Cashback is Cash Forward: Delaying a Discount to Entice Future Spending

ABSTRACT

The authors examine purchase behavior in the context of cashback shopping—a novel form of price promotion online where consumers initiate transactions at the website of a cashback company and, after a significant delay, receive the savings promised to them. Specifically, they analyze panel data from a large cashback company and show that, independent of the predictable effect of cashback *offers* on initial demand, cashback *payments* (1) increase the probability that consumers make an additional purchase via the website of the cashback company, and (2) increase the size of that purchase. These effects pass several robustness checks. They are also meaningful: at the average values in the data an additional $1.00 in cashback payment increases the likelihood of a future transaction by 0.02% and spending by $0.32—figures that represent 10.03% of the overall impact of a given promotion. Moreover, we find that consumers are more likely to spend the money returned to them at generalists such as department stores than at other retailers. The authors consider three explanations for these findings, and the leading hypothesis is that consumers fail to treat money as a fungible resource. They also discuss implications for cashback companies and retailers.

Keywords: Cashback shopping, electronic commerce, sales promotion, pricing, mental accounting.

The continued growth of electronic commerce motivates firms to test new means of reaching and enticing consumers with better prices—anything from voucher codes to different models of daily deals and group buying. Within this context, cashback shopping is a relatively young but increasingly popular alternative. For example, Ebates, the leading cashback company in the United States, has processed cashback payments of over $800 million to more than 10 million consumers since it began operating in 1998. In the United Kingdom, Quidco processed more than $64 million of cashback payments to its seven million registered users in 2016 alone, and facilitated sales of close to $1 billion for 4,300 retailers—a figure that represents 1% of all electronic commerce in the country for that year.[1]

The feature that distinguishes cashback shopping from its peers is that consumers view cashback offers and initiate purchases at the website of the cashback company rather than directly with individual retailers. These offers are negotiated in advance with retailers and posted on the website typically as a percentage of money spent. The cashback company earns a commission on each transaction that eventuates and, upon receiving this commission, deposits cashback payments directly into the bank accounts of consumers. Importantly, the delay between a given purchase and the cashback payment is significant: a minimum of 30 days, but often as much as four months.

We study data from a large cashback company to understand the impact of cashback payments on purchase behavior. The data comprise cashback offers, cashback payments, and

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[1] See https://www.ebates.com/help/article/company-overview-115009254588 and https://www.quidco.com/business/about/, both accessed on November 1, 2017.

individual purchases over a period greater than eight years. Two results stand out. First, cashback payments increase the probability that consumers make an additional purchase via the website of the cashback company. Second, cashback payments increase the size of that purchase. These effects pass several robustness checks. They are also meaningful: at the average values in the data an additional $1.00 in cashback increases the likelihood of a future transaction by 0.02% and spending by $0.32—figures that represent 10.03% of the overall impact of a given promotion. Notably, the impact of cashback payments is separate from that of cashback offers on initial demand—that is, although consumers may already respond positively to cashback offers, they again respond positively to cashback payments.

An interesting finding is that cashback payments impact purchase behavior differently depending on the type of retailer and consumers are more likely to spend the money returned to them at generalists such as department stores than at other retailers. This insight has implications for the design of cashback promotions (which are pertinent to cashback companies) and the logic of participating in such initiatives (which are pertinent to retailers). A more fundamental point, however, is that any such practical advice is beneficial to the extent that the relevant players are conscious of the influence of cashback payments. The following quote from the managing director of the cashback company that facilitated the data suggests that this may not be the case: "We spend a lot of time designing offers that are profitable for retailers and give our users maximum value. Of course, an essential part of our work is to ensure they receive the payments they are promised, but we have never spent time looking at what the repercussions of these payments may be."

From the standpoint of the literature, our first goal is to bridge the gap between the growing use of cashback shopping and the understanding of the phenomenon. Our research adds empirical evidence to studies that are predominantly analytical in nature (Chen et al. 2008; Ho, Ho, and Tan 2017; Zhou et al. 2017). To our knowledge, the only other empirical study on the subject focuses on the relationship between the size and composition of a user's network, and the extent and pattern of navigation at the cashback company's website (Ballestar, Grau-Carles, and Sainz 2016). In contrast, we question how consumers react to cashback offers and payments. The idea that consumers are susceptible to not only the promise of a saving, but also the later payment of that saving is striking because they are free to spend or save this money in any way they deem fit. We consider the possibility that consumers fail to treat cashback payments as a fungible resource, and also that cashback payments act as a scheduling mechanism or prompt some transient state that then affects purchases. The data lend support to the first hypothesis.

Beyond this, we see two contributions. First, we add to research on price promotions online, which to date has focused on instances of group buying (Wu, Shi, and Hu 2014) or daily deals (Aydinli, Bertini, and Lambrecht 2014; Luo et al. 2014). Second, we complement articles that question the logic of delayed discounts. These studies examine the psychology that underlies redemption behavior (Gilpatric 2009; Soman 1998) or the economics of tying the payment of a saving to a second purchase (Raju, Dhar, and Morrison 1994; Dhar, Morrison, and Raju 1996). Although we describe a setting where low redemption and forced purchases are irrelevant (cashback payments are automatic and unconditional), we find that delaying a discount is still beneficial.

EMPIRICAL SETTING

The Data

A nondisclosure agreement prevents us from revealing the name of the cashback company that shared the data, the geography where it operates, or the local currency. For ease of exposition, we convert all monetary values into United States Dollars. The data spans May 2005 (when the firm started operating) to August 2013. We have information on every purchase by a sample of 76,296 registered users (consumers) of the cashback company in response to every cashback offer, and the corresponding cashback payments.[2] We observe 3,433,476 transactions by these consumers at 5,337 retailers. Consumers registered with the cashback company at different points in time and thereafter received emails promoting current cashback offers. The demographic information for a subset of consumers suggests that they are representative of the overall population, albeit somewhat younger and disproportionately male.

Consumers face no restrictions on the number or timing of purchases. We observe the total amount spent by a consumer on a given day, at a given retailer, and for a cashback offer of a given size. We do not observe details such as the type, category, or quantity of the item(s) purchased. If a retailer advertised multiple cashback offers on a given day, and a consumer acted on more than one of these offers, then these are recorded as separate purchases in the data.

Table 1 provides summary statistics. The average tenure of a consumer, measured as the time between the first and last purchase, is 876.8 days. On average, a consumer made 45.0

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[2] We do not observe purchases that are independent of a cashback offer or initiated directly with a retailer. A small (4.80%) set of transactions relates to cashback offers available at the physical premises of a retailer. These are excluded from the analysis, but included in a robustness check.

purchases on 36.9 days, each worth \$305.66, and received a cashback payment on 12.4 days, each worth \$51.44.[3] The mean time between successive purchase days is 24.4 days. The mean time between purchase and cashback payment is 123.9 days, with a standard deviation of 110.9 days (Figure 1).

Insert Table 1 and Figure 1 about here

One reason for the size and variability of the delay between purchases and cashback payments is that retailers process commissions to the cashback company only after the return period for the item(s) in question expires. Return periods vary across retailers according to regulations, policies, and routines. In turn, the cashback company seldom executes a cashback payment before receiving the corresponding commission, and its own processes are subject to delays. A second reason is that the cashback company enters into different agreements with different retailers, often as a function of the product category.

Identification Strategy

Our ability to identify the causal effects of cashback payments on purchase behavior rests on the assumption that their timing and size are exogenous from the standpoint of consumers. That is, consumers should not be able to predict or influence cashback payments, otherwise they can adjust their spending plans.

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[3] The cashback company typically makes a single cashback payment within a seven-day stretch. Within this period, if the cashback company receives more than one commission from retailers pertaining to the same consumer, then it aggregates payments into a single bank transfer (irrespective of amount, type of purchase, or type of retailer).

There are four justifications for this claim. First, the cashback company schedules cashback payments according to the aforementioned internal process, not some strategic consideration. Second, consumers are notified of a deposit only once it is executed. Third, there is considerable irregularity in the time retailers take to pay commissions, and in the time the cashback company takes to execute cashback payments: the coefficient of variation of delay in the data is 0.89. There is also significant variation in the interval between purchases and cashback payments at the level of a single consumer (Figure 2), countering the possibility that the pattern in Figure 1 arises from differences between individuals. Similarly, the interval varies at the level of a retailer, as Figure 3 demonstrates for four retailers selected at random. Figure 5 shows such variation for the purchases at a single generalist retailer for four consumers selected at random but unmatched on any other variables while Figure 5 shows this variation among four consumers matched by gender, age, and spending.[4] Fourth,

Figure **6** displays the delay for a generalist (offering a broad range of products) and a specialist (offering a narrow range), suggesting that the delay is not specific to the range of products offered.

