CENTRE FOR RESPONSIBLE BANKING & FINANCE

CRBF

University of St Andrews
School of Management

WORKING PAPERS IN RESPONSIBLE BANKING & FINANCE

The Influence of Budgets on Consumer Spending

By *Marcel Lukas* and *Ray Charles "Chuck" Howard*

Abstract: Foundational research in behavioral economics and consumer psychology has revealed a great deal about the psychology of budgeting. However, very little is known about the extent to which budgets do (or do not) influence spending in the wild. The present research addresses this gap in the literature using naturally occurring budgeting and spending data provided by a popular financial aggregation app (study 1), and a financial diary study that experimentally manipulates budget forecasts and tracks subsequent spending (study 2). Budget compliance varies according to the nature of spending in the category: the more (less) positively skewed spending is, the weaker (stronger) budget compliance is. However, budgets positively influence spending even when budget compliance is weak. Moreover, this effect is surprisingly persistent: post-budget spending is lower than pre-budget spending even six months after a budget is set. Taken together, our findings show that the influence of budgets on consumer spending is economically meaningful, and that beliefs about the nature of consumer budgeting and planning requiring updating.

WP Nº 21-005

2nd Quarter 2021

University of St Andrews
Scotland's first university

600 YEARS
1413 – 2013

THE INFLUENCE OF BUDGETS ON CONSUMER SPENDING

Marcel Lukas (mfl3@st-andrews.ac.uk), Ray Charles "Chuck" Howard (rhoward@mays.tamu.edu)

Abstract

Foundational research in behavioral economics and consumer psychology has revealed a great deal about the psychology of budgeting. However, very little is known about the extent to which budgets do (or do not) influence spending in the wild. The present research addresses this gap in the literature using naturally occurring budgeting and spending data provided by a popular financial aggregation app (study 1), and a financial diary study that experimentally manipulates budget forecasts and tracks subsequent spending (study 2). Budget compliance varies according to the nature of spending in the category: the more (less) positively skewed spending is, the weaker (stronger) budget compliance is. However, budgets positively influence spending even when budget compliance is weak. Moreover, this effect is surprisingly persistent: post-budget spending is lower than pre-budget spending even six months after a budget is set. Taken together, our findings show that the influence of budgets on consumer spending is economically meaningful, and that beliefs about the nature of consumer budgeting and planning requiring updating.

Keywords: Consumer budgeting, mental accounting, consumer financial decision making, planning fallacy, household finance, forecasting

"If you and your family want financial security, following a budget is the ***only*** *answer."*

- Investopedia, the world's leading source of financial content on the web (Bell 2019)

"Budgeting doesn't work."

- Bill Harris, Former CEO of Intuit, parent company of Mint.com, the USA's largest personal finance service (Olen 2015)

Personal finance advisors frequently invoke budgeting as a way to curb overspending, and therefore increase savings, decrease debt, and improve financial security (Bell 2019; Caldwell 2019; Credit Counselling Society 2019). However, a growing chorus of voices has begun to argue that budgeting simply doesn't work (Elkins 2018; Olen 2015; Pratt 2019). Surprisingly, the academic literature on consumer budgeting has little to offer this debate: for all we know about the psychology of budgeting, we know very little about the extent to which budgets do (or do not) influence spending in the wild (Zhang and Sussman 2018). The goal of the present research is to address this gap in the literature.

Our examination of budget influence utilizes two distinct modes of inquiry. In study 1, we use naturally occurring data provided by a popular financial aggregation app to present a rich descriptive analysis of the relationship between consumers' self-generated budgets and their real world spending behavior. The novel structure of the data allows us to observe each user's pre-budget spending (i.e., how much they spend *before* they set a budget), their budget, and their post-budget spending for six months across three qualitatively different budget categories: dining and drinking, groceries, and fuel. The data also lets us compare the spending behavior of consumers who use the app to budget against the spending behavior of similar consumers who use the app to track their expenses but do not set budgets. In study 2, we supplement this descriptive analysis with an online financial diary study that examines the causal influence of budgets on spending by tracking consumers' spending after they have been randomly assigned to make a relatively high or low budget forecast. In tandem, this multi-method approach contributes an understanding of budget influence that is unprecedented in terms of its scope, longitudinal measurement, and ecological validity. It also contributes to theory by demonstrating a simple way to reconcile competing hypotheses regarding budget compliance, showing that budgets can be simultaneously wildly optimistic and economically meaningful, and examining the persistence of budget influence over time.

The remainder of this article will unfold as follows: we briefly review the theoretical backdrop against which the present research is set and present our hypotheses. We then present our studies, discuss the implications of our work for both theory and practice, and outline directions for future research.

THEORETICAL BACKGROUND AND HYPOTHESES

Do Consumers Comply With Their Budgets?

The consumer budgeting process consists of two stages. First, consumers set a budget by allocating money to an expense category. For example, a consumer may set a monthly budget of £250 to spend on groceries. Second, consumers track their expenses. This requires that expenses be both "booked" (noticed) and "posted" (assigned) to the correct expense category (Heath 1995; Heath and Soll 1996; Thaler 1985).

Consumer budgeting theory asserts that when expenses are easily booked and posted – as is the case when using a personal finance app – budgets will be "inflexible" (Heath and Soll 1996). This characterization of budgets is supported by lab studies showing that budgets constrain individuals' spending and investment decisions by decreasing their perceived disposal income (Heath 1995; Heath and Soll 1996). It is also supported by field studies showing that consumer spending on grocery trips closely approximates spending intentions because consumers build slack into their budgets for unplanned purchases (Stilley, Inman and Wakefield 2010). Taken together, these findings lead to the hypothesis that, generally speaking, consumers will comply with their budgets.

