ARTICLE IN PRESS

International Journal of Research in Marketing xxx (xxxx) xxx

Contents lists available at ScienceDirect

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Consumer sentiment, monetary expenditure, and time use: perspectives from a panel study[1]

Botao Yang [a], Lan Luo [b,*], Brian T. Ratchford [c]

[a] College of Business, California State University, Long Beach, CA 90840, United States
[b] Marshall School of Business, University of Southern California, Los Angeles, CA 90089, United States
[c] Naveen Jindal School of Management, University of Texas at Dallas, Richardson, TX 75080, United States

ARTICLE INFO

Area editor: Pradeep Chintagunta
Accepting editor: Koen Pauwels
Managing editor: Cecilia Nalagon

Keywords:
Consumer sentiment
Monetary expenditure
Time use
Panel data model
Longitudinal study

ABSTRACT

In today's volatile market, it is crucial for firms to understand how consumer sentiment (one's belief about personal finances or regional/national economic conditions) relates to their consumption decisions. We propose a conceptual framework and utilize unique panel data to explore the relationship between individual-level consumer sentiment and consumption of different activities. We collected consumer sentiment from 300 U.S. consumers monthly from January 2014 to February 2016. We also tracked their monthly monetary expenditure and time use across five major activity types during the same time period. In March–June 2022, we recontacted the same panelists and collected similar data from about 25% of the original sample. This study is among the first to use individual-level panel data to examine whether consumer sentiment may explain money and time spent on various activities. We find that individual-level sentiment carries significantly more explanatory power of consumption than aggregate-level sentiment measures such as University of Michigan's Index of Consumer Sentiment. We learn that discretionary activities (e.g., leisure travel, social/recreational events) are more sensitive to sentiment than maintenance activities (e.g., personal care). When the activity is discretionary, current sentiment outperforms past behavior in explaining future consumption. Among all sentiment measures, status of personal finance best explains monetary spending and time use, outweighing perceptions of the regional or national economy. In 2022, panelists spent about the same (after adjusting for inflation) on activities studied. Interestingly, these consumers devoted more time to in-home relaxation and less to social or recreational outings. Overall our research demonstrates that tracking individual-level consumer sentiment—rather than relying on aggregate measures—enables firms, researchers, and policymakers to more accurately gauge demand and make more nuanced economic and strategic decisions.

1. Introduction

In today's volatile market environment, consumers' sentiment regarding their personal financial situations as well as regional and national economic conditions can fluctuate substantially over time. For example, a report by McKinsey & Company shows that,

* Corresponding author.
E-mail addresses: botao.yang@csulb.edu (B. Yang), lluo@marshall.usc.edu (L. Luo), btr051000@utdallas.edu (B.T. Ratchford).

[1] The authors thank seminar participants at Carnegie Mellon University, INFORMS Marketing Science Conference, McGill University, and Washington University for their helpful comments.

https://doi.org/10.1016/j.ijresmar.2026.06.001
Received 13 November 2021;
Available online 9 June 2026

following the outbreak of COVID-19, U.S. consumers became significantly less optimistic about their current and expected household income.[2] The same report also documents noticeable shifts in consumers' spending patterns and consumption habits. These changes highlight the importance for firms to develop a deeper understanding of whether, and how, the sentiment of their focal consumers can help explain subsequent consumption of their products and services.

In this research, we examine the extent to which an individual's sentiment—defined as beliefs about personal financial conditions as well as regional and national economic conditions—relates to consumption decisions, including both monetary expenditure and time allocation.[3] The study of consumer sentiment (often referred to as consumer confidence) has a long history, dating back to the introduction of the University of Michigan Index of Consumer Sentiment in 1946. However, these sentiment indices are constructed using repeated cross-sectional surveys in which different individuals answer the same set of questions at different points in time. While such data allows researchers to track changes in aggregate sentiment over time, the scarcity of longitudinal data at the individual level has limited our ability to examine whether and how a consumer's sentiment relates to his/her subsequent consumption decisions.

Moreover, consumption activities span a continuum from maintenance-oriented activities (e.g., personal care) to highly discretionary ones (e.g., leisure travel), with others falling somewhere in between (e.g., active sports or exercise). It is therefore plausible that the role of consumer sentiment varies across different types of activities. Yet the absence of longitudinal studies that track both sentiment and consumption across a range of activities for the same individual over time has constrained our understanding of this relationship. For example, if Sam is an avid sports fan, without knowing (and controlling for) how much time and money he has historically spent on attending sport games would make it difficult to determine whether his sentiment about personal finances can explain his subsequent decisions on attending games. As a result, it remains unclear whether a relationship exists between consumer sentiment and consumption at the individual level, let alone whether such a relationship varies depending on whether an activity is maintenance or discretionary.

In this paper, we address the above gaps by collecting monthly measures of consumer sentiment from 300 U.S. consumers between January 2014 and February 2016. We also tracked each panelist's monthly monetary expenditure and time allocation across five major activity categories. In March–June 2022, we recontacted the original panelists and collected comparable data from approximately 25% of the initial sample. To our knowledge, this study is among the first to use individual-level panel data to examine how consumer sentiment relates to both time use and monetary spending across a range of consumption activities. This unique longitudinal dataset allows us to investigate the following research questions:

First, does individual-level consumer sentiment provide greater explanatory power for subsequent monetary expenditures and time allocation decisions than aggregate-level sentiment measures? *Second*, does the relationship between consumer sentiment and consumption vary depending on whether an activity is maintenance-oriented or discretionary? *Third*, how do consumer sentiment and past consumption compare in their ability to explain subsequent consumption behavior? *Finally*, which dimension of consumer sentiment—personal financial outlook versus perceptions of regional or national economic conditions—best explains subsequent consumption behavior?

Our research reveals the following key insights:

- Individual-level sentiment carries significantly more explanatory power of consumption than aggregate-level sentiment measures.
- Consumption of maintenance activities (such as personal care) is much less elastic to consumer sentiment compared to discretionary activities (such as leisure-related travel and social/recreational events).
- Consumer sentiment, rather than past consumption, better explains subsequent consumption, particularly when the focal activity is more towards the discretionary spectrum.
- Among all activities studied, sentiment about personal finance (as compared to sentiment about regional and national economy) by far carries the most explanatory power of subsequent monetary expenditure and time use.

Overall, our findings highlight the importance of linking sentiment and consumption of the same individual over time. Without such individual-level data, we would not be able to accurately measure the explanatory power of consumer sentiment above and beyond past consumption. Later in the paper, we also show empirically that, if we track longitudinal sentiment for the same group of individuals over time but use aggregate- rather than individual-level sentiment measures, we lose considerable explanatory power on consumption. The two waves of data collection also allow us to assess the stability of consumption patterns over a period of six to eight years. We find that, in 2022, panelists spent roughly the same amount on the activities studied after adjusting for inflation. However, they allocated more time to in-home relaxation and less to social or recreational outings. These shifts may reflect changes associated

[2] https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/survey-us-consumer-sentiment-during-the-coronavirus-crisis#

[3] Our definition follows the traditional conceptualization of consumer sentiment in economics literature. This notion differs from attitudes or beliefs expressed online that are also commonly referred to as sentiment, such as brand sentiment derived from social media (e.g., Schweidel & Moe, 2014). Whereas social-media sentiment is typically brand-specific, the sentiment measure in our context is individual-specific and independent of any particular brand or consumption activity.

with aging and lifecycle stages, and/or broader lifestyle adjustments following the COVID-19 pandemic.

Our research offers valuable insights for firms, researchers, and policy makers. From firms' perspective, if consumers perceive their offerings as discretionary, firms should leverage their marketing research tools to closely monitor sentiment trajectories of their focal customers.[4] Firms can then leverage these individual-level sentiment measures to make more informed decisions about how demand for their various product offerings may fluctuate across different types of consumer segments. For example, Apple offers products that appeal to different consumer segments—for instance, one iPhone model may primarily target millennials while another appeals more to baby boomers; similarly, the primary customers of one MacBook model may be higher-income consumers, whereas another model may attract lower-income buyers. By collecting individual-level sentiment data, Apple can flexibly segment its customers' sentiment in multiple ways - for example, by age group (millennials vs. baby boomers), income level (high vs. low earners), or technological orientation (tech-savvy vs. non-tech customers) - depending on the target market of the specific product. If Apple detects strong or weak sentiment about personal finances among a product's target customers, it can adjust supply-side decisions—such as production planning and inventory management—to better align with anticipated shifts in demand. Furthermore, when anticipating expansions or contractions in demand for a product, Apple can strategically adjust pricing and promotional strategies to manage these fluctuations more effectively. Such tasks would be challenging without longitudinal tracking of individual-level sentiment.

Our research also offers guidance for researchers who collect consumer sentiment data, such as the University of Michigan Index of Consumer Sentiment, on how such data can be better collected and analyzed. First, researchers should consider using panel data that tracks the same individuals over time rather than relying solely on repeated cross-sectional surveys. Second, because sentiment about personal finances is more strongly associated with future consumption than perceptions of regional or national economic conditions, sentiment surveys should include more questions related to personal financial situations. Finally, in addition to reporting aggregate indices, researchers could provide sentiment measures broken down by key demographic groups to enhance the usefulness and impact of these data.

Finally, our research suggests that policymakers should be mindful of potential aggregation bias when linking consumer sentiment to economic activity. For example, the Council of Economic Advisers uses the University of Michigan Index of Consumer Sentiment to gauge future household spending and assess economic conditions.[5] Our findings, however, show that the relationship between sentiment and consumption varies substantially across individuals and activity types, highlighting the need for more nuanced analysis beyond simple aggregate measures. In political marketing, it is also important to track individual perceptions and responses to political messaging—particularly around economic issues, because they shape political support and voting intentions within the broader political marketing system (Kübler et al., 2025).

2. Conceptual framework and extant literature

2.1. Conceptual framework

In Fig. 1, we depict our hypotheses that the relationship between consumer sentiment and time/money expenditures vary across activities. Inspired by Lee et al. (2009), we define focal activities within our empirical setting as varying along a continuum from routine maintenance to highly discretionary. As a result, we conjecture that the impact of sentiment on these activities should range from negligible to high. Studies by Deleersnyder et al. (2004), Quelch and Jocz (2009), Kamakura and Du (2012) and Dekimpe et al. (2016) have also shown that expenditures on discretionary items (such as vacations and positional goods) are more sensitive to economic cycles than necessities (e.g., food at home). It is our belief that a similar pattern would emerge over a shorter time horizon, with sentiment playing a more integral role in explaining consumption of discretionary activities compared to maintenance activities.