Insert Figures 2-6 about here

One concern is that the delay between purchases and cashback payments varies with the size of the former. This would be the case if, say, more expensive products enjoy longer return

[4] These consumers are the modal gender at the retailer (female), have the median age (35 to 44), are within one standard deviation of the median expenditure per transaction at the retailer, and are within one standard deviation of the median expenditure across all retailers in the data.

periods, and consumers know this. However, our conversations with executives at the cashback company suggest that no such relationship exists, and the data indicate a low correlation between the size of a purchase or cashback payment and the delay in the data: $R^2 = -0.015$, $p < 0.001$ and $R^2 = -0.016$, $p < 0.001$, respectively.

A second concern is that the nature of certain purchases improves the ability of consumers to predict cashback payments. An example is travel, where consumers may infer that a service provider safeguards against cancelations by processing cashback payments only after the event (a flight, hotel stay, etc.) takes place. This scenario affects a small subset of transactions, and even then consumers cannot pinpoint the date of payments. Irrespective, one of our robustness checks excludes observations with long delays. The Web Appendix, Section 1, reports further evidence that consumers are unlikely to predict the timing of cashback payments.

ANALYSIS AND RESULTS

Model-Free Evidence

We explore the possibility of relationships between cashback payments and purchase likelihood, and between cashback payments and spending. With respect to purchase likelihood, we classify every consumer-day observation as a “purchase” or “non-purchase” event depending on whether the consumer transacted at least once through the cashback company on that day. We then compute the average cashback payment received in the seven days prior. The pattern in Figure 7 suggests that cashback payments affect purchase likelihood: on average, consumers receive $2.50 more in the seven days prior to a purchase event than prior to a non-purchase event ($p < 0.001$).

Insert Figure 7 about here

With respect to spending, we associate the cashback paid to a consumer in periods of seven days (from a given Saturday to the next Friday) to the money spent by the same consumer in the following seven days. We use this interval because the cashback company processes 51.5% of deposits on a Thursday or Friday (the results hold for alternative specifications). For each amount of cashback payment, we calculate the average weekly spend across all consumer-week observations. We then correlate the level of cashback payment and the average weekly spend. Figure 8 indicates a positive relationship: as cashback increases, so does spending—the correlation is 0.332 ($p < 0.001$).

Insert Figure 8 about here

These initial analyses clearly do not control for consumer heterogeneity, which matters because consumers who purchase frequently are more likely to receive cashback payments than consumers who purchase infrequently. Similarly, consumers who make large purchases—and are likely to do so in the future—receive larger cashback payments than consumers who do not. We next turn to this concern.

Cashback Payments and Purchase Likelihood

Model setup. We use a semi-parametric, proportional hazard model to estimate whether, on any given day, the cashback payment received by a consumer in the seven days prior increases the probability of a purchase via the cashback company on that day.[5] We model a consumer's purchase decision from the first transaction observed in the data to the last.

In a proportional hazard model, the dependent variable T represents the time (in days) between two consecutive purchase days. We model the hazard of a purchase by consumer *i* on any given day t, $h_i(t|X_{it})$, as

$$h_i(t|X_{it}) = h_{0i}(t)\exp(X_{it}\beta) \tag{1}$$

Here, $h_{0i}(t)$ is the baseline hazard function specific to consumer *i*. To account for individual differences, we take a stratified baseline approach and let the baseline hazard function vary non-parametrically across consumers (Prentice and Gloeckler 1978). The baseline hazard is shifted proportionally by $exp(X_{it}\beta)$, where X_{it} is a vector of time-varying covariates. We specify the vector of covariates as:

$$\begin{aligned} X_{it}\beta = \beta_1 \sum_{k=t-1}^{t-7} CBPayment_{i,k} + \beta_2 AvgCBOffer_t + \beta_3 LastPurchaseSpend_{it} \\ + \beta_4 PurchaseInstance_{it} + \beta_5 DayOfWeek_t + \beta_6 Month_t \end{aligned} \tag{2}$$

The independent variable of interest is $\sum_{k=t-1}^{t-7} CBPayment_{i,k}$: the cashback paid to consumer *i* in the seven days prior to day *t*. We control for the size of cashback offers advertised on day *t* by taking the average percentage of the offers from the 10 largest retailers by number of transactions, $AvgCBOffer_t$. Note that the effects of $\sum_{k=t-1}^{t-7} CBPayment_{i,k}$ and $AvgCBOffer_t$ can be identified simultaneously because the amount of cashback payment is determined not only by the cashback offer, but also the amount a consumer spends, which results in significant variation

5 One alternative is to take a weekly (rather than daily) specification. Given that the median inter-purchase interval is eight days, this option removes significant variation.

in the size of cashback payments related to the same offer. The variable $LastPurchaseSpend_{it}$ captures the amount spent by consumer i on the most recent purchase day, and therefore it controls for consumer-specific purchase trends. $PurchaseInstance_{it}$, the number of transactions made by consumer i up to but not including day t, controls for prior experience with the cashback company. $DayOfWeek_t$ and $Month_t$ control for day-of-week and month fixed effects.

Results. Column (I) of Table 2 shows that larger cashback payments increase purchase likelihood. The associated hazard rate of 1.0002 implies that, on any given day, an additional \$1.00 in cashback in the seven days prior raises the probability of purchase by 0.02%. Columns (II) and (III) measure the effect separately by terciles (< \$8.10, ≥ \$8.10 and < \$35.20, ≥ \$35.20) and quintiles (<\$4.86, ≥\$4.86 and <\$11.34, ≥\$11.34 and < \$27.54, ≥\$27.54 and <\$69.66, ≥69.66), demonstrating that this \$1.00 increment has a stronger impact on purchase likelihood when the cashback payment is small—in other words, the marginal effect of cashback payments decreases as their size increases.[6] Column (IV) shows that the result holds when we specify a frailty model with a gamma-distributed random effect to account for consumer heterogeneity rather than taking the stratified baseline approach (McGilchrist and Aisbett 1991). While in the initial specification the baseline hazard varied non-parametrically across consumers, the frailty model assumes a multiplicative effect of the heterogeneity parameter on the baseline hazard function. Finally, Column (V) shows that the results are robust to using a post-hoc consumer-specific cashback offer variable reflecting only offers by retailers where a consumer shopped in the past.

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[6] Because the data contain many days where consumers receive no cashback payments, we cannot use alternative specifications such as a log function or a quadratic term.

Insert Table 2 about here

With respect to the remaining covariates, we find that purchase likelihood decreases with the number of past purchases, which is consistent with studies on consumer attrition over time (Fader, Hardie, and Shang 2010). Similarly, consumers who recently spent large amounts are more likely to purchase. In line with broader evidence, the size of cashback offers has a positive effect on purchase likelihood.

Cashback Payments and Spending

Model setup. We use a Type-I Tobit specification to estimate the effect of cashback payments in a given week (from a Saturday to the next Friday) on spending at any time in the following seven days. The analysis is at the weekly rather than daily level because the latter yields a large number of null (zero-spend) observations per consumer. For consumer *i* in week *w*, $Spend_{iw}$ is the observed weekly expenditure, $LatSpend_{iw}^{*}$ is the unobserved latent dependent variable, and X_{iw} is the observed vector of independent covariates. We specify the dependent variable as $\log(Spend_{iw}+1)$ rather than $Spend_{iw}$ because of the significant mass of observations in the right tail of spending. Specifically, we estimate:

$$LatSpend_{iw}^{*} = X_{iw}\beta + \varepsilon_{iw}, \quad \varepsilon_{iw} \sim N[0, \sigma_{\varepsilon}^{2}] \tag{3}$$

$$\log(Spend_{iw} + 1 = \begin{cases} LatSpend_{iw}^{*} & if\ LatSpend_{iw}^{*} > 0 \\ 0 & if\ LatSpend_{iw}^{*} \le 0 \end{cases} \tag{4}$$

The vector of covariates is:

$$X_{iw}\beta = \alpha_i + \beta_1 CBPayment_{i,w-1} + \beta_2 AvgCBOffer_w + \beta_3 LastPurchaseSpend_{iw} \\ + \beta_4 PurchaseInstance_{iw} + \beta_5 Month_w + \varepsilon_{iw} \tag{5}$$

The independent variable of interest is *CBPayment*$_{i,w-1}$: the amount of cashback received by consumer *i* in the week prior to week *w*. We control for the size of cashback offers advertised in week *w* by taking the average percentage of cashback offered by the 10 largest retailers, *AvgCBOffer*$_w$. The variable *LastPurchaseSpend*$_{iw}$ captures the amount spent by consumer *i* in the most recent week with a purchase. *PurchaseInstance*$_{iw}$ is the number of transactions made by consumer *i* up to but not including week *w*. *Month*$_w$ controls for month fixed effects.