However, there are also reasons to expect that consumer spending will substantially deviate from budgeted spending. Research on planning fallacies has demonstrated that individuals' plans for the future are generally optimistic (see Buehler, Griffin and Peetz 2010 for a review). This implies that spending will be higher than budget, because budgets are a plan for future spending (Lynch et al. 2010; Novemsky and Kahneman 2005; Ulkumen, Thomas and Morwitz 2008), and optimism in this context is likely synonymous with the belief that certain expenses can be avoided. Similarly, research on consumer budget forecasting has demonstrated that people do not naturally incorporate contingencies into their expense predictions (Sussman and Alter 2012; Ulkumen, Thomas, and Morwitz 2008). This suggests that spending will exceed budget because plans are based on forecasts (Kahneman and Tversky 1979; Buehler, Griffin and Ross 1994), and budget forecasts simply do not account for all expenses that will arise. These findings lead to the hypothesis that consumers will spend significantly more than they budget.

We test these competing hypotheses in study 1 by comparing consumers' budgets and post-budget spending in three qualitatively distinct expense categories: dining and drinking, groceries, and fuel. Our expectation is that the tension between these hypotheses can be resolved by considering the nature of spending in each category. Specifically, we expect that budget compliance will be stronger (weaker) in expense categories in which the distribution of pre-budget spending displays relatively low (high) positive skew. This expectation is supported by research showing that consumers over-spend on exceptional expenses (which are most commonly found in the right-tail of a positively skewed distribution) because they are easily written off as an "exception to the rule" that won't occur again (Sussman and Alter 2012). It is also supported by experimental evidence demonstrating that expense forecasts are shaped by modal spending, which suggests that people will under-budget when their distribution of spending is positively skewed with mode < mean, as compared to when mode = mean (Howard, Hardisty and Sussman 2019). We therefore hypothesize that relative budget compliance will be stronger (weaker) in budget categories that display less (more) positive skew (H1).

Do Budgets Change Spending?

Regardless of whether or not consumers strictly comply with their budgets it is still possible for budgets to influence their spending. To illustrate this possibility, consider a consumer who typically spends £200 on dining and drinking per month, sets a budget of £100 for the next month, then ends up spending £150. All else equal, this consumer's budget has influenced their spending even though they have not strictly complied with their budget.

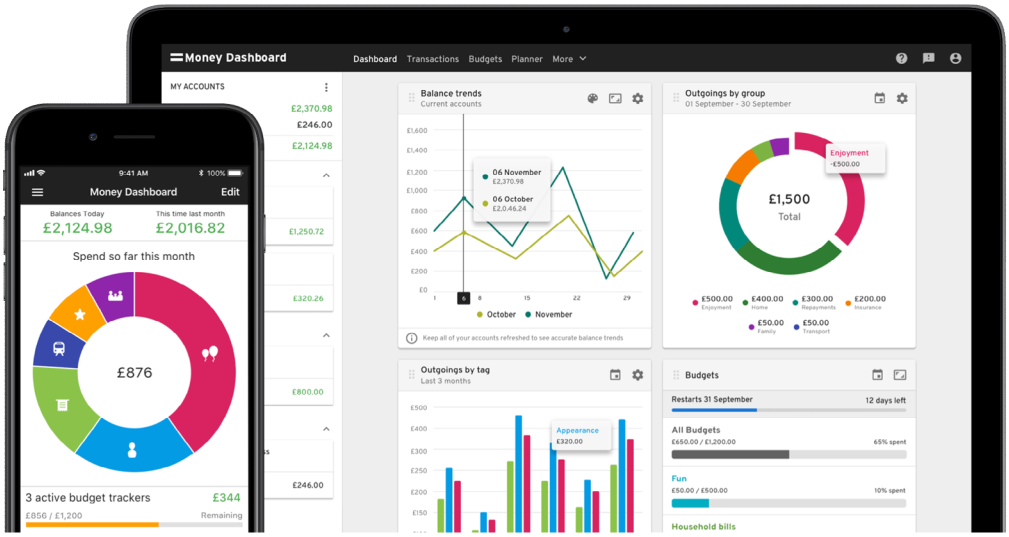
Mental accounting and consumer budgeting theory offer several reasons to believe that budgets will influence a consumer's spending to at least some degree. For example, setting a budget can act as a self-control device that helps consumers limit their spending by creating strict rules to follow like "do not spend more than $X on Y" (Heath and Soll 1996; Thaler 1985). Setting a budget may also constrain spending because once money is labeled for a specific use it can be psychologically challenging to spend it otherwise (Soman 2001; Thaler 1985). Furthermore, the act of expense tracking can impose a psychological tax on budget deviation, creating further incentive to limit spending (Heath and Soll 1996; Thaler and Shefrin 1981).

In tandem, these findings lead to three hypotheses regarding the general influence of budgets on spending. The first is that a higher (lower) budget will be associated with higher (lower) spending (H2). The second is that consumers who set budgets will spend less money post-budget than they did pre-budget (H3). The third is that consumers who set budgets will subsequently change their spending to a greater degree than similar users who do not set a budget (H4). We test each of these hypotheses in study 1.

STUDY 1:
THE RELATIONSHIP BETWEEN BUDGETS AND SPENDING IN THE WILD

We test H1-H4 using data provided by Money Dashboard (MDB), a financial aggregation app with approximately 70,000 active users in the UK. The primary function of MDB is to provide users with a holistic overview of their financial situation. To accomplish this, MDB collects and combines all transactional information across all financial accounts for each user. So, for example, if a user has two credit cards, a chequing account, and a savings account, MDB will aggregate all inflows and outflows across these cards and accounts and present the user with up-to-the-minute information on when, where, and how they are spending their money. Figure 1 shows the user interface for the mobile and web application.

Figure 1: Money Dashboard Interface



Spending Data

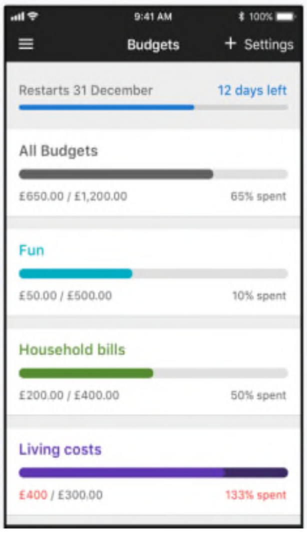
The data set includes all user transactions – more than 350 million – between January 2014 and December 2016. Each transaction is automatically assigned to a spending category by MDB (e.g., “Groceries”), and includes a merchant tag (e.g., “Tesco”) and time stamp. A particularly novel feature of the data is that we are able to observe each user’s transaction history from *before* they download the app and set their first budget, because MDB’s terms of service allow the app to access to each users’ transactional data for one year prior to downloading the app.

