Cashback is Cash Forward: Delaying a Discount to Encourage Further Spending

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22 August 2016

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ABSTRACT

This research examines purchase behavior in the context of cashback shopping—a relatively young but increasingly popular form of sales promotion online. In general, the literature in marketing recognizes two reasons to delay paying a discount: consumers often fail to claim the money promised to them, and tying the refund to a future purchase event. However, in cashback shopping payments are automatic and unconditional, which brings into question the usefulness of the practice. An analysis of panel data from a large cashback company reveals that, aside from the predictable positive effect of cashback offers on demand, cashback payments induce and increase further spending through its website. We propose three explanations that, individually or in combination, may account for this phenomenon, and turn to the data for evidence. The concluding section discusses implications for cashback companies and retailers, and raises some limitations of our work. (144 words)

Keywords: Cashback shopping, electronic commerce, sales promotion, pricing, affiliate marketing.

The continued growth of electronic commerce motivates firms to test new means of reaching and enticing consumers with better prices—anything from the now common voucher codes to different models of daily deals and group buying. Within this context, cashback shopping is a relatively young but increasingly popular alternative.

The feature that distinguishes cashback shopping from its peers is that consumers initiate purchases via the (hyper) links posted on the website of a cashback company rather than directly at the websites of individual retailers. The cashback company claims to drive sales for retailers by offering consumers a refund, or "cashback," on the sales that eventuate. The size of cashback payments—typically expressed as a percentage of money spent—is negotiated in advance with retailers and advertised on the website of the cashback company as cashback offers. The cashback company receives commissions from retailers for the purchases it facilitates and refunds consumers the money promised to them.[1]

The typical cashback company posts offers from a variety of retailers, ranging from generalists such as department stores to specialists in virtually all product and service categories. By way of indication, in 2013 the leading cashback company in the United States generated sales in excess of $2.2 billion for 2,600 retailers. Since 1998, this company has processed cashback payments totaling $325 million. In 2015, the largest cashback company in the United Kingdom saved over $74 million for its six million registered users and generated close to $1.2 billion in sales for 4,300 retailers—a figure that represents 1% of all electronic commerce in the country for that year. Cashback shopping likewise has spread in other countries. For example, the largest cashback company in Spain and Portugal serves two million consumers and generates sales of

[1] To be clear, retailers ultimately fund the promotional activity. A different matter is whether consumers are aware of this or associate cashback offers and payments also (or only) with the cashback company.

$22.6 million each year for more than 500 retailers. The leading company in India and China boasts close to 150 million users and processes 22,000 transactions every day.[2]

To our knowledge, the current paper is the first empirical analysis of purchase behavior in the context of cashback shopping—and only the second empirical study overall. Recently, Ballestar, Grau-Carles, and Sainz (2016) used data from a cashback company in Europe to describe the relationship between the size and composition of a user's network, the diversification of navigation through the website, and the level of engagement with the company. In earlier analytical work, Chen et al. (2008) studied a setting where a search engine shares part of the revenue from online adverting auctions with its users, and Ho, Ho, and Tan (2013) examined the profitability of cashback offers when double marginalization and channel coordination are factors.

The question that interests us is general in nature. At first glance, cashback shopping appears no different to traditional (offline) instances where a firm decides to pay a discount with some delay. The mail-in rebate is perhaps the most familiar example. According to the literature, this decision has two motivations. First, firms can profit from the misjudgment, procrastination, or simple absent-mindedness that causes low redemption rates among consumers (Gilpatric 2009; Gourville and Soman 2011; Soman 1998). Second, firms can tie the payment of the saving to a future purchase event, thereby increasing market share and profits in the long term (Raju, Dhar, and Morrison 1994; Dhar, Morrison, and Raju 1996).[3] Yet cashback payments are

[2] We compiled this information from press articles and the websites of different cashback companies. Details are available on request.

[3] A third, debated motivation is the possibility of sharper price discrimination. For example, Chen, Moorthy, and Zhang (2005) argue that rebates allow for price discrimination not only across different consumers, but also across different states of the same consumer. Lu and Moorthy (2007) compare

automatic (they require no effort on the part of consumers) and unconditional (they are deposited directly into bank accounts), which begs the question of whether cashback shopping offers anything beyond the initial lift in sales to offset the commissions paid to the intermediary and the nuisance of making consumers wait for their money.

We study this issue with the help of a large cashback company. The company shared user-level panel data comprising cashback offers, cashback payments, and individual transactions. We have information on more than 76,000 users making, on average, 45 purchases over 2.4 years. An initial analysis shows that, aside from the positive (and predictable) effect of cashback offers on demand, cashback payments increase the probability that users make additional purchases through the website of the cashback company, and the size of these purchases. These effects are reliable: a battery of robustness checks yields consistent results in each instance. Equally important, the effects are meaningful: at the average values in the data, increasing cashback by $1.00 increases the likelihood of a purchase by 0.02% and spending by $0.32.

The fact that consumers are susceptible to the promise of a saving *and* the later payment of that saving is striking because they are essentially rewarding the cashback company for holding on to their money. Moreover, as mentioned, consumers are free to spend the money in any way they deem fit, or indeed to set it aside. Finally, note that, from a normative standpoint, cashback payments are trivial: if consumers optimize spending across their expected income and over their expected working life (Friedman 1957; Modigliani and Brumberg 1954), then refunds should not influence purchases in any product category, with any retailer, or through any

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rebates to coupons and point out that, if consumers experience uncertain redemption costs, there are conditions whereby each mechanism is optimal.

intermediary in a meaningful way.

Notwithstanding, there are three explanations that, individually or in combination, may account for the results. First, it may be that consumers use cashback payments to schedule future purchases. The motivation for this can be strictly financial: consumers with liquidity problems postpone spending until they receive cashback payments and, therefore, have more money at hand. However, it can also be psychological: consumers who tend toward immediate gratification, but understand that deferring a purchase decision may improve the quality of that decision (Hoch and Loewenstein 1991) or make the purchase more pleasurable (Caplin and Leahy 2001), may treat cashback payments as reminders to be patient.

The second explanation is that consumers fail to treat money as a fungible resource. The separation in time between cashback offers, purchases, and cashback payments allows consumers to segregate the latter and perceive them as windfall gains—an implication of mental accounting that Thaler (1985) and Soman (1998) predicted in the context of mail-in rebates but did not test empirically. People typically code small windfalls as spendable income (Shefrin and Thaler 1988),[4] and match the source of income with its use (Kahneman and Tversky 1984). For example, Kooreman (2000) found that government payments labeled as child benefits directly increased spending on children clothing, and Milkman and Beshears (2009) found that patrons at an online grocery store spent more and in greater variety when redeeming an unexpected coupon than when they did not. Closer to our interest, Reinholtz, Bartels, and Parker (2015) recently showed that consumers treat funds that are specific to a retailer (e.g., gift cards) as a mental account governed by the goal to purchase from the same retailer.

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[4] Indeed, Gourville and Soman (1998) used the term “free money” to describe such gains.

Third, our finding may be justified by a transient effect. One possibility is that cashback payments elicit positive incidental affect—that is, they elevate one's mood (Heilman, Nakamoto, and Rao 2002). Another is that consumers perceive cashback payments as acts of kindness and engage in reciprocity (Rabin 1993). Finally, it is possible that cashback payments simply make shopping through the website of the cashback company more salient (Obermiller 1985). Irrespective, the point is that receiving cashback triggers some temporary state that, in turn, increases the propensities to purchase and spend.

The data provide little support for the first of these arguments. If consumers face liquidity constraints, then the effects of cashback payments should be more (less) pronounced at the end (beginning) of a month when, presumably, less (more) income is available. This does not appear to be the case. Similarly, to find evidence of deferred gratification we compare the effects of cashback payments across consumers who receive money more or less frequently. Consumers in the latter predicament obviously face a longer wait between cashback payments. If deferred gratification is an issue, then we should observe stronger effects for this group. The data again do not support the prediction. At the same time, we observe an inverse relationship between the size of cashback payments and spending. This result matches the observation made by Shefrin and Thaler (1988) that individuals readily spend windfalls to the extent that they appear to be small, meaningless changes to one's wealth; which is consistent with the belief that money is not fungible but tough to reconcile with a theory of incidental affect, reciprocity, or salience.

To conclude the analysis, we study three aspects of the data in greater depth. First, we check whether our results vary with changes in the delay between purchases and cashback payments. There has to be some separation in time for the latter to have a separate effect from cashback offers—indeed, a zero delay converts cashback shopping into a standard price promotion. In fact, the overwhelming majority (98.80%) of cashback payments takes place with a delay of at least 30 days. Yet we find that a larger interval between purchases and cashback payments reduces the effect of on spending, presumably because waiting frustrates consumers. Second, we search for evidence of learning among users. The data provide little evidence, as the response of consumers to cashback payments does not change beyond the first few instances. Third, we analyze the data by category of retailer rather than at the level of the cashback company. We find that generalists such as department stores are more likely to benefit from the effect of cashback payments than specialists are. This makes sense because generalists offer a broad range of products that motivate frequent purchases, which increases the likelihood of a future purchase.

