2) "Not"	(3) "Moderately"	(4) "Quite"
Category Selection Accuracy				
(Baseline: Disagree/Uncertainty)				
Agree	-0.39	0.85***	0.41**	0.41**
	(-1.11)	(4.56)	(2.69)	(2.68)
Stronger Agree	0.60*	0.55**	0.04	-0.25
	-2.07	-3.15	-0.25	(-1.74)
Constant	-4.85***	-3.30***	-1.01*	-0.3
	(-3.83)	(-5.86)	(-2.46)	(-0.74)
Number of Respondents	4,639	4,639	4,639	4,639

NOTE.—Robust standard error in parentheses. This table presents the multinomial logistic regression results with each level of worries about the financial situation as the outcomes of interest and each level of category selection accuracy as a set of predictors using the Survey Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE F19
REGRESSION RESULTS (CONTINUOUS MEASURES)

	(1)	(2)
Category Selection Accuracy	-0.10***	-0.10***
(1=Strongly disagree, 5=Strongly agree)	(-4.85)	(-4.85)
Constant	3.533***	3.533***
	(72.24)	(72.24)
Controls	No	Yes
Number of Respondents	4,639	4,639

NOTE.—Robust standard error in parentheses. This table presents the regression results with a continuous measure of worries about the financial situation as the outcomes of interest and a continuous measure of category selection accuracy as a predictor using the Survey Sample without controls (column (1)) and with controls (column (2)). The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE F20
REGRESSION RESULTS (SURVEY MEASURES)

	(1) Extensive Margin	(2) Intensive Margin
Category Selection Accuracy		
(Baseline: Disagree/Uncertainty)		
Agree	-0.02	0.11
	(0.02)	(0.26)
Stronger Agree	-0.01	0.58*
	(0.01)	(0.25)
Constant	0.78***	2.73**
	(0.05)	(0.87)
Controls	No	Yes
Number of Respondents	4,639	4,639

NOTE.—Robust standard error in parentheses. This table presents the regression results with either the extensive margin (propensity to use customized expense categories) in column (1) or the intensive margin (the number of customized expense categories used) in column (2) as the dependent variable and a continuous measure of category selection accuracy as a predictor using the Survey Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE F21
REGRESSION RESULTS (EXCLUDED MISSING DEMOGRAPHIC INFO)

	(1)	(2)
Date Selection Accuracy		
(Baseline: Disagree/Uncertainty)		
Agree	-0.06	-0.03
	(0.07)	(0.07)
Stronger Agree	-0.17*	-0.12+
	(0.07)	(0.07)
Constant	3.43***	4.11***
	(0.07)	(0.16)
Controls	No	Yes
Number of Respondents	3,476	3,476

NOTE.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and each level of date selection accuracy as a set of predictors using the Survey Sample, excluding individuals who ever select "prefer not to disclose" in demographic questions. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE F22

Regression Results (Restricted Sample)

	(1)	(2)
Date Selection Accuracy		
(Baseline: Disagree/Uncertainty)		
Agree	0.04	0.06
	(0.08)	(0.08)
Stronger Agree	-0.1	-0.06
	(0.08)	(0.07)
Constant	3.33***	4.14***
	(0.08)	(0.17)
Controls	No	Yes
Number of Respondents	2,745	2,745

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and each level of date selection accuracy as a set of predictors using the Restricted Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE F23

Regression Results (Restricted Sample)

	(1)	(2)
Temporal Proximity in Expense Tracking		
(Baseline=On the same day)		
Immediately	-0.08*	-0.05
	(0.04)	(0.04)
Regularly	0.06	0.05
	(0.12)	(0.12)
Flexible	-0.07	0
	(0.11)	(0.10)
No clear patterns	0.13+	0.11+
	(0.07)	(0.07)
Constant	3.31***	4.16***
	(0.03)	(0.16)
Controls	No	Yes
Number of Respondents	2,745	2,745

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and a set of dummy variables capturing each option from the survey question regarding when individuals tend to log their transactions as predictors using the Restricted Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE F24
Regression Results (Excluded Missing Demographic Info)

	(1)	(2)
Temporal Proximity in Expense Tracking		
(Baseline=On the same day)		
Immediately	-0.10**	-0.07+
	(0.04)	(0.04)
Regularly	0	0.01
	(0.10)	(0.09)
Flexible	-0.08	-0.06
	(0.10)	(0.10)
No clear patterns	0.08	0.07
	(0.06)	(0.06)
Constant	3.35***	4.06***
	(0.03)	(0.15)
Controls	No	Yes
Number of Respondents	3,476	3,476

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and a set of dummy variables capturing each option from the survey question regarding when individuals tend to log their transactions as predictors when excluding the respondents who ever selected "Prefer not to disclose" for any demographic questions in the Survey Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE F25
Regression Results (Restricted Sample)

	(1)	(2)
Habit Strength in Expense Tracking	-0.14***	-0.08*
(Weak Habit=1, Strong Habit=5)	(0.03)	(0.03)
Constant	3.94***	4.50***
	(0.16)	(0.21)
Controls	No	Yes
Number of Respondents	2,745	2,745

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and habit strength in expense tracking as a predictor using the Restricted Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

TABLE F26
Regression Results (Excluded Missing Demographic Info)

	(1)	(2)
Habit Strength in Expense Tracking	-0.11***	-0.05+
(Weak Habit=1, Strong Habit=5)	(0.03)	(0.03)
Constant	3.82***	4.28***
	(0.14)	(0.20)
Controls	No	Yes
Number of Respondents	3,476	3,476

Note.—Robust standard error in parentheses. This table presents the regression results without covariates (column (1)) and with covariates (column (2)), with worries about the financial situation as the outcome of interest and habit strength in expense tracking as a predictor when excluding the respondents who ever selected "Prefer not to disclose" for any demographic questions in the Survey Sample. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE F27
Regression Results (Habit Strength)

	(1)	(2)	(3)
Agreement Level	-0.05*	-0.06*	-0.07**
(Strongly Disagree=1, Strongly Agree=5)	(0.02)	(0.02)	(0.02)
Constant	4.33***	4.34***	4.39***
	(0.17)	(0.16)	(0.16)
Controls	Yes	Yes	Yes
Number of Respondents	4,639	4,639	4,639

Note.—Robust standard error in parentheses. This table presents the regression results with worries about the financial situation as the outcome of interest and each individual habit strength in expense tracking question as a predictor. Column (1) shows the results when the agreement level on "Tracking expenses is something that I do frequently" is the independent variable. Column (2) shows the results when the agreement level on "Tracking expenses is something that I do automatically" is the independent variable. Column (3) shows the results when the agreement level on "Tracking expenses is something that belongs to my (daily, weekly, monthly) routine" as the independent variable. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 ***p < .001$

TABLE F28
Regression Results (Tracking Duration)

	(1) # Total Weeks	(2) # Consecutive Weeks
Habit Strength in Expense Tracking	-0.05*	-0.06*
(Weak Habit=1, Strong Habit=5)	(0.02)	(0.02)
Constant	4.33***	4.34***
	(0.17)	(0.16)
Controls	Yes	Yes
Number of Respondents	4,639	4,639

Note.—Robust standard error in parentheses. This table presents the regression results with worries about the financial situation as the outcome of interest and each individual habit strength in expense tracking question as a predictor. Column (1) shows the results when the total number of weeks with expenses is the dependent variable. Column (2) shows the results when the number of consecutive weeks with expenses is the dependent variable. The control variables include age, gender, education, employment status, income, and marital status. Significance levels $+p < .1, *p < .05 **p < .01 *** p < .001$

G Chapter 3: Survey Questions (Translated to English)

1. Research Participant Information and Consent Form

2. How did you learn about this tracking app?

   O Friends

   O Parents or relatives

   O Sharing on social media platforms such as TikTok, Redbook, Weibo, etc.