Cash spending represents 2.90% of total spending in our sample, and it appears in the dataset as ATM withdrawals. So, although we do not observe exactly what users spend their cash on, we do observe exactly how much they withdrawal. This allows us to estimate cash spending in each budget category using spending data from the UK Office for National Statistics (ONS).

Budgeting Data

The MDB budgeting function allows users to set budgets for expenses in multiple categories. For example, a user may set a monthly budget of £150 for dining and drinking, £200 for groceries, and £100 for fuel. MDB then automatically tracks transactions in these categories and allows users to observe their spending against their budget. Users do not receive any push notifications about their budget compliance and they have to manually login to track their expenses. However, when they do login, they are presented with a very salient illustration of their budget and remaining funds in each category, as shown in Figure 2.

Figure 2: Money Dashboard Budget Interface



In total, the dataset includes 9,403 monthly budgets. We focus our analysis on the three most popular budget categories: Dining and Drinking (n = 2,479), Groceries (n = 2,618), and Fuel (n = 1,127). Table 1 summarizes users' demographic, budgeting and account data.

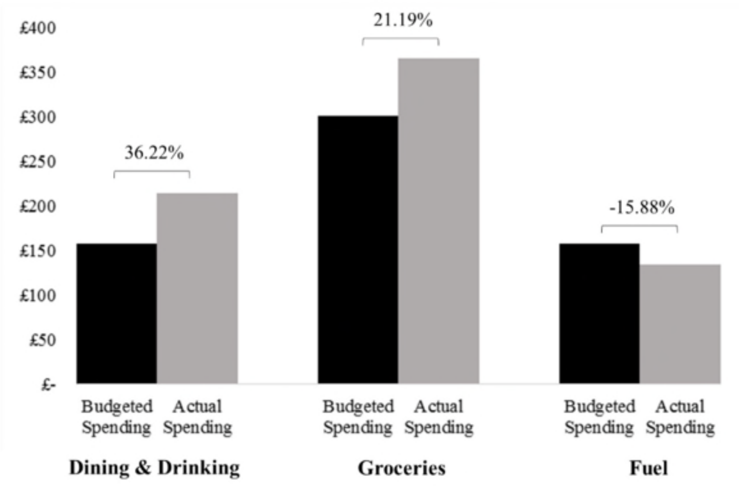
Table 1: User Profile Statistics

	Mean	Median	St. Dev.
Age	36.2	34	9.67
Annual Salary (£ 000's)	28.4	25	14.10
Logins per month	5.8	4	6.41
# of Budget Categories per User	1.58	1	0.709
# of Accounts Linked per User	4.69	4	3.54
% Male	68.2%	N/A	0.47
% England	85.6%	N/A	0.35
% Scotland	9.6%	N/A	0.30
% Wales	4.8%	N/A	0.21

Analysis and Results

Hypothesis 1. Figure 3 illustrates the raw difference between budgeted and actual spending across the three budget categories. Actual spending is significantly higher than budgeted spending for dining and drinking (mean difference = £56.50, SD = 202.00, $t(2,474) = 13.92$, $p < .001$) and groceries (mean difference = £63.48, SD = 259.05, $t(2,638) = 12.58$, $p < .001$), but significantly lower than budgeted spending for fuel (mean difference = -£23.84, SD = 118.26, $t(1,132) = 6.79$, $p < .001$), as revealed by within-subject t-tests.

Figure 3: Mean Budgeted and Actual Spending Across Categories in Study 1



To better understand the robustness of the results illustrated in figure 3 we next examine the percentage change in the price of goods in each budget category during our observation period (2014 to 2016), as reported by the UK Office of National Statistics. The change in the price of goods related to dining and drinking and groceries was negligible: prices related to dining and drinking rose by 2.0% and prices related to groceries fell by 2.53%. However, the price of fuel fell dramatically, by 15.59%, which is remarkably consistent with the difference between the amount consumers budgeted and spent on fuel (15.88%). This suggests that if consumers had known prices were going to fall and adjusted their budgets accordingly, their budgeted spending and actual spending on fuel would not have differed significantly.

Table 2 presents the skewness of pre-budget spending in each budget category for the average consumer, and the relative deviation between budgeted and actual spending adjusted for the change in the price of goods in each category. The results support H1: relative budget compliance corresponds closely to the amount of skew in each category.

Table 2:
Skew in the Distribution of Pre-Budget Spending and Budget Compliance Adjusted for Price Changes

	Skew	Adjusted %Overspend
Dining and Drinking	0.377	34.22%
Groceries	0.239	23.72%
Fuel	0.103	-0.29%

Hypothesis 2. To test our hypothesis that higher (lower) budgets are associated with higher (lower) spending we perform a panel regression analysis with the variables summarized in table 3. Formally, our regression model is:

$$Y_{ict} = \alpha_0 + \beta_0 * Budget_{ic} + \beta_1 * logins_{m_{it}} + \beta_2 * logins\_sq_{m_{it}}$$
$$+ X'_{it}\beta + \varepsilon_{it}$$

Table 3: Study 1 Regression Variables

Formula	Variable	Definition
Y	Dependent Variable:	Spending in the month directly after budget creation.
i	User identifier	Unique identifier for every money dashboard user.
c	Category identifier	Budget category identifier.
t	Date (in months)	Month and year of observation.
Budget	Total Budget	Absolute value of each user's budget.
$login_m$ (squared)	Logins per month (squared)	Sum of daily logins per month. Every day a user logs into their money dashboard account a login is registered. Hence, login ranges from 0 (no logins) to 31 (daily logins) per month. The squared term is included to account for the possibility of a non-linear relationship between login frequency and budget compliance.
X'	Vector of additional control variables	The vector comprises the below listed control variables.
	Age (squared)	The birth year of users is provided. Age is calculated as 2016 - birth year. The squared term is included to account for the possibility of a non-linear relationship between age and budget compliance.
	Gender identifier	This dummy variable is equal to one if the user is male and zero otherwise.
	Salary groups	Dummy variable for salary groups. Groups range from 0 to 10k, up to over 80k. We use the 20k to 30k group as our baseline because this group includes the largest number of users (38.27% of the sample).
	Month-of-the-year-FE	Dummy variable for month and year of budget creation.
	Country-FE	Dummy variables for Scotland and England, Wales is the baseline group.