Consumer-specific random effects, α_i, are distributed $\alpha_i \sim N[0, \sigma_v^2]$ and account for heterogeneity in the average weekly spending level. The likelihood function for the Tobit model must be integrated over the distribution of α_i, which is computationally intensive as integrating over the normal distribution does not yield closed-form expressions and the likelihood is estimated numerically. As such, for all Tobit analyses we randomly select 5,000 consumers. To provide evidence that the findings generalize to the full sample, we also estimate an OLS specification using the full sample. Finally, ε_{iw} is an IID Normal error term.

Results. Column (I) in Table 3 reports the OLS specification using the full sample, where the dependent variable is the weekly amount spent. The effect of cashback payments is significant and positive. Column (II) displays the result of the Tobit specification. Again, the money spent by consumers in any given week increases with cashback payments received in the seven days prior.[7] With respect to the other covariates, we find the expected positive effect of

[7] A reasonable question is whether cashback earned but not yet received affects spending. The problem with such a variable is that it is not exogenous to consumers. Assume that a consumer purchases at time t_1 and considers a purchase at a later time t_2 before receiving the cashback payment associated with the purchase at t_1. When deciding how much to spend, the consumer has a sense of "cashback earned but not yet received" in t_2, as it depends on the purchase in t_1. As the consumer can use this knowledge to make adjustments, it is difficult to make a causal claim. (Even so, we find that cashback payments impact spending when we add this control.)

cashback offers on spending. Similarly, we find that purchase instance has a positive effect on amount spent, consistent with the pattern observed in Fader, Hardie, and Lee (2005).

Insert Table 3 about here

Next, we examine whether the effect of cashback payments on spending is sensitive to the size of cashback payments. Columns (III) and (IV) show that this is the case when we take cashback payments by tercile or quintile: an increase in cashback payment by \$1.00 has a greater effect on spending when that payment is small rather than large. Column (V) shows that the results hold when using a consumer-specific cashback offer variable.

We also evaluate the size of the effect of cashback payments on spending based on estimates from Column (III). We consider the marginal effect of increasing the cashback payment by \$1.00 on the weekly spend as:

$$\frac{\partial \log(Spend_{iw}+1)}{\partial CBPayment_i} = \beta_1 \mathbf{\Phi}\left(\frac{X_{iw}\beta}{\sigma_\varepsilon}\right) \tag{6}$$

Figure 9 plots this effect at the median level of cashback payment in each tercile (\$3.24, \$17.82, and \$81.00). The x-axis reflects the amount spent ($Spend_{iw}$). For each amount, the y-axis reflects the change in spending that would result from the additional \$1.00. At the mean spend of \$69.34 and the median cashback payment of \$17.82, the marginal effect of such an increase is \$0.32. Note again that this result is independent of the impact of cashback offers on initial demand, and that the magnitude of the marginal effect declines with the tercile level of payment: at the same weekly spend of \$69.34, increasing by \$1.00 a cashback payment of \$3.24 contributes \$0.58 in further spending. The Web Appendix, Section 2, provides more detail on the effect of cashback payments on spending.

Insert Figure 9 about here

Finally, we compare the effect of cashback payments on spending to the effect of cashback offers on initial demand. Note that the marginal effects from the Tobit model refer to increases in cashback offers by 1 percentage point and in cashback payments by $1.00. We conclude that, at the average values in the data, the effect of cashback payments accounts for about 10.03% of the overall effect of the promotion (see Web Appendix, Section 3).

Robustness Checks

We complete several checks to ensure the robustness of our findings.[8] First, note that the independent variable to this point is the amount of cashback payment received by a consumer in the prior week. We test whether the results in Column (II) of Table 3 replicate for an interval of 14 or 28 days. Columns (I) and (II) in Table 4 show that this is the case.

Second, recall that the argument of causality hinges on the assumption that cashback payments are exogenous to consumers. The initial analysis supports this idea, but we pointed to a subset of purchases (e.g., travel expenses) for which consumers may have a better sense of the timing of cashback payments. To check this possibility, we estimate the model excluding consumer-week observations with delays exceeding the mean plus one standard deviation. Column (III) in Table 4 replicates the main findings.

Third, we want to know whether the effects of cashback payments are due to the sum paid rather than the mere act of receiving money. For instance, the emails sent by the cashback

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[8] These checks apply to purchase likelihood and spending. As the results are similar, we report only those that pertain to spending. The Web Appendix, Section 4, reports the remainder.

company to notify consumers of a deposit may drive traffic to the website of the cashback company, which in turn impacts spending. Column (IV) shows that the results hold using only the consumer-week observations in which cashback payments are greater than zero.

Insert Table 4 about here

Extensions

We consider three extensions. First, we ask whether the delay between purchases and cashback payments moderates the effect that the latter has on spending. Column (V) of Table 4 reports separate coefficients for cashback payments depending on whether the corresponding delay is in the lower, middle, or upper tercile. Cashback payments have a stronger effect on spending when delays are short, and a weaker effect when delays are long. That is, despite the fact that some lag is necessary to induce and increase future spending through the cashback company, it appears that the greater the lag, the lower the effect—perhaps because excessive delays cause frustration. In the Web Appendix, Section 5, we consider whether consumers respond to perceived rather than absolute delays, and find similar results.

Second, we check for patterns that suggest consumers learn to predict the delay between purchases and the corresponding cashback payments. The results reported in the Web Appendix, Section 5, demonstrate that such learning is unlikely.

Third, we ask whether our results replicate for different categories of retailers. These categories are defined by the cashback company. Table 5 covers the four largest categories in the data. The outcome variable is spending in a particular retailer category. We estimate the effect of cashback payments separately when these originate from retailers in the same or different categories. Column (I) shows that cashback payments from generalists (mostly department stores) affect spending with generalists more than they do with other (more specialized) retailers. The results in Column (II), which relate to travel, are similar but significant only at the 90% confidence level. This may be because in this category consumers purchase infrequently, or because travel products tend to be expensive and time consuming. Columns (III) and (IV) relate to subscription services—mostly utilities and insurance in the first case, mostly magazines in the second. Here, a purchase typically implies a contractual obligation for at least one year. The negative relationship between cashback payments and spending may be because those who recently subscribed to a service are less likely to do so again in the near future. Finally, although the number of transactions by individual consumers with individual retailers is mostly low, we estimate a model for the largest generalist (by number of transactions). Column (V) demonstrates that the effect of cashback payments on spending is significantly higher for the same retailer than it is for other retailers, suggesting that the results in Column (I) hold even at the level of a single retailer.

Insert Table 5 about here

BEHAVIORAL EXPLANATIONS: INITIAL EVIDENCE

Money Is Not Fungible

A basic premise in research on mental accounting is that individuals decompose wealth into categories, including "current assets," where the temptation to spend is low, and "current income," where the temptation to spend is high (Shefrin and Thaler 1988). In addition, people code small windfalls as current income, and tend to match the source of this income with its use. For example, Kooreman (2000) found that government payments labeled as child benefits increased spending on children clothing, and Milkman and Beshears (2009) found that patrons of a grocery store spent more at that store when redeeming an unexpected coupon than when they did not. Closer to our interest, Reinholtz, Bartels, and Parker (2015) showed that consumers perceive funds that are specific to a retailer as an account governed by the goal to purchase from the same retailer.