   O App Store

   O Advertisement

3. What is the reason for you to use this tracking app?

   O To manage personal expenses and income

   O To manage expenses and income for oneself and others (e.g., recording the daily expenses of the entire household)

   O To manage business expenses and income

4. What is the primary purpose for using this tracking app? If multiple options apply, please select the most significant one.

   O Recording expenses or income

   O Avoiding overspending

   O Saving money

5. What is the most important thing you consider when tracking? You may have considered multiple factors below, please select the most important one for you.

   O How to record income or expenses

   O How to control expenses

   O Total amount of expenses

   O Total amount saved

   O I have not considered these specific matters

6. Please indicate your level of agreement with the following statements based on your tracking experience:

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
Tracking expenses is something that I do frequently	○	○	○	○	○
Tracking expenses is something that I do automatically	○	○	○	○	○
Tracking expenses is something that belongs to my (daily, weekly, monthly) routine	○	○	○	○	○

7. Before using this tracking app, have you ever tracked your transactions using other methods?

O Yes

O No

8. Before using this tracking app, for approximately how long did you keep tracking using other methods?

   Within 1 month ... Over 60 months

9. Do you agree with the statement that tracking can help improve your financial situation?

   O Strongly Agree

   O Agree

   O Neutral

   O Disagree

   O Strongly Disagree

10. Generally, when do you tracking your transactions?

    O Record the transaction immediately after it happens

    O Record the transaction on the same date when it happens

    O Record the transaction regularly, such as once a week

    O The timing depends on the nature of the transaction (being flexible), such as recording large purchase immediately and record small purchases regularly

    O There is no clear pattern

11. Based on your tracking behavior, please indicate your level of agreement with the following statements:

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
I always make sure I select the accurate category while tracking	◯	◯	◯	◯	◯
I always make sure I select the date when the transaction happens while tracking	◯	◯	◯	◯	◯

12. Which of the following would hinder you from using the tracking app to record expenses? [Select all that apply]

    O I am not sure about how to categorize spending

    O I forget about the expenses

    O I realize that I have already overspent

    O I am too busy

    O My phone is not with me

    O Other [please specify]

13. To test your focus, please select "Apple" from the following options.

    O Grape

    O Banana

    O Watermelon

    O Apple

O Pineapple

14. Have you ever set the following budgets?

	Yes	No
Total monthly budget, meaning the total spending plan for one month.	◯	◯
Categorical budget, such as food budget or clothing budget.	◯	◯

15. What is the primary purpose of setting your total monthly budget?

O Limiting expenses in all categories, for example, reducing all expenses

O Limiting expenses in most categories, for example, reducing all expenses except rent

O Limiting expenses in some categories, for example, reducing expenses only in clothing and dining

16. What are the reasons for not setting a budget? [Select all that apply]

O I find it difficult to set a budget

O I dislike setting budgets

O I don't think setting a budget helps me

O Because I have enough money, I don't need to set a budget

O Other [please specify]

17. If you were to set some categorical budget, how many category budgets do you think you could manage simultaneously? Categorical budgets refer to spending plans for specific categories, such as food or clothing budgets.

    Please select the number of categorical budgets you could manage.

    0 ... 31 or more

18. If you have set both the total monthly budget and categorical budget, how many categorical budgets do you think you could manage simultaneously? Categorical budgets refer to spending plans for specific categories, such as food or clothing budgets.

    Please select the number of categorical budgets you could manage.

    0 ... 31 or more

19. For you, is it difficult to ensure that expenses do not exceed the following budgets? Please select according to your actual situation.

	Very Difficult	Quite Difficult	Neutral	Quite Easy	Very Easy
I haven't set such budgets					
Total monthly budget, meaning the total spending plan for one month.	◯	◯	◯	◯	◯
ategorical budget, such as food or clothing budget.	◯	◯	◯	◯	◯

20. If your total expenses exceed the total monthly budget for a certain month, what would

you do? Please choose the option that best represents your action.

O Feel discouraged and stop tracking

O Continue tracking, but be more careful when spending money

O Continue tracking, but adjust the corresponding budget amount

O Continue tracking, and do not change any behavior

O Other [please specify]

21. If one of your categorical budgets (e.g., dining budget) exceeds the budgeted amount, but your total expenses are within the total monthly budget, what would you do? Please choose the option that best represents your action.

    O Feel discouraged and stop tracking

    O Continue tracking, but be more careful when spending money

    O Continue tracking, but adjust the corresponding categorical budget amount

    O Continue tracking, and do not change any behavior

    O Other [please specify]

22. Since you started tracking, how often do you think your total expenses exceed the total monthly budget?

    O Never

    O Occasionally

    O Generally

    O Frequently

    O Always

O I don't know

23. Since you started keeping accounts, how often do you think your spending in specific categories exceeds the corresponding categorical budget?

    O Never

    O Occasionally

    O Generally

    O Frequently

    O Always

    O I don't know

24. Based on your accounting behavior, please indicate your level of agreement with the following statements:

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
I keep a careful watch over my spending on a daily basis.	◯	◯	◯	◯	◯
I do not spend money thoughtlessly, I would rather save it for a rainy day.	◯	◯	◯	◯	◯
Putting money into personal savings is a habit for me.	◯	◯	◯	◯	◯

I actively consider the steps I need to take to achieve my personal savings goals.	◯	◯	◯	◯	◯
I like to discuss the topic of saving money with my family and friends.	◯	◯	◯	◯	◯
The goal of saving money is always at the back of my mind.	◯	◯	◯	◯	◯
Saving money is like a lifestyle, you have to keep at it.	◯	◯	◯	◯	◯

25. Based on your actual situation, please indicate your level of agreement with the following statements:

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
My current life is stable.	◯	◯	◯	◯	◯
My financial situation is stable.	◯	◯	◯	◯	◯

26. How much do you worry about your current financial situation?

    O Very

    O Quite

O Moderately

O Not

O Not at all

27. Based on your actual situation, please indicate your level of agreement with the following statements:

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
I often take action without considering all possibilities.	◯	◯	◯	◯	◯
I am good at resisting temptations.	◯	◯	◯	◯	◯
I can work towards long-term goals.	◯	◯	◯	◯	◯

28. Please select your age.

    Under 18 ... Prefer not to disclose

29. What is your level of education?

    O Junior high school or less

    O High school or equivalent

    O Associate degree

    O Bachelor's degree

    O Graduate degree

O Ph.D. or more

O Prefer not to disclose

30. What is your current family situation?

O Unmarried, single

O Unmarried, in a relationship

O Married, no children

O Married, children aged 0-3 (if there are 2 or more children, please choose according to the youngest child's age)

O Married, children aged 3-18 (if there are 2 or more children, please choose according to the youngest child's age)

O Married, children aged 18 or older (if there are 2 or more children, please choose according to the youngest child's age)

O Other [please specify]

O Prefer not to disclose

31. What is your current employment status?

O Full-time

O Part-time

O Self-employed

O Unemployed, currently seeking employment

O Unemployed, preparing for examinations

O Unemployed, currently have no plans

O Retired

O Student

O Other [please specify]

O Prefer not to disclose

32. Which of the following options includes your total monthly income (salary, investment income, pension, etc.)? If you are a student without income, please choose the option that includes your monthly allowance.

O No income

O 1,000 RMB or less

O 1,001 to 3,000 RMB

O 3,001 to 5,000 RMB

O 5,001 to 8,000 RMB

O 8,001 to 10,000 RMB

O 10,001 to 20,000 RMB

O 20,000 RMB or more

O Prefer not to disclose

33. Lastly, please select your province or city.

Beijing ... Overseas

This concludes the survey. Thank you for your participation!