With respect to existing research, this paper makes at least four contributions to the literature on sales promotion. First, we breach the gap between the use of and knowledge about cashback shopping. The practice is growing at an impressive rate, but to date there is little formal research in the area. Our study not only adds empirical evidence to a body of work that is primarily analytical in nature, but also places emphasis on the purchase behavior of consumers—possibly the most relevant question to marketing professionals.

Second, we note that businesspeople who are keen to understand how consumers respond to sales promotion in digital environments will find that academic research adds insight primarily with respect to group buying (Wu, Shi, and Hu 2014) and daily deals (Aydinli, Bertini, and Lambrecht 2014; Luo et al. 2014). These mechanisms are new in the sense that they are unique to the digital economy. Conversely, our research essentially focuses on the online counterpart of mail-in rebates, a tactic that is certainly familiar to firms. This link is interesting because it allows managers to draw comparisons and learn across different domains.

Third, we complement articles that examine the logic of delayed discounts. Some research focuses on identifying and explaining the psychology of redemption failure (Gilpatric 2009; Gourville and Soman 2011; Soman 1998), while other work highlights the possibility of tying redemption to additional purchase events (Raju, Dhar, and Morrison 1994; Dhar, Morrison, and Raju 1996). As mentioned, we study a setting where poor redemption and mandatory purchases are irrelevant. Yet we find that cashback payments benefit the cashback company in two unexpected ways. As such, our research uncovers a third opportunity for firms to benefit from delaying a discount.

Fourth, we want to contribute to what marketing scholars know about the long(er)-term impact of sales promotion efforts. The research that studies this question mostly paints a bleak picture: a campaign today tends to hurt sales tomorrow (for more detail, see Blattberg, Briesch, and Fox 1995). There are different reasons for this conclusion, among them the fact that discounting induces stockpiling (Bucklin and Gupta 1992; Bucklin and Lattin 1991), accelerates purchases (Ailawadi and Neslin 1998; Bell, Chiang, and Padmanabhan 1999), and damages brand perceptions (Blattberg, Briesh, and Fox 1995). In light of these arguments, our findings should be welcome news.

Aside from the large literature on sales promotion, our research is relevant given Hastings and Shapiro’s (2013) call for large-scale evidence of mental accounting “in the wild”—as opposed to evidence from hypothetical choice tasks or incentivized behaviors in the laboratory. From this perspective, our work is perhaps closest to that of Milkman and Beshears (2009), although in reality the comparison ends at the fact that we both study monetary incentives that are exogenous from the perspective of consumers. First, we study the effect of delayed discounts paid as the result of a prior purchase, not standard “dollars-off” coupons. The separation in time between purchases and cashback payments is critical and unique to our setting. Second, cashback payments have no usage or time restrictions. This point is important because consumers spend (disproportionately) through the cashback company money that they can use anywhere and anytime, or save. Instead, Milkman and Beshears (2009) find that people spend more at a grocery store when invited to spend a voucher for that same store. Third, consumers in the data respond to multiple offers of varying amounts, not a single offer of a fixed ($10) amount. Finally, the data that we analyze span many product categories and retailers, a large number of consumers, and eight years of purchases and cashback payments. As such, we provide evidence that the effects generalize across consumers and time.

The plan for the remainder of the paper is the following. First, we describe the empirical setting. Second, in separate sections we report the main analysis and robustness checks, the tests of the possible behavioral mechanisms, and the three extensions. Third, the final section reviews the findings, discusses implications for cashback companies and retailers, and raises possible limitations.

EMPIRICAL SETTING

The Data

A nondisclosure agreement prevents us from revealing the name of the cashback company that shared its data, the country where it operates, or the local currency. For ease of exposition, we convert all monetary values into United States Dollars.

The data comprise information on all the purchases by registered users (consumers) in response to cashback offers, and the corresponding cashback payments, from May 2005 (month in which the company started operating) to August 2013.[5, 6] The cashback company regularly emails consumers about current cashback offers, and in turn consumers share and discuss this information in online forums. We observe each purchase of each consumer through the cashback company in response to a cashback offer.[7] Consumers can purchase at any point in time—there is no restriction on the number of purchases, or their timing relative to cashback payments. We know the total amount spent by each consumer on a given day, at a given retailer, and for a cashback offer of a given size. However, we do not know finer details such as the type, category, or quantity of the item(s) purchased. If a retailer advertises multiple cashback offers on a given day, and a consumer acts on more than one of these offers, then there are separate records of the resulting purchases.

In total, we observe 3,433,476 transactions by 76,296 consumers at 5,337 retailers. Table 1 provides summary statistics. The average tenure of a consumer, measured as the time between the first and last purchase in the data, is 876.8 days. On average, a consumer made 45.0 purchases on 36.9 days, each worth \$305.7, and received a cashback payment every 12.4 days, worth \$51.44.[8] The mean time between successive purchase days is 24.4 days. The mean time

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[5] Consumers registered with the cashback company at different moments during this interval. A small (4.8%) set of transactions relates to in-store cashback offers. These are available at the physical premises of selected retailers, and cashback payments are conditional on consumers using the credit cards on record with the cashback company. Most of the analyses that we report use all the data. However, one of our robustness checks excludes this type of offers.

[6] The demographic information that we have for a subset of consumers indicates that they are broadly similar to the overall population, except for being slightly younger and disproportionately male. This difference may reflect the general nature of Internet audiences.

[7] We do not observe purchases made directly at the website of individual retailers, or purchases that are independent of a cashback offer. Therefore, our research is specific to consumers who transact through the cashback company and in response to the promise of a saving, possibly because they are more sensitive to price or incur lower search cost than others.

[8] The cashback company often bundles cashback payments to the same consumer into one operation, which in turn affects the frequency of such deposits.

between purchase and cashback payment is 123.9 days, with a standard deviation of 110.9 days (see Figure 1).

Insert Table 1 about here

Insert Figure 1 about here

One reason for the size and variability of the interval between purchase and cashback payment is that retailers process commissions to the cashback company only after the return period for the item(s) purchased expired. Return periods and internal processes 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 unexpected or unplanned delays. A second reason is that the cashback company enters into different agreements with different retailers, often as a function of the product category. For example, in the case of insurance it is common for underwriters to defer commissions until they receive several (monthly) payments from their subscribers. For a travel expense, the agency typically waits until the end of a stay or vacation to safeguard against cancelations.

Identification

To identify the causal effects of cashback payments on purchase behavior, the timing and size of the former must be exogenous from the standpoint of consumers. That is, consumers should not be able to predict or influence cashback payments, otherwise they could account for this income in their spending plans.

There are at least three justifications for this assumption. First, the cashback company that shared its data schedules cashback payments (once it receives the commissions from retailers) according to internal processes alone. To our knowledge, this is standard in the industry. Second, consumers receive notification of a deposit only after it is completed. Third, as mentioned, there is considerable irregularity in the time it takes retailers to pay commissions, and the time it takes the cashback company to execute cashback payments. There is significant variation in the interval between purchases and cashback payments even at the level of a single consumer (Figure 2), which counters the possibility that the pattern in Figure 1 arises from individual differences between consumers. Similarly, the interval varies at the level of a single retailer, as Figure 3 demonstrates in the case of four retailers selected at random. Figure 4 shows such variation for the purchases of four consumers selected at random at a single retailer. As such, this evidence also counters the possibility that the pattern in Figure 1 arises from differences between retailers. Fourth, we check whether the delay between purchases and cashback payments is specific to the range of products sold by retailers. Figure 5 compares a specialist that offers a narrow range of products to a generalist that offers a broad range. We find significant variation in the delay across retailers, which suggest that the breadth of the assortment is not a determining factor.

Insert Figures 2-5 about here

One concern is that the interval between purchases and cashback payments varies with the size of the former and, correspondingly, with the size of cashback payments. In principle, such a relation helps consumers predict the timing of cashback payments. This would be the case, for instance, if products that are more expensive enjoy longer return periods and consumers are aware of the policy. Our conversation with the cashback company suggests that there is no such link, procedural or otherwise. Indeed, the data indicate only a low correlation between the size of a purchase and the delay ($R^2 = -0.015$, $p < 0.001$), and a low correlation between the size of cashback payments and the delay ($R^2 = -0.016$, $p < 0.001$). Even if these statistics were more substantial, it is unlikely that consumers are able to pinpoint the specific week (or even day) of a refund.

A second concern is that the nature of certain purchases improves the ability of consumers to predict cashback payments. The example that we have in mind is travel expenses, where consumers may know that deposits trail the date of, say, a vacation. This contingency affects only a small subset of transactions, and it does not allow consumers to pinpoint the precise week or day of a payment. Irrespective, one of our robustness checks excludes observations with long (mean plus one standard deviation) delays.

