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Mental accounting and small windfalls: Evidence from an online grocer

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ABSTRACT

We study the effect of small windfalls on consumer spending decisions by comparing the purchases online grocery customers make when redeeming $10-off coupons with the purchases they make without coupons. Controlling for customer fixed effects and other variables, we find that grocery spending increases by $1.59 when a $10-off coupon is redeemed. The extra spending associated with coupon redemption is focused on groceries that a customer does not typically buy. These results are consistent with the theory of mental accounting but are not consistent with the standard permanent income or lifecycle theory of consumption. While the hypotheses we test are motivated by mental accounting, we also discuss some alternative psychological explanations for our findings.

1. Introduction

In the course of daily life, people occasionally receive small windfalls. Every so often we are handed a gift certificate for $5 off a meal at our favorite local restaurant, find a $10-bill on the street, or win $20 in an impromptu game of poker. According to the standard permanent income or lifecycle theory of consumption (Friedman, 1957; Modigliani and Brumberg, 1954),[2] these types of small windfalls should have no noticeable effect on spending decisions because such windfalls constitute meaningless changes to lifetime wealth. However, if you have ever been the recipient of a small windfall, you may remember thinking about ways to put this unexpected cash to use buying items you might not have otherwise purchased. This kind of behavior can be interpreted as an example of "mental accounting" (Thaler and Shefrin, 1981). In this paper, we present evidence supporting predictions made by the theory of mental accounting about the way consumers respond to small windfalls in the domain of online grocery shopping. We also discuss other psychological explanations that could account for our findings.

Thaler and Shefrin have argued that people create mental accounting systems, similar to the way organizations create accounting systems, to organize and manage their financial decisions (Thaler and Shefrin, 1981; Thaler, 1985, 1990, 1999; Shefrin and Thaler, 1988). According to this theory, rather than grouping all decisions together and optimizing consumption choices over a life-long horizon, people categorize their activities into "mental accounts" and make decisions within the con-

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[2] The "standard" permanent income or lifecycle theory refers to the certainty-equivalent version.

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text of these narrow spending and saving categories. An implication of the theory that individuals create mental accounts to manage their consumption decisions is that they will respond to small, unanticipated windfalls by spending them immediately and purchasing items that they would not buy unless their budget set were significantly expanded. Consumers who engage in mental accounting will behave as if they have received a meaningful wealth shock when they receive a small windfall because that is indeed the case within the relevant, narrowly framed mental account.

The theory of mental accounting motivates the hypotheses tested in this paper. However, there are other psychological explanations that can account for the observation that people increase their spending in a given domain in response to a small windfall in that domain. One relevant explanation is that people engage in reciprocity (Rabin, 1993). It is possible that gratitude towards the provider of a small windfall might inspire a desire to reciprocate, which could lead consumers to substitute away from spending money with the windfall provider's competitors and increase their spending with the windfall provider. Alternatively, happiness triggered by the receipt of an unexpected small windfall might cause people to spend money more freely.

It has been demonstrated in the laboratory that people spend more out of unexpected income than out of anticipated income (Arkes et al., 1994). To extend the study of the effect of small windfalls on spending beyond the laboratory setting and to examine the precise items purchased by the recipients of small windfalls, we analyze a novel data set from an online grocer containing individual-level information about grocery purchases over the course of a year. This data set includes information about the decisions made by thousands of consumers both when they redeem coupons of a certain type for $10 off their online grocery orders and when they order groceries without any such discount.

A $10-off coupon of the type examined in this paper can be sent by a first-time patron of the online grocer we collaborated with to any other person she likes. We argue that the date on which a customer receives such a $10-off coupon is exogenous from the point of view of that customer. Under this assumption, we can estimate the effect of a $10-off coupon on grocery spending by comparing each customer's orders with coupons to her orders without coupons. When we regress spending for a grocery order on an indicator variable for whether or not the order involved a $10-off coupon, we find that coupon use increases spending by $1.59, controlling for customer fixed effects and other factors.[3] We also find evidence that these spending increases are particularly focused on "marginal" grocery items, which we define as items that a customer does not typically purchase.

These results are inconsistent with the standard permanent income or lifecycle theory of consumption, but they are consistent with explanations invoking psychological influences on consumption decisions. As mentioned above, we use the theory of mental accounting to motivate our primary hypotheses, but we also discuss other psychological factors that could explain our findings.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature and formalizes our hypotheses about windfall spending. In Section 3 we describe our data set and regression specification. We present our results in Section 4, and Section 5 concludes.

2. Relevant literature and hypotheses

2.1. Related conceptual literature

As discussed above, we draw from past research on mental accounting to establish the hypotheses tested in this paper. The previous literature on mental accounting argues that people group their financial resources and expenditures into "mental accounts" and make decisions within the context of those narrowly defined accounts instead of integrating all decisions together in a single optimization problem (Thaler and Shefrin, 1981; Thaler, 1985, 1990, 1999; Shefrin and Thaler, 1988; Levav and McGraw, 2009). A number of factors have been posited as drivers of this behavior. One possibility is that mental accounts help people manage their spending in the face of self-control problems—by budgeting only a certain amount of money towards a category of consumption, people may be better able to resist overspending (Thaler and Shefrin, 1981; Shefrin and Thaler, 1988). Mental accounting has also been discussed as a psychological framing device that complements the prospect theory value function. This value function is concave in gains relative to a reference point, and it is both steeper and convex in losses relative to that reference point (Kahneman and Tversky, 1979). An individual who judges outcomes according to a prospect theory value function may use mental accounting to integrate or segregate outcomes in order to achieve favorable evaluations when applying the value function to those outcomes (Thaler, 1985).[4] Finally, mental accounting may be driven by the need to simplify an otherwise complex decision problem because of limitations on cognitive resources (see, for example, Read et al., 1999). A straight-forward prediction of mental accounting is that when consumers receive an unexpected small windfall they will behave as if they have received a meaningful shock to their wealth in the relevant mental account, spending more than usual in that domain and buying items they would not otherwise purchase.