Our regression results are presented in table 4. The positive coefficients for Budget provide support for H2 by demonstrating that lower (higher) budgets are associated with lower (higher) spending. In tandem, the positive coefficients for Logins and the negative coefficients for Logins Squared suggest a quadratic relationship between login frequency and spending, such that the positive marginal effect of login frequency on spending diminishes as the number of logins increases.

Table 4: Study 1 Regression Results for H2

This table summarizes our panel regression analyses for spending in the first month after budget creation. The dependent variable for all models is the spending per category in the relevant month.

VARIABLES	(1) **Dining & Drinking**	(2) **Groceries**	(3) **Fuel**
Budget	0.275***	0.566***	0.303***
	(0.0352)	(0.0342)	(0.0382)
Logins	-12.22***	-12.57***	-2.990***
	(1.479)	(1.992)	(1.080)
Logins squared	0.334***	0.343***	0.0570
	(0.0613)	(0.0850)	(0.0428)
Observations	2,471	2,602	1,124
Adjusted R-sq.	0.225	0.342	0.179
Demographic controls	YES	YES	YES
Salary-FE	YES	YES	YES
Month-of-Year-FE	YES	YES	YES
Country-FE	YES	YES	YES

Robust standard errors in parentheses. *** p<0.001, **p<0.01, *p<0.05

Hypothesis 3. Figure 4 and table 5 summarize the relationship between mean pre-budget spending in the month before budget creation and post-budget spending in the six months after budget creation. Supporting H3, post-budget spending in the month after budget creation is significantly lower than pre-budget spending in all three categories, as revealed by within-subject t-tests. Furthermore, spending continues to decrease for dining and drinking and groceries, such that spending is significantly lower six months after budget creation than it was in the first month after budget creation (although still significantly higher than budgeted spending). Spending on fuel displays the opposite trend, which is entirely consistent with the fact that demand for a good tends to rise when its price drops. Collectively, these results show that actual spending moves toward budgeted spending over time, regardless of whether the initial outcome was spending more than budget (as is the case for dining and drinking and fuel) or spending less than budget (as is the case for fuel).

Figure 4: Longitudinal Analysis of Mean Pre-Budget Spending, Budgets, and Post-Budget Spending

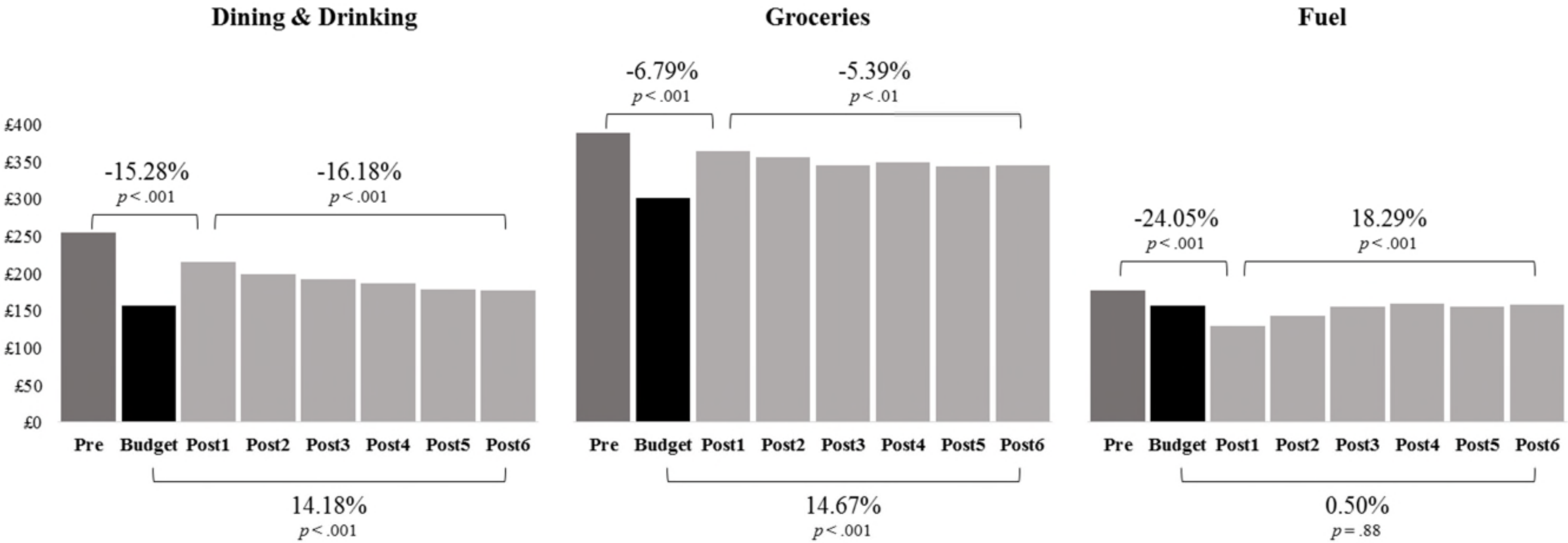


Table 5: Mean Difference between Pre-Budget Spending and Post-Budget Spending in Months 1–6 After Budget Creation in Study 1