MAIN ANALYSIS AND RESULTS

Model-Free Evidence

We explore the possibility of a relationship between cashback payments and two outcome variables: purchase likelihood and spending. To analyze purchase likelihood, we classify every consumer-day observation as a purchase or non-purchase event depending on whether the consumer transacts 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 6 suggests that cashback payments relate to purchase likelihood: on average, consumers receive $2.50 more in the seven days prior to a purchase event than a non-purchase event ($p < 0.001$).

Insert Figure 6 about here

Next, we examine the relationship between cashback payments and spending by associating the money refunded to a consumer in periods of seven days (from a given Saturday to Friday) to the money spent by the same consumer in the next seven days.[9] We calculate the average weekly spend across all consumer-week observations for cashback payments of all sizes received in the preceding week. Figure 7 indicates a positive relationship: as cashback increases, so does spending—the correlation is 0.332 ($p < 0.001$).

Insert Figure 7 about here

These analyses clearly do not control for heterogeneity among consumers. Doing so matters because, for example, consumers who purchase frequently are at any moment in time more likely to receive cashback payments than consumers who purchase infrequently. Similarly, consumers who made larger purchases in the past and are likely to do so again in the future always receive larger cashback payments. We now present models that address this concern and, in addition, control for possible time-dependent patterns in purchase behavior.

[9] We choose this interval because the cashback company processes 51.5% of deposits on a Thursday or Friday. The results are robust to alternative specifications.

Cashback Payments and Purchase Likelihood

Model setup. We use a semi-parametric proportional hazard model to estimate the effect of cashback payments on purchase likelihood (Cox 1972; Jain and Vilcassim 1991; Seetharaman and Chintagunta 2003). Specifically, we measure whether on any given day the cashback payment received by a consumer during the seven days prior increases the probability of a purchase on that day—controlling for the time elapsed since the consumer's previous purchase and a series of covariates.[10]

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 through the cashback company by consumer *i* on any given day t, $h_i(t|X_{it})$, as

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

In the equation, $h_{0i}(t)$ is the baseline hazard function specific to consumer *i*. To account for differences among consumers in the average likelihood of purchase, 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 the term $exp(X_{it}\beta)$, where X_{it} is a vector of time-varying covariates and β is the set of parameters to estimate.

We specify the vector of covariates as:

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

[10] One alternative is to specify a weekly (rather than daily) decision model. Given that the median inter-purchase interval is eight days, this option removes significant variation.

The independent variable of interest is $\sum_{k=t-1}^{t-7} CBPayment_{i,k}$: the cashback received by 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 (by number of transactions) retailers in the data, $AvgCBOffer_t$. The variable $LastPurchaseSpend_{it}$ captures the amount spent by consumer *i* on the most recent day of purchase and, therefore, controls for trends in purchase behavior that are specific to the consumer. $PurchaseInstance_{it}$ is the number of transactions made by consumer *i* up to, but not including, day *t*. This variable controls for the consumer's prior experience with the cashback company. $DayOfWeek_t$ and $Month_t$ control for day-of-week and month fixed effects, respectively.

Results. Column (I) in Table 2 shows that larger cashback payments increase the likelihood of a purchase. The associated hazard rate of 1.0002 implies that, on any given day, an increase of $1.00 in cashback payment in the seven days prior raises the probability of purchase by 0.02%. In Column (II), the effect varies by the size of the payment. We measure the effect separately by tercile of cashback payment (< $8.10, ≥ $8.10 and < $35.20, ≥ $35.20), and find that a $1.00 increase in cashback payment has a significantly higher effect on purchase likelihood when that payment is small (< $8.10) than large (≥ $35.20). Column (III) replicates this result with quintiles. Finally, Column (IV) shows that the result holds when, instead of following a stratified baseline approach, we specify a frailty-model with a gamma-distributed random effect to account for heterogeneity (McGilchrist and Aisbett 1991). While previously the baseline hazard varied non-parametrically across consumers, now we assume a multiplicative effect of the heterogeneity parameter on the baseline hazard function.

Insert Table 2 about here

With respect to the remaining covariates, we find that the likelihood of a purchase decreases with the number of past purchases. This matches the idea that in any relationship between firm and customer, the latter "dies" over time (Fader, Hardie, and Shang 2010). Similarly, consumers who recently spent large amounts tend to be more likely to purchase, indicating some form of state dependence. Importantly, the size of cashback offers has a positive effect on the probability of purchase. This is in line with empirical evidence and common sense: firms presumably engage in sales promotion efforts of any type, including cashback shopping, to drive sales. However, we stress that the effect of cashback payments on purchase likelihood is separate from the effect of cashback offers.

Cashback Payments and Spending

Model setup. We use a Type-I Tobit specification to estimate the effect of cashback payments on spending. This specification takes into account the large number of non-purchase events in the data. We take a similar approach to the one used for the model-free evidence: we focus on the impact of cashback payments in a given week (from a given Saturday to the following Friday) on spending at any time in the next seven days.[11] Because the dependent variable captures the amount spent, it accounts for changes in spending and, therefore, implicitly accounts for the possibility that cashback payments prompt purchases that consumers would not otherwise make.

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[11] The analysis is at the weekly rather than daily level because the latter yields a large number of null (zero-spend) observations per consumer, which complicates estimation.

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 with β the set of parameters to estimate. We operationalize the dependent variable as $\log(Spend_{iw} + 1)$ rather than $Spend_{iw}$ because, while the Tobit model assumes normality of error distributions, the data feature a significant mass of observations in the right tail of spending (see Table 1). Specifically, the model is:

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

$$\log(Spend_{iw} + 1) = \begin{cases} LatSpend^*_{iw} & if\ LatSpend^*_{iw} > 0 \\ 0 & if\ LatSpend^*_{iw} \leq 0 \end{cases} \tag{4}$$

We specify the vector of covariates as:

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

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 again taking the average percentage of cashback offered by the 10 largest retailers in the data, $AvgCBOffer_w$. The variable $LastPurchaseSpend_{iw}$ captures the amount spent by consumer i in the most recent week of purchase and, therefore, controls for patterns of purchase behavior that are specific to the consumer. $PurchaseInstance_{iw}$ is the number of transactions made by consumer i up to, but not including, week w. $Month_w$ controls for month fixed effects.

We assume consumer-specific random effects α_i, to account (in a way that is computationally tractable) for heterogeneity in the average weekly spending level. These random effects are distributed $\alpha_i \sim N[0, \sigma^2_v]$, with σ^2_v the only heterogeneity parameter to estimate. However, this assumption implies that the likelihood function for the Tobit model must be integrated over the distribution of α_i, which is computationally intensive—integrating over the normal distribution does not result in closed-form expressions and the likelihood is estimated numerically. Accordingly, for all Tobit analyses we use a smaller sample of 5,000 randomly selected consumers. To provide some evidence that the findings hold for 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. The dependent variable is the weekly amount spent. The effect of cashback payments on spending 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 preceding seven days.

Next, we examine whether this result is sensitive to the size of cashback payments. Column (III) shows that this is the case when we take cashback payments by tercile: a $1.00 increase in cashback payment has a greater effect on spending when that payment is smaller rather than larger. Column (IV) shows the same pattern when we study quintiles.

Insert Table 3 about here

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

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

Figure 8 plots this effect at the median level of cashback payment in each tercile ($3.24, $17.82, and $81.00; the green, red, and blue line, respectively). The x-axis reflects the amount spent,

$Spend_{iw}$. For each amount, the y-axis reflects the change in spending that would result from increasing the cashback payment by $1.00. At the mean amount of spending 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 effect declines with the tercile level of the 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.

Insert Figure 8 about here

Robustness Checks

We complete several checks to ensure the robustness of our findings. These checks apply to the two outcome measures that interest us: purchase likelihood and spending. However, given that the results are similar throughout, we report only those that pertain to the latter.

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 summarized in Table 3 replicate when we take instead the prior 14 or 28 days. Columns (I) and (II) of Table 4 indicate that this is the case.

Second, recall that identifying a causal effect of cashback payments hinges on the premise that these are exogenous from the perspective of consumers. The exploratory analysis reported earlier in this section supports this idea, but we pointed to a subset of purchases (e.g., travel expenses) for which consumers may have a better (but not accurate) sense of the timing of cashback payments. To check against this contingency, we estimate the model excluding consumer-week observations with delays exceeding the mean in the data plus one standard deviation. Column (III) of Table 4 replicates the main findings.

Insert Table 4 about here

Third, it may be that the effects of cashback payments are due to the mere act of receiving cashback rather than the sum paid. For instance, it may be that the emails sent by the cashback company to notify consumers of a deposit drive traffic to the website, which in turn induces and increases further spending. Accordingly, in Column (IV) we test whether the results hold using only the consumer-week observations in which cashback payments are greater than zero. In Column (V), we use instead the full data set but include an indicator to mark the receipt of a cashback payment in a given week. Again, the direction and significance of the results are consistent with those of the initial analysis. The estimates suggest that the indicator captures the base effect of a cashback payment while, as before, this effect increases with the size of the payment.