These arguments are relevant to our context if one accepts that consumers (a) segregate cashback payments from purchases, and (b) perceive the former as windfalls—a possibility raised by Soman (1998) in the context of mail-in rebates but never tested empirically. If true, then the implication is precisely that consumers spend cashback payments via the cashback company. Moreover, Shefrin and Thaler (1988) stressed that people spend windfalls to the extent that they appear small, meaningless changes in one's wealth. As windfalls grow, they are more likely to be seen instead as assets and, therefore, more likely to be saved.

Consistent with this logic, Columns (II) and (III) of Table 2 and Columns (III) and (IV) of Table 3 report an inverse relationship between the marginal effect of cashback payments on purchase likelihood as well as spending, respectively. However, the data do not tell us whether the money returned to consumers is spent elsewhere or saved. To address this limitation, we surveyed 441 individuals on Amazon's Mechanical Turk platform. Respondents first read general information regarding cashback shopping. They then faced seven different cashback payments ($3, $7, $18, $54, $113, $162, $287) in random order and split each sum into saving and spending.[9] We examine whether the money allocated to saving varies with the size of the cashback payment. Column (I) of Table 6 is an OLS specification, and it shows that the percentage of cashback payment saved increases in the size of the cashback payment after controlling for income, age, gender, and participant fixed-effects. Given the nature of the dependent variable, Column (II) reports a fractional logit specification as a robustness check (Papke and Wooldridge 1996). The Web Appendix, Section 6, provides more detail on the stimulus and Section 7 adds to the analysis. Overall, the result of this survey adds support to the idea that the effects of cashback payments can be traced to a process of mental accounting.

Cashback Payments Are a Scheduling Device

A second explanation is that consumers use cashback payments to schedule future purchases. One motivation for this can be financial: consumers with liquidity problems postpone spending until they receive cashback payments and have more money at hand. However, the evidence presented to this point suggests that consumers cannot predict with reasonable accuracy the timing of cashback payments. Notwithstanding, assume that consumers engage in scheduling and receive a salary at the end of each calendar month. If this were the case, then the effect of cashback payments on spending should be more (less) pronounced at the end (beginning) of a given month. Column (I) of Table 7 displays results for cashback payments executed during the first week of a given month, or at any other time. There are no significant differences across the two estimations. Similarly, in Column (II) we find no significant differences between the last week and any other time in a month.

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9 The cashback payments correspond to the 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentile of cashback payments in the data, rounded to the nearest whole number.

Insert Table 7 about here

A different motivation is self-control. Suppose that people tend toward immediate gratification, but understand that deferring a purchase can improve the quality of the decision or make the purchase more pleasurable (Caplin and Leahy 2001; Hoch and Loewenstein 1991). One way to exercise patience is to tie future purchases to cashback payments, but again the data show no such evidence. While the average interval between successive purchases is 24.4 days, it is 56.1 days in the case of successive cashback payments. The average delay between purchases and cashback payments is 123.9 days. Therefore, consumers make 5.08 purchases between a given purchase and the associated cashback payment, and make 2.21 purchases between successive cashback payments.

Moreover, note that the incidence of cashback payments varies across consumers. Consumers who purchase more frequently experience a shorter delay between successive cashback payments, which makes self-control less relevant. As such, the effect of cashback payments on spending should be weaker for this group. Column (III) of Table 7 compares consumers across three groups that differ in purchase frequency: <19.08 days between purchases, ≥42.68 days, or anytime in between. Column (IV) does the same using quintiles. Contrary to the idea of self-control, the effect of cashback payments is stronger for consumers who purchase more frequently. The results are not significant for the first group, those who purchase infrequently, probably because the estimation contains many cashback payments and spending levels with a value of zero.

Cashback Payments Prompt a Transient State

The third explanation is that cashback payments trigger some transient state. For example, it is possible that cashback payments elevate one's mood, or that consumers perceive them as acts of kindness and reciprocate by spending through the cashback company (Heilman, Nakamoto, and Rao 2002; Rabin 1993). It is also possible that the emails notifying consumers of cashback payments make shopping through the cashback company more salient (Obermiller 1985). Irrespective, the hypothesis is that cashback payments prompt a temporary effect that, in turn, increases the propensities to purchase and spend.

While the data do not allow us to confirm or rule out these related explanations, the last two accounts predict a positive, or at best null, relationship between the size of a cashback payment and its marginal effect on spending. The inverse relationship in Columns (II) and (III) of Table 2, and in Columns (III) and (IV) of Table 3 suggests that other mechanisms such as mental accounting are at play.

CONCLUSION AND IMPLICATIONS

We study how cashback payments impact consumer purchase behavior. We have two main results. First, cashback payments shorten the time consumers take to make additional purchases via the website of the cashback company. Second, cashback payments increase the size of these purchases. Specifically, at the average values in the data, increasing cashback payment by $1.00 increases the probability of a new transaction by 0.02% and spending by $0.32. These figures represent 10.03% of the overall impact of a given promotion.

The finding that consumers are susceptible not only to the promise of a saving but also to the later payment of that saving is surprising because they are free to spend the money in any manner or, indeed, to set it aside. It is also surprising if one considers that cashback payments are trivial within the context of lifetime income—they should not influence purchase behavior in any product category, with any retailer, or through any intermediary in a meaningful way. Irrespective, one possible explanation is that consumers ultimately fail to treat money as a fungible resource. The data lend support to this argument: we observe an inverse relationship between the size of cashback payments and their marginal effect on spending. Other possible explanations are that cashback payments act as a scheduling mechanism or prompt some transient state, but for both we find little support in the data.

With this in mind, our research is relevant given Hastings and Shapiro's (2013) call for more evidence of mental accounting "in the wild." Our work is perhaps closest to that of Milkman and Beshears (2009), although in reality the comparison ends at the fact that we both construe discounts as windfalls. First, we examine the effect of discounts that are delayed and conditional on a prior purchase, not standard "dollars-off" coupons. Second, cashback payments have no usage or time restrictions. This is important because consumers spend (again) via the cashback company money that, at least in principle, is fully fungible. Third, consumers respond to multiple offers of varying amounts, not a single offer of a fixed amount. This allows us to test whether the size of the windfall matters to the extent predicted by mental accounting. Finally, the data span many product categories and retailers, a large number of consumers, and eight years of purchases and cashback payments.

Because the interval between purchases and cashback payments rarely falls below 30 days in the data (and in cashback shopping in general), we cannot make recommendations regarding optimal delays. Future research could address this constraint by implementing experiments that vary the delay, either in the field on in the laboratory. Moreover, while the data provide insight into possible behavioral mechanisms, we do not have direct process evidence.

Again, further studies can take up this challenge by testing specific mediating variables and their logical moderators.

Notwithstanding, the fact that cashback shopping stimulates demand at two different points in time has practical implications. First, it matters to cashback companies, which appear largely unaware of the effects of cashback payments. The analysis suggests that cashback companies can increase revenue by designing promotions to not only attract an initial purchase, but also stimulate future purchases. In addition, consumers appear more likely to spend the money returned to them at generalist retailers such as department stores, and less likely to do so in categories such as travel and subscription-based services, which implies that the selection of participating retailers is important. Finally, if mental accounting explains the psychology of consumers, then cashback companies need to emphasize their link to cashback payments. For example, the emails that notify consumers of recent cashback payments should stress that the cashback company is responsible for the deposit and which retailer funded the payment, with the intent of increasing the probability of a future purchase.

Second, it matters to retailers. Understanding the dual effect of cashback offers and cashback payments is useful to assess the full benefits and costs of collaborating with a cashback company—focusing solely on the ability of cashback offers to generate demand underestimates the full potential. It can also help to make smarter decisions about the timing of cashback payments, as it may be beneficial to execute commissions quickly and, in turn, insist that the cashback company does the same with cashback payments. Finally, while it is not straightforward to compare the effectiveness of different forms of price promotion across studies (as these may focus on different customer segments, product categories, geographies, etc.), we find that the effectiveness of cashback shopping is broadly similar to that of other established online and offline methods of price promotion (Web Appendix, Section 8). This suggests that an individual retailer planning to use price promotions may benefit from considering—and potentially testing—a wide range of options including cashback shopping, daily deals, and e-mail coupons.

