Frugality Is Hard to Afford

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Abstract

Households commonly utilize strategies that provide long-term savings on everyday purchases in exchange for an increase in their short-term expenditures. They buy larger packages of non-perishable goods to take advantage of bulk discounts, and accelerate their purchases to take advantage of temporary discounts. Even though low-income households are more incentivized to save, they are less likely to take advantage of these money-saving strategies. We provide causal evidence that liquidity constraints inhibit low-income households' ability to do so.

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Introduction

Households have several strategies at their disposal to reduce per-unit spending on everyday products. One set of strategies offers consumers immediate financial savings, such as buying cheaper, lower-quality brands or searching for lower prices. In line with the intuition that individuals who have the greatest incentive to save money should be most likely to use these strategies, past research has shown that lower-income households purchase cheaper brands (Ailawadi, Neslin, and Gedenk 2001; Akbay and Jones 2005; Griffith, Leibtag, Leicester, and Nevo 2009; Kalyanam and Putler 1997) and make more of an effort to search more for lower prices (Aguiar and Hurst 2005) than their higher-income counterparts.

A second set of money-saving strategies offers long-term savings in exchange for an increase in short-term expenditure. For example, households may purchase larger packages to take advantage of bulk discounts that offer a lower per-unit price. Similarly, households may accelerate their purchase of a given product when they find an attractive deal. These intertemporal substitution strategies are commonly used for everyday purchases of non-perishable goods. However, low-income households are likely to face higher liquidity constraints that may inhibit them from increasing short-term expenditures. Therefore, these households may fail to utilize intertemporal money-saving strategies to their full potential, even though they have strong incentives to save.

The main objective of this paper is to test whether liquidity constraints inhibit the ability of low-income households to (1) buy in bulk and (2) accelerate purchase timing to take advantage of sales. We quantify the extent to which liquidity constraints, as opposed to other possible limitations (e.g., storage constraints, limited access to channels that provide bulk options, financial illiteracy, less price information if they visit stores less often, consumer myopia), inhibit low-income households from utilizing money-saving strategies that require up-front investments. To this end, we employ time of the month as a liquidity shifter for low-income households and compare (1) the difference in low-income households' tendency to utilize money-saving strategies that require up-front investments at the beginning and end of the month with (2) the difference in higher-income households' tendency to utilize these strategies at the beginning and end of the month. This approach is motivated by the notion that low-income households are likely to be the most liquidity constrained later in the month, because they are more dependent on cash inflows that accumulate earlier in the month and are depleted as the month goes on. By contrast, middle- to high-income households are less likely to be cash constrained for basic necessities at any time of the month. Because we are examining within-household differences in purchase behavior across time, our empirical approach identifies the impact of liquidity constraints on purchase behavior, above and beyond the impact of any household-specific and time-invariant factors. We also demonstrate that our conclusions are robust to potential variations in the availability, affordability, or desirability of products and channels that may be systematically correlated with time of month.

Our analyses are based on purchases of more than 113,000 households over nine years in the toilet paper category. The toilet paper category is suitable for studying consumers' intertemporal substitution strategies for the following reasons. First, bulk and temporary discounts are both common in this category. Second, toilet paper is storable, and therefore bulk buying and accelerating purchase incidence to take advantage of sales are both plausible money-saving strategies. Third, a household's need for toilet paper cannot be satisfied by other product categories; therefore purchasing behavior in this category is unlikely to be influenced by substitution to or from other categories. Finally, the simplicity of the attributes of products in this category allows us to pool our analyses across products using a standardized unit of toilet paper.

The paper proceeds as follows: In the Related Literature section, we discuss relevant previous research and delineate our approach and contribution. In the Data section, we describe the data and document cross-sectional differences in the propensity to utilize intertemporal saving strategies across households of different income groups. We show that lower-income households are less likely to utilize money-saving strategies that require up-front investments than households with higher-incomes. Why are consumers with the greatest incentive to save the least likely to employ intertemporal money-saving strategies? In the Empirical Analyses section, we show that low-income households would utilize these money-saving strategies more often, even in the presence of other money-saving opportunities, if they had greater liquidity. Specifically, we find that when their liquidity constraints are partially relaxed, households making less than $20,000 are able to close at least 3-4% of the bulk buying gap and 100% of the purchase acceleration gap relative to the purchasing practices of the highest-income households. We offer several robustness checks and related discourse in the Discussion section. In the Conclusion section, we review the potential implications for retailers and policy makers.

Related Literature

This paper investigates the extent to which liquidity constraints inhibit low-income households' ability to utilize two common intertemporal money-saving strategies: bulk buying and purchase acceleration. Our work draws from and contributes to the literature on (1) the various financial burdens shouldered by the poor (the "poverty penalty") and (2) the impact of liquidity constraints on spending.

Related research on the poverty penalty can be broadly classified into three streams. The first stream aims to document cross-sectional differences in the prices that different income groups pay to receive similar services or products. Most applicable to this paper, several researchers (Attanasio and Frayne 2006; Beatty 2010; Frank, Douglas, and Polli 1967; Griffith et al. 2009; Kunreuther 1973; Rao 2000) have investigated whether households from different income groups differ in their propensity to purchase in bulk, which affects the per-unit prices they pay. The second stream of research documents the ways in which low-income households are disadvantaged by their shopping environments. For example, these households live in areas where retail competition is sparse, retail costs are high, and large supermarkets are absent or hard to get to, which leads them to pay higher shelf prices (Kaufman et al.

1997; Chung and Meyers, 1999; Talukdar 2008). The third stream of research investigates the extent to which differences in household resources, rather than shopping environments, contribute to the poverty penalty. This paper contributes mainly to the last of these research streams, as our primary objective is to investigate how liquidity constraints affect low-income households' choices within the shopping environment these households face.