To empirically test our conceptual framework, we choose a variety of common activities for this study: personal care, active sports/exercise, in-home relaxation, leisure-related travel, and social/recreational events. We decided on this set of activities based on the following three reasons. First, according to the American Time Use Survey (ATUS) conducted by the U.S. Department of Labor, American consumers spend considerable time on these activities in their daily lives. Second, we conjecture that these activities fall on a continuum between maintenance and discretionary (we will provide empirical evidence on this later in this section) which is crucial for us to examine our conceptual underpinning. Lastly, these activities provide wide variation in time and money requirements, which is also ideal for our empirical investigations. In what follows, we provide the ATUS definitions of these activities along with corresponding sub-activities, adding our insights into the potential impact of sentiment on each activity. Specifically:

1. **Personal care** *includes washing and grooming oneself; medical-related self-care such as going to the doctor.* Apart from doctor visits, these are routine activities. They also require a steady stream of routine expenditures on items such as soap, shampoo, haircuts, and the like that do not require high expenditures. Doctor visits may be costly but many individuals have medical insurance. These visits are, either routine or the result of a medical problem. Sentiment should not have much to do with personal care.

[4] Many firms (e.g., Apple; Amazon; Procter & Gamble; Unilever) have had a long history of established consumer panels for tracking consumption and marketing research (see examples here: https://www.amazon.com/gp/help/customer/display.html?nodeId=201909060; https://www.bizjournals.com/cincinnati/stories/2009/03/30/story17.html; https://www.marketingweek.com/unilever-readies-new-customer-insight-panel; https://appleinsider.com/articles/11/05/05/apple_initiates_customer_pulse_market_research_focus_group.)

[5] https://bidenwhitehouse.archives.gov/wp-content/uploads/2024/03/ERP-2024.pdf

	Activity Type	Expected Association with "Consumer Sentiment" $_{t-1}$	
		Time Use $_t$	***Monetary Expenditure*** $_t$
Maintenance	Personal Care	None/Little	None/Little
↓	Active Sports/Exercise	Little/Moderate	Little/Moderate
↓	In-Home Relaxation	Little/Moderate	Little/Moderate
↓	Leisure-Related Travel	Moderate/High	Moderate/High
Discretionary	Social/Recreational Events	Moderate/High	Moderate/High

Fig. 1. Conceptual framework.

2. **Participating in active sports/exercise** *in one's metropolitan area includes playing basketball/football/soccer/baseball; playing volleyball/tennis/table tennis; hiking/biking/walking/jogging/running; going to the gym/cardiovascular equipment/ weightlifting/strength training/treadmill; and other active sports/exercise in one's metropolitan area.* Since a motive for participation can be to improve one's physical conditioning and well-being, we consider this activity to be towards the spectrum of maintenance activities yet more discretionary than personal care. In some time periods our respondents did not participate in this activity at all. Overall, we believe that a positive sentiment about present and future economic conditions could have a small or moderate positive impact on participation.
3. **In-home relaxation** *includes watching TV/videos/movies at home; playing video and other games at home; computer/tablet use for leisure (excluding video games); listening to music; other media use for leisure; chatting with friends/family face to face; arts and crafts; and other non-physical in-home relaxation activities*. We hypothesize that these activities lie in the middle of the spectrum in between maintenance and discretionary activities. Give that these activities are likely to be pursued for personal pleasure, we conjecture that they might be affected by sentiment.
4. **Leisure-related travel** *outside of one's metropolitan area includes vacation/sightseeing to tourist destinations; vacation to visit family/ friends; and other leisure-related travel.* This is the least frequent and most expensive of the five activities. Frequency is limited by available time, but time use can be flexible within this constraint. Since there is room for discretion over time and money expenditures, we expect expenditures of time and money on leisure-related travel to be moderately/highly positively related to sentiment. But the incidence of these expenditures should be limited.
5. **Attending sports/social/recreational events** *in one's metropolitan area includes going to movies/concerts/performances; attending social events such as parties; going to bars/clubs/restaurants; watching live sports/games/competition; and attending other sports/social/ recreational events in your metropolitan area*. These activities are discretionary and can require substantial monetary expenditures. Accordingly, we expect a moderate/high relationship between consumer sentiment and expenditures of time and money on this activity.

To provide empirical evidence of our conjectures around how U.S. consumers perceive these activities on the spectrum of maintenance vs. discretionary, we collected survey responses from 100 U.S. consumers from CloudResesarch Connect Panel (see Web Appendix A for additional information). To ensure that our findings are generalizable to the broader population, we used CloudResearch Connect's census-matched sample feature so that the demographic distribution of our participants is comparable to the US Census in terms of age, gender, race, and ethnicity. We also restricted our sample to individuals with a 95% or higher approval rate to ensure data quality.

We start by asking open-ended questions about how our respondents decide whether an activity is maintenance, discretionary, or somewhere in between. Using ChatGPT 4o to summarize consumer responses, we identify the following themes for each type of consumption. Consistent with our conceptual framework, consumers generally believe that maintenance consumption is driven by daily essential needs (such as rent, utilities, and food) which tend to happen regularly and are part of a normal routine. In contrast, consumers characterize discretionary consumption as items or activities that are not necessary for survival and that often involve consumption for fun and personal enjoyment. Consumers describe activities that fall between maintenance and discretionary as activities that are combinations of needs and wants, such as items that fulfill a need but also bring enjoyment. We manually cross-checked the open-ended responses and confirmed that the GPT-generated summaries are accurate.

To verify that consumers perceive the activities used in our study on a continuum between maintenance and discretionary, we asked respondents to rate on a 7-point scale to what extent they consider each activity to be maintenance vs. discretionary (1, highly maintenance; 7: highly discretionary). For each activity, we also asked respondents how far in advance they plan for each activity. In line with our conjectures, consumers perceive the five activities on a continuous spectrum, with personal care (average: 1.83) scoring the most towards maintenance activity, leisure-related travel (average: 5.89) and social-recreational events (average: 6.19) being the most discretionary, and active sports/exercise (average: 4.46) and in home relaxation (average: 5.43) in between.[6] Additionally, consistent with the open-ended responses, activities that score more towards the maintenance end also tend to have a shorter planning cycle, making this a characteristic/artifact for these types of activities (Web Appendix A).

Lastly, other than the five focal activities in our study, we asked respondents to provide some examples of activities/products/goods that they believe are maintenance vs. discretionary. Again, we use ChatGPT 4o to provide a summary of the examples (Web Appendix A) and manually cross check the raw responses. In addition to the five focal activities in our study, we learn that consumers perceive a wide range of activities, goods, and services along the spectrum from maintenance to discretionary. Therefore, as we suggested earlier in the paper, it is crucial for firms to assess where their target consumers perceive their products or services to fall on this spectrum. Such knowledge will subsequently help firms understand to what extent consumer sentiment may help explain consumption in their core business domains.

2.2. Prior literature on consumer sentiment

Our consumer sentiment measure is derived from three well-known and long-running sentiment indices: 1) the University of Michigan's Index of Consumer Sentiment (started in 1946, still ongoing); 2) the Conference Board's Consumer Confidence Index (began in 1967, still ongoing); and 3) Washington Post/ABC News' Consumer Comfort Index (dates back to 1985, discontinued in 2007). These indexes, which use different groups of individuals to complete each survey wave, are based on sets of four or five questions about personal, regional, or national economic conditions.

To date, several studies have employed either the Michigan index (e.g., Barsky & Sims, 2012; Carroll et al., 1994; Christiansen et al., 2014; Eppright et al., 1998; Souleles, 2004), or the Conference Board's Consumer Confidence Index in their investigations (Eppright et al., 1998; Ludvigson, 2004) to examine the aggregate relationship between consumer sentiment and various economic/consumption measures. Overall, researchers have reported mixed findings (e.g., Carroll et al., 1994; Christiansen et al., 2014; Eppright et al., 1998; Ludvigson, 2004; Vuchelen, 2004), with a roughly equal number of studies finding that these sentiment indexes had incremental explanatory power on aggregate measures of future consumption, beyond other economic indicators.

Nevertheless, aggregation over consumers, different goods, and different time periods (often quarterly), offer limited information about the actual relationships between individual sentiment and subsequent individual behavior, which also creates potential aggregation biases. In attempts to mitigate such biases, Souleles (2004) used demographic variable matching (e.g., household income; size; region of residence) between the Michigan Consumer Sentiment data and the Consumer Expenditure Survey data to examine the relationship between sentiment and household expenditures across demographic groups.

Instead of relying on these external agencies to obtain consumer sentiment data as in prior studies, we set up our own panel where we track the sentiment of the same set of individuals over time on a monthly basis. Our unique data collection effort allows us to empirically investigate the incremental explanatory power of individual-level sentiment over publicly available aggregate sentiment measures on individual-level subsequent consumption. In order to obtain a better understanding of whether and how different aspects of consumer sentiment relate to time use and monetary expenditure decisions, we developed seven scales from the battery of sentiment questions used in the surveys described above. A complete discussion of our sentiment measures is deferred to Section 3 and Table 1. Detailed information on procedures used in constructing our sentiment measures is presented in Web Appendix B.

2.3. Prior literature on money and time use

Due to their importance in our daily lives, a stream of research has emerged to measure whether time and monetary expenditures are substitutes or complements in household production (e.g., Aguiar & Hurst, 2007; Dane et al., 2014; Jera-Diaz et al., 2016; Nevo & Wong, 2019). Several researchers (e.g., Aguiar et al., 2013; Aguiar & Hurst, 2007) have also examined the cyclical effects of time use, mostly using repeated cross sectional American Time Use Survey data (ATUS). As pointed out by Aguiar et al. (2012) and Luo et al. (2013), there has always been a lack of micro data on time allocation. We contribute to both streams of research by exploring whether and how a consumer's sentiment can explain his/her subsequent money and time allocation for specific activities, particularly depending on where the focal activity lies on the continuum of maintenance vs. discretionary activities. This issue has been left unexplained by prior work.

[6] One may argue that personal care (other than routine doctor checkups) is a necessity rather than maintenance activity. As we learn from the open-ended responses, necessity is indeed an integral theme within maintenance activities. We decide to use the term "maintenance" rather than "necessity" activities to be in line with the prior literature (Lee et al., 2009). Additionally, our conceptual framework aims to provide a broader perspective which would cover not only activities that are essential for survival but also those that are functional and often are part of a routine. Personal care is just one example activity we empirically examine in our research.

Table 1
Questions used to measure scales of consumer sentiment.