Fourth, we examine a boundary condition. In Column (VI), we classify consumers based on the largest cashback payment they receive (< \$38.90, ≥ \$38.90 and < \$132.80, ≥ \$132.80), and find no significant effect of cashback payments in the bottom tercile, that is for consumers who only ever receive small payments. Note, however, that this may also be a result of the difficulty to identify the effect for this group of consumers as we observe fewer instances where consumers purchase or when they receive cashback payments for the lowest tercile relative to the middle and upper tercile.

Fifth, we take inspiration from the broader literature on sales promotion that has focused on state dependence and evaluate whether the effect of a cashback payment on spending changes if more time has passed since the consumer made their last purchase (Seetharaman 2004; Gedenk and Neslin 2000). Given the difficulty of interpreting interactions in nonlinear models, Column (VII) displays the results of an OLS estimation where we interact cashback payments with the time since the consumer made their last purchase. We continue to see that cashback payments increase spending, though the effect decreases somewhat as the last purchase is further in the past.

Finally, we check whether the effects of cashback payments are sensitive to the way we specify the control $AvgCBOffer_w$.[12] Instead of estimating the model with $AvgCBOffer_w$ as the average percentage of the cashback offers from the 10 largest retailers, we consider all retailers or only the five largest retailers. We also specify $AvgCBOffer_w$ at the level of the consumer: that is, the average percentage of the cashback offers (from any retailer) taken up by a given consumer. The sign and magnitude of the coefficient on $CBPayment_{iw}$ are robust to these alternative specifications. Next, we exclude the small number of purchases and cashback payments related to in-store cashback offers. Again, the results are consistent. Finally, we check for a quadratic effect of cashback payments but find this to be not significant.

BEHAVIORAL EXPLANATIONS

The effect of cashback payments on the likelihood and size of a future purchase is

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[12] The results of these tests are available on request.

surprising for the reasons already mentioned: redemption in cashback shopping is unconditional, consumers are essentially rewarding the cashback company for holding on to their money, and the phenomenon is inconsistent with normative benchmarks (Friedman 1957; Modigliani and Brumberg 1954). In this section, we examine three possible explanations for the findings. Given that spending captures purchase behavior more broadly and, implicitly, accounts for purchase likelihood, we use it as the focal outcome variable in the analysis that follows. Overall, we find stronger evidence that consumers fail to treat money as a fungible resource. The remaining accounts are less likely, but we cannot rule them out conclusively.

Cashback Payments as a Scheduling Mechanism

The first possibility is that consumers use cashback payments to schedule purchases. This behavior may be the consequence of a liquidity constraint: consumers with limited financial resources postpone spending until they receive cashback payments and, therefore, have more disposable income at hand. If this is true, then the effects of cashback payments that we observe in the data should be more (less) pronounced at the end (beginning) of a month when less (more) income is available. This argument rests on the assumption that, in general, consumers receive a salary at the end of each calendar month. Column (I) of Table 5 displays the results of estimating the effect of cashback payments on spending separately for cashback payments executed during the first week or at any other time in a given month.[13] There are no significant differences across the two estimations. Similarly, in Column (II) the comparison is between the last week and any other time in a given month. Again, we do not find significant differences.

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[13] Consistent with the preceding estimations, we use periods of seven days running from a given Saturday to the following Friday. The first week of a given month is the first such period that does not include one or more days of the previous calendar month. Similarly, the last week of a given month is the last such period that does not include one or more days of the following calendar month.

Insert Table 5 about here

A second reason to schedule purchases based on cashback payments is self-control. Suppose that people tend toward immediate gratification, but they understand that deferring a purchase decision may improve the quality of that decision (Hoch and Loewenstein 1991) or make the purchase itself more pleasurable (Caplin and Leahy 2001). One way consumers can exercise patience is by tying future purchase events to cashback payments.

The data do not suggest that consumers follow this strategy. While the average interval between successive purchases is 24.4 days, the average time between two cashback payments is 56.1 days. The average delay between purchases and cashback payments is 123.9 days. Therefore, together this implies consumers make 5.08 purchases between the time it takes from a purchase to receiving the associated cashback payment and instead of scheduling their purchases as described, consumers make on average 2.3 transactions from the time they receive one deposit to the time they receive the next. Moreover, note that the incidence of cashback payments varies across consumers. Because consumers who purchase more often and receive cashback more frequently have to wait less for the next payment to arrive, exercising self-control is less relevant. As such, the effect of cashback payments on the size of a future purchase should be weaker for this group. Columns (III) of Table 5 compares consumers grouped by whether they are infrequent shoppers (an average time between purchases ≥ 42.68 days), frequent shoppers (an average time < 19.08 days) or in between. Column (IV) of Table 5 tests the same with quintiles of customer frequency. Contrary to the prediction, the effect of cashback payments on spending is stronger for those who purchase more frequently. The fact that the results are not significant for the first group of consumers, those who purchase infrequently, may be because a large number of observations enter the estimation with cashback payments and spending as zero and, therefore, the effect is harder to establish.

Money as a Non-fungible Resource

The second possibility is that consumers fail to treat money as a fungible resource. A basic principle in mental accounting is that individuals integrate and segregate gains and losses opportunistically to portray outcomes in whatever way makes them happiest (Thaler 1985). Accordingly, the separation in time between cashback offers, purchases, and cashback payments suggests two outcomes. First, a consumer presented with a cashback offer integrates the promised saving into the purchase price, thereby making that purchase more appealing. This, of course, is the intended effect of any sales promotion effort. Second, the same consumer segregates the cashback payment from the earlier transaction and perceives the former as a windfall gain—an argument that Thaler (1985) and Soman (1998) made in the context of mail-in rebates but never tested empirically. Because individuals tend to code windfalls as spendable income (Shefrin and Thaler 1988), and match the source of income with its use (Kahneman and Tversky 1984), the prediction is that consumers spend cashback payments disproportionately through the cashback company. We observe this phenomenon empirically.

Shefrin and Thaler (1988) also made the point that people readily spend windfalls to the extent that they appear small, meaningless changes to one's wealth. In our context, cashback payments should be more consequential or "wealth-like" to consumers the greater the amounts and, therefore, more likely to be saved (rather than spent). Accordingly, we test a mental accounting explanation in the data by checking whether the size of deposits plays a moderating role. While we are unable to observe whether cashback payments are spent elsewhere or indeed saved, the results in Columns (II) and (III) of Table 2, and Columns (III) and (IV) of Table 3, are consistent with Shefrin and Thaler's (1988) observation.

A Transient Effect

The third and last possibility is that cashback payments provoke a transient effect that, in turn, affects purchase behavior. First, it may be cashback payments elicit incidental affect (Heilman, Nakamoto, and Rao 2002). This would increase the propensity to spend in general, including through the cashback company. Second, consumers perhaps perceive cashback payments as acts of kindness and spend disproportionately through the cashback company in reciprocity (Rabin 1993). Third, it may be that the emails notifying consumers of cashback payments make shopping through the website of the cashback company more salient (Obermiller 1985).

Each of these arguments suggests a positive or, at best, null relationship between the size of cashback payments and the size of a future purchase. The results in Columns (II) and (III) of Table 2 and Columns (III) and (IV) of Table 3, which show a stronger effect for smaller rather than larger cashback payments, are not consistent with this prediction.

EXTENSIONS

This section extends the initial analysis in three ways. First, we check whether the results vary with changes in the delay between purchases and cashback payments. Second, we search for evidence of learning among consumers. Third, we study the data by category of retailer rather than at the level of the cashback company. This section again adopts spending as the focal outcome variables.

Delay

The notion of "cashback" relies on some separation in time between purchases and the money returned to consumers. As such, it is pertinent to check whether the delay plays a role in the relationship between cashback payments and spending. Column (I) of

Table 6 reports coefficients for cashback payments separately depending on whether the associated delays are in the lower, middle, or upper tercile. Recall that the mean value in the data is 123.9 days, and 98.80% of deposits take place at least 30 days after the corresponding purchases (Figure 1).[14] The analysis shows that cashback payments have a larger effect on spending when delays are shorter, and a smaller effect when delays are longer. That is, despite the fact that some separation in time is necessary to induce and increase future spending through the cashback company, it appears that the greater the separation, the lower these effects.[15] The reason for this may be that excessive delays cause frustration, which turns consumers away from the cashback company.

Insert Table 6 about here

A related possibility is that consumers perceive delays differently depending on whether they are short or long relative to what, on average, they experienced in the past. In Column (II) of Table 6, we estimate separate coefficients for cashback payments depending on whether the associated delays are short for that particular consumer (below the mean minus one standard

[14] As mentioned, this is the case mostly because retailers process commissions to the cashback company only after the return period has expired and, in turn, the cashback company seldom executes cashback payments before receiving the corresponding commissions.