While mental accounting predicts that online grocery spending will be responsive to the receipt of a $10-off coupon, there are other models motivated by psychological considerations that might also make this prediction. One relevant stream

[3] In this paper, we use the term "spending" to denote the total price of the groceries in a customer's order, ignoring the effects of taxes, delivery fees, and coupons on the customer's out-of-pocket expenses.

[4] Also see Prelec and Loewenstein (1998) for a discussion of the hedonic implications of these kinds of framing effects.

of previous research has demonstrated that people tend to engage in reciprocity (see Rabin, 1993 for a discussion). In a study of reciprocity conducted by Goranson and Berkowitz (1966), subjects worked considerably harder on a laboratory task when their performance improved the pay of someone who had previously helped them than when it improved the pay of someone who had not. If people experience a positive emotional response towards a company (in this case, an online grocer) that provides a small windfall, they may want to engage in reciprocity by substituting away from spending money with the company's competitors and by increasing their spending with the company. This could also lead people to increase their spending on "marginal" goods with a given company when they receive a small windfall.

Another possibility is that the receipt of a small windfall induces happiness in consumers, which causes them to spend money more freely. Positive affect has not previously been shown to increase spending (see Isen, 2000 or Isen, 2008 for a review), and there is in fact evidence that sadness increases spending relative to a baseline state (Lerner et al., 2004; Cryder et al., 2008). Nonetheless, it is still possible that the happiness induced by the receipt of a small windfall leads people to spend more than usual. Positive affect has been shown to increase variety-seeking behavior (Kahn and Isen, 1993), so the receipt of a small windfall could lead people to increase their spending on goods they do not usually buy.

2.2. Related empirical literature

Our findings build on past research examining the responsiveness of spending to the receipt of windfalls. A series of papers studying windfalls that were considerably larger than those analyzed in this paper demonstrated that households have a higher propensity to consume out of windfall income than out of regular income and that this propensity to consume decreases as the size of a windfall increases (Bodkin, 1959; Kreinin, 1961; Bird and Bodkin, 1965; Doenges, 1966; Landsberger, 1966; Abdel-Ghany et al., 1983; Keeler et al., 1985). Another set of empirical studies has analyzed the response of consumption to anticipated changes in income rather than unanticipated wealth shocks. According to the standard permanent income or lifecycle theory, changes in consumption should coincide with the announcement of an income change and not with the anticipated change itself, but the results of many studies contradict this hypothesis (Poterba, 1988; Wilcox, 1989; Parker, 1999; Souleles, 1999, 2002; Johnson et al., 2006).[5] In a paper that specifically addresses the implications of mental accounting, Baker et al. (2007) documented a strong response of consumption to the receipt of stock dividends, controlling for total stock returns. This evidence is consistent with mental accounting and inconsistent with standard economic models, which predict that only total returns (not the decomposition of returns into dividends and capital gains) should affect consumption.

Experimental studies have also found evidence consistent with the predictions of mental accounting. Arkes et al. (1994) demonstrated that unexpected small windfalls ($3–5) are more likely to be spent on gambling or at a basketball game than anticipated windfalls of the same size. Heilman et al. (2002) examined the effect of $1 coupons for particular grocery items on the behavior of grocery shoppers and found that the coupons increased consumers' unplanned spending as well as their total spending.[6] Finally, in research contemporaneous with ours, Abeler and Marklein (2008) studied how restaurant patrons responded to an unexpected windfall in the form of a discount on their bill. They found that customers who received an €8 discount spent an average of €3.52 more than other patrons.

Our results are complementary to those presented in the studies discussed above, but the unique nature of our data set helps to distinguish our contribution from much of the prior literature. Previous field studies have predominantly focused on people's responses to moderate or large windfalls, typically with average values on the order of $500 (at today's price levels). People may use different decision-making processes when faced with small windfalls as opposed to large windfalls, perhaps relying more heavily on heuristics to govern spending because of the low perceived costs of errors, so it is interesting to study responses to small windfalls separately from responses to large ones, especially if systematic patterns in small-stakes choices can aggregate across multiple decisions to have a large cumulative impact. Another important advantage of our data set is that it allows us to directly examine the purchases customers make after receiving a windfall rather than relying on survey data to determine how windfall income is spent. This feature of the data also enables us to disaggregate total spending to the level of individual grocery items, making it possible to perform a detailed comparison of the products purchased in grocery orders with coupons and those purchased in grocery orders without coupons. Finally, because our data set is from the online grocery domain, we can infer that the $10 windfalls we study are inconsequential in the context of the overall wealth of the consumers who receive them and that they do not meaningfully ease these consumers' liquidity constraints. In order to be included in our sample, consumers must be able to afford both Internet access and the fees associated with ordering groceries for delivery.

2.3. Hypotheses

Applying the theory of mental accounting to the online grocery shopping context, we posit that customers assess their online grocery spending in the context of a specific mental account, such as their "weekly living expenses" account or

[5] Others, however, find evidence consistent with the standard permanent income or lifecycle theory (see Hsieh, 2003, for example). For a more thorough review of the literature on excess sensitivity, see Browning and Lusardi (1996).

[6] Of course, these results may be due to substitution effects induced by category-specific coupons, which change the relative prices of goods. This explanation is supported by the authors' observation that spending increased for goods that are complements to the discounted groceries.

their "monthly groceries" account. Because individuals who engage in mental accounting apply category labels both to expenditures that fall in a particular account and to the financial resources that are available in the account, the $10-off online grocery coupon that we study is likely to be coded as a windfall in the mental account that includes online grocery spending. Even though the $10-off coupon represents an immaterial windfall in the context of the online grocery customer's lifetime wealth, it may constitute a meaningful unexpected increase in the financial resources devoted to the mental account that encompasses the customer's current online grocery order. Since resources have limited fungibility across mental accounts, we expect the customer to use the additional financial resources in this mental account to increase expenditures associated with the account, including expenditures on online groceries.