Scale	Source	Main Sample Mean	Main Sample SD
Personal future			
Now looking ahead, do you think a year from now your financial situation will be (better off, about the same, or worse off)?	U Mich	2.32	0.60
How would you guess your total family income to be six months from now (higher, the same, or lower)?	Conf Board	2.21	0.56
Personal present			
Would you describe the state of your own personal finances these days as (excellent, good, not so good, or poor)?	Post/ABC	2.44	0.76
Considering the cost of things today and your own personal finances, how would you describe the current timing of buying the things you want and need (an excellent time, a good time, a not so good time, or a poor time)?	Post/ABC	2.30	0.78
Personal past			
Compared to a year ago, your household's financial situation is (better off, about the same, or worse off)?	U Mich	2.15	0.66
Regional future			
Six months from now, do you think general business conditions in your area will be (better, the same, or worse)?	Conf Board	2.05	0.45
Six months from now, do you think the jobs available in your area will be (more, the same, or fewer)?	Conf Board	2.02	0.47
Regional present			
How would you rate the present general business conditions in your area (good, normal, bad)?	Conf Board	1.96	0.53
What would you say about available jobs in your area right now (plenty, not so many, or hard to get)?	Conf Board	2.03	0.62
National future			
Now turning to business conditions in the country as a whole. Do you think that during the next twelve months, we will face (good times financially, about the same financially, or bad times financially)?	U Mich	1.98	0.52
Looking ahead, which would you say is more likely in the next five years or so (continuous good time, about the same, or periods of widespread unemployment or depression)?	U Mich	1.98	0.58
You would describe the nation's economy as (getting better, getting worse, or staying the same)?	Post/ABC	2.06	0.59
National present			
Would you describe the state of the nation's economy these days as (excellent, good, not so good, or poor)?	Post/ABC	2.41	0.64

All scales are reversed so that higher values represent more positive sentiment
U.Mich, – University of Michigan Index of Consumer Sentiment (3 pt. scale)
Conf. Board - The Conference Board Consumer Confidence Index (3 pt. scale)
Post/ABC – Washington Post/ABC Consumer Comfort Index (4 pt. scale)

3. Data

The data used in this study comprise a longitudinal panel documenting how a group of U.S. consumers felt about their personal, regional, and national economic conditions as well as how they spent time and money on a monthly basis. We recruited our panelists from Amazon Mechanical Turk (MTurk), with the restriction that only people residing in the United States were able to participate.[7] We collected two waves of data from this panel. In the first wave, the panelists were invited to participate in a series of monthly surveys for a consecutive 25 months from January 2014 to February 2016. Four hundred individuals signed up for the panel study. To construct a longitudinal panel with a sufficient number of observations per person, we retained only participants who completed 12 or more months of surveys by February 2016. This resulted in the 300 respondents (75% among those who signed up) included in our empirical analysis.[8] During March to June 2022, we recontacted the 300 panelists in our first study. Although six years have passed, about 25% of the original panelists agreed to participate in the second wave of our study. At the end, we received valid responses from 69 of the original panelists.[9]

In our empirical analysis, we used responses from our first wave of data to estimate our formal econometric model. This model leverages the larger number of panelists as well as the longer data collection duration. By comparing "before" and "after" panels, we

[7] We compared the demographic information of our panelists with public data from the U.S. Census. The overall demographic makeup of our panelists is generally similar to the U.S. Census data based on age, gender, ethnicity, marital status, regional population distribution, and income distribution.

[8] Among those who completed fewer than 12 surveys, most respondents only submitted 1 or 2 surveys. We did not find significant differences between the panelists that we retained and those who dropped out in terms of time and monetary expenditures, sentiment responses, or major demographic characteristics.

[9] We did not run the second panel for an extended period of time because our main insights from comparing the two waves of the panel data become more or less stable after four months of data collection. We do not think it would have made a material difference if we ran the panel for a much longer time the second time around.

can obtain an understanding of whether consumption patterns are stable 6–8 years later.

Our sentiment measures were derived from the existing battery of scale questions as described in Section 2.2. The resulting scales measure each panelist's beliefs about personal finance (past, present, and future), regional economy (present and future), and national economy (present and future). These scales comprise the measures of sentiment used in our empirical analysis. The scale items that emerged from our data are summarized in Table 1. We describe the procedures used in constructing and validating the scales in Web Appendix B.[10] Table 1 presents the wording of each item, the source of each item, and the means and standard deviations for each. Items were scored to give more positive responses with higher values.

As noted earlier, we focused on the following five activity types in our panel data collection: 1) personal-care; 2) active sports/exercise in own metropolitan area; 3) non-physical in-home relaxation; 4) leisure-related travel outside of own metropolitan area; and 5) social/recreational events in own metropolitan area. We identified these as major non-work activity types in our daily lives besides work based on the ATUS survey. Following the ATUS, within each activity, we further broke down each main activity type (referred to as first-tier activity in ATUS) into sub-activities (referred to as second-tier activity in ATUS) to help our respondents more accurately recall their time use and monetary expenditure allocations. The sub-activity types in our survey were chosen due to their notable shares in the amount of time spent within the main activity type based on the ATUS. We provide the detailed list of sub-activities under each focal activity type in Section 2.1.

Prior to the panel data collection, we conducted a pretest asking our respondents whether it would be easier for them to recall time use and monetary expenditure on a weekly or monthly basis. This pretest revealed that U.S. consumers tend to budget time on a weekly basis but plan for monetary expenditures each month. Therefore, we asked each respondent to recall, in the previous month, the average number of hours he/she spent on each activity in a given week, as well as the amount of money he/she spent on each activity in that month. Because most consumers do not engage in leisure-related travel outside of own metropolitan area on a weekly basis, we asked about the number of days and the dollar amount the respondent spent on this activity in the previous month.[11] In our empirical analysis, we converted the unit of analysis to number of hours and dollars spent per month for all activities.

Table 2 presents the descriptives of time use and monetary expenditure in both the original and the follow-up waves of panel data. In the first panel of Table 2, we provide the average time use and monetary consumption across all individuals and across time in the five focal activity types along with their standard deviations. It is apparent that there is considerable variation in time and money spent by the study participants across these activities during the time of our data collection. By comparing the demographics of the panelists from the two waves of data collection (second panel of Table 2), we see that the demographic make-ups of the two groups are by and large comparable. The average age of the panelists in the second wave is 8 years older than that from the first wave, which is understandable because the two waves of data collection were 6–8 years apart. Table A4 in the appendix shows that, in 2022, panelists spent roughly the same amount on the activities studied after adjusting for inflation. The only notable change is that, in 2022, our panelists spent more time on in-home relaxation and less time on social/recreational events.

Given our interest in demonstrating the unique value of a longitudinal panel, we present some data visualization of our panel data (wave 1) in Figs. 2a) to 2c). Taking Fig. 2a) as an example, we present the scatterplots of average and overtime variations in sentiment scores across panelists, with scores related to the current situation of personal finance situation (personal present) on the left and those related to outlook on personal finance future (personal future) on the right. We choose to focus on the data visualization on these two sentiment measures because they are the only statistically significant sentiment measures for time/money spent. Each dot in the figure represents one individual in our panel. The y-axis depicts the average sentiment score, and x-axis illustrates the standard deviation of the sentiment-score during the 25-month of the panel data collection for each panelist. As evident, there exists considerably heterogeneity across individuals in terms of mean sentiment about their personal finance (y-axis) as well as ample heterogeneity in within-individual overtime variations across these individuals (x-axis). In Figs. 2b) and 2c), we present similar scatterplots for money and time spent for each activity type.

Additionally, we present scatterplots of personal present sentiment against money and time expenditures by activity type in Figs. 2d) and 2e), providing model-free evidence that the relationship between sentiment and consumption behavior varies across activity types. The fitted lines by and large suggest that the positive relationship between sentiment and consumption strengthens as we move along the spectrum from maintenance-oriented activities to more discretionary ones. Note that these patterns should be interpreted as purely descriptive correlations in the raw data, as we have not controlled for a range of potential confounding factors, including observed and unobserved individual characteristics, state dependence, and seasonality. All such visualizations provide support for the importance of collecting and analyzing longitudinal sentiment and consumption data at the individual-level by activity type.

Last but not least, we also collected information related to work time in each of our monthly surveys. Our panelists also exhibited rich variation in work time, with 73.4% of our panelists self-identified as either working full-time (55.76%) or part-time (17.65%). Overall, the considerable variation across individuals, over time, and across activities in our panel provides us with a suitable setting to examine our research questions.

[10] One may question whether the sentiment data in our consumer panel are consistent with the publicly available sentiment data at the aggregate level. In Web Appendix B, we show that these two sets of consumer sentiment are by and large comparable during the time frame of our data collection.

[11] Since consumers sometimes engage in advanced booking for travel, we examined the percentage of times that our panelists reported zero-time spent but non-zero monetary expenditure on travel. Among those observations with zero-time spent on travel, only 0.3% reported a positive money expenditure. As evident, the vast majority of our panelists reported expenses related to travel during the actual month that the trip took place.

Table 2
Descriptives of time use, monetary expenditure, and panelist demographics.

	Time Use and Monetary Expenditure							
	Original panel				69 Panelists in 2022			
	Time Spent (hrs per week)		*Money spent ($ per month)*		*Time spent*		*Money spent (in 2015 dollars)*	
Activity	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Personal Care	8.14	7.24	122.94	317.84	6.44	3.67	128.17	211.07
In-Home Relaxation	39.71	23.36	175.63	151.00	50.75	25.31	172.50	212.77
Active Sports/Exercise	4.74	6.70	18.11	69.31	4.05	5.23	10.58	28.90
Leisure-Related Travel	1.61*	4.01	116.75	446.84	0.99	2.57	106.34	355.89
Social/Recreational Events	4.73	7.00	89.66	138.84	3.32	5.26	88.83	150.04

*note that "time spent" for travel is reported as "days per month" other than "hours per week" as other activities because most individuals do not engage in leisure-related travel every week.