H Chapter 4: Additional Analyses for Study 1

TABLE H36

Estimates of the Change in the Daily Number of Downloads, and Number of Registrations Over Time (Holiday Dummies)

	#Downloads	#Registration
Days since the start of the week (Monday)	-476.03***	-319.94***
	(75.69)	(51.14)
Days since the start of the month	-578.94***	-395.74***
	(34.48)	(23.34)
Months since the start of the year	-632.33*	-436.15*
	(252.02)	(172.59)
First workday after New Year	-11,606.62***	-7,433.34***
	(3,314.33)	(2,241.53)
First workday after Lunar New Year	325.00	145.10
	(2,808.72)	(1,899.17)
First workday after Qingming Festival	1,875.94	1,307.70
	(2,831.72)	(1,914.12)
First workday after Labor Day	-931.76	-602.28
	(2,843.73)	(1,922.05)
First workday after Dragon Boat Festival	535.87	365.40
	(2,931.39)	(1,981.44)
First workday after Mid-autumn Festival	1,670.97	1,145.30
	(2,831.80)	(1,914.17)
First workday after National Day	4,339.83	3,052.18
	(2,827.70)	(1,912.11)
Constant	29808.95***	20123.16***
	(2,862.75)	(1,964.53)
Linear time trend & Control for special periods	Yes	Yes
R-squared	0.43	0.43
DW-statistic(transformed)	1.78	1.78
N	729	729

Note.—Standard errors in parentheses. Downloads refers to the number of downloads of the tracking app per day; Registrations refers to the number of registrations in the tracking app per day. I regressed these dependent variables on temporal landmarks (days since the start of the week, days since the start of the month, months since the start of the year, and the first workday after each holiday in China), a linear time trend, and a set of control variables (dummies indicating each Chinese holiday, whether the date is associated with an online sales event, and whether the data is the first workday following an online sales event) with robust standard errors, respectively. Additionally, I accounted for special periods when downloads and registrations were likely to be affected. There are three special time periods: January 3rd 2018 to January 10th 2018, and January 19th 2018 to July 5th. From January 3rd, 2018, to January 10th, 2018, the app's paid features in the Apple App Store were temporarily free, and thus, there was a spike in the number of downloads and registrations on that day. For some reason, individuals were unable to use "expense tracking" as a keyword to search for this tracking app in the Apple App Store from January 3rd 2018 to January 10th 2018 and January 19th 2018 to July 5th. Each column represents a regression with different dependent variables. Only the key predictor variables and constant terms are presented in this table. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

TABLE H37

Estimates of the Changes in the Daily Downloads, and Registrations Over Time (No Covariates)

	# Downloads	# Registrations
Temporal Landmarks		
Days since the start of the week (Monday)	-492.35***	-330.94***
	(76.34)	(51.52)
Days since the start of the month	-563.42***	-385.78***
	(33.83)	(22.88)
Months since the start of the year	-584.28*	-404.84*
	(251.58)	(172.44)
First workday after a national holiday	1644.57+	1147.78+
	(964.42)	(650.79)
Constant	28700.33***	19705.48***
	(2854.72)	(1974.08)
Linear time trend	Yes	Yes
Control for special periods	Yes	Yes
R-squared	0.4	0.4
DW-statistic(transformed)	1.83	1.82
N	729	729

Note.—Standard errors in parentheses. Downloads refers to the number of downloads of the tracking app per day; Registrations refers to the number of registrations in the tracking app per day. I regressed these dependent variables on temporal landmarks and a linear time trend with robust standard errors, respectively. Additionally, I accounted for special periods when downloads and registrations were likely to be affected. There are three special time periods: January 3rd 2018 to January 10th 2018, and January 19th 2018 to July 5th. From January 3rd, 2018, to January 10th, 2018, the app's paid features in the Apple App Store were temporarily free, and thus, there was a spike in the number of downloads and registrations on that day. For some reason, individuals were unable to use "expense tracking" as a keyword to search for this tracking app in the Apple App Store from January 3rd 2018 to January 10th 2018 and January 19th 2018 to July 5th. Each column represents a regression with different dependent variables. Only the key predictor variables and constant terms are presented in this table. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

TABLE H38

Estimates of the Changes in the Daily Downloads, and Registrations Over Time (Alternative Starting Dates)

	#Downloads	#Registration
Days since the start of the week (Monday)	-485.65***	-325.79***
	(84.11)	(56.43)
Days since the start of the month	-559.24***	-383.59***
	(36.04)	(24.32)
First workday after the national holiday	-1742.38	-1093.74
	(1201.99)	(807.46)
Months since the start of spring (Feburary)	127.23	110.37
	(216.86)	(148.88)
Months since the start of summer (May)	377.11+	260.26+
	(210.21)	(144.43)
Months since the start of autumn (August)	-127.62	-84.47
	(211.79)	(145.52)
Months since the start of winter (November)	369.16+	249.79+
	(209.51)	(143.91)
Constant	24539.95***	16248.27***
	(4634.99)	(3175.56)
R-squared	0.32	0.33
DW-statistic(transformed)	1.94	1.93
N	729	729

Note.—Standard errors in parentheses. Downloads refers to the number of downloads of the tracking app per day; Registrations refers to the number of registrations in the tracking app per day. I regressed these dependent variables on temporal landmarks and a linear time trend with robust standard errors, respectively. Additionally, I accounted for special periods when downloads and registrations were likely to be affected. There are three special time periods: January 3^{rd} 2018 to January 10^{th} 2018, and January 19^{th} 2018 to July 5^{th}. From January 3^{rd}, 2018, to January 10^{th}, 2018, the app's paid features in the Apple App Store were temporarily free, and thus, there was a spike in the number of downloads and registrations on that day. For some reason, individuals were unable to use "expense tracking" as a keyword to search for this tracking app in the Apple App Store from January 3^{rd} 2018 to January 10^{th} 2018 and January 19^{th} 2018 to July 5^{th}. Each column represents a regression with different dependent variables. Only the key predictor variables and constant terms are presented in this table. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

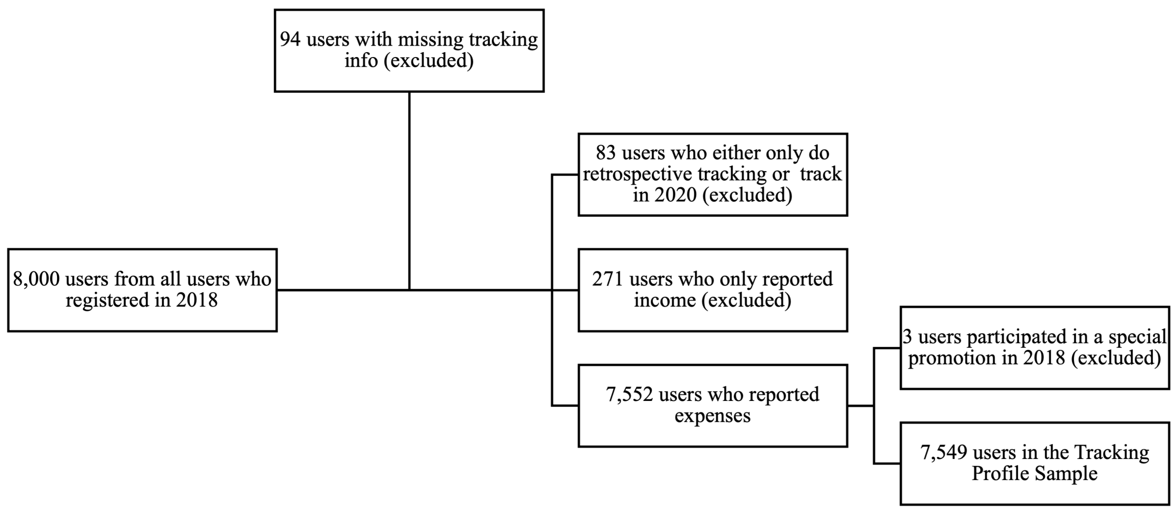
TABLE H39
ESTIMATES OF THE CHANGES IN THE DAILY SEARCH INDICES OVER TIME

	Daily Search Volume for "Expense Tracking"
Temporal Landmarks	
Days since the start of the week (Monday)	-13.99***
	(0.84)
Days since the start of the month	-2.69***
	(0.37)
Months since the start of the year	-8.68***
	(2.43)
First workday after the national holiday	20.08+
	(12.09)
Constant	154.46
	(124.65)
Controls	Yes
Linear time trend	Yes
R-squared	0.37
Durbin–Watson statistic (transformed)	2.29
N	729