This reasoning underlies the two primary hypotheses we examine in this paper. First, we test the hypothesis that:

H1. The redemption of a $10-off discount coupon is associated with a significant increase in online grocery spending. This hypothesis is inconsistent with the predictions of the standard permanent income or lifecycle theory but consistent with the predictions of mental accounting. Second, because the receipt of a $10-off coupon leads a customer to allocate more money to online grocery purchases than she otherwise would, the coupon's impact on the composition of groceries in a customer's order should be analogous to the impact of a wealth increase in the customer's choice problem over groceries. That is, we expect customers who receive such a windfall to substitute higher quality products for lower quality ones and to purchase products that they would not normally purchase unless their budget set were significantly expanded. Our second hypothesis is therefore that:

H2. The redemption of a $10-off discount coupon is associated with an increase in spending on goods that customers do not purchase in the absence of a coupon. Our empirical analysis supports both hypotheses.

3. Data set and empirical strategy

3.1. Online grocery business model

The online grocer we collaborated with operates in North America and serves urban customers. Its customers place orders by visiting a website where they may tour virtual supermarket aisles or search for specific products as they make decisions, one by one, about what items to add to their online shopping carts. Returning customers have easy access to the lists of items they purchased on their previous shopping trips to facilitate repeat purchases. Customers can schedule a delivery in the near term or many days in advance. During the period studied, the grocer charged a delivery fee for all orders. In addition, customers were required to spend a minimum dollar amount on each order.[7]

3.2. Online grocery data set

We obtained a novel panel data set from the aforementioned online grocery company containing information about the orders placed by all of the company's customers between January 1, 2005 and December 31, 2005. The online grocery company provided a record of each item in each order as well as the price each customer paid for each item, the date of each order, the date of each order's delivery, and the customer who placed each order. In addition, if a discount coupon was used during an order, we were given information about the type of coupon the customer used and the size of the discount he or she received. If a customer modified his or her order, we were told how many times order modifications were made, as well as the first and last dates when the customer modified his or her shopping basket. All customer accounts in our data set are labeled by anonymous, unique ID numbers, and all customer ID numbers are accompanied by the date when a customer first placed an online grocery order. Our online grocery collaborator also provided us with detailed information about the items available for purchase through its website, including their category and brand.

We restrict our analysis to customers who made use of a particular $10-off discount coupon sometime between January 1, 2005 and December 31, 2005. New patrons of the online grocer in 2005 were allowed to send one of these coupons to an e-mail address of their choice, excluding their own. The motivation for offering these coupons was to thank customers who encouraged others to order from the online grocer. We assume that the timing of the receipt of such a coupon is exogenous from the recipient's point of view, since customers have little if any control over when they will receive this coupon.

In total, between January 1, 2005 and December 31, 2005, there were 4435 customers who used a $10-off discount coupon of the type described above. We eliminate spending outliers (top 1 percent), outliers in the number of visits made to the grocer's website during an order (top 1 percent),[8] any orders that made use of other kinds of discount coupons,[9] orders by

[7] This minimum dollar amount was well above $10, so our empirical results are not driven by customers using their $10-off coupons for orders larger than $10 and placing orders for less than $10 without coupons.

[8] We eliminate spending outliers and orders involving an unusually large number of visits to the grocer's website so that these observations do not exert undue influence on the results of our regression analyses. We drop orders that are outliers relative to the entire universe of online grocery orders from 2005, not relative to the data set that only includes customers who redeemed a $10-off coupon in 2005. This procedure eliminates 2058 data points. Our results do not rely on the elimination of these outliers. In fact, including outliers in the data set strengthens our results considerably.

[9] We eliminate orders involving all other types of discount coupons for two reasons. First, we are concerned that many of these coupons impose conditions on customers when redeemed that may induce atypical shopping behavior. For example, some coupons expire quickly, some impose a higher than usual

Table 1
Grocery order summary statistics.

	Mean	Standard deviation
Spending	150.23	57.47
Number of groceries	59.38	23.16
Number of web visits for order	3.88	2.86
Days between first and last web visits for order	7.54	16.87
Days since last delivery	17.69	21.20

This table reports grocery order summary statistics describing our primary data set.

Table 2
Coupon use summary statistics.

	Percentage of a customer's orders involving a coupon redemption	Number of orders per customer involving a coupon redemption
Min	1.49	1
25th percentile	6.67	1
Median	12.50	1
75th percentile	25.00	1
Max	50.00	5
Mean	17.95	1.08

This table reports coupon use summary statistics from our primary data set. For each customer, we calculate the percentage of orders involving a coupon redemption and the number of orders involving a coupon redemption. We then present the distributions of these statistics across customers (customers = 2889; coupons = 3110; orders = 34,410).

customers who never shopped in 2005 without redeeming a coupon,[10] and each customer's first order of the year.[11] We are left with 34,410 grocery orders placed by 2889 customers, giving us an average of 11.9 order observations per customer. The average dollar size of an order in this sample is $150.23, and the average grocery order consists of 59 items. Of the orders in our data set, 3110 (approximately 9 percent) involve the redemption of a $10-off coupon. The average date when a customer in our data set placed her first order with the online grocer is April 21, 2004. For additional summary statistics, see Table 1.

Table 2 shows summary statistics about the percentage of a customer's 2005 orders that involved coupon redemptions. The summary statistics presented in this table suggest that online grocery customers did not find ways to send themselves $10-off discount coupons, as nearly all customers in our data set redeemed just one such coupon in 2005. Another piece of evidence suggesting that customers rarely if ever found ways to send themselves $10-off discount coupons is that after a customer redeemed her first coupon she placed an average of seven subsequent orders without a coupon. This statistic would be much lower if customers regularly created new accounts with which to send themselves $10-off coupons. In addition, by dropping all customers' first orders of the year and all orders placed by customers who never shopped without a $10-off coupon in 2005, we necessarily drop any orders placed by customers who created new accounts solely to receive and redeem $10-off coupons they managed to send themselves. Finally, even though some customers may have created a new account associated with a new e-mail address in order to place a "first order" with the online grocer and send a $10-off coupon to another account under their control, new accounts do not give customers access to their previous shopping lists, so customers would have to fill their baskets from scratch without the benefit of easily viewing and selecting items they had previously purchased. The online grocer believes that this creates a fairly strong disincentive for customers to create fake "new" accounts in order to send themselves coupons.