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Table 1: SUMMARY OF DATA ACROSS CONSUMERS

Variable	Mean	SD
Across consumers		
Number of transactions	44.9997	99.1416
Number of transactions days	36.8435	58.7409
Number of transaction weeks	27.0091	34.5744
Amount spent per transaction ($)	305.6598	396.2032
Amount spent per day ($), days with at least one transaction	339.6962	428.2690
Amount spent per week ($), weeks with at least one transaction	389.0472	480.3486
Number of cashback payments	29.5141	60.6436
Number of days with at least one cashback payment	12.4130	14.1282
Number of weeks with at least one cashback payment	11.0970	15.5075
Cashback payment per deposit ($)	25.3925	29.4263
Cashback payment per day with deposit > 0 ($)	51.4399	54.0315
Cashback payment per week with deposit > 0 ($)	52.1265	54.4228
Tenure with cashback company (days)	876.8391	717.8193
Across purchases		
Inter-purchase time (days)	24.3582	61.5523
Across cashback payments		
Interval between purchase and payment of cashback (days)	123.8624	110.9093
Cashback payment per week ($)	42.2606	74.3290

Table 2: CASHBACK PAYMENTS AND PURCHASE LIKELIHOOD

Dependent variable	(I) Linear specification of cashback payment			(II) Tercile split specification of cashback payment			(III) Quintile split specification of cashback payment			(IV) Frailty model			(V) Consumer-specific cashback offer size		
Time to next purchase (in days)	Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE	
Independent variables															
Cashback payment ($)	0.0002	0.0000	***							0.0006	0.0002	***	0.0006	0.0002	***
Cashback payment in the lower tercile (< $8.10)				0.0035	0.0006	***									
Cashback payment in the middle tercile (≥ $8.10 to < $35.20)				0.0018	0.0001	***									
Cashback payment in the higher tercile (≥ $35.20)				0.0002	0.0000	***									
Cashback payment in the first quintile (< $4.86)							0.0032	0.0010	***						
Cashback payment in the second quintile (≥ $4.86 to < $11.34)							0.0037	0.0004	***						
Cashback payment in the third quintile (≥ $11.34 to < $27.54)							0.0022	0.0002	***						
Cashback payment in the fourth quintile (≥ $27.54 to < $69.66)							0.0012	0.0001	***						
Cashback payment in the fifth quintile (≥ $69.66)							0.0002	0.0000	***						
Average cashback offer (%) of top 10 retailers in the current week	0.0335	0.0015	***	0.0339	0.0015	***	0.0341	0.0015	***	0.0386	0.0131	***			
Average cashback offer (%) in the current week of retailers specific to a consumer													0.0442	0.0083	***
Amount spent in the most recent purchase ($)	0.0000	0.0000	***	0.0000	0.0000	***	0.0000	0.0000	***	0.0000	0.0000		0.0000	0.0000	
Purchase instance	-0.0001	0.0000	***	-0.0001	0.0000	***	-0.0001	0.0000	***	0.0002	0.0001	**	0.0003	0.0001	**
Consumer heterogeneity	Stratified baseline			Stratified baseline			Stratified baseline			Gamma frailty			Stratified baseline		
Day of week fixed effect	Yes			Yes			Yes			Yes			Yes		
Month fixed effect	Yes			Yes			Yes			Yes			Yes		
Number of consumers	76,296			76,296			76,296			1,000			1,000		
N	66,908,111			66,908,111			66,908,111			873,119			873,119		
LL	-9,553,060			-9,552,958			-9,552,883			-327,586			-119,030		

* p < 0.10, ** p < 0.05, *** p 0.01

Table 3: CASHBACK PAYMENTS AND SPENDING

Dependent variable	(I) OLS: Linear specification of cashback payment			(II) Tobit: Linear specification of cashback payment			(III) Tobit: Tercile split specification of cashback payment			(IV) Tobit: Quintile split specification of cashback payment			(V) Tobit: Consumer-specific cashback offer size		
Log (Amount spent in the week ($))	Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE	
Independent variables															
Cashback payment ($)	0.0007	0.0001	***	0.0025	0.0004	***							.0024	0.0004	***
Cashback payment in the lower tercile (< $8.10)							0.0346	0.0121	***						
Cashback payment in the middle tercile (≥ $8.10 to < $35.20)							0.0184	0.0028	***						
Cashback payment in the higher tercile (≥ $35.20)							0.0023	0.0004	***						
Cashback payment in the first quintile (< $4.86)										0.0234	0.0209				
Cashback payment in the second quintile (≥ $4.86 to < $11.34)										0.0291	0.0090	***			
Cashback payment in the third quintile (≥ $11.34 to < $27.54)										0.0204	0.0038	***			
Cashback payment in the fourth quintile (≥ $27.54 to < $69.66)										0.0077	0.0017	***			
Cashback payment in the fifth quintile (≥ $69.66)										0.0021	0.0004	***			
Average cashback offer (%) of top 10 retailers in the current week	0.0352	0.0020	***	0.1662	0.0346	***	0.1672	0.0346	***	0.1676	0.0346	***			
Average cashback offer (%) in the current week of retailers specific to a consumer													0.1268	0.0091	***
Amount spent in the most recent purchase ($)	0.0000	0.0000		0.0000	0.0000		0.0000	0.0000		0.0000	0.0000		0.0000	0.0000	
Purchase instance	0.0002	0.0001	***	0.0027	0.0003	***	0.0026	0.0003	***	0.0026	0.0003	***	0.0042	0.0002	***
Consumer heterogeneity	FE			RE			RE			RE			RE		
Month fixed effect	Yes			Yes			Yes			Yes			Yes		
Number of consumers	76,296			5,000			5,000			5,000			5,000		
N	9,620,542			640,784			640,784			640,784			640,784		
LL				-621669.78			-621650.87			-621650.09			-623331.4		

* p < 0.10, ** p < 0.05, *** p 0.01

Table 4: ROBUSTNESS CHECKS AND EXTENSION: DELAY

	(I)			(II)			(III)			(IV)			(V)		
Dependent variable	Tobit: Cashback payment in the prior two weeks			Tobit: Cashback payment in the prior four weeks			Tobit: No long delays			Tobit: Only observations with cashback payments > 0			Tobit: Extension: Cashback payment and delay		
Log(Amount spent in the week ($))	Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE	
Independent variables															
Cashback payment ($)	0.0023	0.0003	***	0.0022	0.0002	***	0.0029	0.0004	***	0.0009	0.0004	**			
Cashback payment ($) when delay < 76 days													0.0040	0.0008	***
Cashback payment ($) when delay ≥ 76 and < 112 days													0.0029	0.0006	***
Cashback payment ($) when delay ≥ 112 days													0.0002	0.0007	
Average cashback offer (%) of top 10 retailers in the current week	0.1653	0.0346	***	0.1640	0.0346	***	0.1614	0.0348	***	0.1779	0.0967	*	0.1712	0.0344	***
Amount spent in the most recent purchase ($)	0.0000	0.0000		0.0000	0.0000		0.0000	0.0000		0.0001	0.0000	***	0.0006	0.0000	***
Purchase instance	0.0027	0.0003	***	0.0026	0.0003	***	0.0027	0.0003	***	0.0080	0.0005	***	0.0029	0.0003	***
Consumer heterogeneity	RE			RE			RE			RE			RE		
Month fixed effect	Yes			Yes			Yes			Yes			Yes		
Number of consumers	5,000			5,000			5,000			3,974			5,000		
N	640,784			640,784			640,784			56,019			640,784		
LL	-621657.43			-621634.14			-616501.05			-75347.03			-620789.87		

* p < 0.10, ** p < 0.05, *** p 0.01

Table 5: EXTENSION: RETAILER CATEGORY ANALYSIS

	(I)			(II)			(III)			(IV)			(V)		
Dependent Variable	Tobit: General retailer category			Tobit: Travel category			Tobit: Services category			Tobit: Publishing category			Tobit: Single General-category retailer		
Log (amount spent in the week ($))	Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE	
Independent Variables															
Cashback payment from same retailer category($)	0.0045	0.0007	***	0.0023	0.0013	*	-0.0082	0.0024	***	-0.0101	0.0038	***	.0078	0.0003	***
Cashback payment from all other retailer categories ($)	0.0029	0.0010	***	0.0001	0.0011		-0.0002	0.0018		-0.0032	0.0013	**	0.0014	0.0005	**
Average cashback offer (%) of all retailers of same category in the current week	6.4217	0.4102	***	4.5943	0.6481	***	-0.7482	0.2917	**	-0.5436	0.2718	**			
Cashback offer (%) of the individual retailer													0.9881	0.0387	***
Amount spent in the most recent purchase ($)	-0.0002	0.0000	***	0.0006	0.0000	***	0.0007	0.0000	***	-0.0003	0.0000	***	-0.0002	0.0000	***
Purchase instance	0.0001	0.0001		-0.0011	0.0002	***	-0.0006	0.0003	**	-0.0012	0.0002	***	-0.0004	0.0001	***
Consumer heterogeneity	RE			RE			RE			RE			RE		
Monthly fixed effect	Yes			Yes			Yes			Yes			Yes		
Number of consumers	5,000			5,000			5,000			5,000			3,863		
N	589,240			427,313			454,340			324,603			486,994		
LL	-503,525.95			-208,860.06			-134,400.22			-95,353.85			-221423.66		