NOTE.—Standard errors in parentheses. "Expense tracking" is the daily search index for "expense tracking." I regressed it on temporal landmarks, a linear time trend, and a set of control variables (dummies indicating whether the date is a Chinese holiday, whether the date is associated with an online sales event, and whether the data is the first workday following an online sales event) with robust standard errors, respectively. Each column represents a regression with different dependent variables. Only the key predictor variables and constant terms are presented in this table. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

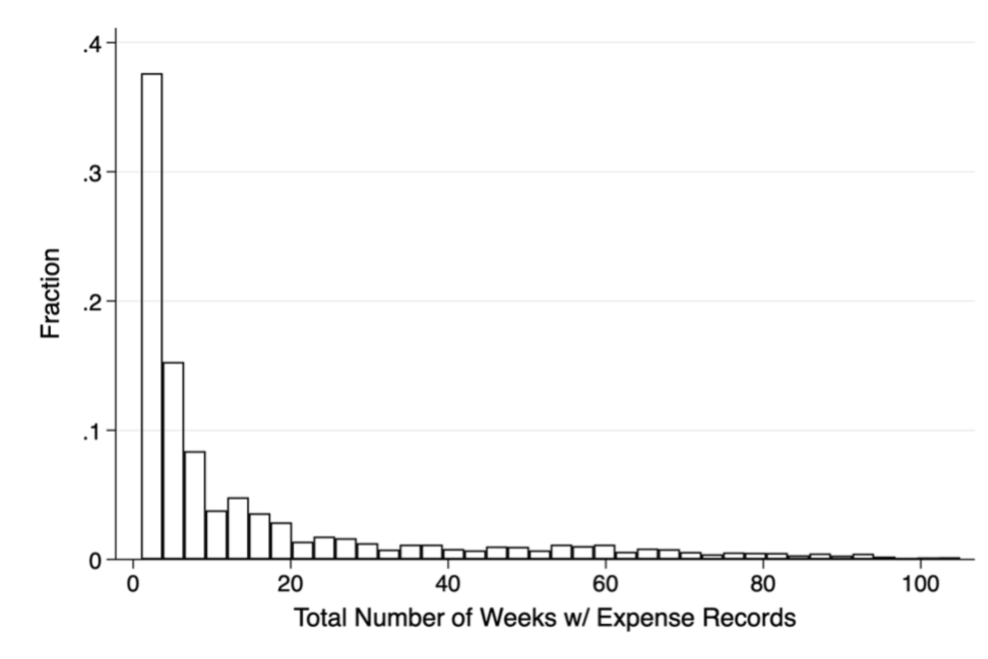
I Chapter 4: Additional Analyses for Study 2

Fig. I40.—Sample Cleaning Process



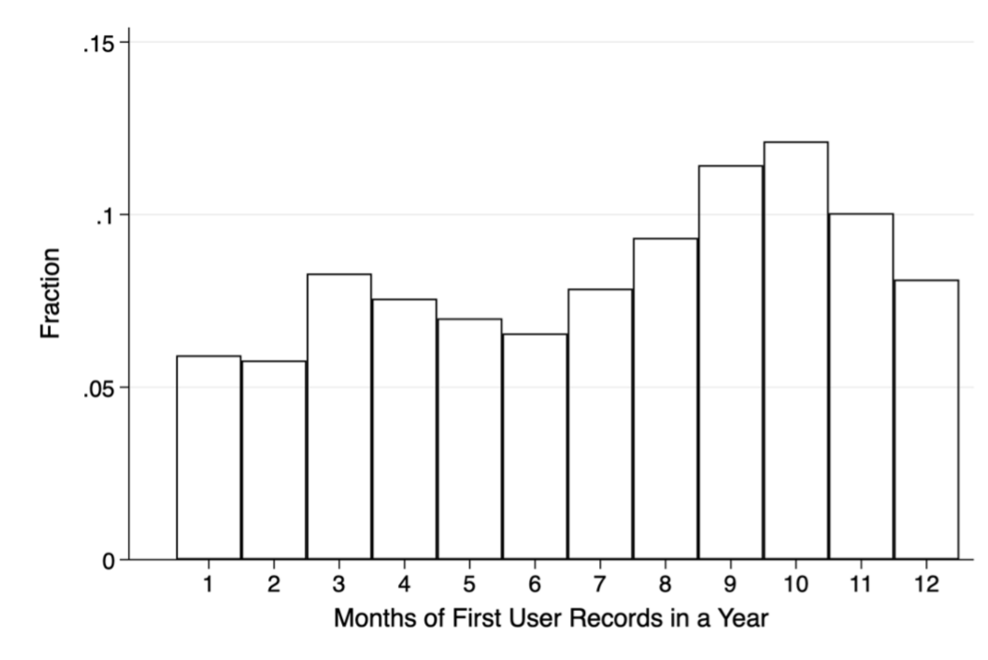
This figure illustrates the process of cleaning the randomly selected sample from all users registered in 2018.

Fig. I41.—Distribution of the Total Number of Weeks with Expense Records in the Tracking Profile Sample



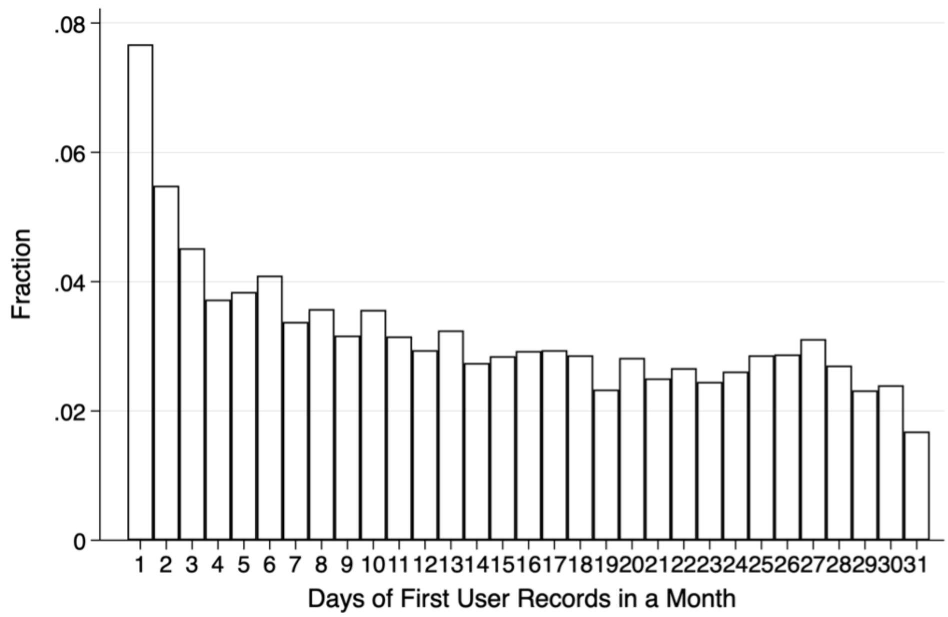
This histogram illustrates the distribution of the total number of weeks with expense records for users in the Tracking Profile Sample since their first record to December 31^{st} 2019. The x-label represents each number of the week. The height of the bar indicates the fraction of users with each number of weeks.

Fig. I42.—The Distribution of Months of First User Records in a Year in the Tracking Profile Sample



This histogram illustrates the distribution of users' first record months in the Tracking Profile Sample. The x-label represents each month of the year. The height of the bar and value above each bar indicate the percentage of users registered in the corresponding month.

Fig. I43.—The Distribution of Days of First User Records in a Month in the Tracking Profile Sample



This histogram illustrates the distribution of the users' first record days of the month in the Tracking Profile Sample. The x-label represents each day of the month. The height of the bar and the value above each bar indicate the percentage of users who registered on the corresponding day.