Demographics	Original Panel		69 Panelists in 2022	
	Mean	SD	Mean	SD
Age	36.6	12.5	45.08	11.54
	Percentage		Percentage	
Northeast	19.70%		22.22%	
Midwest	23.49%		30.16%	
South	39.44%		34.92%	
West	17.37%		12.70%	
Male	48.50%		49.21%	
Caucasian	84.76%		95.24%	
Single	47.06%		42.86%	

4. Models

Let M_{ijt} denote the observed monetary expenditure of individual i in activity j during time t (e.g., one month). Let T_{ijt} denote the observed time use of individual i in activity j during time t. In what follows, we outline a set of empirical models in which we first examine the role of consumer sentiment $X_{i,t-1}$ at time t-1 on monetary expenditures in each of the five activities at time t (Section 4.1), followed by the role of sentiment in time use decisions (Section 4.2).[12] We then jointly estimate equations for time use and monetary expenditure for each activity (Section 4.3).[13]

4.1. The role of consumer sentiment in monetary expenditures

Let M^*_{ijt} represent the corresponding expenditure utility of individual i in activity j during time t. Given that consumers may not spend money on some activities in a given time period, we specify:

$$\begin{aligned} M_{ijt} &= M^*_{ijt} \quad \text{if} \quad M^*_{ijt} > 0 \\ M_{ijt} &= 0 \quad \text{if} \quad M^*_{ijt} \leq 0 \end{aligned} \tag{1}$$

This leads to a Tobit model for individual i's monetary expenditure in activity j at time t:

$$M^*_{ijt} = \beta_{ij0} + \delta_{ij} {}^* M_{ij,t-1} + \beta_j {}^* X_{i,t-1} + \varphi_j {}^* D_i + \vartheta_j {}^* S_t + \varepsilon_{ijt} \tag{2}$$

where $M_{ij,t-1}$ captures the amount of money individual i spent on activity j at time t-1; $X_{i,t-1}$ is a vector denoting consumer i's response to the list of consumer sentiment questions at time t-1; D_i represents household income; S_t captures possible seasonality in monetary spending on activity j; and ε_{ijt} is the error term.[14] Additionally, we model the intercept β_{ij0} in Eq. (2) as follows to capture the potential heterogeneity in consumer i's intrinsic preference towards activity j:

[12] We empirically explored the right number of lag periods to use our panel data. We find that past sentiment can explain monetary expenditures up to t-3 (for time use up to t-2). Nevertheless, we learn that the model with one-period sentiment lag has the best fit compared to models with more periods of lags. A drawback with using t-2 or further lagged measures is that observations are lost in order to construct lagged variables, which can be problematic since our panel is not very long.

[13] Given the large number of parameters involved in estimating ten equations all-together (which further leads to potential instability of estimation results as well as exponentially increased computation time), we opt for jointly estimating time use and monetary expenditure at each activity category.

[14] Alternatively, one might suggest that we use changes in sentiment to explain changes in consumption. This setup is not ideal in our context because our dependent variable is censored (an individual may not engage in or spend money on some activities in any given time period).

a) Scatterplot of Avg. and Overtime Variations in Sentiment Scores Across Panelists: Personal Present (Left) and Personal Future (Right)

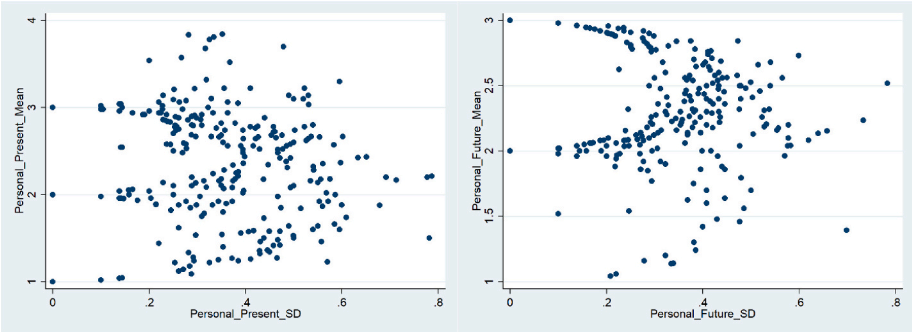

Fig. 2a. Data Visualization of Our Panel Data
Scatterplot of Avg. and Overtime Variations in Sentiment Scores Across Panelists: Personal Present (Left) and Personal Future (Right)
Each dot in the figure represents one individual in our panel. For example, for the sentiment question about current personal financial situation (left figure), we calculated an average sentiment score (y-axis) and a standard deviation of the sentiment score (x-axis) for each panelist. The former captures the heterogeneity across individuals in terms of mean sentiment about their personal finance. The latter captures the heterogeneity in within-individual overtime variations across these individuals.

$$\beta_{ij0} \sim N\left(b_j + B_j\Lambda_i, \sigma_{0j}^2\right) \tag{3}$$

with Λ_i being a vector of consumer demographic variables, including gender, ethnicity, marital status, age, and region of residence.[15] We also employ a random coefficient for the parameter δ_{ij} in Eq. (2) to capture the possibility that consumers may be heterogeneous in their state dependence tendencies.

Lastly, because there might be unobserved correlations across monetary expenditures on these activities, we specify the error term in Eq. (2) to follow $\varepsilon_{ijt} \sim N\left(0, \sum_{J*J}\right)$, with $\sum_{J*J}$ being the variance-covariance matrix of the error terms in J categories. Consequently, we have the following simultaneous equations Tobit model for individual i in all J activity types at time t:

$$\begin{aligned}
M_{i1t}^* &= \beta_{i10} + \delta_{i1}*M_{i1,t-1} + \beta_1*X_{i,t-1} + \varphi_1*D_i + \vartheta_1*S_t + \varepsilon_{i1t}\\
M_{i2t}^* &= \beta_{i20} + \delta_{i2}*M_{i2,t-1} + \beta_2*X_{i,t-1} + \varphi_2*D_i + \vartheta_2*S_t + \varepsilon_{i2t}\\
M_{i3t}^* &= \beta_{i30} + \delta_{i3}*M_{i3,t-1} + \beta_3*X_{i,t-1} + \varphi_3*D_i + \vartheta_3*S_t + \varepsilon_{i3t}\\
M_{i4t}^* &= \beta_{i40} + \delta_{i4}*M_{i4,t-1} + \beta_4*X_{i,t-1} + \varphi_4*D_i + \vartheta_4*S_t + \varepsilon_{i4t}\\
M_{i5t}^* &= \beta_{i50} + \delta_{i5}*M_{i5,t-1} + \beta_5*X_{i,t-1} + \varphi_5*D_i + \vartheta_5*S_t + \varepsilon_{i5t}
\end{aligned} \tag{4}$$

where

$$\varepsilon_{ijt} \sim N\left(0, \sum_{J*J}\right), J = 5 \tag{5}$$

For each activity type, there are variables common to all J equations and a unique variable (the state dependence term $M_{ij,t-1}$). As such, Eq. (4) fulfills the order condition and the rank condition in a simultaneous equation model which makes the system of equations as specified above identified. Then, we can write the likelihood function as follows:

$$L1_{i,t} = \frac{1}{R}\sum_{r=1}^{R}\prod_{j=1}^{5}\left[f\left(M_{ij,t} > 0|X_{ij,t}, M_{ij,t-1}, \Theta\right)\right]^{I_{iMj,t}}\left[P\left(M_{ij,t} = 0|X_{ij,t}, M_{ij,t-1}, \Theta\right)\right]^{1-I_{iMj,t}} \tag{6}$$

where $I_{iMj,t}= 0$, if $M_{ij,t}= 0$ and $I_{iMj,t}= 1$, if $M_{ij,t}> 0$; Θ represents all parameters to be estimated; R is the total number of random draws to simulate $\sum_{J*J}$.

[15] We employ a random (rather than fixed) effects model because our dependent variable is censored (a consumer may not engage in or spend money on some activities in a given time period). Simply adding fixed effects to such nonlinear models will lead to inconsistent and biased coefficient estimates (Greene, 2004). Additionally, because the lagged dependent variable (monetary expenditure in the previous period) is included in our model, a standard fixed effects approach is invalid under this modeling setup (Nickell, 1981; Rossi, 2014).

b) Scatterplot of Avg. and Overtime Variations in Money Spent Across Panelists by Activity Type

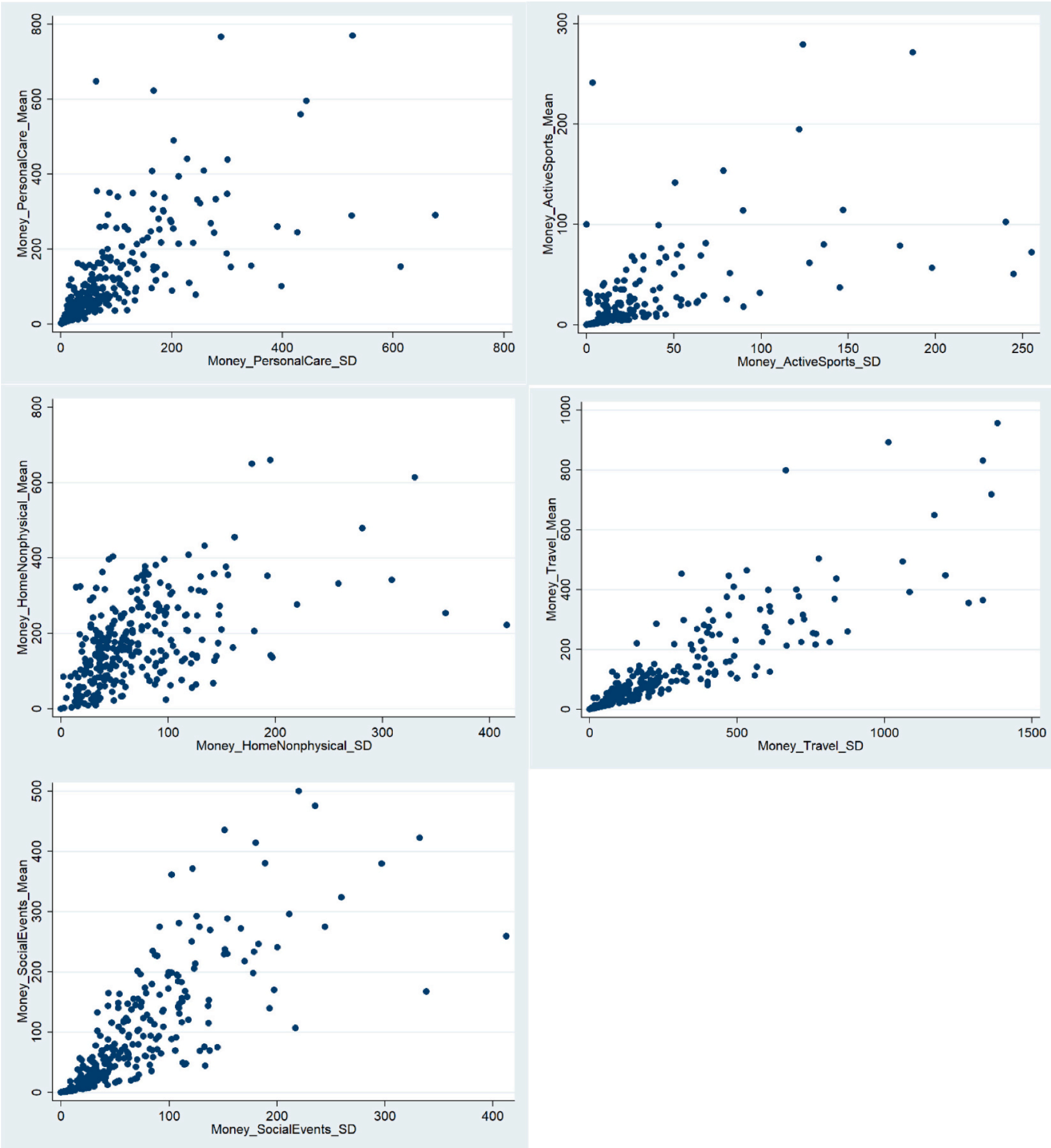

Fig. 2b. Scatterplot of Avg. and Overtime Variations in Money Spent Across Panelists by Activity Type
Each dot in the figure represents one individual in our panel. For example, for money spent on personal care (top left figure), we calculated an average monetary expenditure (y-axis) and a standard deviation of the monetary expenditure (x-axis) for each panelist. The former captures the heterogeneity across individuals in terms of avg. money spent on personal care. The latter captures the heterogeneity in within-individual overtime variations across these individuals. We use dollars per month for all activities. We remove the top 1% of outliers in each activity solely for better data visualization (all panelists' data were retained in analyses for completeness).