	Panel A: First month					Panel B: Second month				
	mean	relative	sd	n	p-value	mean	relative	sd	n	p-value
Dining and drinking	37.87	15.28%	144.53	2,477	< 0.001	54.02	21.79%	154.30	2,478	< 0.001
Groceries	25.29	6.79%	191.41	2,612	< 0.001	31.19	8.37%	211.97	2,608	< 0.001
Fuel	43.98	24.05%	80.71	1,125	< 0.001	34.63	18.94%	93.76	1,124	< 0.001
	Panel C: Third month					Panel D: Fourth month				
	mean	relative	sd	n	p-value	mean	relative	sd	n	p-value
Dining and drinking	66.66	23.63%	169.93	2,478	< 0.001	74.68	26.89%	176.69	2,478	< 0.001
Groceries	38.56	10.17%	226.33	2,593	< 0.001	45.23	10.35%	231.78	2,591	< 0.001
Fuel	20.90	13.92%	91.42	1,121	< 0.001	22.81	11.43%	93.69	1,120	< 0.001
	Panel E: Fifth month					Panel F: Sixth month				
	mean	relative	sd	n	p-value	mean	relative	sd	n	p-value
Dining and drinking	66.66	30.13%	169.93	2,478	< 0.001	74.68	29.26%	176.69	2,478	< 0.001
Groceries	38.56	12.14%	226.33	2,593	< 0.001	45.23	12.45%	231.78	2,591	< 0.001
Fuel	20.90	12.47%	91.42	1,121	< 0.001	22.81	12.22%	93.69	1,120	< 0.001

Hypothesis 4. To test H4 we perform a propensity score matching analysis (Rosenbaum and Rubin, 1983; Imbens and Rubin, 2015) that allows us to compare the spending of budgeters to similar non-budgeters. Analytically, this parallels the approach taken by marketing researchers who have used secondary data of a similar nature to investigate the listening behavior of music streaming platform users (Datta, Knox and Bronnenberg, 2018). For budgeters, our dependent variable is the difference between their pre- and post-budget spending. For non-budgeters, the dependent variable is the same difference over the same time period but without a budget having been created. So, for example, if a user sets a budget on May 1st we compare the change in their spending from April to May against the change in spending of similar non-budgeters over the same two months.

We match budgeters and non-budgeters on login frequency, salary, age, gender, and country of residence. We then estimate differences between budgeters and non-budgeters for all of these matching variables (Leuven and Sianesi 2003). If matching is successful these variables should not differ significantly from each other ($p > 0.1$). Table 6 shows that this condition is fulfilled. However, even though our estimators are not significantly biased, we also report the results of a nearest-neighbour analysis which uses bias-corrected matching estimators as a robustness test (Abadie and Imbens 2011).

Table 6: Study 1 Propensity Score Bias Analysis

Variable	Treated	Control	%bias	t	*p*-value
age	37.34	37.061	2.8	0.8	0.426
salary	28.43	28.18	1.7	0.5	0.620
logins	7.4682	7.2759	3.1	0.8	0.422
male	0.69028	0.71134	-4.4	-1.33	0.184
England	0.84694	0.85426	-2	-0.59	0.553
Scotland	0.10324	0.1015	0.6	0.17	0.868
Wales	0.04982	0.04424	2.7	0.76	0.447

As can been seen in table 7, the results of our propensity score matching analysis support H4: budgeters were able to decrease their spending to a larger degree than similar non-budgeters across all three budget categories.

Table 7: Study 1 Matching Analysis

Coefficients represent average treatment effects. The first row shows results for the propensity score matching analysis. The second row shows results for the nearest neighbor analysis that makes use of the bias adjusted estimator developed by Abadie and Imbens (2011). The dependent variable is the month-to-month difference in spending before and after a budget was set. The selected matching variables are age, gender, salary groups, number of logins per month, month of the year, country (Wales, England, Scotland).

Delta Spending	(1) Dining and Drinking		(2) Groceries		(3) Fuel	
Treatment PSM	39.73***		34.34***		20.35**	
	(4.264)		(6.289)		(9.872)	
Treatment NN		42.57***		34.45***		22.32**
		(4.666)		(6.595)		(10.60)
Observations	70,476	63,467	80,840	76,358	54,931	42,355
Matching Variables						
Age	Yes	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes	Yes
Logins	Yes	Yes	Yes	Yes	Yes	Yes
Salary group	Yes	Yes	Yes	Yes	Yes	Yes
Month of the year	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Discussion

Study 1 offers a number of valuable insights regarding the relationship between budgets and spending. Budget compliance is shown to vary across categories, such that compliance is significantly stronger (weaker) in categories wherein spending is relatively less (more) skewed (H1). However, higher (lower) budgets are associated with higher (lower) spending across all three budget categories (H2), suggesting that budgets can influence spending even when budget compliance is weak. We also observe that post-budget spending is lower than pre-budget spending in all three categories (H3), and that this effect is surprisingly sticky. Finally, MDB users who set budgets subsequently decrease their spending to a greater degree than those who do not (H4).

Empirically speaking, the strengths of study 1 include unprecedented scope, ecological validity, and longitudinal measurement. One limitation of study 1 is that it is entirely descriptive, and budgeters may differ from non-budgeters in unobservable ways. To address this concern we begin by offering the following thought experiment: what if the budgeters in the data set are inherently more financially responsible than the non-budgeters? If true, then the budget compliance results become even more interesting because this implies that even relatively responsible consumers have trouble accurately forecasting their expenses and sticking to their budgets. It is also informative to consider the inverse: what if the budgeters in the data set are somehow *less* financially responsible than the non-budgeters? If true, then the results of the propensity score matching analysis become even more interesting because this implies that budgeting helped relatively less responsible consumers decrease their spending to a greater degree than their relatively more responsible peers. Furthermore, there is no reason to believe that MDB budgeters are any different from the tens of millions of consumers who currently use budgeting apps world-wide, which implies that are our results are likely indicative of a large group of consumers whose budgeting and spending behavior is of immense interest to marketing researchers. Nonetheless, we next present an experimental study that controls for unobserved individual differences through random assignment.