TABLE I44

Estimates of the Impact of Fresh Start Effect on Goal Persistence with Holiday Dummies

	Number of Weeks with Expense Records
Temporal Landmarks	
Days since the start of the week (Monday)	0.22+
	(0.12)
Days since the start of the month	-0.08**
	(0.03)
Months since the start of the year	-0.45***
	(0.08)
First Workday After New Year	16.15*
	(7.36)
First Workday After Lunar New Year	-0.14
	(4.65)
First Workday After Qingming Festival	-4.38
	(3.84)
First Workday After Labor Day	0.99
	(4.62)
First Workday After Dragon Boat Festival	3.18
	(6.10)
First Workday After Mid-Autumn Festival	-3.88
	(4.10)
First Workday After National Day	-1.72
	(1.76)
Constant	20.52***
	(1.12)
Controls	Yes
R-squared	0.14
N	7,549

Note.—Standard errors in parentheses. "Number of Weeks with Expense Records" captures the duration of expense tracking. I regressed it on temporal landmarks in China based on when the user made the first record (days since the start of the week, days since the start of the month, months since the start of the year, and the first workday after each holiday) and a set of control variables with robust standard errors. These controls include dummy variables indicating whether the user only records expenses, has a paid subscription, uses an iPhone, switched phone types during the data collection period, identifies as female, sets any monthly spending limits, and each holiday dummy. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

TABLE I45
ESTIMATES OF THE IMPACT OF FRESH START EFFECT ON GOAL PERSISTENCE WITH ALTERNATIVE STARTING DATES

	Number of Weeks with Expense Records	
Days since the start of the week (Monday)	0.08	0.16
	(0.13)	(0.12)
Days since the start of the month	-0.09**	-0.08**
	(0.03)	(0.03)
First workday after the national holiday	1.48	1.32
	(1.81)	(1.69)
Months since the start of spring (Feburary)	-0.13	-0.12
	(0.12)	(0.11)
Months since the start of summer (May)	0.29**	0.21*
	(0.11)	(0.10)
Months since the start of autumn (August)	0.22*	0.11
	(0.10)	(0.09)
Months since the start of winter (November)	-0.01	-0.08
	(0.09)	(0.08)
Constant	14.73***	16.62***
	(2.25)	(2.23)
Controls	No	Yes
R-squared	0.01	0.13
N	7549	7549

NOTE.—Standard errors in parentheses. "Number of Weeks with Expense Records" captures the duration of expense tracking. I regressed it on temporal landmarks in China based on when the user made the first record (days since the start of the week, days since the start of the month, the first workday after each holiday, and the number of months since the start of spring, summer, autumn, and winter) with or without a set of control variables with robust standard errors. These controls include dummy variables indicating whether the user only records expenses, has a paid subscription, uses an iPhone, switched phone types during the data collection period, identifies as female, sets any monthly spending limits, and each holiday dummy. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

TABLE I46
Estimates of the Impact of Fresh Start Effect on Persistent Expense Tracking Behavior

	Number of Days with Expenses Records
Temporal Landmarks	
Days since the start of the week (Monday)	1.1
	(1.90)
Days since the start of the month	-1.64***
	(0.42)
Months since the start of the year	-2.90*
	(1.18)
First workday after the national holiday	32.03
	(30.14)
Control Variables	
National holidays in China	19.75
	(14.60)
Online sales day	-29.01
	(33.98)
First workday after an online sales day	25.39
	(42.36)
Record expenses only	-129.72***
	(6.90)
With paid subscription	23.95
	(18.88)
Female	17.87*
	(7.92)
With spending limits	273.03***
	(24.37)
iPhone users	-24.33**
	(8.52)
Switch phone types	197.29***
	(27.81)
Constant	248.27***
	(17.07)
R-squared	0.11
N	7549

Note.—Standard errors in parentheses. "Number of Days with Expense Records" captures the duration of expense tracking. I regressed it on temporal landmarks in China based on when the user made the first record (days since the start of the week, days since the start of the month, months since the start of the year, and the first workday after each holiday) and a set of control variables with robust standard errors. These controls include dummy variables indicating whether the user only records expenses, has a paid subscription, uses an iPhone, switched phone types during the data collection period, identifies as female, sets any monthly spending limits, and each holiday dummy. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

TABLE I47
Estimates of the Impact of Fresh Start Effect on Persistent Expense Tracking Behavior (Refined Sample)

	Number of Weeks with Expense Records
Temporal Landmarks	
Days since the start of the week (Monday)	0.22
	(0.14)
Days since the start of the month	-0.11**
	(0.03)
Months since the start of the year	-0.39***
	(0.09)
First workday after the national holiday	0.77
	(2.01)
Control Variables	
National holidays in China	1.46
	(1.14)
Online sales day	0.37
	(2.67)
First workday after an online sales day	7.83+
	(4.18)
Record expenses only	-8.74***
	(0.54)
With paid subscription	-0.09
	(1.28)
Female	2.37***
	(0.58)
With spending limits	16.30***
	(1.51)
iPhone users	-2.32***
	(0.66)
Switch phone types	16.20***
	(2.06)
Constant	19.92***
	(1.34)
R-squared	0.13
N	5,297

Note.—Standard errors in parentheses. “Number of Weeks with Expense Records” captures the duration of expense tracking. I regressed it on temporal landmarks based on the user’s first record and a set of control variables with robust standard errors using the refined sample. These controls include dummy variables indicating whether the user only records expenses, has a paid subscription, uses an iPhone, switched phone types during the data collection period, is identified as female, and sets any monthly spending limits. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

TABLE I48
Estimates of the Impact of Fresh Start Effect on Persistent Expense Tracking Behavior

	Number of Weeks with Expense
Temporal Landmarks	
Days since the start of the week (Monday)	0.12
	(0.13)
Days since the start of the month	-0.09**
	(0.03)
Months since the start of the year	-0.59***
	(0.08)
First workday after a national holiday	1.11
	(1.77)
Control Variables	
National holidays in China	2.01*
	(1.02)
Online sales event	-0.91
	(2.34)
First workday after an online sales event	2.23
	(3.07)
Constant	20.70***
	(0.97)
R-squared	0.01
N	7,643

Note.—Standard errors in parentheses. "Number of Weeks with Expense Records" captures the duration of expense tracking. I regressed it on temporal landmarks based on the user's first record with robust standard errors. This analysis included 94 users who lacked initial tracking information; for these users, the tracking duration was treated as zero, with their registration date serving as the start of expense tracking. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

TABLE I49

Estimates of the Impact of Fresh Start Effect on Persistent Expense Tracking Behavior (Time-to-Event Analysis)

	Stop Expense Tracking
Temporal Landmarks	
Days since the start of the week (Monday)	-0.008
	(0.01)
Days since the start of the month	0.006***
	(0.00)
Months since the start of the year	0.021***
	(0.00)
First workday after the national holiday	-0.061
	(0.07)
Control Variables	
National holidays in China	-0.085+
	(0.05)
Online sales day	0.113
	(0.13)
First workday after an online sales day	-0.224
	(0.15)
Record expenses only	0.650***
	(0.03)
With paid subscription	-0.078
	(0.05)
Female	-0.112***
	(0.03)
With spending limits	-0.594***
	(0.05)
iPhone users	0.036
	(0.03)
Switch phone types	-0.570***
	(0.06)
N	7549

Note.—Standard errors in parentheses. "Stop expense tracking" captures the event of stopping expense tracking. I regressed it on temporal landmarks based on the user's first record and a set of control variables using time-to-event analysis. These controls include dummy variables indicating whether the user only records expenses, has a paid subscription, uses an iPhone, switched phone types during the data collection period, is identified as female, and sets any monthly spending limits. Individuals with records in 2020 were right-censored because they did not stop expense tracking by the end of the sample period (December 2019). Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