We use a modified GHK algorithm to evaluate the above likelihood function by sequentially calculating the probability of observing monetary expenditure (zero or positive value) in each activity type by simulating correlated errors. The procedure is based on the standard GHK simulator in estimating a multivariate Probit model. The complication is to use a PDF value to approximate the likelihood when we observe a positive monetary expenditure, and a corresponding CDF value to approximate the likelihood for a zero observation.

c) Scatterplot of Avg. and Overtime Variations in Time Use Across Panelists by Activity Type

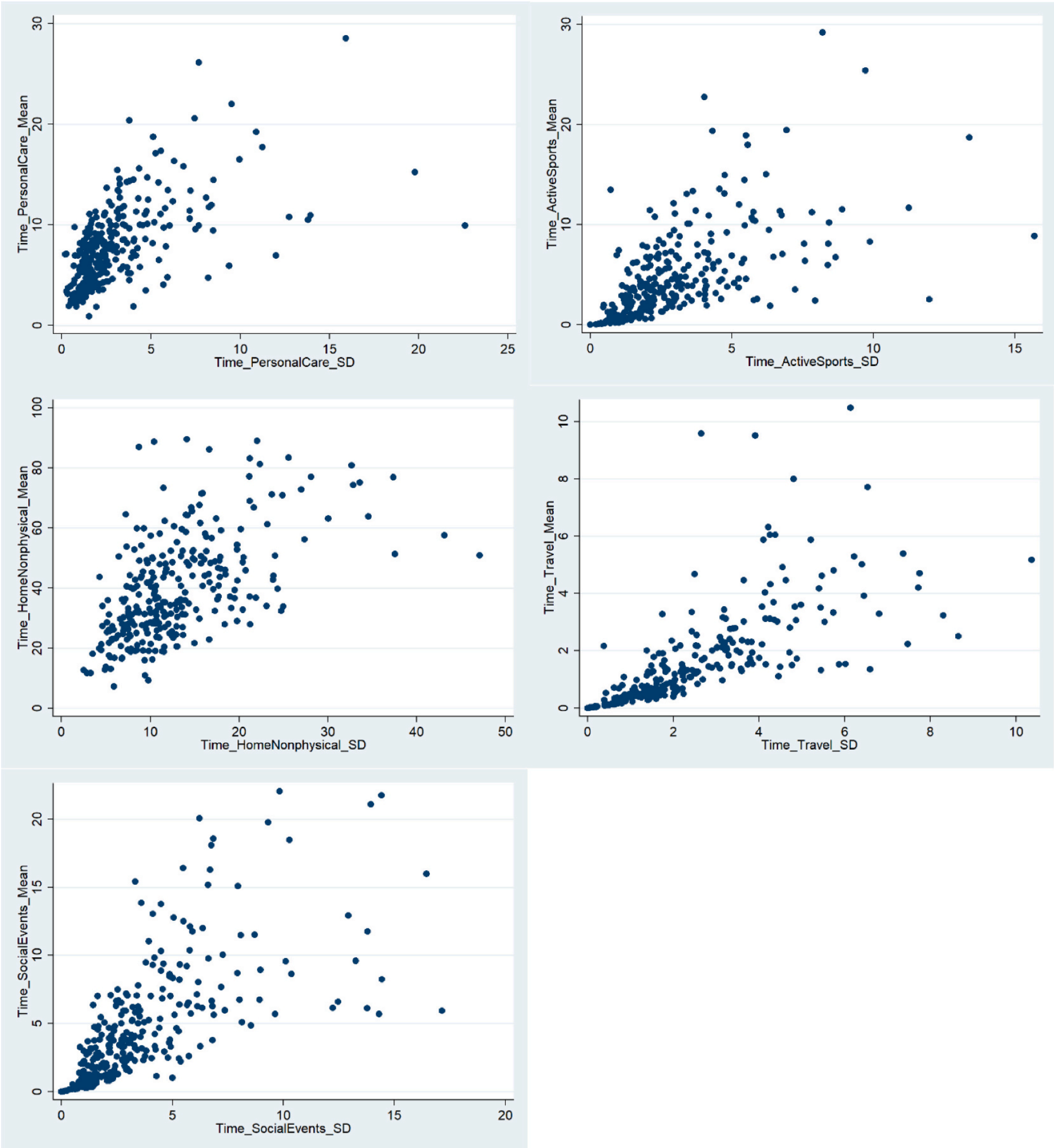

Fig. 2c. Scatterplot of Avg. and Overtime Variations in Time Use Across Panelists by Activity Type
Each dot in the figure represents one individual in our panel. For example, for time use in personal care (top left figure), we calculated an average time use (y-axis) and a standard deviation of the time use (x-axis) for each panelist. The former captures the heterogeneity across individuals in terms of avg. time use in personal care. The latter captures the heterogeneity in within-individual overtime variations across these individuals. We use number of hours per week for all activities except for travel, which is measured by number of days per month. We remove the top 1% of outliers in each activity solely for better data visualization (all panelists' data were retained in analyses for completeness).

4.2. The role of consumer sentiment in time use

In a similar fashion, we outline a system of equations to examine how consumer sentiment relates to time use, with T^*_{ijt} representing the corresponding utility. Because consumers may not participate in some activities in a given time period, we specify:

$$\begin{aligned} T_{ijt} &= T^*_{ijt} \quad \text{if} \quad T^*_{ijt} > 0 \\ T_{ijt} &= 0 \quad \text{if} \quad T^*_{ijt} \le 0 \end{aligned} \tag{7}$$

Therefore, we can write out a simultaneous equations Tobit model as in Eq. (8):

d) Scatterplot of Individual-level Money Spent and Personal Present Sentiment by Activity Type

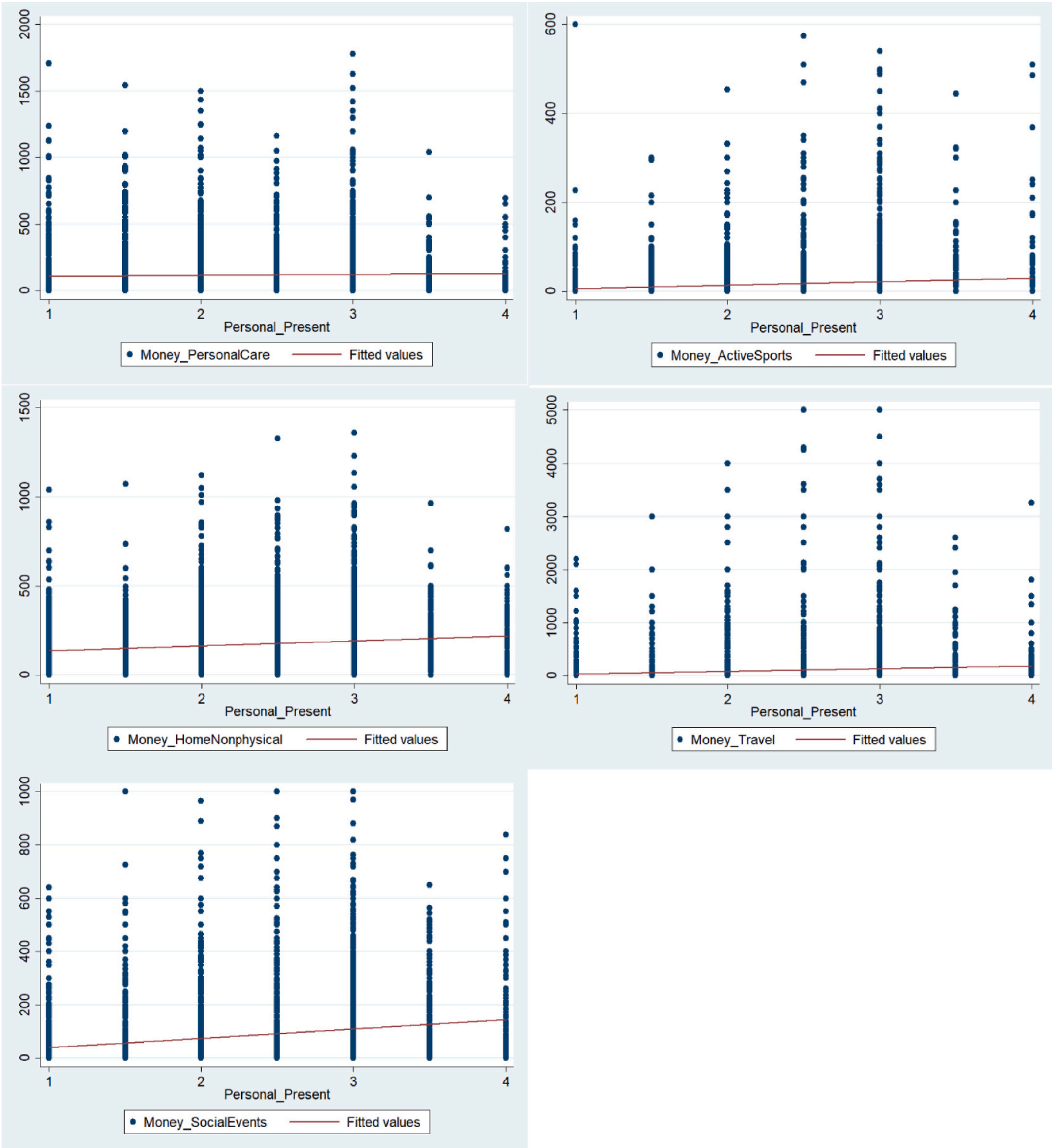

Fig. 2d. Scatterplot of Individual-level Money Spent and Personal Present Sentiment by Activity Type
Each dot in the figure represents one observation in our panel data. For example, for money spent on personal care (top left figure), we present the monetary expenditure (y-axis) and the corresponding personal present sentiment score (x-axis) for each observation. We use dollars per month for all activities. We remove the top 1% of outliers in each activity solely for better data visualization (all panelists' data were retained in analyses for completeness). The fitted lines indicate a positive association between monetary expenditure and personal present sentiment metric across all activities except personal care. These patterns should be interpreted as purely descriptive correlations in the raw data, as we have not controlled for a range of potential confounding factors, including observed and unobserved individual characteristics, state dependence, and seasonality.