[15] Note that the estimation of a quadratic effect did not show a significant inverse U-shape relationship.

deviation of the delay this consumer experiences), long (above the mean plus one standard deviation), or of medium length (between these two values). In line with what we observe in Column (I), we again find that longer delays are associated with a lower effect of cashback payments on spending. Moreover, the results add support to the argument that cashback payments are exogenous shocks: if consumers integrate deposits in their purchase plans, then we should observe a stronger effect for cashback payments executed with a medium delay—that is, a delay that consumers are more likely to anticipate.

Learning

We examine the possibility that consumers learn about the effect of cashback payments on spending and adjust their purchase behavior. If this is the case, then we should observe a stronger effect as the number of deposits previously received increases. Accordingly, we separate consumer-week observations based on whether consumers received a small (< 3), medium (≥ 3 and < 19), or large (≥ 19) number of cashback payments to that point. The results, summarized in Column (I) of Table 7, show no significant effect of cashback payments in the first group. This may be because the data contain many weeks without cashback payments, or because consumers may not trust the cashback company or the idea of cashback shopping at first. Importantly, we also find no significant difference in the comparison between the middle and upper tercile, which suggests that there is little learning beyond the initial exposure.[16]

Given that the analysis in Column (I) conflates learning and heterogeneity among consumers, Column (II) focuses on consumers who received at least 19 cashback payments and

[16] A different argument, which relates to mental accounting, is that consumers learn about the arrival of cashback payments and, therefore, no longer view cashback payments as windfalls. If this were true, then the effect of cashback payments on spending should be lower for consumers with relatively more exposure. The results do not support this prediction either.

follows them over time. This means that each consumer is present in each tercile and we measure how their response to cashback payments changes as they increase in number. The results resemble those in Column (I). Lastly, Column (III) refers to an OLS estimation where we interact the size of cashback payments with the number of such payments received by consumers. The results again provide little evidence for learning.

Insert Table 7 about here

Category of Retailer

Our analysis studies cashback shopping primarily from the perspective of the cashback company. Yet we can also ask whether the effects that we observe replicate at the level of retailers. We focus on the category of retailer because in most cases the data at the level of the retailer is sparse, which makes convergence difficult—the cashback company works with a large range of retailers, most consumers do not purchase every week, and transactions spread across retailers.

Table 8 provides the results for the four largest categories. The outcome variable is spending through a particular retailer category, and we estimate the effect of cashback payments separately when these originate from retailers in the same or different categories. Column (I) focuses on generalists (mostly department stores), which offer many product types and variants. We find that cashback payments from such retailers affect spending with retailers in the same category more than spending with retailers in other categories.

Column (II) relates to travel products including hotels, flights, car hire, and cruises. The results are qualitatively similar to those of Column (I), but significant only at the 90% confidence level. This may be because consumers purchase in the category infrequently and travel products tend to be expensive and require consumers not only to pay for the purchase, but also to take the time to travel. These characteristics suggest that cashback payments play a lesser role in the minds of consumers when purchasing in this category.

Columns (III) and (IV) relate to subscription services—primarily utilities and insurance in the first case, and primarily magazines in the second case. In these instances, a purchase typically implies a contractual obligation that spans at least one year. The negative correlation that we observe may again be because consumers purchase infrequently in these categories: those who recently subscribed to a service are less likely to do so again in the near future.

Although the number of transactions by individual consumers with a particular retailer is low for most retailers in the data, we were able to estimate a model for the largest generalist (by number of transactions). Column (V) demonstrates that the effect of cashback payments on spending with the same retailer is significantly higher than that with other retailers, which suggests that the results in Column (I) hold also at the level of individual retailers.

Insert Table 8 about here

Overall, this analysis indicates that cashback payments benefit retailers that offer a large range of products or motivate frequent purchases. These aspects are obviously related. In turn, the cashback company not only has an incentive to select and work with retailers of this sort, but also it can point to the effects of cashback payments when negotiating terms.

CONCLUSION AND IMPLICATIONS

This paper examines purchase behavior in the context of cashback shopping—a relatively young but increasingly popular form of sales promotion online. Specifically, we studied consumer response to cashback offers and payments using panel data from a large cashback company. These data span 3,433,476 transactions by 76,296 consumers at 5,337 retailers from May 2005 to August 2013. A critical feature is that the timing and size of cashback payments is unknown to consumers and, therefore, exogenous from their standpoint.

Two results stand out in the analysis. First, we find that receiving cashback payments shortens the time consumers take to make subsequent purchases through the cashback company. Second, receiving cashback payments increases the size of these new purchases. These effects are reliable, in the sense that they hold across several robustness checks. Importantly, the effects are meaningful: at the average values in the data, increasing cashback payment by $1.00 increases the likelihood of a purchase by 0.02% and spending by $0.32.

We proceeded to test three possible explanations: consumers use cashback payments to schedule payments (because of a liquidity problem or as a means of self-control), consumers fail to treat money as a fungible resource (a characteristic of mental accounting), and cashback payments trigger a transient state (one or more of positive affect, reciprocity, and salience). While the data provide some evidence in favor of the first account, and no evidence in favor of the last, there is relatively strong support for the second: we observe the inverse relationship between the size of cashback payments and spending originally predicted by Shefrin and Thaler (1988).

To conclude, we focused on three aspects of the data. First, we checked whether the results vary with changes in the delay between purchases and cashback payments. While some delay is critical for cashback payments to have a separate effect from cashback offers, longer delays weaken this effect. Second, we search and find no evidence of learning among consumers. Third, we study the data by category of retailer rather than at the level of the cashback company. This analysis indicates that generalists—retailers such as department stores that offer a large range of products that motivate frequent purchases—are more likely to benefit from the effects of cashback payments than specialists are.

From the perspective of practice, the fact that cashback shopping stimulates demand at multiple points in time matters in at least three ways. First, and most clearly, it matters to the cashback company. The companies we spoke to are unaware of the effects of cashback payments. We talked to the Managing Director of a major cashback company, who explained: "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 really spent time looking at what the repercussions might be." Similarly, the President of a different cashback company emphasized that negotiations with retailers focus on maximizing the likelihood of a first purchase: "Whenever we negotiate with retailers, we argue that higher commissions imply higher cashback offers to users, and it is proven that they are motivated most by as large a saving as possible."

The implication, of course, is that the cashback company can boost revenue by adjusting its policies in light of our results. The task is to consider how to design campaigns to maximize the effects of cashback offers and payments jointly—or, at least, to make the most of the latter. For example, our analysis suggests that one relevant criterion is the type of retailer: the cashback company should include in its portfolio generalists such as a department stores where consumers are more likely to spend the cashback payment received.

Second, our results matter to retailers that want to move their promotional spend online and consider cashback shopping as a route to market. The point here is that, in evaluating the effectiveness of cashback shopping, retailers should collect the necessary data to measure the effects observed in our research. An important motivation of cashback shopping is to generate and convert leads—the same motivation of any other form of sales promotion, for that matter. However, focusing solely on the (predictable) effect of cashback offers leads retailers to underestimate the merit of cashback shopping. In addition, retailers that can estimate the extent to which their collaboration with a cashback company contributes to the effect of cashback payments on future purchase behavior may be able to negotiate terms that are more favorable.

Finally, our results have implications outside the context of cashback shopping. In principle, any company, offline or online, that chooses to pay discounts with some delay stands to benefit from the effects of these payments. The example that comes to mind is mail-in rebates. While the results that we observe are probably harder to observe in a conventional (non-digital) setting where the necessary data may be hard to collect, the benefit may be sufficient to warrant exerting the necessary effort. A second example is financial institutions that offer cashback on credit card transactions. It is in their interest to verify whether the tactic increases future usage and spending. Our research suggests that it may affect not only the choice of card itself, but also the likelihood and size of purchases once cashback is paid.

This said; the contributions of our work have limitations. The data allow the study of purchase behavior when cashback payments are present and vary in size. Yet we cannot draw conclusions about the effectiveness of cashback shopping relative to a setting where retailers opt for other forms of sales promotion, other marketing activities aimed at driving sales, or indeed no intervention of any kind. We also cannot compare the purchases of consumers in response to cashback offers and payments relative to no incentive of any kind. Moreover, while the data show that delaying a discount improves the likelihood and size of a future purchase, we cannot fully ascertain the boundaries of these relationships. With respect to the interval between purchases and cashback payments, for example, while we see that an excessive delay may frustrate consumers, we have no insight for delays that the company (or the industry, for that matter) does not use—essentially, anything shorter than 30 days. In our opinion, a clear opportunity is to search for an optimal delay but, admittedly, such a move takes the researcher away from the reality of cashback shopping that we find compelling. Finally, while the data permit to shed light on a number of possible behavioral mechanisms, we cannot provide direct process evidence and, as such, cannot provide a definite answer. Further research can take up this challenge, perhaps by studying the phenomenon in a controlled laboratory environment.