Research in this third stream has investigated several resource constraints that may inhibit households from taking advantage of money-saving opportunities, even when those opportunities are available in their shopping environment. For example, Aguiar and Hurst (2005) show that consumers with a higher opportunity cost of time are less likely to engage in price search and thus pay higher prices. Talukdar (2008) shows that a lack of access to transportation inhibits low-income households from engaging in price search as much as higher-income households. Bell and Hilber (2006) show that consumers with greater storage constraints (smaller-sized residences) shop more often and purchase smaller quantities. Other researchers have found that the attentional demands of poverty reduce the cognitive resources of the poor (Mani et al. 2013) and that low-income households may be more myopic or present-biased (Delaney and Doyle 2012; Griskevicius et al. 2011). Because intertemporal money-saving strategies require planning for the future, the results of these studies suggest that lower-income households may be less able or less inclined to utilize these strategies, even when they are available. Finally, liquidity constraints can affect low-income households' ability to make immediate investments for future gains.

The limiting effect of liquidity constraints on lower-income households' ability to take advantage of money-saving strategies that require up-front investment is perhaps intuitive. Indeed, earlier work has speculated that liquidity constraints may be a driver of cross-sectional differences in the propensity to buy in bulk (Griffith et al. 2009; Kunreuther 1973). However, previous work does not formally test for a relationship between liquidity constraints and bulk buying. The empirical literature studying purchase acceleration (Erdem, Imai, and Keane 2003; Hendel and Nevo 2006; Neslin Henderson, and Quelch 1985) does not provide any evidence that households of different income levels differ in their utilization of this strategy, nor does it study the role of liquidity constraints. Therefore, empirical evidence of a relationship between liquidity constraints and these intertemporal money-saving strategies is lacking.

Macroeconomics literature has studied how total spending may be impacted by large, one-time shifts in wealth, such as economic stimulus payments (Broda and Parker 2014; Misra and Surico 2014; Parker et al. 2013) and tax refunds and rebates (Agarwal, Liu, and Souleles 2007; Bertrand and Morse 2009; Johnson, Parker, and Souleles 2006; Johnson, Parker, and Souleles 2009; Shapiro and Slemrod 1995; Souleles 1999). It has also examined how a household's ability to purchase expensive, durable items, such as automobiles (Attanasio, Goldberg, and Kyriazidou 2008; Benmelech, Meisenzahl, and Ramcharan 2015) and houses (Engelhardt 1996), is affected by such shifts. Other researchers investigate the impact of smaller but recurring shifts in income, such as the receipt of paychecks (Stephens 2006; Zhang 2013), food stamps (Beatty and Tuttle 2014; Hastings and Shapiro 2017), or Social Security checks (Stephens 2003) on household spending. Our work differs from this literature insofar as we examine individual households' propensity to utilize specific money-saving strategies, rather than merely quantifying changes in their total spending.

Relatedly, Nevo and Wong (2014) and Dubé, Hitsch, and Rossi (2015) recently investigated how households' propensity to purchase private labels and redeem coupons was affected by large changes in wealth during the Great Recession. However, both the particular money-saving strategies and the type of liquidity shifter we study are different from those examined in these papers. First, we focus on money-saving strategies that require an increase in up-front spending. Second, we utilize a partial but recurring relaxation of liquidity constraints for low-income households, proxied for by the influx of cash they receive at the the beginning of the month. Using recurring fluctuations in liquidity instead of large, one-time shifts in wealth provides important advantages for our research. First, recurring fluctuations are easier to disentangle from unobserved factors because they are not one-time events. Second, they do not create structural changes in a household's behavior as, for example, the purchase of a car might. Third, the results are likely to be more relevant for common policy interventions (e.g., food stamps) that provide small, recurring infusions of liquidity.

Data and Cross-Sectional Patterns

For our analyses, we use the Nielsen consumer panel data for the years 2006–2014, provided by the Kilts Center for Marketing at the University of Chicago Booth School of Business. This data set contains all purchases by participating households during the period for which they were members of the panel.[1] For each purchase occasion, the data provide the retail channel shopped in; the price, quantity, and package size of each UPC (Universal Product Code) purchased; an indicator for whether each UPC purchased was on sale; and the purchase date.

Our analyses focus on the toilet paper category. In this category, there are many opportunities to save. Brands vary considerably in their prices, and bulk and temporary discounts are common and substantial. Table 1 documents price variation and illustrates the magnitude of bulk discounts by comparing prices across major brands and sizes.[2] In general, the brands that have relatively low everday prices offer shallower bulk discounts and are purchased on sale less frequently.[3]

[Insert Table 1 about here]

[1] A well-known limitation of the data set is that there are some notable recording discrepancies apparent in the raw data. Some listed package sizes are clearly erroneous (e.g., one UPC was reported to contain 1,296 rolls of toilet paper). In addition, a few households seem not to have reported all their purchases (e.g., for some households, several years elapse between reported purchases). Einav, Leibtag, and Nevo (2010) note the importance of accounting for potential recording discrepancies in the Nielsen data set. We therefore make a conservative effort to clean the data, correcting or removing entries that suffer from severe and obvious discrepancies. We retain 91% of observations for our analyses, and our conclusions are not sensitive to the removed entries. We provide a detailed description of our cleaning approach in the Online Appendix.

[2] The most commonly purchased package sizes are 1-, 4-, 6-, 9-, 12-, 24-, 30-, and 36-roll packages, which together account for 91% of purchases. The top five brands (Angel Soft, Charmin, Kleenex, Quilted Northern, and Scott) account for 73% of purchases, and private labels account for another 20%.

[3] We describe each product by the number of standardized rolls it contains to facilitate more accurate comparisons across products, as rolls may differ in ply and the number of sheets they contain. We use 275 sheets of two-ply toilet paper as the standardized unit, as it reflects the average number of two-ply sheets per roll in the UPCs in our data set. Unit prices are also measured in terms of standardized rolls.