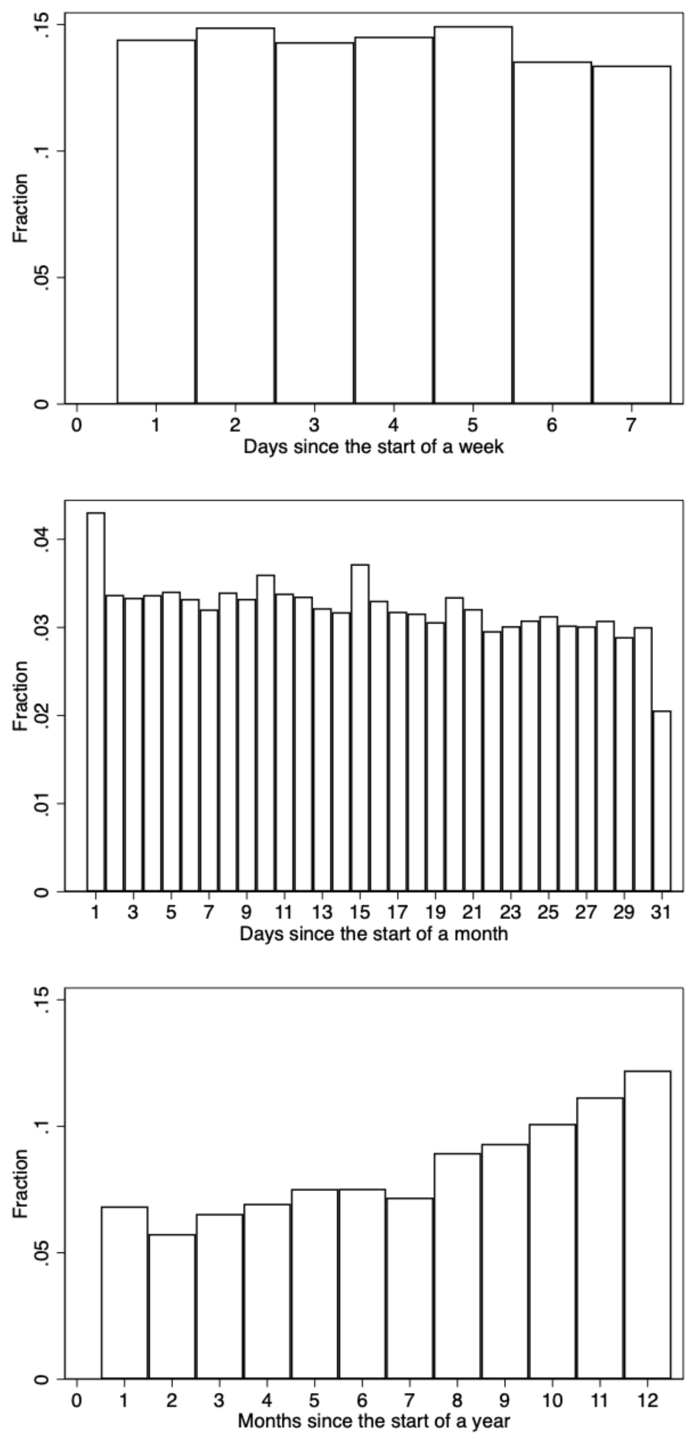
TABLE I50

Estimates of the Impact of Fresh Start Effect on Persistent Expense Tracking Behavior (One-year Observation Window)

	Number of Weeks with Expense
Temporal Landmarks	
Days since the start of the week (Monday)	0.16
	(0.09)
Days since the start of the month	-0.06**
	(0.02)
Months since the start of the year	-0.14*
	(0.06)
First workday after the national holiday	-0.1
	(1.12)
Constant	16.28***
	(0.82)
Control Variables	Yes
R-squared	0.15
N	7549

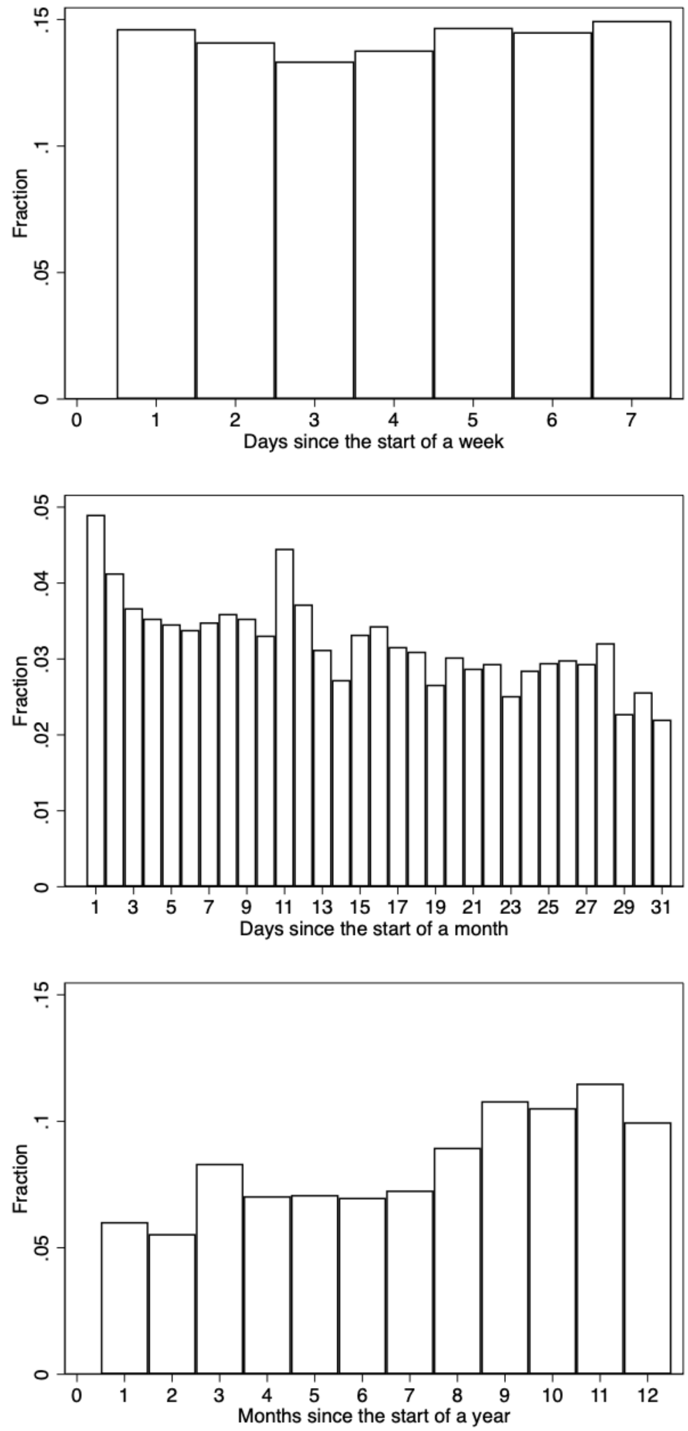
Note.—Standard errors in parentheses. "Number of Weeks with Expense Records" captures the duration of expense tracking. I regressed it on temporal landmarks based on the user's first record and a set of control variables, focusing solely on individuals within a one-year window from the onset of tracking. These controls include dummy variables indicating whether the user only records expenses, has a paid subscription, uses an iPhone, switched phone types during the data collection period, is identified as female, and sets any monthly spending limits. Individuals with records in 2020 were right-censored because they did not stop expense tracking by the end of the sample period (December 2019). Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

Fig. I51.—Income Occurrence Distribution Among Users Who Reported Income



This figure displays the distribution of income occurrences among users who reported income in the Tracking Profile Sample. The first histogram shows the frequency of income occurrences by day of the week, the second histogram shows the distribution by day of the month, and the third histogram shows the distribution by month of the year.