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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

	(I)			(II)			(III)			(IV)		
Dependent variable	Linear specification of cashback payment			Tercile split specification of cashback payment			Quintile split specification of cashback payment			Frailty model		
Time to next purchase (in days)	Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE	
Independent variables												
Cashback payment ($)	0.0002	0.0000	***							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 (≥ $69.66)							0.0002	0.0000	***			
Average cashback offer (%) of top 10 retailers in the current week	0.0335	0.0015	***	0.0339	0.0015	***	0.0341	0.0015	***	0.0386	0.0131	***
Amount spent in the most recent purchase ($)	0.0000	0.0000	***	0.0000	0.0000	***	0.0000	0.0000	***	0.0000	0.0000	
Purchase instance	-0.0001	0.0000	***	-0.0001	0.0000	***	-0.0001	0.0000	***	0.0002	0.0001	**
Consumer heterogeneity	Stratified baseline			Stratified baseline			Stratified baseline			Gamma frailty		
Day of week fixed effect	Yes			Yes			Yes			Yes		
Month fixed effect	Yes			Yes			Yes			Yes		
Number of consumers	76,296			76,296			76,296			1,000		
N	66,908,111			66,908,111			66,908,111			873,119		
LL	-9,553,060			-9,552,958			-9,552,883			-327,586		

* 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		
Log (Amount spent in the week ($))	Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE	
Independent variables												
Cashback payment ($)	0.0007	0.0001	***	0.0025	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 (≥ $69.66)										0.0021	0.0004	***
Average cashback offer (%) of top 10 retailers in the current week	0.0352	0.0020	***	0.1662	0.0346	***	0.1672	0.0346	***	0.1676	0.0346	***
Amount spent in the most recent purchase ($)	0.0000	0.0000		0.0000	0.0000		0.0000	0.0000		0.0000	0.0000	
Purchase instance	0.0002	0.0001	***	0.0027	0.0003	***	0.0026	0.0003	***	0.0026	0.0003	***
Consumer heterogeneity	FE			RE			RE			RE		
Month fixed effect	Yes			Yes			Yes			Yes		
Number of consumers	76,296			5,000			5,000			5,000		
N	9,620,542			640,784			640,784			640,784		
LL				-621669.78			-621650.87			-621650.09		

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

Table 4: ROBUSTNESS CHECKS

	(I)			(II)			(III)			(IV)			(V)			(VI)			(VII)		
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: Cashback payment indicator			Tobit: Consumers with small/large cashback payments			OLS: Time since last purchase		
Log(Amount spent in the week ($))	Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE		Estimate	SE	
Independent variables																					
Cashback payment indicator													0.2394	0.0417	***						
Cashback payment ($)	0.0023	0.0003	***	0.0022	0.0002	***	0.0029	0.0004	***	0.0009	0.0004	**	0.0013	0.0005	***				0.0014	0.0002	***
Cashback payment to consumers with largest cashback payment < $38.90																-0.0054	0.0114				
Cashback payment to consumers with largest cashback payment ≥ $38.90 and < $132.80																0.0037	0.0016	**			
Cashback payment to consumers with largest cashback payment ≥ $132.80																0.0024	0.0004	***			
Average cashback offer (%) of top 10 retailers in the current week	0.1653	0.0346	***	0.1640	0.0346	***	0.1614	0.0348	***	0.1779	0.0967	*	0.1685	0.0346	***	0.1661	0.0346	***	0.0314	0.0077	***
Amount spent in the most recent purchase ($)	0.0000	0.0000		0.0000	0.0000		0.0000	0.0000		0.0001	0.0000	***	0.0000	0.0000		0.0000	0.0000		0.0000	0.0000	*
Purchase instance	0.0027	0.0003	***	0.0026	0.0003	***	0.0027	0.0003	***	0.0080	0.0005	***	0.0026	0.0003	***	0.0027	0.0003	***	0.0000	0.0003	
Time since last purchase (days)																			-0.0062	0.0003	***
Cashback payment ($) x Time since last purchase																			-0.0002	0.0000	***
Consumer heterogeneity	RE			RE			RE			RE			RE			RE			FE		
Month fixed effect	Yes			Yes			Yes			Yes			Yes			Yes			Yes		
Number of consumers	5,000			5,000			5,000			3,974			5,000			5,000			5,000		
N	640,784			640,784			640,784			56,019			640,784			640,784			640,784		
LL	-621657.43			-621634.14			-616501.05			-75347.03			-621653.31			-621669.23					

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

Table 5: 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

Table 6: THE ROLE OF DELAY

	(I)			(II)		
Dependent variable	Tobit: Cashback payment and delay			Tobit: Cashback payment and unexpected delay		
Log (amount spent in the week ($))	Estimate	SE		Estimate	SE	
Independent variables						
Cashback payment ($) 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				
Cashback payment ($) when delay is unexpectedly short (less than mean - one standard deviation)				0.0049	0.0019	**
Cashback payment ($) when delay is in the expected range (between mean +/- one standard deviation)				0.0030	0.0004	***
Cashback payment ($) when delay is unexpectedly long (more than mean + one standard deviation)				-0.0002	0.0010	
Average cashback offer (%) of top 10 retailers in the current week	0.1712	0.0344	***	0.1528	0.0356	***
Amount spent in the most recent purchase ($)	0.0006	0.0000	***	0.0000	0.0000	***
Purchase instance	0.0029	0.0003	***	0.0032	0.0003	***
Consumer heterogeneity	RE			RE		
Monthly fixed effect	Yes			Yes		
Number of consumers	5,000			3,523		
N	640,784			586,869		
LL	-620789.87			-586504.1		

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

Table 7: ANALYSIS OF LEARNING

	(I)			(II)			(III)		
Dependent variable	Tobit: Consumer cashback instances			Tobit: Consumers with total number of cashback payments received ≥ 19			OLS: Consumers with total number of cashback payments received ≥ 19		
Log (amount spent in the week ($))	Estimate	SE		Estimate	SE		Estimate	SE	
Independent variables									
Cashback payment ($) to consumer when the total number of cashback payment instances < 3	0.0001	0.0017		-0.0002	0.0024				
Cashback payment ($) to consumer when the total number of cashback payment instances ≥ 3 and < 19	0.0023	0.0009	***	0.0028	0.0009	***			
Cashback payment ($) to consumer when the total number of cashback payment instances is ≥ 19	0.0027	0.0005	***	0.0026	0.0004	***			
Cashback payment ($)							0.0007	0.0002	***
Number of cashback payment instances							-0.0166	0.0039	***
Cashback payment ($) x Number of cashback payment instances							0.0000	0.0000	
Average cashback offer (%) of top 10 retailers in the current week	0.1662	0.0346	***	0.1339	0.0379	***	0.0314	0.0105	***
Amount spent in the most recent purchase ($)	0.0000	0.0000		0.0001	0.0000	***	0.0000	0.0000	***
Purchase instance	0.0027	0.0003	***	0.0021	0.0003	***	0.0097	0.0028	***
Consumer heterogeneity	RE			RE			FE		
Month fixed effect	Yes			Yes			Yes		
Number of consumers	5,000			1,959			1,959		
N	640,784			409,400			409,400		
LL	-621668.6			-485765.81					