* p < 0.10, ** p < 0.05, *** p 0.01

Table 6: CASHBACK PAYMENTS: SPENDING VS. SAVING

	(I)			(II)		
Dependent variable	OLS			Fractional logit		
Percentage of cashback payment saved	Estimate	SE		Estimate	SE	
Independent variables						
Cashback payment of $3	-	-		-	-	
Cashback payment of $7	3.1034	1.7038	*	0.2341	0.1370	*
Cashback payment of $18	5.4149	1.7038	***	0.4140	0.1288	***
Cashback payment of $54	15.5083	1.7050	***	1.1362	0.1249	***
Cashback payment of $113	22.5465	1.7027	***	1.6394	0.1238	***
Cashback payment of $162	23.3308	1.7038	***	1.6821	0.1235	***
Cashback payment of $287	26.1542	1.7027	***	1.8953	0.1294	***
Age	1.3534	0.7113	*	0.0632	0.0261	**
Male	-10.0000	13.5147		-15.7248	3.9702	***
Income <$25,000	-	-		-	-	
Income $25,000-$50,000	58.5714	13.5147	***	3.2787	0.8311	***
Income $50,000-$75,000	-32.6316	14.6983	**	-1.5394	0.4828	***
Income $75,000-$100,000	2.8195	11.7095		0.1444	0.5371	
Income >$100,000	-16.6541	18.4665		-16.0226	2.5748	***
Respondent fixed effects	Yes			Yes		
Number of respondents	441			441		
N	3,087			3,087		
LL				-1264.18		

* p < 0.10, ** p < 0.05, *** p 0.01

Table 7: EVIDENCE FOR BEHAVIORAL MECHANISM

Dependent variable	(I) Tobit: First week of the month			(II) Tobit: Last week of the month			(III) Tobit: Three-way split of shopping frequency			(IV) Tobit: Five-way split of shopping frequency		
Log (amount spent in the week) ($)	Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE	
Independent variables												
Cashback payment during the first week of the month	0.0026	0.0007	***									
Cashback payment during other weeks of the month	0.0025	0.0005	***									
Cashback payment during the last week of the month				0.0020	0.0010	**						
Cashback payment during other weeks of the month				0.0026	0.0004	***						
Cashback payment to consumers with average inter-purchase time < 19.08 days							0.0002	0.0015				
Cashback payment to consumers with average inter-purchase time ≥ 19.08 and < 42.68 days							0.0013	0.0009				
Cashback payment to consumers with average inter-purchase time ≥ 42.68 days							0.0030	0.0005	***			
Cashback payment to consumers with average inter-purchase time < 12.95 days										-0.0017	0.0023	
Cashback payment to consumers with average inter-purchase time ≥ 12.95 and < 22.03 days										0.0016	0.0016	
Cashback payment to consumers with average inter-purchase time ≥ 22.03 and < 35.69 days										0.0021	0.0011	*
Cashback payment to consumers with average inter-purchase time ≥ 35.69 and < 64.28 days										0.0034	0.0010	***
Cashback payment to consumers with average inter-purchase time ≥ 64.28 days										0.0027	0.0005	***
Average cashback offer (%) of top 10 retailers in the current week	0.1662	0.0346	***	0.1668	0.0347	***	0.1662	0.0346	***	0.1663	0.0346	***
Amount spent in the most recent purchase ($)	0.0000	0.0000		0.0000	0.0000		0.0000	0.0000		0.0000	0.0000	
Purchase instance	0.0027	0.0003	***	0.0027	0.0003	***	0.0027	0.0003	***	0.0027	0.0003	***
Consumer heterogeneity	RE			RE			RE			RE		
Month fixed effect	Yes			Yes			Yes			Yes		
Number of consumers	5,000			5,000			5,000			5,000		
N	640,784			640,784			640,784			640,784		
LL	-621669.77			-621669.6			-621667.1			-621667.4		