In total, the panel data set contains more than 113,000 households that purchased in the toilet paper category. These households made a total of 3.2 million purchases from 2006 to 2014 in this category, primarily at grocery stores (47% of purchases), discount stores (29%), warehouse stores (8%), drug stores (6%), and dollar stores (6%). The average household purchase pattern indicates a consumption rate of slightly less than a roll of toilet paper per capita, per week. Based on households' yearly income levels reported in the Nielsen data, we sort households into five annual household income groups that closely mirror the income quintiles in the United States. Specifically, we configure income groups as follows: Income Group 1 = <$20K, Income Group 2 = $20K–$40K, Income Group 3 = $40K–$60K, Income Group 4 = $60K–$100K, and Income Group 5 = >$100K.[4] Table 12 in the Appendix presents some basic statistics about other household demographics.

Previous research has established that low-income households are more price sensitive (Ailawadi, Neslin, and Gedenk 2001). Therefore, we expect these households to have greater incentives to save. Table 2 suggests several ways to save in this category. Households can save by purchasing cheaper brands, by purchasing larger package sizes, and by timing their purchases to take advantage of temporary discounts. In our preliminary analyses presented here, we ask how households of different income groups differ in their propensity to take advantage of these strategies. Previous work has found that low-income bouseholds are more likely to buy cheaper brands, such as store brands (Ailawadi, Neslin, and Gedenk 2001; Akbay and Jones 2005; Griffith, Leibtag, Leicester, and Nevo 2009; Kalyanam and Putler 1997). To check whether these cross-sectional differences also hold true for our data set, we perform the following cross-sectional regression:

$$Y_{htp} = \beta_1 + \sum_{i=2}^{5} \beta_i I[INC_{ht} = i] + \sum_{j=1}^{3} \mu_j [Consumption]_h^j + \epsilon_{ht}$$

The binary variable (Y_{hpt}) either indicates whether purchase p made by household h dur-

[4] Actual quintiles in 2011 were $0–$25K, $25K–$45K, $45K–65K, $65K–105K, and >$105K (see http://en.wikipedia.org/wiki/Household_income_in_the_United_States). The income buckets used by Nielsen, though fairly granular, do not allow for groupings that perfectly match these quintiles. Compared to the national income distribution, the panel data set provides fairly good coverage of each income group, although it slightly overrepresents the middle-income groups.

ing trip t was (1) the cheapest brand in the household's designated market area (DMA), given the size purchased, or (2) a store brand.[5] The income group dummy variable, $I[INC_{ht} = i]$, is equal to 1 if household h is a member of income group i during the year of purchase, where $i = 1$ corresponds to households with incomes less than $20K, $i = 2$ corresponds to households in the $20K–$40K income range, $i = 3$ corresponds to households in the $40K–$60K income range, $i = 4$ corresponds to households in the $60K–$100K income range, and $i = 5$ corresponds to households with incomes higher than $100K. A third-order polynomial of the household's average consumption rate, $[Consumption]_h$, controls for heterogeneity in shopping behavior that is driven by differences in consumption rates that may otherwise be attributed to differences in income.[6]

[Insert Table 2 about here]

The results in Table 2 show that households in the lowest-income group are the most likely to choose lower-priced brands. For example, compared with households in the highest-income group that have a similar consumption rate, households in the lowest-income group are 10% more likely to buy store brands and 4% more likely to buy the cheapest brand of a given size. In contrast, low-income households are less likely to save by purchasing large packages. The last column of Table 2 reports the results of regressing the package size purchased (in standardized rolls) by household h during trip t on the same explanatory variables. The results suggest that low-income households purchase UPCs containing 4.64 fewer standardized rolls than higher-income households with similar consumption rates.[7]

[5] The Online Appendix provides details of how we identified the cheapest brand, and presents results from alternative definitions of the cheapest brand at both the DMA and DMA-channel levels. Lower-income households are more likely to buy the cheapest brand, regardless of how it is defined. The Online Appendix also presents cross-sectional differences in coupon usage. Lower-income households are less likely to use coupons, in line with previous findings of the literature (e.g., Bawa and Shoemaker 1987).

[6] We detail the calculation of consumption rate in the Online Appendix. We use a polynomial to avoid assuming a strictly linear relationship between consumption and size purchased. Without consumption controls, the cross-sectional differences between income groups are larger.

[7] Some of the previous work examining cross-sectional differences in bulk buying has also found that low-income households are less likely to purchase larger-sized packages (Attanasio and Frayne 2006; Frank, Douglas, and Polli 1967; Kunreuther 1973; Rao 2000). Others, however, have reached the opposite conclusion (Beatty 2010; Griffith et al. 2009).

Because low-income households are more price sensitive than other households, they would presumably want to utilize all money-saving strategies available to them to the same extent as, if not more so than, higher-income households. It is important to note that different money-saving strategies are not mutually exclusive options. All brands in this category are available in bulk, therefore households do not have to choose between buying cheaper brands and purchasing larger package sizes. It is puzzling, then, that they use one money-saving strategy (buying cheaper brands) more than other households, but use another strategy (bulk buying) less. This is made all the more puzzling by the fact that the potential savings from buying in bulk are quite substantial, even for the brands low-income households prefer. The data suggest that low-income households could save an additional 8.8% per standardized roll if they purchased larger sizes of the brands they prefer at to the degree that the highest-income households do. Importantly, these foregone savings are in line with the savings they accrue by purchasing cheap brands. Purchasing cheaper brands than the highest-income households saves these households 9.6% per standardized roll compared to what they would pay if they purchased the brands the highest-income households did.[8] The potential savings available from buying in bulk and buying cheaper brands are generally comparable, even at the extremes. Low income households could save an additional 21.7% by always purchasing the largest package size available, while keeping their brands purchased the same. They could save 24.6% by keeping by always purchasing the store brand, but keeping their package size purchased the same. These numbers convey that low-income households could achieve significant savings, comparable to the levels that other savings strategies provide, if they purchased larger package sizes. Therefore, low income households' tendency to buy in bulk less than higher income households cannot be a consequence of insufficient savings offered through bulk discounts for the cheaper brands they prefer.