$$
\begin{aligned}
T^{*}_{i1t} &= \alpha_{i10} + \gamma_{i1}{}^{*}T_{i1,t-1} + \alpha_1{}^{*}X_{i,t-1} + \varsigma_1{}^{*}T_{iwt} + \eta_1{}^{*}S_t + v_{i1t}\\
T^{*}_{i2t} &= \alpha_{i20} + \gamma_{i2}{}^{*}T_{i2,t-1} + \alpha_2{}^{*}X_{i,t-1} + \varsigma_2{}^{*}T_{iwt} + \eta_2{}^{*}S_t + v_{i2t}\\
T^{*}_{i3t} &= \alpha_{i30} + \gamma_{i3}{}^{*}T_{i3,t-1} + \alpha_3{}^{*}X_{i,t-1} + \varsigma_3{}^{*}T_{iwt} + \eta_3{}^{*}S_t + v_{i3t}\\
T^{*}_{i4t} &= \alpha_{i40} + \gamma_{i4}{}^{*}T_{i4,t-1} + \alpha_4{}^{*}X_{i,t-1} + \varsigma_4{}^{*}T_{iwt} + \eta_4{}^{*}S_t + v_{i4t}\\
T^{*}_{i5t} &= \alpha_{i50} + \gamma_{i5}{}^{*}T_{i5,t-1} + \alpha_5{}^{*}X_{i,t-1} + \varsigma_5{}^{*}T_{iwt} + \eta_5{}^{*}S_t + v_{i5t}
\end{aligned}
\tag{8}
$$

where T_{iwt} represents work time of individual i at time t, and S_t captures possible seasonality in time use. With Λ_i being a vector of

e) Scatterplot of Individual-level Time Use and Personal Present Sentiment by Activity Type

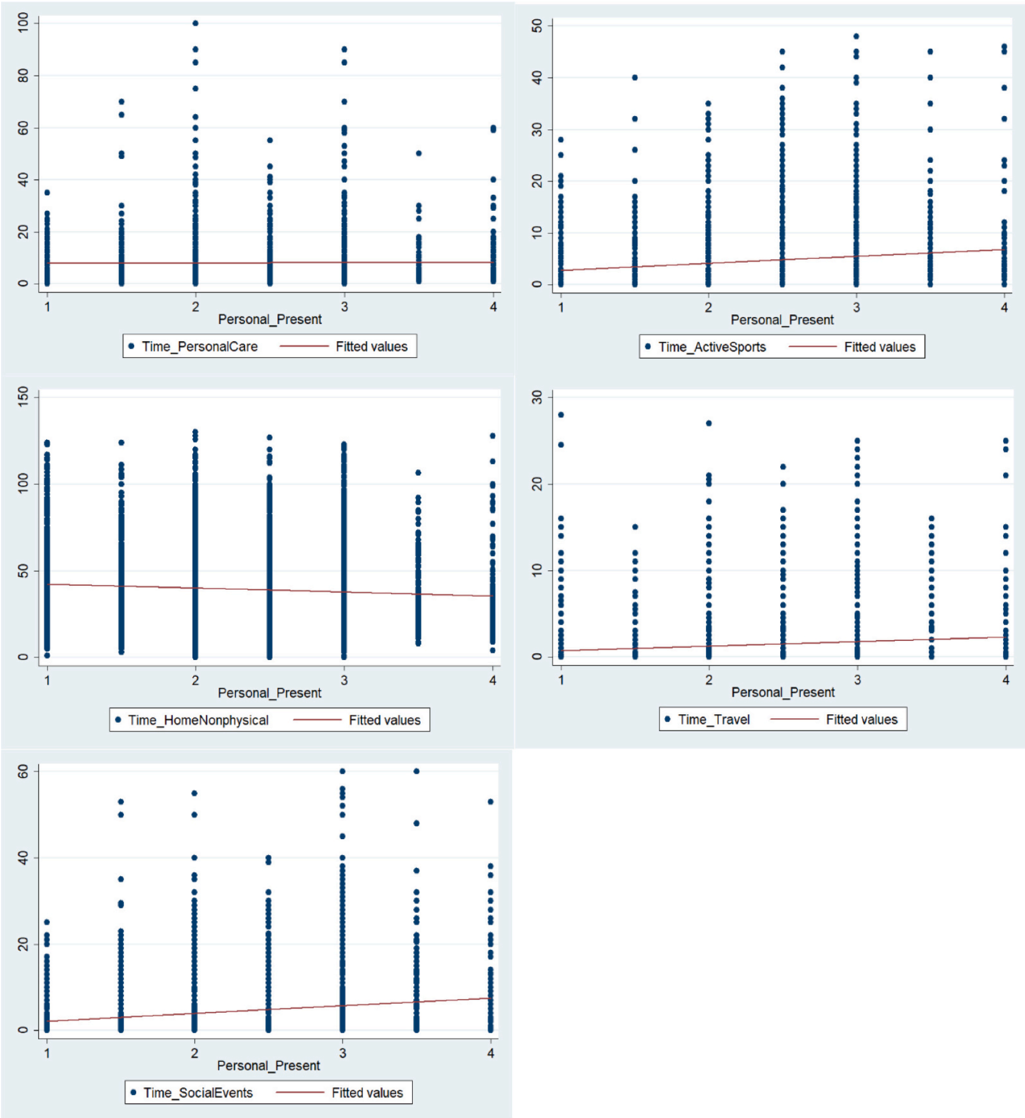

Fig. 2e. Scatterplot of Individual-level Time Use and Personal Present Sentiment by Activity Type
Each dot in the figure represents one observation in our panel data. For example, for time use on personal care (top left figure), we present the time spent (y-axis) and the corresponding personal present sentiment score (x-axis) for each observation. We use number of hours per week for all activities except for travel, which is measured by number of days per month. We remove the top 1% of outliers in each activity solely for better data visualization (all panelists' data were retained in analyses for completeness). The fitted lines indicate a positive association between time use and the personal present sentiment measure across all activities except personal care and in-home relaxation. These patterns should be interpreted as purely descriptive correlations in the raw data, as we have not controlled for a range of potential confounding factors, including observed and unobserved individual characteristics, state dependence, and seasonality. As such, it is not surprising that our formal analyses later uncover a positive relationship between sentiment and time spent on in-home relaxation once these confounders are taken into account.

consumer demographic variables as in eq. (3), the distributions of the relevant parameters are specified below:

$$\alpha_{ij0} \sim N\left(\alpha_j + A_j\Lambda_i,\ \eta_{0j}^2\right);\quad \gamma_{ij} \sim N\left(0,\ \sigma_{\gamma j}^2\right);\quad \nu_{ijt} \sim N\left(0,\ \Gamma_{J^*J}\right),\ J = 5 \tag{9}$$

The likelihood function to estimate Eqs. (8) and (9) is given in Eq. (10):

$$L2_{i,t} = \frac{1}{R}\sum_{r=1}^{R}\prod_{j=1}^{5}\left[f\left(T_{ij,t} > 0|X_{ij,t}, T_{ij,t-1}, \Phi\right)\right]^{I_{iTj,t}}\left[P\left(T_{ij,t} = 0|X_{ij,t}, T_{ij,t-1}, \Phi\right)\right]^{1-I_{iTj,t}} \tag{10}$$

where $I_{iTj,t}= 0$, if $T_{ij,t}= 0$ and $I_{iTj,t}= 1$, if $T_{ij,t}> 0$; Φ represents all parameters to be estimated; R is the total number of random draws to simulate Γ_{J^*J}. The GHK algorithm used to estimate the time allocation model is similar to that used for the monetary expenditure model.

4.3. Joint estimation of monetary expenditure and time use for each activity

We now explore a joint estimation of monetary expenditure and time use. Simply estimating the systems of Eqs. (4) and (8) altogether would be extremely computationally burdensome. Unobserved correlations between time and money across activity types are also hard to interpret and justify. For example, it is not intuitive to think about how money spent on personal care might be positively or negatively correlated with time spent on in-home relaxation.

Given these considerations, we decided to jointly estimate monetary expenditure and time for each activity in our study. Besides its simplicity, this approach has two desirable properties. First, it is intuitive to conceptualize a potentially unobserved correlation between monetary expenditure and time use for the same activity.[16] Second, this setup allows us to obtain insights for different types of activities respectively, particularly given that these activities fall on the continuous spectrum of maintenance and discretionary consumptions. Specifically, we estimate a system of two equations in activity j together as follows (we use tilde to denote coefficients from the estimations in this section):

$$\begin{aligned} M^*_{ijt} &= \widetilde{\beta}_{ij0} + \widetilde{\delta}_{ij}{}^*M_{ij,t-1} + \widetilde{\beta}_j{}^*X_{i,t-1} + \widetilde{\varphi}_j{}^*D_i + \widetilde{\vartheta}_j{}^*S_t + \varsigma_{ijMt} \\ T^*_{ijt} &= \widetilde{\alpha}_{ij0} + \widetilde{\gamma}_{ij}{}^*T_{ij,t-1} + \widetilde{\alpha}_j{}^*X_{i,t-1} + \widetilde{\zeta}_j{}^*T_{iwt} + \widetilde{\eta}_j{}^*S_t + \varsigma_{ijTt} \end{aligned} \tag{11}$$

where

$$(\varsigma_{ijMt},\ \varsigma_{ijTt}) \sim N(0,\ \Psi_{j,2^*2}) \tag{12}$$

The likelihood function to estimate Eqs. (11) and (12) are given in Eq. (13):

$$\begin{aligned} L3_{ij,t} = \frac{1}{R}\sum_{r=1}^{R} & \left[f\left(M_{ijt} > 0|X_{it}, M_{ij,t-1}, \Omega\right)\right]^{I_{ijMt}} \left[P\left(M_{ijt} = 0|X_{it}, M_{ij,t-1}, \Omega\right)\right]^{1-I_{ijMt}} \\ & \left[f\left(T_{ijt} > 0|X_{it}, T_{ij,t-1}, \Omega\right)\right]^{I_{ijTt}} \left[P\left(T_{ijt} = 0|X_{it}, T_{ij,t-1}, \Omega\right)\right]^{1-I_{ijTt}} \end{aligned} \tag{13}$$

where $I_{ijMt}= 0$, if $M_{ijt}= 0$, and $I_{ijMt}= 1$, if $M_{ijt}> 0$; $I_{ijTt}= 0$, if $T_{ijt}= 0$, and $I_{ijTt}= 1$, if $T_{ijt}> 0$; Ω includes all parameters to be estimated; R is the total number of random draws to simulate $\Psi_{j,2^*2}$. We estimate this system of two equations using a similar GHK algorithm as described in section 4.1.