* p < 0.10, ** p < 0.05, *** p 0.01

Figure 1: DELAY BETWEEN PURCHASE AND CASHBACK PAYMENT

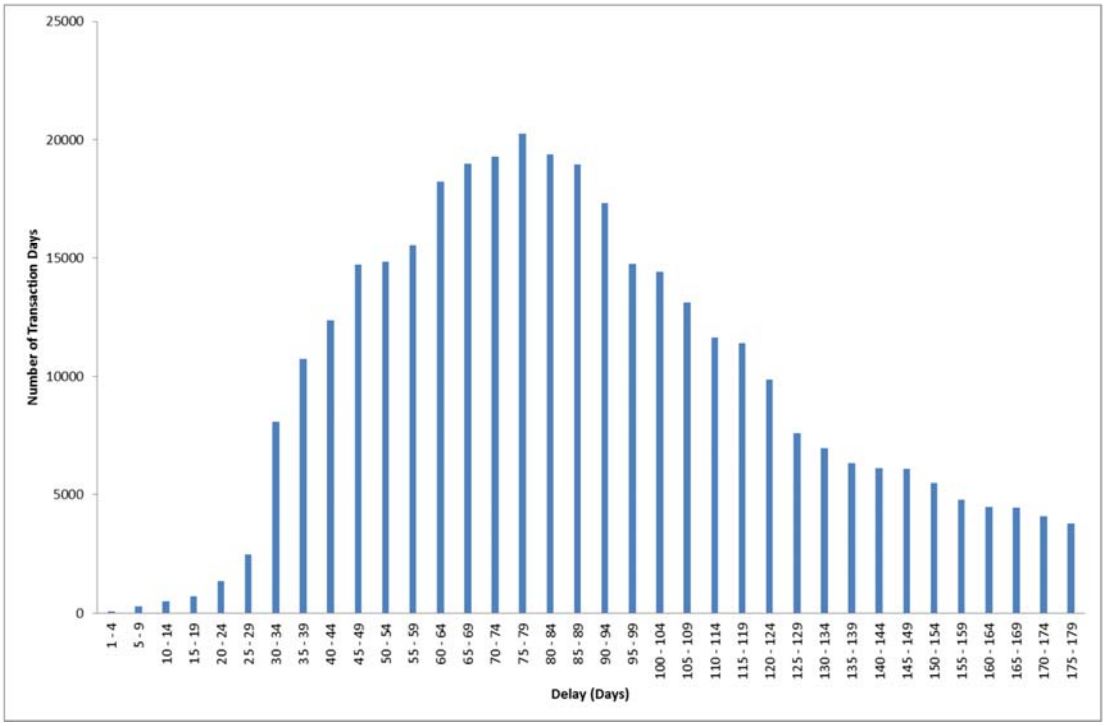

Figure 2: DELAY FOR FOUR RANDOMLY SELECTED CONSUMERS

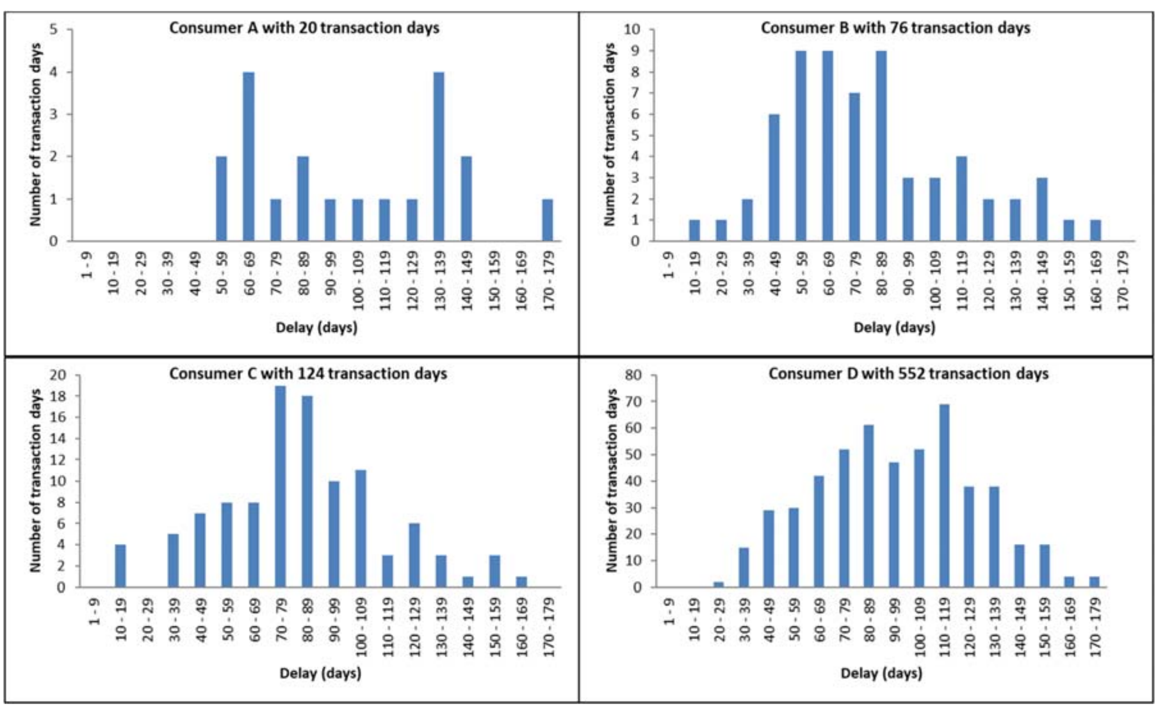

Figure 3: DELAY AT FOUR RANDOMLY-SELECTED RETAILERS

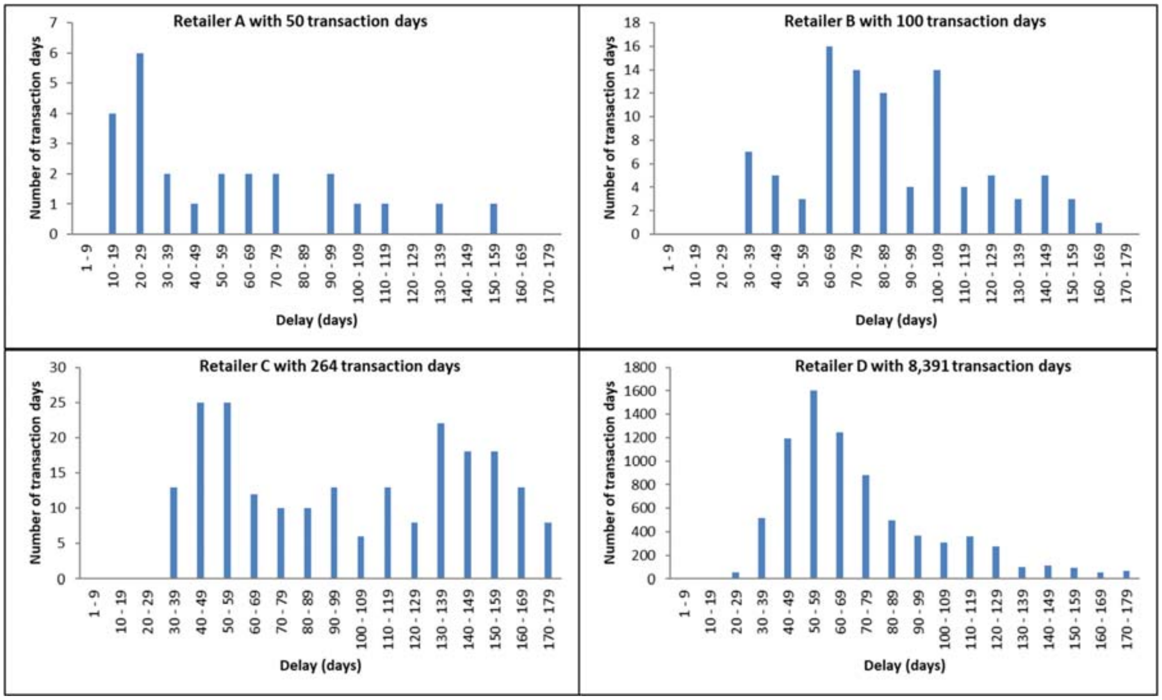

Figure 4: DELAY FOR FOUR RANDOMLY-SELECTED UNMATCHED CONSUMERS AT A SPECIFIC RETAILER

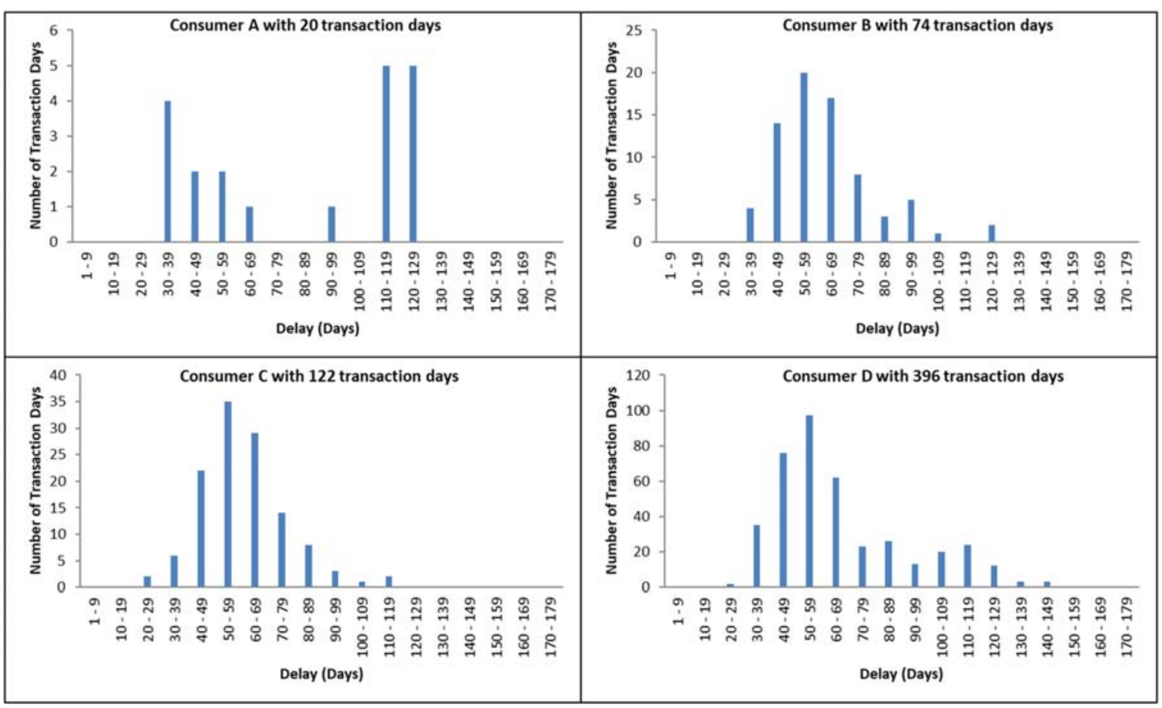