What, then, could explain the gap between low- and high-income households' propensity

[8] Note that our calculations of savings along the package size and brand dimensions are done holding the other dimension constant. The Online Appendix provides details on how we calculate the savings numbers referenced in this section, provides a full set of comparisons between all income groups rather than just the lowest- and highest-income groups, and provides a more thorough discussion for the interested reader.

to buy in bulk? The literature has speculated that several factors could contribute to this gap, including lack of transportation, lack of storage, lack of access to stores that carry bulk items, lack of financial sophistication, and liquidity constraints.[9] This paper examines the liquidity constraints hypothesis–that low income households may not buy in bulk as much as they would like to because they cannot afford the increase in up-front expenditure buying in bulk requires.

If liquidity constraints inhibit low-income households from taking advantage of money-saving opportunities that require an increase in up-front expenditure, we would also expect low-income households to be less likely to accelerate purchase incidence to take advantage of temporary discounts. As Neslin, Henderson, and Quelch (1985) and Hendel and Nevo (2006) point out, if a household is buying earlier than it otherwise would (i.e., accelerating its purchase timing) to take advantage of a sale, then the household's average interpurchase time preceding sale purchases should be shorter than the household's average interpurchase time preceding non-sale purchases. To check whether households from different income groups differ in their propensity to accelerate their purchase timing to take advantage of sale, we evaluate whether the difference between sale and nonsale interpurchase times is less pronounced for low-income households than for high-income households with the following regression:

$$IPT_{htp} = \alpha_h + \delta_h I[sale]_{htp} + \sum_{i=2}^{5} \nu_i I[INC_{ht} = i] + \epsilon_{ht}$$

where $\delta_h = \delta_1 + \sum_{i=2}^{5} \delta_i I[INC_{ht} = i] + \sum_{j=1}^{3} \mu_j [Consumption]_h^j$. Here, we regress the interpurchase time preceding a purchase, IPT_{htp}, on household fixed effects, α_h, to account for households' baseline interpurchase times; an indicator for whether the purchase was made on sale ($I[sale]_{htp}$); and its interaction with the household's income group and with the third polynomial of the household's consumption rate, to test for income-level heterogeneity in the interpurchase time response to sale, while controlling for systematic

[9]In the Appendix, we report changes in our cross-sectional estimates across multiple specifications that include controls for geographic access and other household characteristics for the interested reader. These results are consistent with past research.

differences in consumption across households. The regression also includes household income group dummies to account for variations in household income over time. Table 3 shows that the estimate of δ_1 (the baseline coefficient for $I[sale]_{htp}$ is negative suggesting that for low-income households, the length of time between a sale purchase and a household's previous purchase is shorter than the length of time between a nonsale purchase and a household's previous purchase.[10] This result is consistent with findings in the previous literature (Neslin, Henderson and Quelch 1985; Hendel and Nevo 2006).[11] Moreover, the estimates for all higher-income groups (δ_i for $i > 1$) are negative and decreasing, indicating that higher-income households accelerate their purchase timing even more than low-income households do.[12] Specifically, the interpurchase time for low-income households' sale purchases is only 1 day shorter than that for their non-sale purchases, while the difference for the highest-income households is 2.5 days.

[Insert Table 3 about here]

The results of our cross-sectional analyses provide evidence that low-income households utilize intertemporal savings strategies *less often* than higher-income households do. These findings are consistent with previous research that found similar cross-sectional differences in bulk buying behavior. Why do the households with the strongest incentives to save utilize these money-saving strategies the least? In the empirical analysis that follows, we depart from prior work by testing whether and to what degree liquidity constraints inhibit low-income households from utilizing money-saving strategies that require up-front investments.

[10] Note that not all sale purchases involve acceleration; at times, households are planning to buy and, by chance, happen to find a sale on the same day. These estimates should therefore be interpreted as lower bounds on the magnitude of purchase acceleration, as the parameter estimates measure the average difference between sale and nonsale interpurchase times, regardless of whether a sale purchase was due to acceleration or not.

[11] Similar to this previous literature, we also present results showing that the interpurchase times after sale purchases are longer than interpurchase times after nonsale purchases (Appendix, Table 14). The results support the notion that households are not merely buying earlier to consume more in the current period, but are storing for future consumption.

[12] To the best of our knowledge, the only previous research to test for purchase acceleration differences between income groups, Neslin, Henderson, and Quelch (1985), did not find any significant differences, potentially due to a much smaller sample (N=2,293). The sample size is important to identify differences across income groups because the within-household variance in interpurchase times is quite large.

We detail how our empirical strategy isolates the impact of liquidity constraints on low-income households' propensity to use these strategies from the impact of other potential limitations in household resources (e.g., storage constraints, geographical access, myopia, financial illiteracy).

Empirical Analysis: The Role of Liquidity Constraints

Identification Strategy: Liquidity Shifter for Low-Income Households

Our central hypothesis is that liquidity constraints inhibit low-income households from utilizing intertemporal money-saving strategies as much as they would if they were unconstrained. Because we cannot experimentally vary the cash reserves of low-income households directly, we instead rely on a proxy that is generally associated with higher liquidity for these households: the beginning of the month. Specifically, our difference-in-differences analyses compare (1) the difference in low-income households' tendency to utilize these strategies in the beginning of the month versus other times throughout the month with (2) the differences in higher-income households' tendency to utilize these strategies across the span of the same time periods. Because we expect liquidity constraints to be binding only for low-income households when it comes to low-priced, everyday goods like toilet paper, we expect to observe larger differences in purchase behavior at the beginning versus the end of the month for low-income households than for other households.