Throughout the year, a relatively constant proportion of orders placed by the customers in our sample involved the redemption of a $10-off discount coupon.[12] Fig. 1 presents a graph over time of the fraction of orders placed that involved the use of such a coupon.

minimum spending requirement, and some are only redeemable for certain types of groceries. Second, many of these coupons are not awarded at random but are instead offered to customers when they exhibit certain purchasing patterns. We address potential biases resulting from our exclusion of these coupons when we present our results (see Section 4.3). By dropping these orders, we eliminate 7736 data points.

[10] We eliminate orders placed by customers who never shopped in 2005 without redeeming a coupon because such customers may be different from the population of customers who shopped both when in possession of a coupon and when no coupon was available. By dropping these orders, we eliminate 696 data points.

[11] In our regression analyses, we control for the amount of time that has elapsed since a customer's previous order. We eliminate each customer's first order of the year because we are unable to calculate this variable for these observations. By dropping these orders, we eliminate 2,889 data points. If we instead include these orders in our sample and drop from our regression specifications the control variables for the amount of time since a customer's previous order, the magnitude and statistical significance of our results are weakened in regression (3) but not in any other regressions.

[12] Although we do not have detailed information about the lag time between when a customer received such a coupon and when it was redeemed, the online grocer informs us that such coupons are typically redeemed about one month after they are received. Since the median customer in our data set placed 12 orders in 2005, this suggests that when customers receive this type of coupon, they often redeem it on the next grocery order they place.

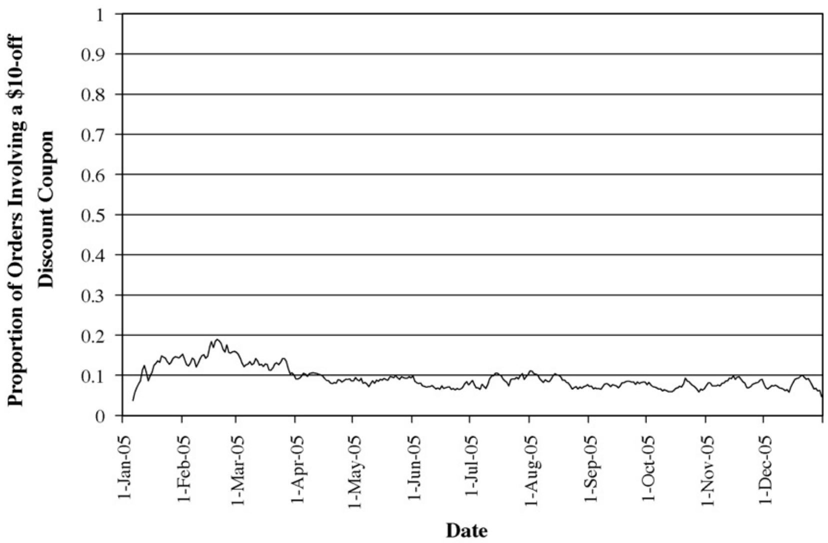

Fig. 1. The seven-day moving average of the proportion of orders involving $10-off coupon redemptions in our primary data set.

3.3. Regression specification

To study the effect of coupon redemptions on spending in our online grocery data set, we use the following regression specification:

$$spending_{it} = \alpha_i + \gamma\, coupon\_used_{it} + \theta' X_{it} + \varepsilon_{it} \tag{1}$$

where $spending_{it}$ is the number of dollars spent by customer *i* for order *t* or the logarithm of one plus the number of dollars spent by customer *i* for order *t*, α_i is an unobserved customer-specific effect, $coupon\_used_{it}$ is a dummy variable that takes a value of one when an order involves the redemption of a $10-off coupon and a value of zero otherwise, X_{it} is a vector of other variables (including interactions of some control variables with $coupon\_used_{it}$), and ε_{it} is the error term. We estimate the equation using a fixed effects regression and cluster standard errors by customer. Under our assumptions about the timing of coupon receipt, our estimates of the coefficient γ give the effect of coupon redemption on spending.

4. Results

4.1. Do customers spend more when redeeming a $10-off discount coupon?

In Table 3 we present the results of regressions estimating the relationship between the amount a customer spends on groceries and whether or not she redeems a $10-off discount coupon of the type described in Section 3.2. In these regressions and in subsequent regressions, the explanatory variables include a coupon redemption dummy, the number of times the customer visited the online grocer's website in the course of placing an order, the number of days between the first and last visits the customer made to the grocer's website in the course of placing an order, an interaction between the coupon redemption dummy and the number of website visits during an order, an interaction between the coupon redemption dummy and the days between the first and last visits to the grocer's website during an order, the number of days since a customer last received a grocery delivery as well as the square and cube of this term, the number of days between when the customer's order was placed and when it was delivered, the number of days since the customer's first order with the online grocer, the number of orders placed by the customer year to date, dummies for the day of the week when the order was placed, dummies for the day of the week when the order was delivered, dummies for each week in 2005, and customer fixed effects. The two variables that are interacted with the coupon redemption dummy were normalized before being included in these regressions.

We include the aforementioned control variables in our regressions to account for factors other than coupon redemption that may affect online grocery spending. However, when we drop all control variables except customer fixed effects from our regression specifications, the coefficient on the coupon redemption dummy remains statistically different from zero at the 5 percent level or lower in all of our analyses, and our results are even somewhat strengthened.

The two interaction terms included in our regression specifications allow us to examine some of the more nuanced ways in which coupon use influences spending. If a customer receives a $10-off coupon after having filled most of her online grocery basket, the coupon might not have a large impact on her spending since she did not know about the coupon when selecting many of her groceries. On the other hand, if a customer receives a $10-off coupon before filling her online grocery

Table 3
The effect of coupons on spending: main results.