Figure 5: DELAY FOR FOUR RANDOMLY-SELECTED MATCHED CONSUMERS AT A SPECIFIC RETAILER

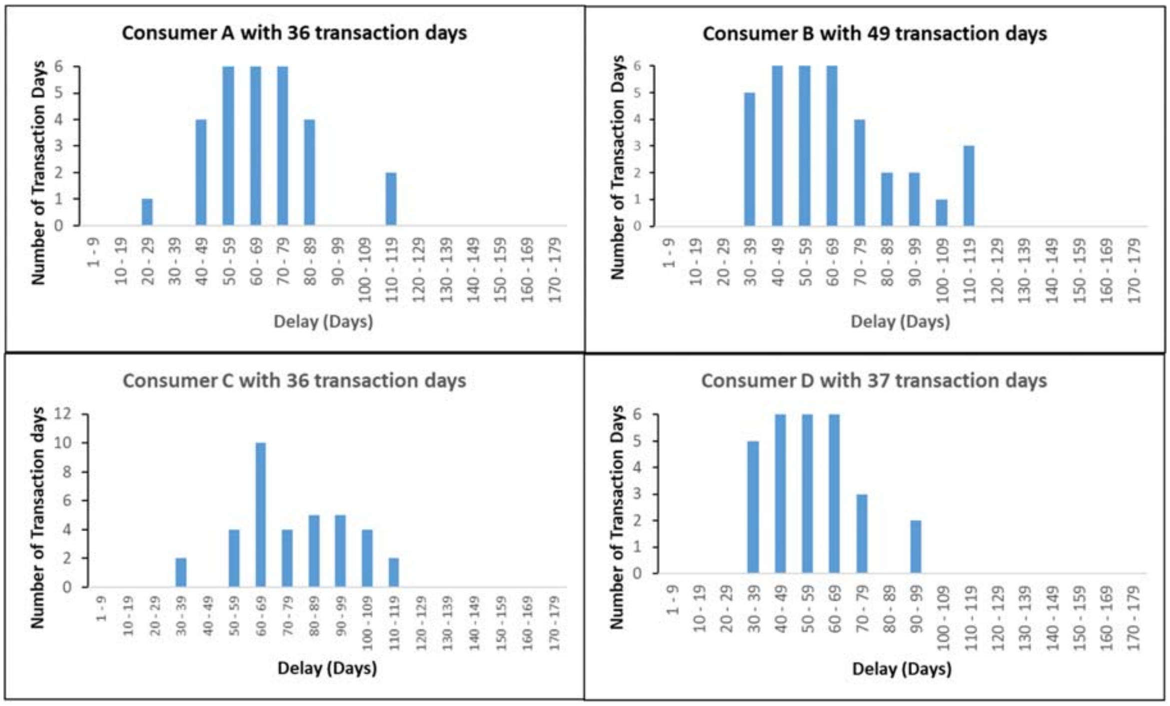

Figure 6: DELAY AT A MUSIC RETAILER AND AT A GENERAL RETAILER

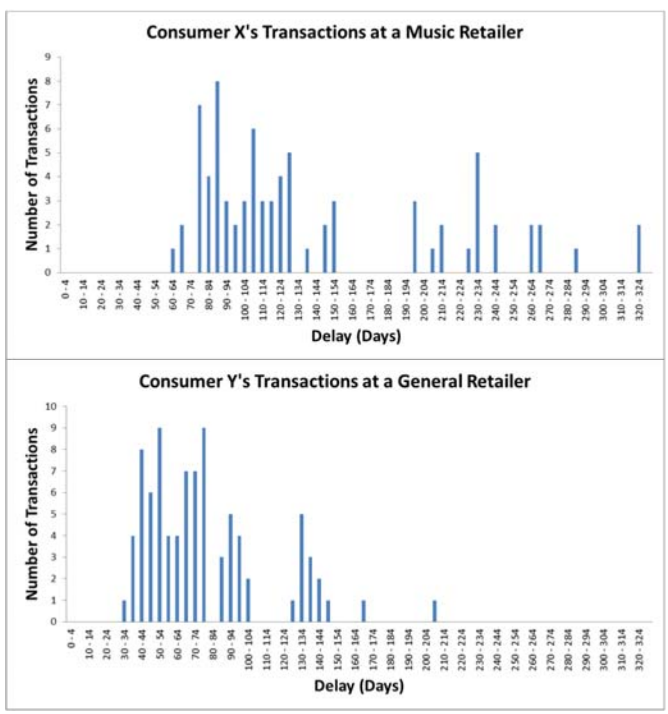

Figure 7: MODEL-FREE EVIDENCE FOR PURCHASE LIKELIHOOD

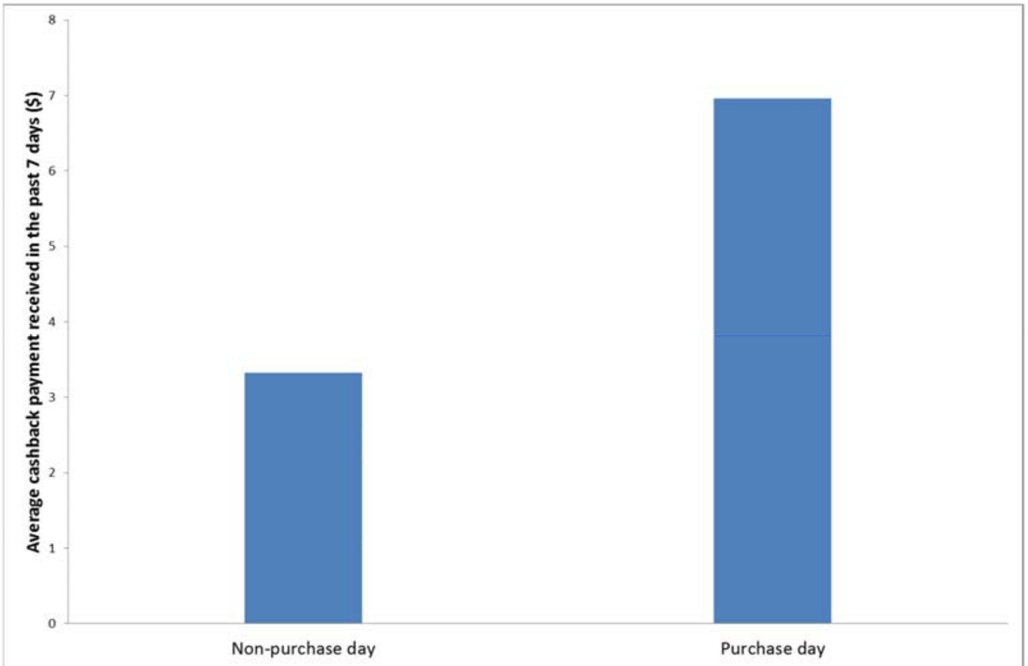

Figure 8: MODEL-FREE EVIDENCE FOR SPENDING

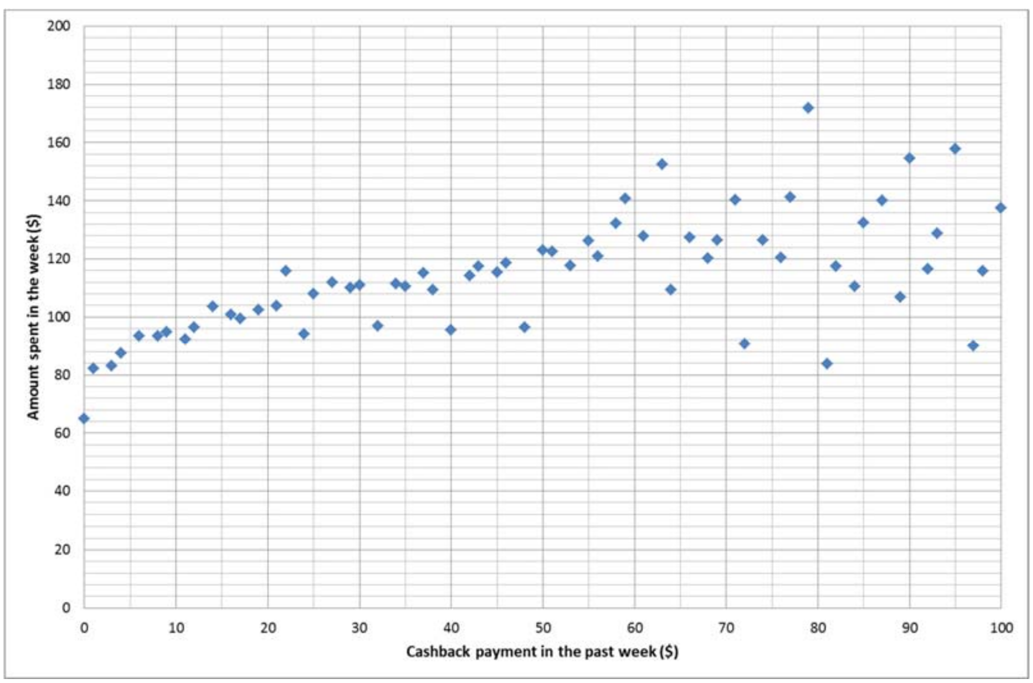

Figure 9: MARGINAL EFFECT OF CASHBACK PAYMENT ON OBSERVED SPEND, BY TERCILE OF CASHBACK PAYMENT