5. Results

5.1. Which consumer sentiment measure best explains consumption

Given that the primary goal of this research is to understand how consumer sentiment can be used to explain individual-level consumption decisions, we start by examining which sentiment measure best explains consumption. We carry out this investigation by altering the operationalization of the consumer sentiment measure in our monetary expenditure and time use estimations (Eqs. (4) and (8)) and compare the statistical fit under each specification. Namely, we keep all other aspects of our panel data and model structure intact, just changing the specifications of the sentiment measures.

First, we are interested in exploring whether we should use questions related to personal finance, regional economy, national economy, or some combination of the three to measure consumer sentiment. In Table 3a, we present the log likelihood and BIC of the monetary expenditure and time use estimates under five different specifications of consumer sentiment: 1) personal sentiment only; 2) regional sentiment only; 3) national sentiment only; 4) personal sentiment + regional sentiment; 5) personal sentiment + regional sentiment + national sentiment. Comparing the log likelihood and BIC of the first three specifications, it is evident that personal sentiment best explains both monetary expenditure and time use, followed by sentiment about regional then national economy. Therefore, we decided to further explore the incremental value of adding regional sentiment (specification 4) and adding both regional and national sentiment (specification 5). We find that there are no statistical gains in including sentiment about regional or national

[16] Note that we do not directly model the substitution/complementarity relationship between time and money by adding money to the time equation and adding time to the money equation. Because current time period monetary expenditure and time use decisions influence each other, such a modeling setup will result in a simultaneity bias. Namely, the time (money) variable in the money (time) equation is correlated with the error term in the focal equation. Therefore, we explored an alternative setup by estimating the two equations separately such that time (money) can be added to the money (time) equation. Under this specification, the time coefficient in the money equation and the money coefficient in the time equation are both positive and significant (meaning that time use and monetary expenditure decisions are positively correlated), with coefficients on other variables qualitatively similar to those from our Equation (11). Nevertheless, an ideal setting to directly examine time and money substitution would be to carefully document exogenous shocks to available time and disposable income. We leave such endeavors to future research.

Table 3
Model fit comparisons under different sentiment measures.

a: Comparison of Personal vs. Regional vs. National Sentiment Measures

Model Specifications	Monetary Expenditure		Time Use	
	Log Likelihood	BIC	Log Likelihood	BIC
Personal Sentiment Only	−23,462	47,890.4	−26,189	53,345.2
Regional Sentiment Only	−23,691	48,304.7	−26,346	53,615.3
National Sentiment Only	−23,743	48,408.5	−26,373	53,668.9
Personal + Regional Sentiment	−23,449	47,952.3	−26,170	53,393.6
Personal + Regional + National Sentiment	−23,435	48,012.1	−26,153	53,448.3

b: Comparison of Individual vs. Aggregate vs. No Sentiment Measures.

Model Specifications	Monetary Expenditure		Time Use	
	Log Likelihood	BIC	Log Likelihood	BIC
Personal Sentiment (Individual)	−23,462	47,890.4	−26,189	53,345.2
Michigan Consumer Sentiment Measures (Aggregate; No “Personal Present” Metric)	−24,476	49,874.5	−27,248	55,418.3
Personal Sentiment (Aggregate of Our Panelists)	−23,867	48,701.0	−26,484	53,935.0
Sentiment Measures Omitted	−24,589	50,012.6	−27,376	55,586.0

*All sentiment measures in Table 3 are constructed at the monthly level; Number of observations: 6540.

economy in our model. Therefore, we decided to drop the regional and national sentiment scales from subsequent analyses.

Next, perhaps more importantly, we would like to examine whether our individual-level sentiment measures carry more explanatory power of consumption as compared to the publicly available University of Michigan Consumer Sentiment Measure, which is aggregated across cross-sectional sample of consumers.[17] In particular, we constructed an alternative monthly measure of consumer sentiment by using sentiment measures from the University of Michigan Consumer Sentiment Index during the same time of our data collection. Table 3b presents the log likelihood and BIC comparisons from using our individual-level personal sentiment vs. the Michigan Sentiment measures. It is apparent that the individual-level sentiment data we collected outperforms the University of Michigan sentiment measure by a considerable margin in terms of both log likelihood and BIC. This is not surprising for two reasons. First, in each month, while the vector of Michigan sentiment measure contains a fixed value for everyone, the sentiment measures from our panel data have rich variations because it captures the sentiment of each panelist in that month. Second, although our sentiment measure includes questions about one's sentiment about past, present, and future personal finance, the Michigan sentiment measure omits the crucial questions related to how an individual feels about his/her current financial situation. As we will show later in this section, sentiment towards the present status of personal finance by and large holds the greatest explanatory power in describing subsequent consumption, as compared to sentiment about past or future personal financial situation.

One may argue that, because the Michigan Sentiment Index collects data from a different set of consumers, it is unclear whether the statistical gain from our sentiment measures can be attributed to sampling differences or the difference between individual vs. aggregate sentiment measures. In order to rule out this alternative explanation, we test another alternative measure of consumer sentiment by using the monthly average of our panelists' sentiment. In this case, there are no sampling differences and the only difference in the sentiment measures is individual vs. aggregate-level sentiment. Not surprisingly, the individual-level sentiment measures outperform the aggregate-level sentiment measures constructed from our own panel, which can also better explain subsequent consumption than the Michigan sentiment data. Lastly, we include the fit statistics from a model specification that does not include consumer sentiment at all for completeness. This specification performs the worst among the four model specifications. To summarize, these comparisons indicate that 1) individual-level consumer sentiment carries significantly more explanatory power for individual-level time and money expenditures compared to aggregate-level sentiment measures; 2) using aggregate-level consumer sentiment derived from our panel is better than using those from the University of Michigan Consumer Sentiment data; and 3) incorporating any type of sentiment measure is better than not using sentiment measures at all.

5.2. Role of consumer sentiment on monetary expenditures

We present results for the monetary expenditure model described in Eq. (4) in Table 4. As expected, monetary expenditure on personal care is insensitive to consumer sentiment. This is consistent with our view of personal care as a maintenance activity. Given that goods used in personal care are often necessities or routine consumption, this finding is analogous to Quelch and Jocz (2009) and Kamakura and Du (2012) which suggest that such consumption is inelastic to economic changes.

For the rest of the five focal activities, interestingly, when income is controlled for, the only significant sentiment variable that can help explain monetary expenditures among the three measures of sentiment is one's current financial situation. Although prior

[17] We omitted similar comparisons for the Conference Board's Consumer Confidence Index because access to this index is limited to commercial subscribers only. We also did not include comparisons with the Washington Post/ABC New Consumer Comfort Index because the data collection for this index was discontinued after 2007.

Table 4
Monetary expenditures by activity type.

Parameter	Personal care		Active sports/exercise		In-home relaxation		Leisure-related travel		Social/recreational events	
	estimate	s.e.	estimate	s.e.	estimate	s.e.	Estimate	s.e.	estimate	s.e.
Intercept	3.039	17.101	−6.997	17.716	1.555	13.894	−8.835	25.813	−2.833	23.909
SD of Intercept	1.642*	0.449	4.089*	0.908	1.376*	0.501	10.658*	1.219	1.265	0.727
Consumer Sentiment										
Personal Future $_{t-1}$	−1.385	1.552	2.591	1.702	−0.034	1.663	0.787	3.204	2.711	2.367
Personal Present $_{t-1}$	0.875	1.440	6.897*	1.686	1.375*	0.513	20.154*	0.974	7.086*	1.674
Personal Past $_{t-1}$	−0.980	1.407	2.376	1.774	−1.283	1.267	1.164	2.496	−0.927	1.860
State Dependence										
Monetary Expenditure $_{t-1}$	−0.131	0.243	−0.559	1.734	−0.155	0.090	0.112	0.265	0.174	0.538
SD of Expenditure $_{t-1}$	0.269	0.333	3.011	1.978	0.006	0.261	0.385	0.301	0.134	0.470
Household Income										
Household Income	2.627*	1.197	0.003	0.265	1.191*	0.465	1.253*	0.387	−0.813	0.511
Demographics										
Male	−4.763*	1.790	23.039*	3.247	2.272	1.473	−1.274	3.106	0.072	2.370
Caucasian	0.732	2.386	1.119	2.938	2.849	2.008	1.257	4.006	8.579*	2.041
Single	−7.600*	2.626	−18.306*	3.904	−5.909*	2.323	−24.555*	6.032	−17.925*	2.316
Age	9.114*	2.732	3.047	5.255	7.103*	3.467	−8.520	7.282	5.859	6.391
Age^2	−1.213*	0.258	−1.011	0.616	−0.857*	0.368	0.376	0.804	−1.167	0.677
Residence: Midwest	1.214	2.302	−11.476*	2.350	−4.873*	1.930	−9.345*	4.247	−3.953	3.284
Residence: South	1.010	2.090	−10.002*	2.306	−2.885	1.801	−4.218	3.652	−1.792	2.888
Residence: West	1.795	2.530	6.393*	2.877	−5.014*	2.093	4.252	4.926	−7.359*	3.194
Seasonality										
Spring	−0.547	2.132	0.393	2.598	−0.995	1.803	−1.346	4.186	−0.682	3.040
Summer	0.661	2.199	2.552*	1.228	−0.833	1.828	9.707*	3.716	0.422	2.961
Fall	−0.380	2.055	−0.996	2.744	−1.252	1.921	−3.076	3.888	−2.576	2.940

* significant at 0.05.
Number of observations: 6540.
Log Likelihood: −23,462.

research has discussed the relationship between sentiment and spending in general, our research is among the first to uncover the nuances of how different types of sentiment are more or less associated with how U.S. consumers spend money on major activities in their daily lives.

More importantly, Table 4 suggests that while the explanatory power of sentiment around "personal present" on monetary expenditures is not significant for personal care (a maintenance activity), this effect is significant for the other four activities, which are more towards the discretionary spectrum. In line with what we learn from the CloudResearch Connect Panel survey, the magnitude of this effect falls on a continuous spectrum, ranging from a smaller value for in-home relaxation and a large value for leisure-related travel. To the best of our knowledge, no prior research has documented such differential roles of sentiment across different types of activities.[18]

Another interesting finding from Table 4 is that state dependence (i.e., monetary expenditure on focal activity in time t-1) does not explain monetary expenditure in the current period for any of the five activities. Based on Table 4, factors such as consumer sentiment, household income, and demographic characteristics, rather than state dependence, seem to better explain how much money an individual is willing to allocate to each of these activities. In other words, individual heterogeneity rather than state dependence better explains monetary expenditure on each of the five activities in our study. Such insights won't be revealed without our individual-level panel data on both sentiment and consumption.