	Spending in dollars (1)	Log(1 + spending in dollars) (2)
Coupon used	1.59** (0.79)	0.0129** (0.0052)
Number of web visits for order (standardized)	7.57*** (0.39)	0.0515*** (0.0025)
Days between first and last web visits for order (standardized)	−2.24*** (0.43)	−0.0164*** (0.0032)
Coupon used × number of web visits	−2.13*** (0.73)	−0.0152*** (0.0046)
Coupon used × days between first and last web visits	0.62 (0.70)	0.0050 (0.0049)
Days since last delivery	0.85*** (0.06)	0.0056*** (0.0004)
(Days since last delivery)^2 ÷ 100	−0.82*** (0.07)	−0.0055*** (0.0005)
(Days since last delivery)^3 ÷ 10,000	0.20*** (0.02)	0.0014*** (0.0015)
Days between order and delivery	0.32* (0.20)	0.0014 (0.0013)
Days since first order with grocer	0.07** (0.03)	0.0005** (0.0002)
Orders year to date	−0.05 (0.08)	−0.0004 (0.0005)
Day of the week order placed dummies	Yes	Yes
Day of the week order delivered dummies	Yes	Yes
Week of the year dummies	Yes	Yes
Customer fixed effects	Yes	Yes
Observations	34,410	34,410
Customers	2,889	2,889
Coupons	3,110	3,110
R^2	0.63	0.63

Columns (1) and (2) report OLS coefficients from regressions of customer spending and the logarithm of one plus spending on a dummy indicating whether an order involved the redemption of a $10-off discount coupon, controlling for the other variables listed. Standard errors (in parentheses) are clustered by customer.

* Significance at 10 percent level.

** Significance at 5 percent level.

*** Significance at 1 percent level.

basket, the coupon may have a stronger influence on her choices, perhaps inducing her to substitute expensive, high-quality items for lower quality ones. The two interaction terms allow for these possibilities to emerge from our regression results because the number of times a customer visited the online grocer's website in the course of placing an order and the number of days between the first and last visits the customer made to the grocer's website in the course of placing an order are both negatively related to the likelihood that the customer received the $10-off coupon before selecting most of the items in her online grocery basket.[13]

The coefficient estimate on the coupon redemption dummy in regression (2) of Table 3 indicates that holding all else constant, the dollar size of a grocery order increases by approximately 1.3 percent when a customer redeems a $10-off discount coupon. Regression (1) indicates that this effect corresponds to $1.59 in additional spending. The results presented in Table 3 support the hypothesis that customers spend small windfalls when they are obtained rather than dividing their use of this additional wealth over the course of a lifetime.

The results also indicate that if the number of trips a customer makes to modify her grocery order online is one standard deviation below its mean value of 3.88, the effect of redeeming a coupon on spending is increased by 1.5 percentage points (or $2.13). This pattern may be due to the fact that the fewer times a customer visits her online grocery basket, the higher the odds are that she makes the majority of her purchasing decisions while thinking about her coupon. However, it is important to note that the coefficient on the interaction between our coupon dummy and the variable indicating how many times a customer returned to her online grocery basket is mostly identified off of the cross section in our data set rather than within person, so this result may be due to customer-level heterogeneity in shopping habits that is correlated with heterogeneity in customer responsiveness to coupons.

4.2. Do customers increase their spending on "marginal" goods when redeeming a $10-off coupon?

The theory of mental accounting suggests that when redeeming a $10-off coupon, online grocery shoppers will purchase "marginal" groceries, or items that they would not purchase otherwise. If individuals have heterogeneous preferences, one way to test this hypothesis empirically is to examine whether people redeeming coupons spend more money than usual on items they never purchased before and will never purchase again in our data set.[14] In Table 4 we present the results of two regressions estimating the relationship between coupon redemption and the amount a customer spends on groceries that

[13] Excluding the two interaction terms from our regression specifications does not meaningfully alter the results, although the statistical significance of the coefficient on the coupon redemption dummy is somewhat weakened in regression (1).

[14] When we calculate how much money customers spend during an order on groceries they have not ordered before and will not order again, our data set does not include customers' first orders of 2005, orders involving the redemption of other coupons, or orders that were eliminated because they were spending or web visit outliers. In creating this "marginal spending" variable, we intend to capture spending on groceries that a customer would not purchase under typical ordering conditions, so our calculations rely only on orders in our trimmed, final data set.

Table 4
The effect of coupons on spending on "marginal" groceries.

	Spending on "marginal" groceries (3)	Log(1 + spending on "marginal" groceries) (4)
Coupon used	1.56*** (0.52)	0.0485*** (0.0139)
Number of web visits for order (standardized)	4.80*** (0.22)	0.1644*** (0.0072)
Days between first and last web visits for order (standardized)	−0.93*** (0.25)	−0.0485*** (0.0087)
Coupon used × number web visits	−0.59 (0.51)	−0.0473*** (0.0110)
Coupon used × days between first and last web visits	0.29 (0.53)	0.0102 (0.0108)
Days since last delivery	0.03 (0.03)	0.0028*** (0.0010)
(Days since last delivery)^2 ÷ 100	0.05 (0.04)	−0.0002 (0.0011)
(Days since last delivery)^3 ÷ 10,000	−0.03* (0.01)	−0.0002 (0.0030)
Days between order and delivery	0.12 (0.10)	−0.0008 (0.0034)
Days since first order with grocer	0.03** (0.01)	0.0002 (0.0005)
Orders year to date	−0.14*** (0.04)	0.0006 (0.0018)
Day of the week order placed dummies	Yes	Yes
Day of the week order delivered dummies	Yes	Yes
Week of the year dummies	Yes	Yes
Customer fixed effects	Yes	Yes
Observations	34,410	34,410
Customers	2,889	2,889
Coupons	3,110	3,110
R^2	0.65	0.56

Columns (3) and (4) report OLS coefficients from regressions of customer spending on "marginal" groceries and the logarithm of one plus spending on "marginal" groceries on a dummy indicating whether an order involved the redemption of a $10-off discount coupon, controlling for the other variables listed. "Marginal" groceries are defined as items that a customer has not purchased before and will not purchase again in an order included in our data set. Standard errors (in parentheses) are clustered by customer.