Two important features of the difference-in-differences analysis are worth highlighting. First, inferences are based on within-household variation in purchase behaviors. Therefore, inherently household-specific and time-invariant differences across households, such as storage constraints, transportation constraints, access to different stores, myopia, or financial literacy are controlled for and do not confound the estimates of interest. Second, because systematic differences in the shopping environment from week to week (e.g., perhaps temporary discounts for bulk sizes are more common during the first week of the month) are available to all households that shop in that environment, differences in the estimates of households' reactions to liquidity relaxation are not contaminated by such fluctuations. In the Discussion section, we provide additional analyses to show that controlling for time variation in the shopping environment or in the desirability of options does not affect our conclusions and that our assumptions for the difference-in-differences approach are appropriate.

Admittedly, each low-income household has its own unique cash-flow schedule, and thus there is great variation in liquidity across households at any given time of the month. Payments (e.g. earnings, Social Security payments, food stamps) may arrive at different times, and spending patterns fluctuate as well.[13] Therefore, the beginning of the month is a noisy instrument, and our results should be treated as conservative (as we detail further in the Discussion section). However, the proxy is valid as long as it exogenously shifts liquidity availability for low-income households. Both previous research (e.g., Stephens 2003) and the shopping patterns reflected in the Nielsen data indicate that low-income households are more likely to have higher liquidity at the beginning of the month. Previous research has shown that households respond to temporary increases in liquidity by increasing their total spending (Stephens 2006; Zhang 2013). Consistent with this, the low-income households in the Nielsen data experience significant increases in their average daily expenditures early in the month, but the high-income households do not. For each income group, Figure 1 displays the percentage deviation of the group's average daily trip incidence and expenditure from the group's average monthly pattern of trips and expenditure, for all categories (in the left panel) and the toilet paper category (in the right panel). For all categories, the figure shows a clear decline in propensity to shop and daily expenditure for low-income households over the course of the month, a more modest decline for the second income group ($20–$40K annual salary), and virtually no change for the other income groups once patterns that affect

[13] Social Security payments are usually distributed on the last day or the first week of the month. Most of the low-income households in our panel live in states where the distribution dates for food stamps correspond to the beginning of the month. Finally, monthly or bi-weekly paychecks also boost liquidity at the beginning of the month.

all income groups are accounted for.[14] For the toilet paper category, low-income households' shopping propensity and spending per trip is highest in the beginning of the month and sharply declines over the rest of the month, whereas the trip incidence and spending patterns of households making more than $40K are fairly stable across the month. Note that the change in the second income group's behavior is much less pronounced in the toilet paper category, possibly because these households do not feel as constrained for purchases with such a low price point.[15] Therefore, while in general time of the month may impact the liquidity of the second income group, we expect the proxy to impact primarily the purchase behavior of the lowest-income group in the toilet paper category.

To provide a robust set of analyses, we employ five different liquidity shifters. Each measure is a dummy variable indicating whether the purchase was made at a time of relatively high liquidity. The five measures correspond to the following conditions: (1) the purchase was made during the first week of the month, (2) the purchase was made during the first week of the month and on the household's first trip to a store that month (to purchase from any product category), (3) the purchase was made during the first week of the month and on the household's first or second trip to a store that month, (4) the purchase was made during the first ten days of the month and on the household's first trip to a store that month, and (5) the purchase was made during the first ten days of the month and on the household's first or second trip to a store that month. Measures 2–5 consider a household's first one or two trips to the store during a given month under the assumption that a household's liquidity should be highest during its first trip since receiving a liquidity boost and should decrease thereafter. Measures 4-5 recognize that low-income households may have relatively

[14] There are two noticeable spikes in the data experienced by all income groups. The first is a dip on the 25th of the month, explained by decreased spending on Christmas. The second is a spike at the end of the month, potentially explained by an increase in promotional activity by stores to meet quotas.

[15] We also provide additional evidence from a survey of 413 households in the Online Appendix. We find that the households in the low-income group are the most likely to report being cash constrained for basic necessities. Among the households that report feeling cash constrained for basic necessities at least once a month, low-income households are more likely (than any other household) to feel most constrained during the end of the month compared to the beginning of the month. Also, the degree to which the second income group households feel cash constrained compared to how constrained the lowest income group feels, is most divergent for basic necessities, while being most similar for large ticket items.

high liquidity in the first 10 days of the month, rather than just the first week, as reflected in Figure 1. Table 4 provides summary statistics illustrating what percentage of trips are made during time periods indicated by each of these five variables.[16]

[Insert Table 4 about here]

How Do Liquidity Constraints Affect the Ability to Take Advantage of Bulk Discounts?

We measure the degree to which a low-income household's purchases during times of higher liquidity (at the beginning of the month) are larger than those made during times of lower liquidity (later in the month), above and beyond any change observed for higher-income households. We estimate five regressions (one for each of our previously defined liquidity shifters) that take the following form:

$$S_{htp} = \alpha_h + \psi_1 I[LiqHi]_t + \sum_{i=2}^{5} \psi_i I[INC_{ht} = i] I[LiqHi]_t + \sum_{i=2}^{5} \nu_i I[INC_{ht} = i] + \varepsilon_{ht} \tag{1}$$

where S_{htp} is the package size of product p purchased by household h during shopping trip t, and $I[LiqHi]_{ht}$ is one of the five dummy variables identifying periods of higher liquidity for the low-income households at the beginning of the month. Household fixed effects, α_h, capture the time-invariant shopping behavior of each household. The income-group dummy variables are equal to 1 if household h is a member of income group i during the year of trip t. The regression includes income dummies to account for changes in household income over time. We test our hypothesis using the comparisons afforded by the interaction of the indicator for liquidity relaxation and the dummy variables for Income Groups 2–5. We specify the