STUDY 2: THE FINANCIAL DIARY STUDY

The purpose of study 2 is to complement and extend the rich descriptive analysis in study 1 with experimental evidence that allows us to more cleanly examine the causal influence of budgets on spending. To accomplish this we randomly assigned consumers recruited via Amazon Mechanical Turk to one of two budget forecast conditions that were designed to produce relatively more or less optimistic budget forecasts. Participants then reported their actual spending in a series of online financial diary entries. Our principle expectation was that participants assigned to make more optimistic budget forecasts would subsequently spend less than those assigned to make less optimistic budget forecasts (H2).

Method

Participants. We recruited 450 American residents via Amazon Mechanical Turk to participate in a week long consumer finance diary study that required completing eight surveys (one survey per day from Sunday to Sunday). Payment for completing the first seven surveys was $0.50 and payment for completing the eighth survey was $7.00. Each survey took approximately 5 minutes to complete. Three hundred and forty participants completed the study in full (47.9% female; M_{age} = 39.34).

Procedure. In the first survey participants were randomly assigned to one of two budget forecast conditions: a control condition or an "outside-view" condition in which participants were prompted to consider their past spending before forecasting their future spending (Buehler, Griffin and Ross 1994; Kahneman and Tversky 1979). In the control condition we instructed participants to “Please take some time to estimate your expenses for the **next** week (i.e., the next 7 days).” On the following page we then asked participants to “Please enter your total estimated expenses (in dollars) for the **next** week.” Consistent with the results of study 1, our expectation was that budget forecasts in this condition would be relatively optimistic.

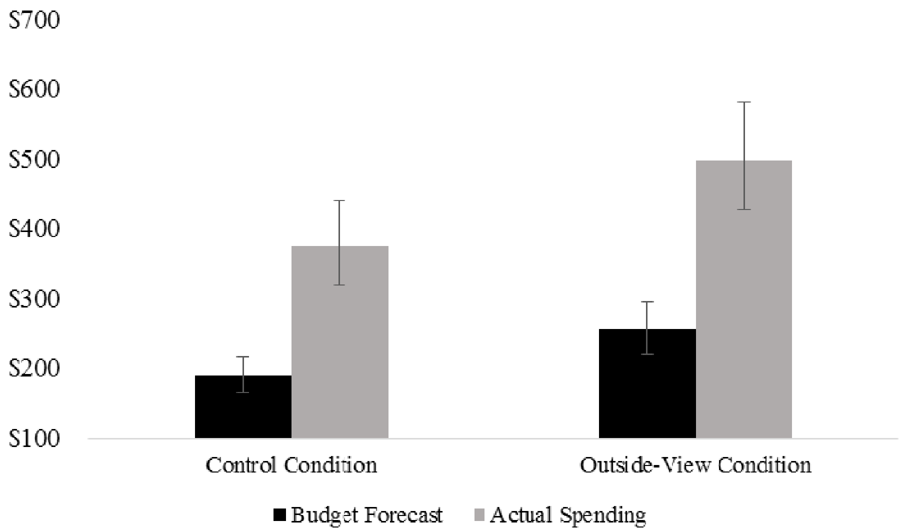
In the outside-view condition we instructed participants to “Please take some time to estimate your expenses for the **past** week (i.e., the past 7 days)” and “Please enter your total estimated expenses (in dollars) for the **past** week.” We then provided participants with the same forecast instructions as in the control condition. Our expectation was that forecasts in the outside-view condition would be less optimistic (i.e., higher) than in the control condition, because prompting people to take an outside-view (i.e., consider relevant past behavior) has been shown to produce higher forecasts regarding future behavior (Buehler, Griffin and Ross 1994; Peetz and Buehler 2012).

The seven “diary” surveys were fielded at 9pm EST Monday – Sunday during the target week. Participants who did not complete a diary survey within 24 hours of it being launched were excluded from the remaining diary surveys. Each of these surveys asked participants to describe each expense they had incurred that day (e.g., “groceries”) and report the amount of each expenses (e.g., “$57.39”) so that we could compare forecasted and actual spending.

Results

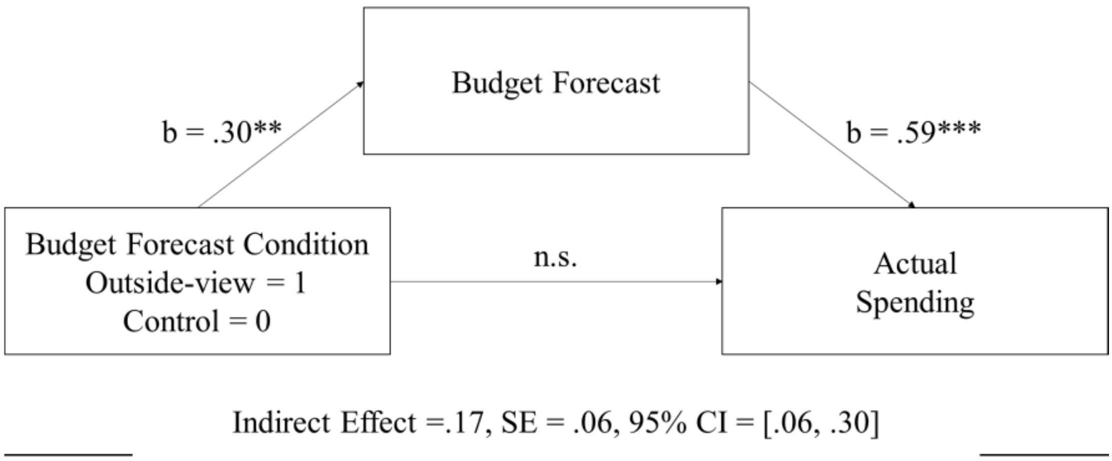
As illustrated in figure 5, participants in the outside-view condition made significantly higher budget forecasts (M = \$255.44, $CI_{95\%}$ = [220.15, 296.43]) than participants in the control condition (M = \$189.88, $CI_{95\%}$ = [165.64, 217.65]), as revealed by an independent samples t-test (t(336) = 2.91, *p* = .004). Participants in the outside-view condition also reported higher spending during the target week (M = \$498.35 $CI_{95\%}$ = [426.92, 581.73]) than participants in the control condition (M = \$374.32, $CI_{95\%}$ = [318.68, 439.70]). Finally, the difference between budget forecast and actual spending did not differ between conditions (t(336) = .17, *p* = .87).