* Significance at 10 percent level.
** Significance at 5 percent level.
*** Significance at 1 percent level.

were not included in her other orders. On average, customers spend $39.24 per order on groceries they have not purchased before and will not purchase again in our data set. The coefficient estimate on the coupon redemption dummy in regression (4) of Table 4 indicates that holding all else constant, spending on these groceries increases by approximately 4.9 percent when a customer redeems a $10-off coupon. Regression (3) indicates that this effect corresponds to $1.56 in additional spending on these groceries. These results are consistent with our hypothesis that people purchase "marginal" items when they receive a $10 windfall.

In order to paint a clearer picture of the types of items that absorb the additional $1.59 in grocery spending associated with the redemption a $10-off coupon, we examine how redeeming a coupon affects spending on each of the 112 grocery categories in our data set. Groceries in our data set have all been classified by our online grocer into 1 of 112 categories (e.g., Frozen Vegetables, Cream, Cosmetics, and Cookies). We run 112 regressions in which the outcome variable in a given regression is spending on one category of groceries and 112 regressions in which the outcome variable in a given regression is the logarithm of one plus spending on one category of groceries. The primary predictor in all of these regressions is a coupon redemption dummy, and the same controls are included as in regressions (1)–(4). For each set of 112 regressions, Table 5 lists the five categories with the most positive coefficient estimates for the coupon redemption dummy and the five categories with the most negative coefficient estimates for the coupon redemption dummy. Casual inspection suggests that the grocery categories with the most positive coefficient estimates are relatively luxurious (e.g., Produce-Fruits, Meat-Fresh, Seafood-Frozen, Produce-Vegetables), particularly when compared to those categories with the most negative coefficient estimates (e.g., Baby Food, Dish Care, Household Cleaners, Pasta/Grains), which seem more like necessities. However, these results are merely suggestive.

4.3. Robustness of results

The first robustness issue we address is a potential feedback problem in our primary regression analyses. We have estimated the effect of coupon redemptions on grocery spending using a regression with customer fixed effects. The consistency of our estimates relies on the "strict exogeneity" assumption—that the error term in Eq. (1) (see Section 3.3) has an expectation of zero conditional on the unobserved, customer-specific effect and the right-hand side variables for all of the customer's orders. Mathematically, this assumption can be expressed as

$$E(\varepsilon_{it}|\alpha_i, coupon\_used_{i1}, \ldots, coupon\_used_{iT}, X_{i1}, \ldots, X_{iT}) = 0.$$

However, this assumption may be invalid because of feedback effects in some of the variables in X_{it}. For instance, if customer i places a large grocery order because of a high realization of ε_{it}, she may not need to return to the online grocer in the near future. Therefore, ε_{it} may be correlated with the $t+1$ values of the variables days since last delivery, days since last delivery squared, days since last delivery cubed, and days since first order with grocer. Under some assumptions, the inconsistency due

Table 5
The effect of coupons on spending at the grocery category level, sorted by effect size.

Five categories with the largest coefficient estimates			Five categories with the smallest coefficient estimates		
Category name	Coefficient on coupon use dummy	Std. Err.	Category name	Coefficient on coupon use dummy	Std. Err.
Spending regressions					
Produce-Fruits	0.32***	0.13	Baby Food	−0.21***	0.09
Meat-Fresh	0.26	0.20	Household Cleaners	−0.14**	0.07
Produce-Vegetables	0.18	0.14	Pasta/Grains	−0.11*	0.06
Seafood-Frozen	0.16**	0.08	Frozen Snacks/Appetizers	−0.10**	0.05
Laundry Care	0.12	0.09	Spices/Extracts	−0.08***	0.04
Log(1 + spending) regressions					
Seafood-Frozen	0.0376***	0.0147	Household Cleaners	−0.0269*	0.0150
Laundry Care	0.0313*	0.0185	Dish Care	−0.0239	0.0353
Produce-Fruits	0.0294*	0.0152	Frozen Snacks/Appetizers	−0.0229**	0.0116
Meat-Fresh	0.0257	0.0213	Frozen Dinners/Entrees	−0.0144	0.0187
Deli-Packaged	0.0249	0.0188	Baby Food	−0.0142	0.0110

For each grocery category, we performed a regression of customer spending on the category and a regression of the logarithm of one plus customer spending on the category on a dummy indicating whether an order involved the redemption of a $10-off discount coupon, controlling for the other variables listed in regressions (1)–(4). We then sorted each set of 112 regressions according to the size of the coefficient on the coupon dummy variable. This table reports the top five and bottom five categories from each set of 112 regressions, as well as the associated coupon dummy coefficient estimates and standard errors. Standard errors are clustered by customer.

* Significance at 10 percent level.
** Significance at 5 percent level.
*** Significance at 1 percent level.

to the violation of strict exogeneity is less severe for panel data sets with a large time series dimension. Because our data set has a relatively large time series dimension, we have presented fixed effects regression results despite the potential feedback problem. However, we can also conduct our analysis under the less restrictive assumption of “sequential exogeneity”:

$$E(\varepsilon_{it}|\alpha_i, coupon\_used_{i1}, \ldots, coupon\_used_{it}, X_{i1}, \ldots, X_{it}) = 0.$$

This assumption may hold even in the presence of the feedback effects discussed above. Instead of using a fixed effects regression to estimate Eq. (1), we estimate the equation in first differences,

$$\Delta spending_{it} = \gamma\, \Delta coupon\_used_{it} + \theta'\, \Delta X_{it} + \Delta\varepsilon_{it}, \qquad (2)$$

using a pooled OLS regression. We use the first lags of the variables with potential feedback problems as instruments for the first differences of these variables, and the standard errors are clustered by customer. The estimates of γ from these first-difference regressions that correspond to the fixed effect regressions (1)–(4) are still statistically significant (although the coefficient corresponding to regression (1) is only significant at the 10 percent level), and they are slightly larger in magnitude.[15]

The second issue we address is the implication of dropping orders from our data set when they involved the redemption of coupons besides the $10-off coupons we are studying. As discussed in Section 3.2, many of these other types of coupons could only be redeemed on orders that met certain requirements. For example, one common condition for coupon redemption was that the size of a customer’s order exceed a minimum dollar threshold (the minimum dollar threshold for using such coupons was higher than the threshold that applied to all other orders). The $10-off coupons we are studying had no such elevated minimum spending requirement. In order to avoid confounding the interpretation of our results, our data set does not include any orders involving the redemption of coupons other than the $10-off coupons. Of course, it is possible that eliminating these observations biased our results in favor of supporting the mental accounting hypothesis by removing large orders that did not involve $10-off coupons from our data set. To check the robustness of our results, we restore the orders that involved other types of coupons to our data set, and we treat them as if they were not associated with any type of coupon. When we repeat our analysis of the impact of a $10-off coupon on total spending with this altered data set, our main results in regressions (1) and (2) are actually strengthened, both in terms of statistical significance and in terms of effect size.