5.3. Role of consumer sentiment on time use

In Table 5, we present results related to time use by activity type as described in Eq. (8). We find that sentiment about personal financial situation (present or future) is the only significant sentiment variable that can help explain next-period time use. Interestingly, when consumers feel that their personal finances are going to improve in the future, they tend to spend more time on personal care and exercising. It is possible that consumers view time use on such activities as an investment for the future. Upon expecting a

[18] Although we do not aim to claim causality in our results, we did explore the Granger causality of sentiment on consumption. Given that "personal present" sentiment by and large best explains time use and monetary expenditure, we test the Granger causality of "personal present" on consumption by activity via following the approach by Lopez and Weber (2017) "Testing for Granger causality in panel data". We found that "personal present" does Granger cause both monetary expenditure and time use in each of the five focal activities.

brighter personal financial future, consumers behave rationally by spending more time caring for self and getting into a better shape so that they can live longer and enjoy the good life ahead. For in-home relaxation and social/recreational events, one's current personal financial situation is positively associated with subsequent time use, with the latter being more elastic to consumer sentiment given its discretionary nature. Interestingly, sentiment on both personal present and personal future carries significant explanatory power for time spent on leisure-related travel in the subsequent period. This is consistent with the hypothesis that leisure-related travel is a discretionary activity.

In line with our findings for monetary expenditures, state dependence does not seem to explain subsequent time use on these activities, except for time spent on social/recreational events. Regarding work time, consistent with Aguiar et al. (2013), we find that individuals who work longer hours tend to spend less time engaging in in-home relaxation and leisure-related travel, suggesting that work time and time spent on relaxing at home and leisure travels are substitutes.

5.4. Relation between money and time

As outlined in Section 4.3, we estimate five separate sets of bivariate Tobit regressions of money and time spent on each activity with correlated error terms. The results are presented in Table 6. Overall, the results for the sentiment measures are qualitatively similar to those in Tables 4 and 5. Interestingly, all correlated error terms between money and time equations are positive and statistically significant. In particular, the correlation is low for personal care (0.147) and in-home relaxation (0.112); higher for active sports (0.486) and social/recreational events (0.593); and quite high for leisure-related travel (0.799). This indicates that money and time tend to be used together for the latter three activities, suggesting that they tend to be complements in producing these activities.

6. Conclusion

This study is among the first to use panel data to examine whether individual-level consumer sentiment (defined as beliefs about personal financial conditions and regional or national economic conditions) can better explain time use and monetary spending across a range of activities than publicly available aggregate sentiment measures such as the University of Michigan Index of Consumer Sentiment. We collected monthly sentiment data from 300 U.S. consumers between January 2014 and February 2016 and tracked their

Table 5
Time use estimates by activity type.

Parameter	Personal Care		Active Sports/Exercise		In-Home Relaxation		Leisure-Related Travel		Social/Recreational Events	
	estimate	s.e.	estimate	s.e.	estimate	s.e.	estimate	s.e.	estimate	s.e.
Intercept	−10.289	17.914	−59.714	41.773	7.032	32.530	−44.659	39.803	−22.092	36.392
SD of Intercept	5.230*	1.673	8.228*	2.802	16.777*	1.989	3.585	3.135	3.318	2.107
Consumer Sentiment										
Personal Future $_{t-1}$	6.500*	3.139	50.319*	3.517	1.768	4.585	24.558*	6.595	0.679	2.095
Personal Present $_{t-1}$	9.290	19.761	9.702	5.678	5.835*	1.855	29.696*	5.305	16.142*	3.879
Personal Past $_{t-1}$	−2.165	2.855	10.134	6.076	−1.494	4.286	−8.546	6.271	−7.553	4.557
State Dependence										
Time Use $_{t-1}$	0.276	0.316	0.416	0.493	−0.033	0.092	−0.511	0.811	0.095*	0.031
SD of Time Use $_{t-1}$	0.034	0.158	0.083	0.434	0.001	0.049	0.552	0.759	0.056	0.282
Work Time										
Work Time	0.044	0.074	−0.063	0.057	−0.149*	0.019	−0.248*	0.034	0.061	0.083
Demographics										
Male	−6.018*	1.318	19.559*	6.291	−1.970	4.947	−10.953	7.275	−7.821	6.863
Caucasian	−3.850	4.763	−10.937	10.057	2.847	7.836	8.064	10.149	−8.605	9.248
Single	0.811	1.126	2.313	5.806	19.335*	5.950	−28.927*	5.470	−7.818	4.993
Age	−1.353	7.103	−8.894	6.371	1.079	14.858	5.589	16.643	−21.942	16.517
Age^2	1.868	8.872	1.185	0.853	0.045	1.758	−4.418	18.065	1.724	1.974
Residence: Midwest	0.155	5.809	−24.474*	10.441	−1.265	6.537	−19.041	10.386	−1.609	8.564
Residence: South	2.979	5.293	−27.181*	10.033	5.160	5.737	−23.240*	9.948	−14.073*	6.716
Residence: West	−1.037	6.399	−12.467	10.768	−4.448	7.220	−12.884	12.555	−24.223*	8.622
Seasonality										
Spring	0.795	5.156	2.553	10.416	−1.487	6.836	7.881	9.746	−7.494	7.487
Summer	0.622	5.001	3.954	9.579	−3.458	5.878	18.759*	9.204	−0.745	10.133
Fall	−1.439	4.925	−17.362	9.367	−5.941	5.647	−4.380	9.593	−12.181	6.368

Number of observations: 6540.
Log Likelihood: −26,189.
* significant at 0.05.

Table 6
Money and time use estimates by activity.

Parameter	Personal Care		Active Sports/ Exercise		In-Home Relaxation		Leisure-Related Travel		Social/ Recreational Events	
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Consumer Sentiment for money										
Personal Future $_{t-1}$	−0.930	0.931	0.965	0.541	−0.692	0.421	3.752	3.078	0.289	0.485
Personal Present $_{t-1}$	0.791	0.644	3.033*	0.435	2.440*	0.314	24.231*	2.551	5.195*	0.350
Personal Past $_{t-1}$	2.167	7.404	0.391	0.515	0.250	0.347	−0.470	2.667	0.367	0.437
Consumer Sentiment for time										
Personal Future $_{t-1}$	8.878*	1.776	14.656*	2.419	1.654	5.664	7.828*	3.026	7.936*	2.350
Personal Present $_{t-1}$	1.096	1.417	14.530*	1.713	15.209*	4.512	20.983*	2.110	24.844*	1.754
Personal Past $_{t-1}$	−1.169	1.531	3.746	2.118	1.956	5.206	−1.125	2.571	−0.592	2.143
Correlation between money and time error terms	0.147*	0.012	0.486*	0.012	0.112*	0.013	0.799*	0.007	0.593*	0.009
State Dependence	✓		✓		✓		✓		✓	
Demographics including Household Income/Work Time	✓		✓		✓		✓		✓	
Seasonality	✓		✓		✓		✓		✓	
Log Likelihood	−14,021		−6741		−13,698		−5908		−10,525	

Number of observations: 6540.
◆ These are five separate sets of bivariate Tobit regressions of money spent for each activity, and of time spent for the same activity.
* significant at 0.05.

monetary expenditures and time allocation across five major activity types during the same period. In March–June 2022, we recontacted the same individuals and collected comparable data from approximately 25% of the original sample.

Our findings show that individual-level sentiment has significantly greater explanatory power for consumption behavior than aggregate sentiment measures based on repeated cross-sectional surveys. In particular, discretionary activities (e.g., leisure travel and social/recreational events) are more sensitive to sentiment than maintenance activities (e.g., personal care). For more discretionary activities, current sentiment also outperforms past behavior in explaining future consumption. Among the different sentiment dimensions, perceptions of personal financial conditions best explain both monetary spending and time use, exceeding the explanatory power of sentiment about regional or national economic conditions. To our knowledge, this study provides one of the first conceptual frameworks and empirical evidence demonstrating these effects.

Our research offers insights for firms on whether and how consumer sentiment may help explain subsequent consumption of their products and services. Because consumption activities lie along a continuum from maintenance to discretionary, firms should first understand where their offerings fall on this spectrum, particularly from the perspective of their target customers. If consumers perceive a firm's offerings as more discretionary, firms should consider incorporating questions about personal financial sentiment into their marketing research. As noted in the Introduction, it is relatively straightforward for firms to survey customers and track sentiment over time, enabling them to segment sentiment across different target groups for specific products. By monitoring whether sentiment among a product's target segment is trending upward or downward, firms can better align their manufacturing and marketing efforts with anticipated shifts in demand.

Our findings also offer guidance for researchers who collect consumer sentiment data, such as those behind the University of Michigan Index of Consumer Sentiment, on how these data can be better collected and analyzed. In particular, longitudinal panel data that track the same individuals over time are preferable to repeated cross-sectional surveys. Sentiment surveys should also include more questions related to personal financial conditions, and the resulting indices should be reported separately for key demographic groups. In addition, our results suggest that policymakers should encourage more careful investigation of the relationship between sentiment and subsequent economic activity at the individual level and across different activity types, as aggregate analyses may obscure important behavioral differences.

Our research is subject to several limitations that suggest promising avenues for future work. First, although we find that sentiment about one's “personal present” financial situation Granger-causes both monetary expenditure and time use across the five focal activities, our study does not claim causal inference. Moreover, because individual-level spending and time allocation in any given period are inherently difficult to predict with high precision, our goal is not to develop a predictive model. Instead, we focus on a descriptive framework that helps illuminate how sentiment plays different roles across major daily activities. Future research may build on our work to explore predictive or causal relationships between sentiment and consumption behavior.

Second, while we attempt to examine the relationship between time and money spent on the focal activities, our data is not sufficient to fully determine the extent to which time and monetary expenditures act as complements or substitutes. Within our empirical setting, time and money jointly contribute to producing activities in each period, so greater time investment is often associated with higher monetary spending—particularly for travel, social or recreational events, and sports activities. A more suitable context for studying substitution between time and money would involve clearly identifying exogenous shocks to available time or disposable income. Although we explored this possibility, our dataset does not contain enough such shocks to conduct a systematic analysis.

Lastly, we note that although our results show that sentiment about personal finances has greater explanatory power for subsequent consumption decisions than sentiment about regional or national economic conditions, this finding may partly reflect the relatively short time span of our panel data. Because our data covers only two years and does not include major economic fluctuations, consumer sentiment about regional or national economic conditions may play a larger role during a prolonged time period with pronounced economic expansion or contraction. We leave such endeavors for future research.

CRediT authorship contribution statement

Botao Yang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lan Luo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Brian T. Ratchford:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2026.06.001.

Data availability

Data will be made available on request.

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