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

Table 8: 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

Figure 1: DISTRIBUTION OF DELAY BETWEEN PURCHASE AND CASHBACK PAYMENT

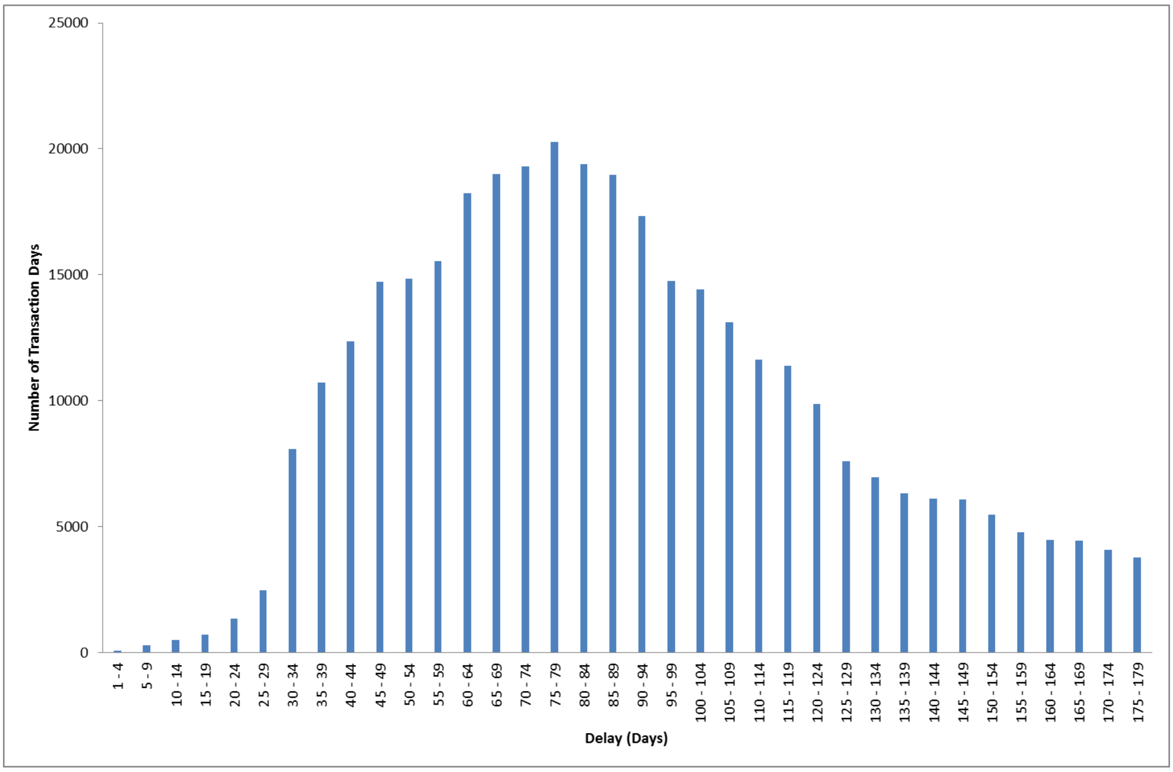

Figure 2: DISTRIBUTION OF DELAY FOR FOUR RANDOMLY SELECTED CONSUMERS

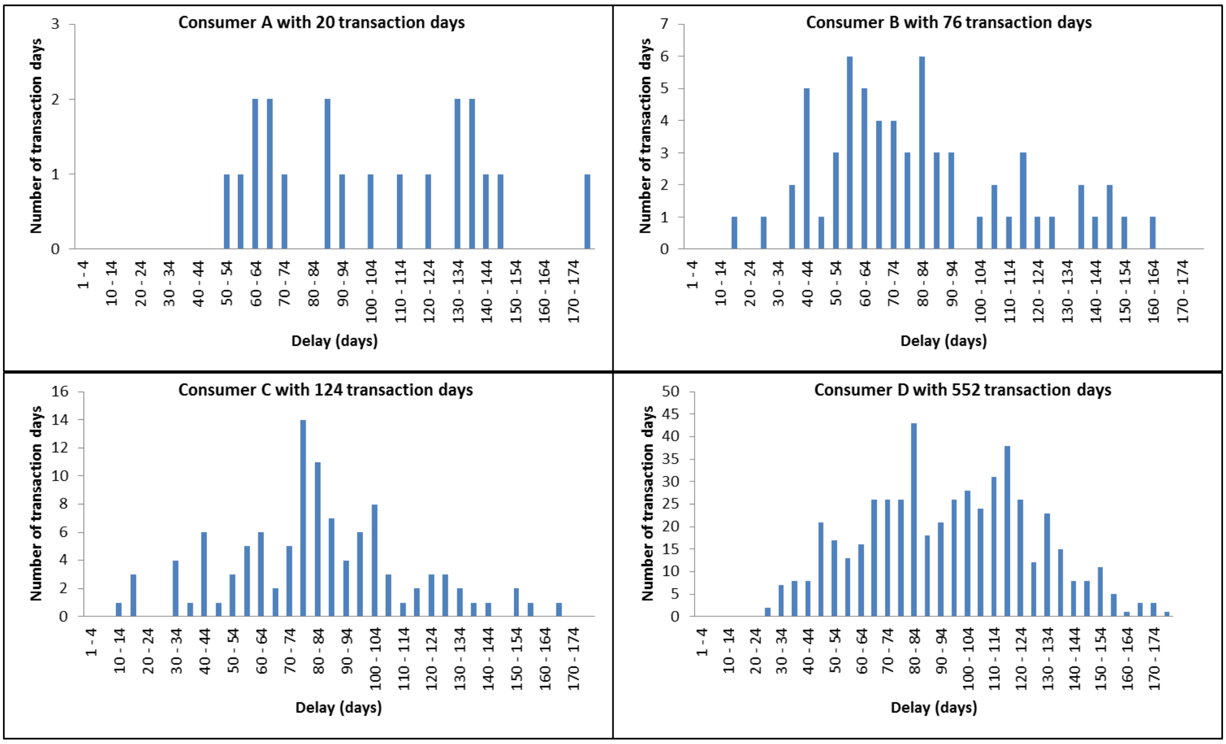

Figure 3: DISTRIBUTION OF DELAY AT FOUR RANDOMLY SELECTED RETAILERS

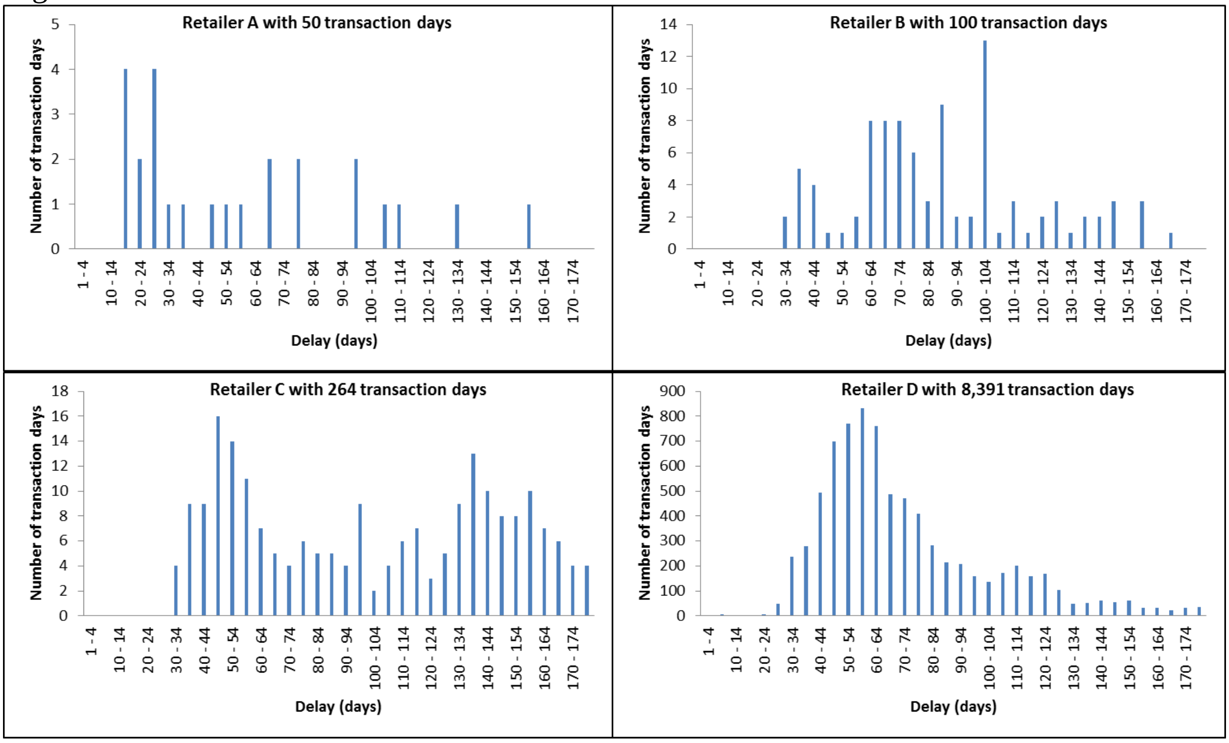