[16] In the online appendix, we also utilize a different specification that examines whether low-income households' ability to buy in bulk and accelerate purchase timing in response to sale is generally decreasing over the course of the month, as opposed to differing only during the first week of the month.

low-income group (Income Group 1) as the baseline, such that ψ_1 captures the change in the lowest-income group's package size choice during periods of liquidity relaxation. Although ψ_1 might be greater than 0, the model cannot establish whether this is due to low-income households choosing to buy in bulk more often or to differences in the shopping environment that made bulk buying more attractive or feasible for all households at the beginning of the month. Therefore, ψ_i are the main parameters of interest, as they capture the extent to which changes in low-income households' package size choice differ from changes in the higher-income income households' package size choice. Note that the regression accounts for common differences that all households experience between periods where $LiqHi = 1$ and $LiqHi = 0$. We hypothesize that the lowest-income households will increase their relative propensity to purchase in bulk compared to higher-income households (i.e., $\psi_i < 0$). We do not expect the liquidity shifter to affect other income groups differentially, because only the lowest-income group is expected to face liquidity constraints that inhibit the purchase of low-priced, everyday items such as toilet paper.[17]

[Insert Table 5 about here]

The results (presented in Table 5) suggest that low-income households might buy in bulk more if they did not face liquidity constraints. Specifically, across the five high-liquidity-period proxies defined previously, we find that low-income households increase their average package size purchased, relative to higher-income households, by .14 to .19 more standardized rolls at the beginning of the month than during the rest of the month (the estimates of ψ_i for $i \geq 2$ across our five specifications).[18] This represents 3%–4% of the previously identified

[17]In the Online Appendix, we explore another specification that does not assume a threshold separates a single "high liquidity" and a single "low liquidity" period. The results are consistent with those presented here.

[18]Recall that the first high-liquidity proxy was the first week of the month, and that the second and third proxies were the first trip and the first two trips made to a store during the first week of the month, respectively. The second and third proxies were designed to capture a smaller number of observations for which households had an even higher level of liquidity than for the first proxy, on the premise that low-income households might have expended their limited liquidity by their third trip of the month. Consistent

4.64-roll deficit compared with high-income households (Table 2). Because this increase is relative to any observed increases for other income groups, it rules out the possibility that the increase is due to changes in shopping environment during the beginning of the month that are common to all income groups (e.g., greater frequency of sales on large products during the first week of the month).

How Do Liquidity Constraints Affect the Ability to Accelerate Purchases in Response to a Sale?

To investigate whether the liquidity boost received in the beginning of the month allows low-income households to accelerate their purchases in response to sales to a greater degree than during the rest of the month, we run the following regression (again using five specifications, one for each of our five high-liquidity-period variables):

$$\begin{aligned} IPT_{htp} &= \alpha_h + \delta_h I[sale]_{htp} + \gamma_h I[LiqHi]_t \\ &\quad + \psi_h I[LiqHi]_t I[sale]_{htp} + \sum_{i=2}^{5} \nu_i I[INC = i] + \varepsilon_{htp} \end{aligned} \tag{2}$$

where

$$\begin{aligned} \delta_h &= \delta_1 + \textstyle\sum_{i=2}^{5} \delta_i I[INC = i] + \sum_{i=1}^{3} \mu_i [Consumption]_h^j \\ \gamma_h &= \gamma_1 + \textstyle\sum_{i=2}^{5} \gamma_i I[INC = i] + \sum_{i=1}^{3} \kappa_i [Consumption]_h^j \\ \psi_h &= \psi_1 + \textstyle\sum_{i=2}^{5} \psi_i I[INC = i] + \sum_{i=1}^{3} \phi_i [Consumption]_h^j. \end{aligned}$$

Given household fixed effects, the income dummies included linearly in the regression simply control for changes in household income over time. The baseline impact of $I[sale]$,

with this premise, the differences between the first income group and the other income groups (as measured by ψ_i for $i \geq 2$) are slightly stronger for specifications that use the second and third proxies, than for the specification that uses the first. The fourth and fifth proxies reflect the first trip and the first two trips made to a store during the first ten days of the month, respectively. Because of the restrictions on the number of trips, these proxies are likely to capture shopping trips associated with higher liquidity, but also extend the time period to 10 days. Consequently, the absolute magnitude of the estimated ψ_is may be larger or smaller than those estimated based on the first proxy.

estimated by δ_1, captures the degree to which low-income households' interpurchase times decrease in response to a sale outside the high-liquidity period, and δ_i reflects the degree to which other income groups differ in this baseline sale response. The high-liquidity-period dummies ($I[LiqRel]_{ht}$) equal 1 if trip t falls in the high-liquidity time period. The baseline estimate, γ_1, captures the degree to which the interpurchase time changes for low-income households' nonsale purchases during times of relatively high liquidity, and γ_i measure the degree to which other income groups differ. The main coefficients of interest in this regression are ψ_i. The baseline coefficient ψ_1 captures whether the difference between low-income households' sale and nonsale interpurchase times changes during times of higher liquidity, where $\psi_1 < 0$ indicates that sale interpurchase times are shorter during high-liquidity periods than nonsale interpurchase times. The ψ_i coefficients reflect the degree to which higher-income households differ in this response. Our primary hypothesis is that low-income households' tendency to accelerate purchase timing in response to a sale will increase relative to that of higher-income households during periods of higher liquidity. Thus, the appropriate test for this hypothesis is whether $\psi_i > 0$ for $i \geq 2$.