Figure 5: Mean Budget Forecast and Actual Spending in Study 2



Mediation Analysis. To investigate the relationship between budget forecast condition, budget forecasts, and actual spending we tested a mediation model with condition (control = 0, outside-view = 1) as the independent variable, actual spending as the dependent variable, and budget forecast as the mediating variable. The indirect effect of condition on actual spending via budget forecast was significant (indirect effect =.17, SE = .06, 95% CI = [.06, .30]). Specifically, the model confirms that budget forecasts were significantly higher in the outside-view condition than in the control (b = .30, 95% CI = [.10, .50]; t(336) = 2.91, *p* = .004), and demonstrates that higher budget forecasts are associated with higher actual spending even while controlling for condition (b = .59, 95% CI = [.50, .70]; t(335) = 11.56, p < .001). This result holds controlling for participant income, self-reported average weekly spending, and age (indirect effect =.10, SE = .04, 95% CI = [.02, .19]).

Figure 6: Study 2 Mediation Analysis



Discussion

Study 2 complements and extends study 1 by examining the causal influence of budgets on spending. Consistent with the descriptive results of study 1, a higher (lower) budget causes higher (lower) spending, even though budget compliance is weak. Taken together, the results of study 2 provide further evidence that budgets are simultaneously optimistic and influential.

GENERAL DISCUSSION

The present research was motivated by a question of substantive importance to consumers, the firms that serve them, and the scholars who study their behavior: do budgets work? The evidence suggests that they do, although not perfectly. We now discuss the implications of our findings and directions for future research.

Budget Compliance and Distributional Skew

In study 1 we demonstrate that budget compliance corresponds closely with the amount of skew in the distribution of pre-budget spending (H1). We argue that this is because budget compliance is a two sided variable: it first requires consumers to accurately plan or forecast what they need, then it requires them to stick to their budget. Distributional skew is therefore a useful predictor of budget compliance because it captures both sides of this equation: higher positive skew makes *under*-budgeting more likely (Howard et al. 2019), and it represents the exceptional expenses that consumers are most likely to *over*-spend on (Sussman and Alter 2012).

By providing evidence that compliance and skew are related in the real world, we extend lab research showing that experimentally increasing the amount of skew in a spending distribution makes forecasts lower and less accurate (Howard et al. 2019). In tandem, these findings make an important contribution to the forecasting literature by documenting the ways in which distributional skew can negatively impact forecast accuracy. These findings also have implications for firms that need to predict consumers' ability to stay on budget (e.g., loan service or debt collection companies), because it suggests that spending skew is a simple way to do so. Similarly, consumers who need to accurately predict their own future spending (e.g., when taking out a mortgage) should be advised to consider the right tail of their spending distribution so that they don't overspend today as a result of underestimating what they will spend tomorrow.

One fruitful avenue for future research in this area is to better understand the extent to which skew captures under-budgeting versus overspending. Similarly, we think it is well worth identifying outcomes that are negatively skewed and investigating the extent to which negative skew represents over-budgeting and/or underspending. Finally, it is important to gain a better understanding of what psychological concepts can be mapped onto skew (or vice versa). For example, does low versus high positive skew reflect the continuum between ordinary and exceptional expenses (Sussman and Alter 2012)?

Optimism and Influence

Research on planning and forecasting is often focused on reducing prediction optimism (e.g., Buehler et al. 1994; Howard et al. 2019; Peetz and Buehler 2012; Peetz et al. 2015; Ulkumen et al. 2008). One reason for this is undoubtedly that de-biasing techniques can inform theory, but this focus is also driven in large part by the assumption that optimistic forecasts are detrimental, and that realistic forecasts are beneficial (Howard et al. 2019). This assumption is undoubtedly true in some circumstances: for example, consumers who take out a mortgage or lease a car based on an optimistic forecast of their future spending will likely find themselves in a financial bind that could have been avoided had they made a more realistic forecast that led them to borrow less. However, the present research provides evidence that budget optimism is, with respect to ongoing monthly expenditures, generally a good thing. Future work can and should look deeper into the boundary conditions of this effect and identify when or for whom budget optimism backfires, and more clearly delineate the types of circumstances in which optimism and realism are preferred.

Longitudinal Influence

Past research has shown that plans and forecasts either do not influence behavior (Buehler et al. 1994; Peetz and Buehler 2009; Ulkumen et al. 2008), or that their influence diminishes quickly (Buehler et al. 2010). However, we found in study 1 that actual spending continued to move toward budgeted spending even six months after a budget was set. Moreover, this occurred regardless of whether the initial outcome was spending more than budget (as was the case for dining and drinking and groceries) or less than budget (as was the case for fuel). This not only suggests that budgets influence spending, it suggests that budget influence is remarkably sticky.

We believe one explanation for the difference between our results in this regard and past research is that MDB users engage in a relatively high degree of expense tracking (i.e., behavior monitoring). Thus, their budget becomes a very salient reference point against which they can compare their spending behavior. Moreover, because the app makes past spending behavior easily accessible, it is likely that consumers are motivated by the observation that they are spending less than they used to, rather than becoming demotivated by the observation that they have spent more than they budgeted (Soman and Cheema 2004). Future research on the temporally extended influence of plans and predictions on behavior should test this conjecture. It is also well worth investigating the extent to which behavior-monitoring can ameliorate the planning fallacy.

The Nature of Budgeting

The present research offers a great deal of insight into the nature of budgeting. First and foremost, we demonstrate that budgets influence spending, even when budget compliance is weak. We also provide evidence that budget influence is sticky, and that it is not contingent on initial success. In sum, these results indicate that budgets do work, even if they are not quite as inflexible as was once believed.