FIG. I52.—Expenses Occurrence Distribution Among Users Who Reported Income



This figure displays the distribution of the largest expense recorded among by each user in the Tracking Profile Sample. The first histogram shows the frequency of expense occurrence by day of the week, the second histogram shows the distribution by day of the month, and the third histogram displays the distribution by month of the year.

TABLE I53

ESTIMATES OF THE IMPACT OF FRESH START EFFECT ON THE NATURE OF THE EXPENSES

	# Total Expense Categories	# Customized Categories	# Preset Categories
Days since the start of the week (Monday)	-0.02	0	-0.02
	(0.05)	(0.02)	(0.04)
Days since the start of the month	-0.05***	0	-0.05***
	(0.01)	0.00	(0.01)
Months since the start of the year	-0.11***	-0.04**	-0.06**
	(0.03)	(0.01)	(0.02)
First workday after the national holiday	0.67	0.03	0.64
	(0.58)	(0.19)	(0.49)
Constant	13.14***	2.03***	11.12***
	(0.42)	(0.20)	(0.34)
Control Variables	Yes	Yes	Yes
R2	0.17	0.04	0.15
N	7549	7549	7549

NOTE.—Standard errors in parentheses. "# Total Expense Categories" captures the total number of expense categories used by each user; "# Customized Categories" captures the total number of user-generated expense categories used by each user; "# Preset Categories" captures the total number of preset expense categories used by each user. I regressed them on temporal landmarks based on the user's first record and a set of control variables using OLS regression, respectively. These controls include dummy variables indicating whether the user only records expenses, has a paid subscription, uses an iPhone, switched phone types during the data collection period, is identified as female, and sets any monthly spending limits. Significance levels $+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$

Bibliography

Ansolabehere, S., & Hersh, E. (2012). Validation: What big data reveal about survey misreporting and the real electorate. *Political Analysis*, *20*(4), 437–459.

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational behavior and human decision processes*, *50*(2), 248–287.

Bandura, A., & Cervone, D. (1983). Self-evaluative and self-efficacy mechanisms governing the motivational effects of goal systems. *Journal of personality and social psychology*, *45*(5), 1017.

Bandura, A., & Simon, K. M. (1977). The role of proximal intentions in self-regulation of refractory behavior. *Cognitive therapy and research*, *1*(3), 177–193.

Barsalou, L. W. (1991). Deriving categories to achieve goals. In *Psychology of learning and motivation* (pp. 1–64, Vol. 27). Elsevier.

Baumeister, R. F., Schmeichel, B. J., & Vohs, K. D. (2007). Self-regulation and the executive function: The self as controlling agent. *Social psychology: Handbook of basic principles*, *2*, 516–539.

Bearden, W. O., & Haws, K. L. (2012). How low spending control harms consumers. *Journal of the Academy of Marketing Science*, *40*, 181–193.

Beshears, J., Dai, H., Milkman, K. L., & Benartzi, S. (2021). Using fresh starts to nudge increased retirement savings. *Organizational Behavior and Human Decision Processes*, *167*, 72–87.

Bondy, H. (2019, September). Women are more financially stressed than men — Here's how to overcome it. Retrieved January 28, 2021, from https://www.nbcnews.com/know-your-value/feature/women-are-more-financially-stressed-men-here-s-how-overcome-ncna1055901

Brandstätter, V., & Bernecker, K. (2022). Persistence and disengagement in personal goal pursuit. *Annual Review of Psychology*, *73*, 271–299.

Brindley, E. F. (2010). *Individualism in early china: Human agency and the self in thought and politics*. University of Hawaii Press.

Burke, L. E., Wang, J., & Sevick, M. A. (2011). Self-monitoring in weight loss: A systematic review of the literature. *Journal of the American Dietetic Association*, *111*(1), 92–102.

Carver, C. S., & Scheier, M. F. (2001). *On the self-regulation of behavior*. cambridge university press.

Cheng, D. (2022, June). China's food delivery market is a game for two. Retrieved May 3, 2023, from https://daxueconsulting.com/o2o-food-delivery-market-in-china/

Choe, Y., & Kan, C. (2021). Budget depreciation: When budgeting early increases spending. *Journal of Consumer Research*, *47*(6), 937–958.

Cochran, W., & Tesser, A. (2014). The" what the hell" effect: Some effects of goal proximity and goal framing on performance. In *Striving and feeling* (pp. 99–120). Psychology Press.

Dai, H. (2018). A double-edged sword: How and why resetting performance metrics affects motivation and performance. *Organizational Behavior and Human Decision Processes*, *148*, 12–29.

Dai, H., Mao, D., Riis, J., Volpp, K. G., Relish, M. J., Lawnicki, V. F., & Milkman, K. L. (2017). Effectiveness of medication adherence reminders tied to "fresh start" dates: A randomized clinical trial. *Jama Cardiology*, *2*(4), 453–455.

Dai, H., Milkman, K. L., & Riis, J. (2014). The fresh start effect: Temporal landmarks motivate aspirational behavior. *Management Science*, *60*(10), 2563–2582.

Dai, H., Milkman, K. L., & Riis, J. (2015). Put your imperfections behind you: Temporal landmarks spur goal initiation when they signal new beginnings. *Psychological science*, *26*(12), 1927–1936.

Daniel Dorfman, Laura Erhard, Graham Jones, Brandon Kopp, Parvati, Parvati Krishnamurty, & Brett McBride. (2021, April). *Large Scale Feasibility Test Preliminary Report* (tech. rep.). U.S. Bureau of Labor Statistics. Retrieved August 20, 2023, from https://www.bls.gov/cex/research_papers/pdf/dorfman-et-al-large-scale-feasibility-test-preliminary-report.pdf

Davydenko, M., & Peetz, J. (2019). Does it matter if a week starts on monday or sunday? how calendar format can boost goal motivation. *Journal of Experimental Social Psychology*, *82*, 231–237.

Duckworth, A. L., Taxer, J. L., Eskreis-Winkler, L., Galla, B. M., & Gross, J. J. (2019). Self-control and academic achievement. *Annual review of psychology*, *70*, 373–399.

Duckworth, A. L., White, R. E., Matteucci, A. J., Shearer, A., & Gross, J. J. (2016). A stitch in time: Strategic self-control in high school and college students. *Journal of educational psychology*, *108*(3), 329.

Fishbach, A., & Hofmann, W. (2015). Nudging self-control: A smartphone intervention of temptation anticipation and goal resolution improves everyday goal progress. *Motivation Science*, *1*(3), 137.

Furrebøe, E. F., Nyhus, E. K., & Musau, A. (2023). Gender differences in recollections of economic socialization, financial self-efficacy, and financial literacy. *Journal of Consumer Affairs*, *57*(1), 69–91.

Gardner, B., & Lally, P. (2018). Modelling habit formation and its determinants. *The psychology of habit: Theory, mechanisms, change, and contexts*, 207–229.

Gourville, J. T. (1998). Pennies-a-day: The effect of temporal reframing on transaction evaluation. *Journal of Consumer Research*, *24*(4), 395–408.

Gutter, M., & Copur, Z. (2011). Financial behaviors and financial well-being of college students: Evidence from a national survey. *Journal of family and economic Issues*, *32*, 699–714.

Heath, C., & Soll, J. B. (1996). Mental budgeting and consumer decisions. *Journal of consumer research*, *23*(1), 40–52.

Heckhausen, J., & Heckhausen, H. (2018). Motivation and action: Introduction and overview. *Motivation and action*, 1–14.

Hennecke, M., & Converse, B. A. (2017). Next week, next month, next year: How perceived temporal boundaries affect initiation expectations. *Social Psychological and Personality Science*, *8*(8), 918–926.

Hernandez, L., Jonker, N., & Kosse, A. (2017). Cash versus debit card: The role of budget control. *Journal of Consumer Affairs*, *51*(1), 91–112.

Heyen, N. B. (2020). From self-tracking to self-expertise: The production of self-related knowledge by doing personal science. *Public Understanding of Science*, *29*(2), 124–138.