[Insert Table 6 about here]

Table 6 presents the results from the regressions using each of the five liquidity shifters. The findings support the hypothesis that low-income households accelerate their purchase timing to take advantage of sales more during the first week of the month than they do during the rest of the month (by 1.1 – 1.3 days; ψ_1 across our five specifications) and to a greater degree than higher-income households ($\psi_i > 0$ for $i \geq 2$).[19] In fact, higher-income households do not appear to accelerate their purchase timing more during the first week of the month at all, as might be expected given that they likely have sufficient liquidity to take advantage of saving strategies that require up-front investments for everyday goods like toilet paper at any point in time.

[19]The magnitude of the differences between the first income group and others in response to liquidity relaxation (ψ_i) are lowest for the first liquidity proxy. Again, this is because other proxies reflect shopping occasions in which households had a higher level of liquidity than for the first proxy.

Importantly, our results show that low-income households are able to accelerate their purchase incidence in response to sales at least as much as higher-income households during times of higher liquidity, even though they are at a considerable disadvantage at other times. To be more specific, the interpurchase times preceding sale purchases tend to be about 2.0 – 2.5 days shorter ($\delta_1 + \delta_5 + \psi_1 + \psi_5$ for the high liquidity period, $\delta_1 + \delta_5$ for the rest of the month) than those preceding nonsale purchases for the highest-income households, regardless of the time of the month. This difference is similar to, but a little larger than, the difference between sale and non-sale interpurchase times observed for the lowest-income households during times of relative high liquidity, which tends to be around 1.8 – 2.0 days ($\delta_1 + \psi_1$). However, the difference between interpurchase times for the lowest-income households is only 0.7 – 0.8 days at other times (δ_1), which suggests that they experience a significant decline in their ability to accelerate purchase timing in response to sales as the month goes on. In summary, the liquidity boost that low-income households receive at the beginning of the month helps them completely close the gap between their ability to accelerate purchase incidence in response to sales and higher-income households' ability to do so.

Discussion and Robustness

In summary, our empirical results show that low-income households buy in bulk and accelerate purchase incidence to take advantage of sales more often when they have higher liquidity at the beginning of the month, after controlling for other time-varying factors that affect all households. The results suggest that low-income households would likely utilize money-saving strategies that require up-front investment more if they had greater liquidity. In what follows, we discuss the magnitude of the effects, explore the extent to which liquidity constraints affect channel and brand choices, present several robustness analyses that support our identifying assumption, and discuss the ancillary effects of not being able to take advantage of bulk discounts.

A Caution Regarding the Magnitude of the Impact of Liquidity

The results we report provide causal evidence that liquidity constraints influence shopping behavior in everyday product categories. However, we caution readers that our estimates should be interpreted as a lower bound for the impact of liquidity constraints on low-income households for three reasons. First, our liquidity instrument is a noisy proxy for the underlying and unobserved changes in liquidity that households experience. Second, the full impact of liquidity constraints on the purchase behaviors we study could not be measured even if we observed the exact times at which households received cash inflows, as these inflows likely only partially relax low-income households' liquidity constraints and would not allow us to observe household behavior when they are completely unconstrained. Third, we determine that a household is in the low-income category based on its reported annual income. More comprehensive measures of wealth, as well as data on household debt and spending, would provide greater precision regarding which households are most likely to be affected by cash fluctuations over the course of the month. These three factors contribute to the noise in our liquidity shifter, increase measurement error in our regressions, and bias magnitudes toward zero. Future research that uses a more precise measure of liquidity or explicit budgets for shopping trips (as in Stilley, Inman, and Wakefield 2010) could determine the extent to which we underestimate the impact of liquidity constraints.

Accounting for Changes in Store and Brand Preferences

A majority of the households' shopping environments are fixed over time. However, a household's preferences for stores and brands may differ in times of increased liquidity. Given that stores and brands may systematically differ in the extent to which they provide opportunities for intertemporal savings, some of the behavioral responses we document may be indirectly driven by store or brand choice responses to liquidity. For example, at times of lower liquidity, households may be less likely to visit stores that offer bulk options, either because they choose not to visit these stores when they cannot afford to buy in bulk or because they cannot afford to travel to these stores except in times of higher liquidity.[20] In line with this example, the estimates of the impact of liquidity on shopping behavior in Regression 1 capture both (1) the direct impact of liquidity relaxation on the household's size choice given the store it visited and (2) the indirect effect arising from the fact that the household visited a store in which bulk options are more readily available.

However, the reader may be interested in teasing out indirect effects that may arise from the underlying prevalence of behaviors in the chosen channel or brand. Here, we offer results from a specification that adds brand and channel fixed effects to regressions 1 and 2 to account for the degree to which behaviors of interest vary with changes in households' brand and channel choices across shopping occasions. In particular, we estimate the following:

$$
\begin{aligned}
(3) \qquad S_{htp} = {} & \alpha_h + \psi_1 I[LiqHi]_t + \sum_{i=2}^{5} \psi_i I[INC = i] I[LiqHi]_t \\
& + \lambda [BrandChannel]_{htp} + \sum_{i=2}^{5} \nu_i I[INC = i] + \varepsilon_{htp}
\end{aligned}
$$

$$
\begin{aligned}
(4) \qquad IPT_{htp} = {} & \alpha_h + \delta_h I[sale]_{htp} + \gamma_h I[LiqHi]_t + \psi_h I[LiqHi]_t I[sale]_{htp} \\
& + \lambda [BrandChannel]_{htp} + \sum_{i=2}^{5} \nu_i I[INC = i] + \varepsilon_{htp}
\end{aligned}
$$

where all parameters and variables are as defined previously, and $[BrandChannel]_{htp}$ controls for the brand the household bought and the channel it shopped in during trip t. We consider two specifications, in which $[BrandChannel]_{htp}$ either includes brand and channel fixed effects separately (i.e., $[BrandChannel]_{htp} = I(Brand)_{htp} + I(Channel)_{ht}$) or includes fixed effects for each brand-channel pair (i.e., $[BrandChannel]_{htp} = I(Brand_{htp}) \cdot I(Channel_{ht})$). Table 7 and Table 8 present the estimates from the bulk-buying and purchase acceleration regressions, respectively. The results suggest that while low-income households are slightly

[20] We thank an anonymous referee for this comment.

more likely to visit stores and purchase brands that offer bulk-buying opportunities during times of higher liquidity, this shift in behavior is small. We do not find evidence of a shift in brand or channel preferences that has any bearing on purchase acceleration.