Figure 4: DISTRIBUTION OF DELAY FOR FOUR RANDOMLY SELECTED CONSUMERS AT A SPECIFIC RETAILER

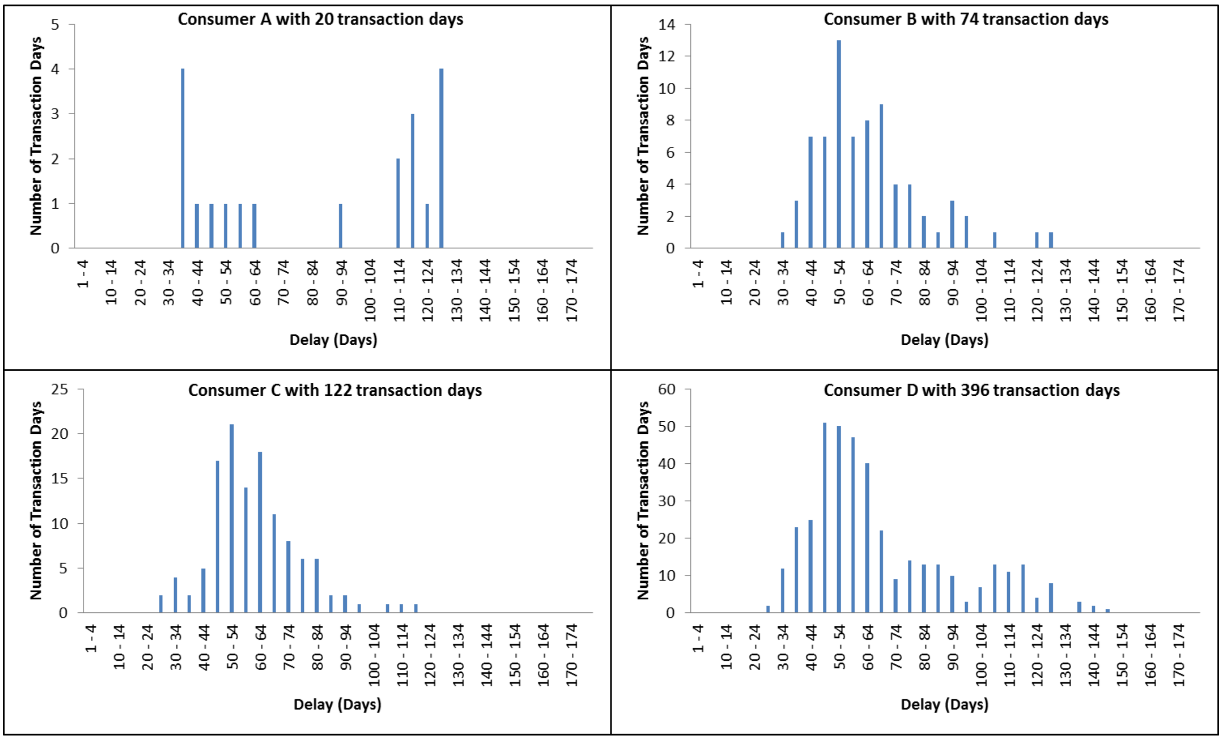

Figure 5: DISTRIBUTION OF DELAY AT A MUSIC RETAILER AND AT A GENERAL RETAILER

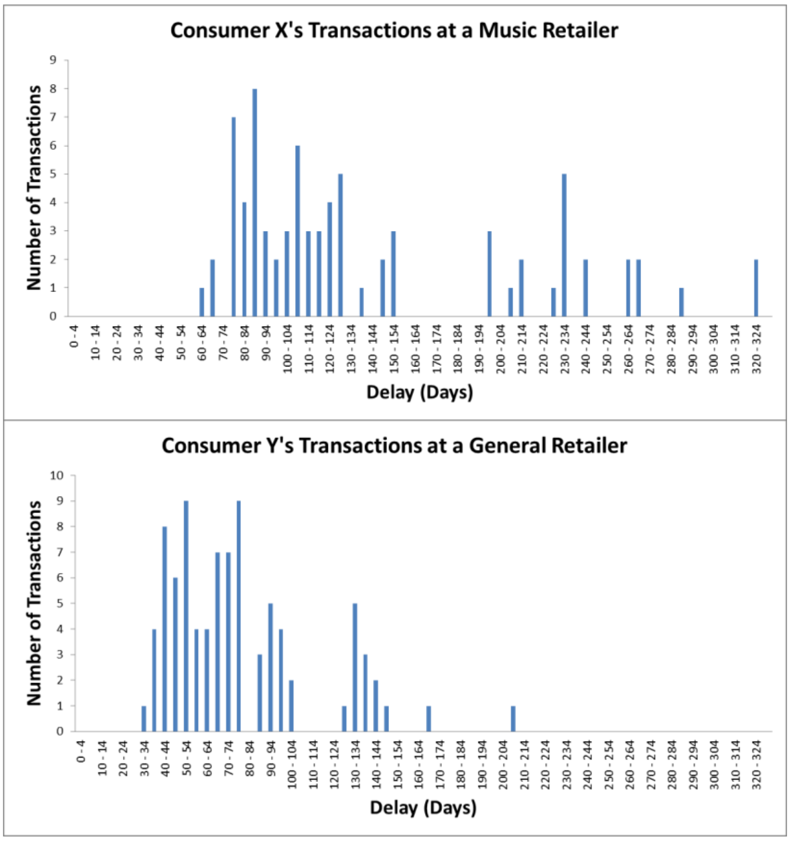

Figure 6: MODEL-FREE EVIDENCE FOR PURCHASE LIKELIHOOD

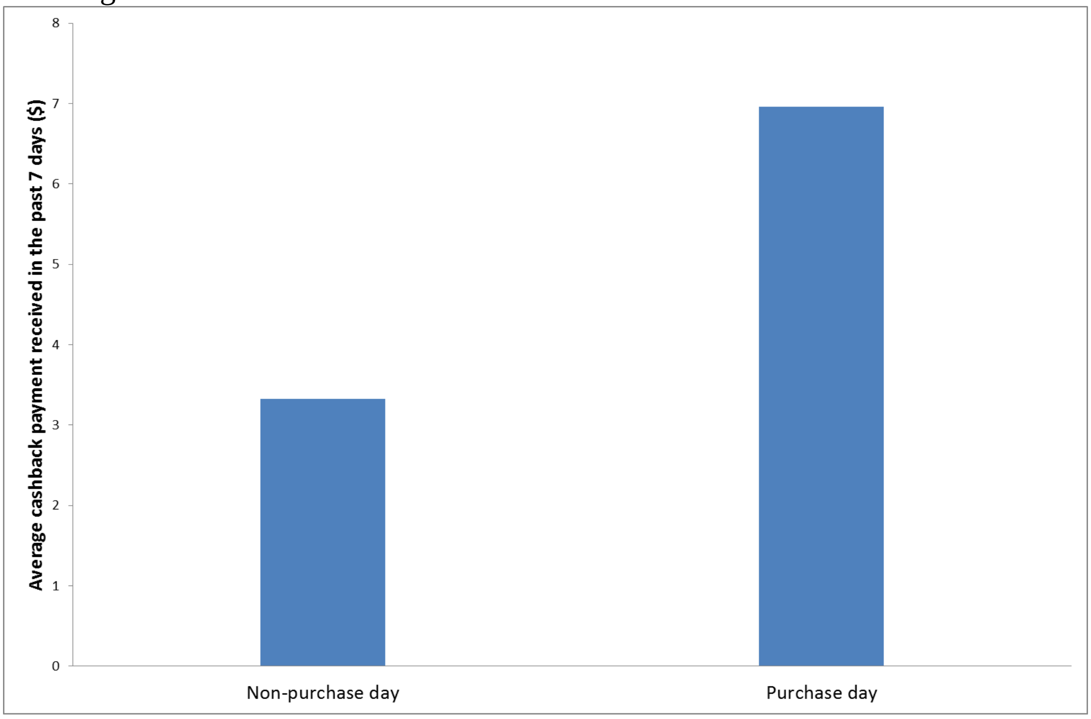

Figure 7: MODEL-FREE EVIDENCE FOR SPENDING

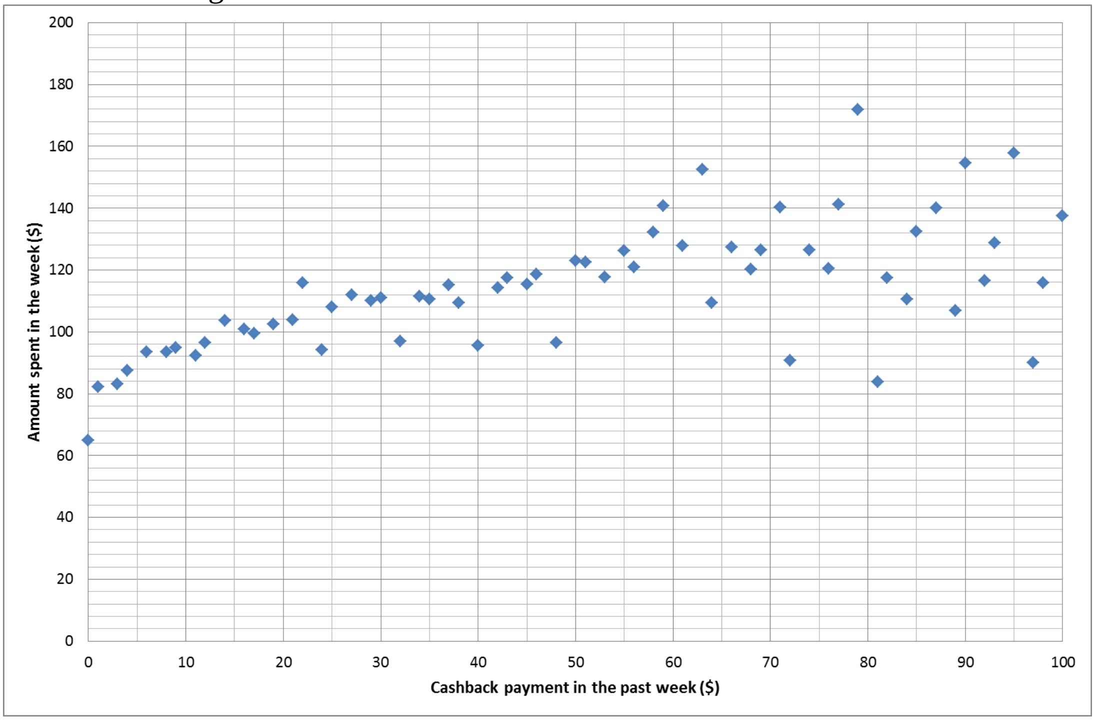

Figure 8: MARGINAL EFFECT OF CASHBACK PAYMENT ON OBSERVED SPEND, BY TERCILE OF CASHBACK PAYMENT