The third issue we discuss is the implication of the reduced cost of ordering groceries for delivery that is induced by the receipt of a $10-off coupon. Although the $10-off coupon we are studying does not change the relative prices of groceries available from the online grocer, it does reduce the price per order of having groceries delivered, which is a potential concern. Customers may respond to the reduced price per order by increasing the frequency of their orders from the online grocer. Of course, we would expect an increase in ordering frequency to decrease the dollar size of individual grocery orders. If a customer purchases the same total number of groceries but distributes those groceries across more orders, her orders will become smaller. Similarly, if a customer increasingly uses online grocery shopping as a substitute for trips to

[15] Our discussion of the concepts and techniques in this paragraph is derived entirely from Wooldridge (2002).

Table 6
The effect of coupons on order frequency.

	Days since last delivery (5)	Log(days since last delivery) (6)
Coupon used on last order	0.58 (0.47)	0.0093 (0.0142)
Coupon used on this order	0.92** (0.39)	0.0390*** (0.0115)
Number of web visits for order (standardized)	−1.24*** (0.21)	0.0041 (0.0072)
Days between first and last web visits for order (standardized)	12.38*** (0.69)	0.2841*** (0.0207)
Days between order and delivery	0.31*** (0.05)	0.0315*** (0.0022)
Orders year to date	−0.63*** (0.05)	−0.0180*** (0.0015)
Day of the week order placed dummies	Yes	Yes
Day of the week order delivered dummies	Yes	Yes
Week of the year dummies	Yes	Yes
Customer fixed effects	Yes	Yes
Observations	34,410	34,410
Customers	2,889	2,889
Coupons	3,110	3,110
R^2	0.67	0.62

Columns (5) and (6) report OLS coefficients from regressions of days since a customer's last grocery delivery and the logarithm of days since a customer's last grocery delivery on a dummy indicating whether the customer's previous order involved the redemption of a $10-off discount coupon, controlling for the other variables listed. Standard errors (in parentheses) are clustered by customer.
** Significance at 5 percent level.
*** Significance at 1 percent level.

purchase a few items at, say, a small convenience market, additional online orders are likely to be smaller in size. This potential bias should reduce the likelihood of finding evidence consistent with the mental accounting hypotheses we test.

4.4. Alternative interpretations

The first alternative explanation for our findings that we address is the possibility that there are certain times when a customer is better able to plan her future food consumption and also more likely to redeem a $10-off coupon. When customers are in this "planning mode," they may have larger grocery orders and longer lags between grocery orders, and they may be more prone to redeem a $10-off coupon. In order to test the plausibility of this explanation, we run two regressions, which are presented in Table 6. In regression (5), the outcome variable is the number of days between the current online grocery delivery and the previous delivery, and in regression (6) it is the logarithm of this value. The explanatory variables are an indicator for whether a $10-off coupon was used on the previous grocery order, an indicator for whether a $10-off coupon was used on the current grocery order, and all of the control variables from the previous regressions except the following: the interaction between the coupon redemption dummy and the number of website visits during the order, the interaction between the coupon redemption dummy and the number of days between the first and last visits to the grocer's website during the order, the number of days since the customer's previous grocery delivery (and the square and cube of this term), and the number of days since the customer's first online grocery order.[16] The coefficient on the indicator for whether a $10-off coupon was used on the previous grocery order is positive but not statistically significant. Thus, coupon redemption appears to result in larger grocery orders without significantly reducing the rate at which customers return to the online grocer for their next order. This result neither confirms nor rules out the proposed alternative explanation. However, in order to be viable, the "planning mode" explanation must also rationalize the evidence that coupon redemption is associated with increased spending on particular types of grocery items. Spending increases are often focused on perishable foods (see Table 5), and it is not clear that planning for the future should increase purchases of foods that are probably intended for relatively immediate consumption.

Modified versions of the permanent income or lifecycle theory provide another potential interpretation of our results. Although our results are inconsistent with the standard theory, adding liquidity constraints to the standard model can give agents a high propensity to consume out of windfalls (Zeldes, 1989; Deaton, 1991, 1992). Judging from the demographic characteristics of online grocery shoppers, it does not seem likely that the consumers in our data set are liquidity constrained, but we cannot rule out this possibility or related explanations for our findings.

Finally, our discussion assumes that the increases in grocery spending we observe when consumers redeem $10-off coupons are not offset by spending reductions in other domains. While this assumption seems reasonable, we ultimately cannot verify it because we observe only the online grocery expenditures of the customers in our data set.

[16] We exclude the interaction terms from the regressions because they no longer have an interesting interpretation, and we exclude the variables having to do with the number of days since a prior order since they are so similar to (if not identical to) the outcome variables in the regressions.

5. Conclusion

In this paper, we present evidence indicating that the redemption of a $10-off coupon increases an individual's spending in the domain of online groceries, as predicted by the theory of mental accounting. We also find evidence, consistent with the theory of mental accounting, that the increase in spending stimulated by the redemption of a $10-off coupon is focused on groceries that customers would not purchase in the absence of such a coupon ("marginal" goods). Our analysis uses a novel panel data set, which allows us to observe precisely what goods consumers purchase following the receipt of a windfall. In addition, our study focuses on windfalls that are considerably smaller than those examined in past field studies. Although the types of decisions analyzed in this paper involve small stakes, the cumulative effect of many small-stakes decisions may be significant. Examining the aggregate impact of small-stakes decisions driven by mental accounting may therefore be an interesting topic for future research.