Howlett, E., Kees, J., & Kemp, E. (2008). The role of self-regulation, future orientation, and financial knowledge in long-term financial decisions. *Journal of Consumer Affairs*, *42*(2), 223–242.

Inzlicht, M., Werner, K. M., Briskin, J. L., & Roberts, B. W. (2021). Integrating models of self-regulation. *Annual review of psychology*, *72*, 319–345.

Ivanhoe, P. J. (2000). *Confucian moral self cultivation*. Hackett Publishing.

Kan, C., M. Fernbach, P., & Lynch, J. (2018). Personal budgeting: Does it work? *ACR North American Advances*.

Karlsson, N., Loewenstein, G., & Seppi, D. (2009). The ostrich effect: Selective attention to information. *Journal of Risk and uncertainty*, *38*, 95–115.

Karoly, P. (1993). Mechanisms of self-regulation: A systems view. *Annual review of psychology*, *44*(1), 23–52.

Lally, P., Van Jaarsveld, C. H., Potts, H. W., & Wardle, J. (2010). How are habits formed: Modelling habit formation in the real world. *European journal of social psychology*, *40*(6), 998–1009.

Laran, J., & Janiszewski, C. (2009). Behavioral consistency and inconsistency in the resolution of goal conflict. *Journal of consumer research*, *35*(6), 967–984.

Liu, H.-H., & Chou, H.-Y. (2016). Do longer or shorter budget temporal frames matter? numerosity effects, mental budgets, and purchase intentions. *Journal of Marketing Theory and Practice*, *24*(4), 422–441.

Lupton, D. (2014). Self-tracking cultures: Towards a sociology of personal informatics. *Proceedings of the 26th Australian computer-human interaction conference on designing futures: The future of design*, 77–86.

Mairs, L., & Mullan, B. (2015). Self-monitoring vs. implementation intentions: A comparison of behaviour change techniques to improve sleep hygiene and sleep outcomes in students. *International journal of behavioral medicine*, *22*, 635–644.

Marlatt, G. A., & Kaplan, B. E. (1972). Self-initiated attempts to change behavior: A study of new year's resolutions. *Psychological Reports*, *30*(1), 123–131.

Meyer, B. D., Mok, W. K., & Sullivan, J. X. (2015). Household surveys in crisis. *Journal of Economic Perspectives*, *29*(4), 199–226.

Min, B., & Ulkumen, G. (2014). The effect of default time units on budget estimation. *ACR North American Advances*.

Munro, D. J. (1985). Individualism and holism: Studies in confucian and taoist values.

Norcross, J. C., Mrykalo, M. S., & Blagys, M. D. (2002). Auld lang syne: Success predictors, change processes, and self-reported outcomes of new year's resolvers and nonresolvers. *Journal of clinical psychology*, *58*(4), 397–405.

O'Curry, S. (2002). Budgeting and mental accounting. In *The Elgar companion to consumer research and economic psychology* (pp. 63–67). Edward Elgar Publishing Limited.

Olafsson, A., & Pagel, M. (2017). *The ostrich in us: Selective attention to financial accounts, income, spending, and liquidity* (tech. rep.). National Bureau of Economic Research.

O'Neill, B., Sorhaindo, B., Xiao, J. J., & Garman, E. T. (2005). Financially distressed consumers: Their financial practices, financial well-being, and health. *Journal of Financial Counseling and Planning*, *16*(1).

Palmer, L., Richardson, E. W., Goetz, J., Futris, T. G., Gale, J., & DeMeester, K. (2021). Financial self-efficacy: Mediating the association between self-regulation and financial management behaviors. *Journal of Financial Counseling and Planning*, *32*(3), 535–549.

Peetz, J., & Davydenko, M. (2022). Financial self-regulation. *Social and Personality Psychology Compass*, *16*(5), e12663.

Price, L. L., Coulter, R. A., Strizhakova, Y., & Schultz, A. E. (2018). The fresh start mindset: Transforming consumers' lives. *Journal of Consumer Research*, *45*(1), 21–48.

Reinfelder, L., Benenson, Z., & Gassmann, F. (2014). Differences between android and iphone users in their security and privacy awareness. *Trust, Privacy, and Security in Digital Business: 11th International Conference, TrustBus 2014, Munich, Germany, September 2-3, 2014. Proceedings 11*, 156–167.

Robson, J., & Peetz, J. (2020). Gender differences in financial knowledge, attitudes, and behaviors: Accounting for socioeconomic disparities and psychological traits. *Journal of Consumer Affairs*, *54*(3), 813–835.

Schmall, T. (2018). Iphone and android users are completely different people. Retrieved October 25, 2018, from https://nypost.com/2018/10/25/iphone-and-android-users-are-completely-different-people/

Sinnewe, E., & Nicholson, G. (2023). Healthy financial habits in young adults: An exploratory study of the relationship between subjective financial literacy, engagement with finances, and financial decision-making. *Journal of Consumer Affairs*, *57*(1), 564–592.

Soster, R. L., Monga, A., & Bearden, W. O. (2010). Tracking costs of time and money: How accounting periods affect mental accounting. *Journal of Consumer Research*, *37*(4), 712–721.

Strack, F., & Deutsch, R. (2004). Reflection and impulse as determinants of conscious and unconscious motivation. *Social motivation: Conscious and unconscious processes*, 91–112.

Strizhakova, Y., Coulter, R. A., & Price, L. L. (2021). The fresh start mindset: A cross-national investigation and implications for environmentally friendly global brands. *Journal of International Marketing*, *29*(4), 45–61.

Su, L., Monga, A. (B., & Jiang, Y. (2021). How life-role transitions shape consumer responses to brand extensions. *Journal of Marketing Research*, *58*(3), 579–594.

Sussman, A. B., & Alter, A. L. (2012). The exception is the rule: Underestimating and overspending on exceptional expenses. *Journal of Consumer Research*, *39*(4), 800–814.

Sussman, A. B., Sharma, E., & Alter, A. L. (2015). Framing charitable donations as exceptional expenses increases giving. *Journal of Experimental Psychology: Applied*, *21*(2), 130.

Thaler, R. (1985). Mental accounting and consumer choice. *Marketing science*, *4*(3), 199–214.

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral decision making*, *12*(3), 183–206.

Thompson-Felty, C., & Johnston, C. S. (2017). Adherence to diet applications using a smartphone was associated with weight loss in healthy overweight adults irrespective of the application. *Journal of diabetes science and technology*, *11*(1), 184–185.

Todd, J., & Mullan, B. (2014). The role of self-monitoring and response inhibition in improving sleep behaviours. *International journal of behavioral medicine*, *21*, 470–477.

Verplanken, B., & Orbell, S. (2003). Reflections on past behavior: A self-report index of habit strength. *Journal of applied social psychology*, *33*(6), 1313–1330.

Webb, E., & Spiller, S. (2014). As good as spent: Earmarking money leads to a sense of spending. *Proceedings of Society of Consumer Psychology*, 316–318.

Williamson, L. Z., & Wilkowski, B. M. (2020). Nipping temptation in the bud: Examining strategic self-control in daily life. *Personality and social psychology bulletin*, *46*(6), 961–975.

Xiao, J. J., Sorhaindo, B., & Garman, E. T. (2006). Financial behaviours of consumers in credit counselling. *International Journal of Consumer Studies*, *30*(2), 108–121.

Zhang, C. Y., & Sussman, A. B. (2018). Perspectives on mental accounting: An exploration of budgeting and investing. *Financial Planning Review*, *1*(1-2), e1011.

Zhang, C. Y., Sussman, A. B., Wang-Ly, N., & Lyu, J. K. (2022). How consumers budget. *Journal of Economic Behavior & Organization*, *204*, 69–88.

Zhang, M. L., Brooks, M. R., Ding, D., Ding, H., He, H., Lu, J., & Mano, R. (2018). *China's high savings: Drivers, prospects, and policies*. International Monetary Fund.