REFERENCES

Abadie A & Imbens GW (2011). Bias-corrected matching estimators for average treatment effects. In *Journal of Business Economics and Statistics* (Vol. 29: pp. 1–11)

Bell, A. (2019). “Six Reasons Why You Need a Budget,” https://www.investopedia.com/financial-edge/1109/6-reasons-why-you-need-a-budget.aspx

Buehler, R., Griffin, D., & Peetz, J. (2010). The planning fallacy: Cognitive, motivational, and social origins. In *Advances in experimental social psychology* (Vol. 43, pp. 1-62). Academic Press.

Caldwell, M. (2019). “Reasons Why You Should Budget Your Money,” https://www.thebalance.com/reasons-to-budget-money-2385699

Credit Counselling Society 2019. “What is Budgeting? What is a Budget?” https://www.mymoneycoach.ca/budgeting/what-is-a-budget-planning-forecasting

Elkins, K (2018). “39-year-old retired millionaire: ‘Budgets don’t work’—do this instead,” https://www.cnbc.com/2018/12/26/39-year-old-retired-millionaire-budgets-dont-work-do-this-instead.html

Heath, Chip (1995), "Escalation and De-escalation of Commitment in Response to Sunk Costs: The Role of Budgeting in Mental Accounting," *Organizational Behavior and Human Decision Processes*, 62, 38-54.

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

Howard, C., Hardisty, D., Sussman, A. (2019a). *Working paper.* A Prototype Theory of Consumer Misprediction.

Imbens, GW & Rubin, DB (2015) Causal Inference in Statistics, Social, and Biomedical Sciences. Cambridge University Press, New York.

Kahneman, Daniel and Amos Tversky (1979), “Intuitive prediction: Biases and corrective procedures,” *TIMS Studies in Management Science, 12,* 313-327.

Leuven, E & Sianesi, B. (2003). "PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing," Statistical Software Components S432001, Boston College Department of Economics, revised 01 Feb 2018

Olen, H. (2015). Toss Your Budget - Why a pillar of personal finance isn’t nearly as essential as we think. On http://www.slate.com/articles/business/the_bills/2015/06/ personal_budgets_are_overrated_seriously.single.html, accessed: 15.01.2019

Pratt, B. (2019). “Why Budgets Don’t Work,” https://www.themoneyprofessors.com/why-budgets-dont-work/

Peetz, J., & Buehler, R. (2009). Is there a budget fallacy? The role of savings goals in the prediction of personal spending. *Personality and Social Psychology Bulletin*, 35(12), 1579-1591.

Point of Purchase Advertising Institute (1995), The 1995 POPAI Buying Consumer Habits Study, Englewood, NJ: Point of Purchase Advertising Institute.

Rosenbaum, P. & Rubin, DB. (1983) The central role of the propensity score in observational studies for causal effects. In *Biometrika*, 70(1), 41–55.

Soman, D. (2001). Effects of payment mechanism on spending behavior: The role of rehearsal and immediacy of payments. *Journal of Consumer Research*, *27*(4), 460-474.

Soman, D. and Cheema, A., 2004. When goals are counterproductive: The effects of violation of a behavioral goal on subsequent performance. Journal of Consumer Research, 31(1), pp.52-62.

Stilley, K. M., Inman, J. J., & Wakefield, K. L. (2010). Planning to make unplanned purchases? The role of in-store slack in budget deviation. *Journal of Consumer Research*, 37(2), 264-278.

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

Thaler, R. H., & Shefrin, H. M. (1981). An economic theory of self-control. *Journal of political Economy*, *89*(2), 392-406.

Thaler, R. (1985), "Mental Accounting and Consumer Choice," *Marketing Science*, 4, 119-214.

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

Ülkümen, G., Thomas, M., & Morwitz, V. G. (2008). Will I spend more in 12 months or a year? The effect of ease of estimation and confidence on budget estimates. *Journal of Consumer Research*, *35*(2), 245-256.

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

The Centre for Responsible Banking & Finance
CRBF Working Paper Series
School of Management, University of St Andrews
The Gateway, North Haugh,
St Andrews, Fife,
KY16 9RJ.
Scotland, United Kingdom
http://www.st-andrews.ac.uk/business/rbf/

Recent CRBF Working papers published in this Series

First Quarter | 2021

21-004 **Ross Brown and Marc Cowling:** The Geographical Impact of the Covid-19 Crisis for Firms and Jobs: Evidence from the 100 Largest Cities and Towns of the UK.

21-003 **Javier Gomez-Biscarri, Germán López-Espinosa, Andrés Mesa Toro:** Drivers of Depositor Discipline in Credit Unions.

21-002 **Manthos D. Delis, Iftekhar Hasan, Maria Iosifidi, Steven Ongena:** Gender, Credit, and Firm Outcomes.

21-001 **I-Ju Chen, Iftekhar Hasan, Chih-Yung Lin, Tra Ngoc Vy Nguyen:** Do Banks Value Borrowers' Environmental Record? Evidence from Financial Contracts.

Fourth Quarter | 2020

20-018 **Angelos Kanas and Philip Molyneux:** Systemic Risk and CO2 Emissions in the US.

20-017 **Bill Francis, Iftekhar Hasan, Yinjie (Victor) Shen, Qiang Wu:** Do Activist Hedge Funds Target Female CEOs? The Role of CEO Gender in Hedge Fund Activism.

20-016 **Iftekhar Hasan, Qing He, Haitian Lu:** Social Capital, Trusting, and Trustworthiness: Evidence from Peer-to-peer Lending.

20-015 **Javier Gomez Biscarri, Germán López-Espinosa, Andrés Mesa Toro:** Remuneration as a Motivation of Earnings Management in Credit Unions.

Third Quarter | 2020

20-014 **Ross Brown, Jose M. Liñares-Zegarra, John O.S. Wilson:** Innovation and Borrower Discouragement in SMEs.

University of St Andrews
Scotland's first university

600 YEARS
1413 – 2013