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References

Abdel-Ghany, M., Bivens, G.E., Keeler, J.P., James, W.L., 1983. Windfall income and the permanent income hypothesis: new evidence. Journal of Consumer Affairs 17, 262–275.
Abeler, J., Marklein, F., 2008. Fungibility, labels, and consumption. IZA Discussion Paper No. 3500.
Arkes, H.R., Joyner, C.A., Pezzo, M.V., Nash, J.G., Siegel-Jacobs, K., Stone, E., 1994. The psychology of windfall gains. Organizational Behavior and Human Decision Processes 59, 331–347.
Baker, M., Nagel, S., Wurgler, J., 2007. The effect of dividends on consumption. Brookings Papers on Economic Activity 2007, 231–276.
Bird, R., Bodkin, R.G., 1965. The national life-insurance dividend of 1950 and consumption: a further test of the 'strict' permanent-income hypothesis. Journal of Political Economy 73, 499–515.
Bodkin, R.G., 1959. Windfall income and consumption. American Economic Review 49, 602–614.
Browning, M., Lusardi, A., 1996. Household saving: micro theories and micro facts. Journal of Economic Literature 34, 1797–1855.
Cryder, C.E., Lerner, J.S., Gross, J.J., Dahl, R.E., 2008. Misery is not miserly: sad and self-focused individuals spend more. Psychological Science 19, 525–530.
Deaton, A., 1991. Saving and liquidity constraints. Econometrica 59, 1221–1248.
Deaton, A., 1992. Understanding Consumption. Clarendon Press, Oxford.
Doenges, C.R., 1966. Transitory income size and savings. Southern Economic Journal 33, 258–263.
Friedman, M., 1957. A Theory of the Consumption Function. Princeton University Press, Princeton.
Goranson, R.E., Berkowitz, L., 1966. Reciprocity and responsibility reactions to prior help. Journal of Personality and Social Psychology 3, 227–232.
Heilman, C.M., Nakamoto, K., Rao, A.G., 2002. Pleasant surprises: consumer response to unexpected in-store promotions. Journal of Marketing Research 39, 242–251.
Hsieh, C., 2003. Do consumers react to anticipated income changes? Evidence from the Alaska permanent fund. American Economic Review 93, 397–405.
Isen, A., 2000. Positive affect and decision-making. In: Lewis, M., Haviland-Jones, J. (Eds.), Handbook of Emotion, 2nd edition. Guilford, New York, pp. 417–435.
Isen, A., 2008. Some ways in which positive affect influences decision making and problem solving. In: Lewis, M., Haviland-Jones, J., Barrett, L.F. (Eds.), Handbook of Emotion, 3rd edition. Guilford, New York, pp. 548–573.
Johnson, D.S., Parker, J.A., Souleles, N.S., 2006. Household expenditure and the income tax rebates of 2001. American Economic Review 96, 1589–1610.
Kahn, B.E., Isen, A.M., 1993. The influence of positive affect on variety seeking among safe, enjoyable products. Journal of Consumer Research 20, 257–270.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263–291.
Keeler, J.P., James, W.L., Abdel-Ghany, M., 1985. The relative size of windfall income and the permanent income hypothesis. Journal of Business & Economic Statistics 3, 209–215.
Kreinin, M.E., 1961. Windfall income and consumption: additional evidence. American Economic Review 51, 388–390.
Landsberger, M., 1966. Windfall income and consumption: comment. American Economic Review 56, 534–540.
Lerner, J.S., Small, D.A., Loewenstein, G., 2004. Heart strings and purse strings: carryover effects of emotions on economic decisions. Psychological Science 15, 337–341.
Levav, J., McGraw, P.A., 2009. Emotional accounting: how feelings about money influence consumer choice. Journal of Marketing Research 46, 66–80.
Modigliani, F., Brumberg, R., 1954. Utility analysis and the consumption function: an interpretation of cross-section data. In: Kurihara, K.K. (Ed.), Post-Keynesian Economics. Rutgers University Press, New Brunswick, NJ, pp. 388–436.
Parker, J.A., 1999. The reaction of household consumption to predictable changes in social security taxes. American Economic Review 89, 959–973.
Poterba, J.M., 1988. Are consumers forward looking? Evidence from fiscal experiments. American Economic Review Papers and Proceedings 78, 413–418.
Prelec, D., Loewenstein, G., 1998. The red and the black: mental accounting of savings and debt. Marketing Science 17, 4–28.
Rabin, M., 1993. Incorporating fairness into game theory and economics. American Economic Review 83, 1281–1302.
Read, D., Loewenstein, G., Rabin, M., 1999. Choice bracketing. Journal of Risk and Uncertainty 19, 171–197.
Shefrin, H.M., Thaler, R.H., 1988. The behavioral life-cycle hypothesis. Economic Inquiry 26, 609–643.
Souleles, N.S., 1999. The response of household consumption to income tax refunds. American Economic Review 89, 947–958.
Souleles, N.S., 2002. Consumer response to the Reagan tax cuts. Journal of Public Economics 85, 99–120.
Thaler, R.H., 1985. Mental accounting and consumer choice. Marketing Science 4, 199–214.
Thaler, R.H., 1990. Anomalies: savings, fungibility, and mental accounts. Journal of Economic Perspectives 4, 193–205.
Thaler, R.H., 1999. Mental accounting matters. Journal of Behavioral Decision Making 12, 183–206.
Thaler, R.H., Shefrin, H.M., 1981. An economic theory of self-control. Journal of Political Economy 89, 392–406.
Wilcox, D.W., 1989. Social security benefits, consumption expenditure, and the life cycle hypothesis. Journal of Political Economy 97, 288–304.
Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge.
Zeldes, S.P., 1989. Consumption and liquidity constraints: an empirical investigation. Journal of Political Economy 97, 305–346.