[Insert Table 7 about here]

[Insert Table 8 about here]

Robustness Checks for Supply-Side Variations That Correspond to Times of Greater Liquidity

An assumption in our main analyses is that during times of higher liquidity for the low-income households (e.g., the first week of the month), the desirability of particular options remains the same as during the rest of the month. However, retailers or brands that appeal predominantly to low-income consumers may be more likely to put larger package sizes on sale during the first week of the month. Or, by coincidence, large package sizes might be more likely to be in stock during the first week of the month in channels or for brands that low-income consumer prefer. Such changes over time within a channel or brand would not be accounted for by the brand and channel fixed effects we have considered. Therefore, we present two extensions that can account for systematic temporal changes in the availability, affordability, and desirability of choice options.

First, we control for the possibility that the availability of sales may systematically differ between high-liquidity periods and other times of the month. We construct the average sale frequency (percentage of UPCs purchased on sale) of each product and size combination in each channel within a DMA during the days that correspond to relatively high-liquidity times ($I[LiqRel]_{ht} = 1$) and days that correspond to relatively low-liquidity times ($I[LiqRel]_{ht} = 0$) in a given calendar year. For our regression of package size purchased by household h on trip t (S_{htp}), we include the sale frequency variable for each size k available for the product purchased corresponding to the period during which each purchase was being made (high or low liquidity; $[SaleFreqHi]_{htpk}$ or $[SaleFreqLo]_{htpk}$). If more large package sizes (e.g., 24-roll UPCs) are on sale during high-liquidity periods, the inclusion of these variables will absorb any change in package size due to such changes at the DMA level. For our interpurchase time regressions, we include the overall sale frequency for the product purchased (irrespective of size). Specifically, we estimate the following:

$$(5)\quad S_{htp} = \alpha_h + \psi_1 I[LiqHi]_t + \sum_{i=2}^{5} \psi_i I[INC = i] I[LiqHi]_t + \sum_{i=2}^{5} \nu_i I[INC = i]$$
$$+ \sum_{k=1}^{K} \tau_k([SaleFreqHi]_{htpk} I[LiqHi]_t + [SaleFreqLo]_{htpk}(1 - I[LiqHi]_t)) + \varepsilon_{htp}$$

$$(6)\quad IPT_{htp} = \alpha_h + \delta_h I[sale]_{htp} + \gamma_h I[LiqHi]_t + \psi_h I[LiqHi]_t I[sale]_{htp} + \sum_{i=2}^{5} \nu_i I[INC = i]$$
$$+\tau([SaleFreqHi]_{htp} I[LiqHi]_t + [SaleFreqLo]_{htp}(1 - I[LiqHi]_t)) + \varepsilon_{htp}$$

Second, in an alternative specification, we include the interaction of environment controls with the liquidity indicator, to control for any systematic supply-side changes in the affordability, desirability or availability of products and channels. In particular, we estimate the following:

$$(7)\quad S_{htp} = \alpha_h + \psi_1 I[LiqHi]_t + \sum_{i=2}^{5} \psi_i I[INC = i] I[LiqHi]_t + \sum_{i=2}^{5} \nu_i I[INC = i]$$
$$+\lambda[BrandChannel]_{htp} + \kappa[BrandChannel]_{htp} I[LiqHi]_t + \varepsilon_{htp}$$

$$(8)\quad IPT_{htp} = \alpha_h + \delta_h I[sale]_{htp} + \gamma_h I[LiqHi]_t + \psi_h I[LiqHi]_t I[sale]_{htp} + \sum_{i=2}^{5} \nu_i I[INC = i]$$
$$+\lambda[BrandChannel]_{htp} + \kappa[BrandChannel]_{htp} I[LiqHi]_t + \varepsilon_{htp}$$

where all parameters and variables are as defined previously, and $[BrandChannel]_{ht}$ controls for the brand the household bought and the channel it shopped in during trip t.

Note that these two specifications represent different sets of assumptions. The first approach, including DMA-level sale variables, assumes that time-varying changes in shopping environment are limited to sale frequency. The second approach is far stricter, absorbing all variation for a given channel and brand between the high-liquidity period and the rest of the month regarding the desirability and availability of options. While this accounts for the possibility that changes other than promotional efforts may be occuring, it also strips out any variation in package size purchased or purchase acceleration due to households changing channels or brands in response to having greater liquidity (e.g., a low-income household choosing to go to a warehouse store to take advantage of higher-than-usual liquidity).

[Insert Table 9 about here]

[Insert Table 10 about here]

We present the estimates from these specifications in Tables 9 and 10. Noting the modest changes in the estimates of interest, we conclude that supply-side changes are small and do not confound our conclusions. Even when we control for systematic changes in the desirability of choice options during times of higher liquidity, low-income households are relatively more likely to utilize intertemporal money-saving opportunities when they have more liquidity.

Placebo Tests

To further bolster the causal interpretation of our results and to rule out concerns about supply-side changes in the environment that systematically correspond to the first week of the month, we present three placebo tests. Our conjecture relies on the assumption that liquidity relaxation allows low-income households to make up-front investments in intertemporal money-saving strategies. Therefore, low-income households should not be more likely to use static money-saving strategies that do not require up-front investments (using coupons, searching for lower prices, purchasing store brands) in response to liquidity shifters, after controlling for time-varying factors that affect all households. Therefore, in the following regression, where the dependent variable Y_{htp} is an indicator variable for the behavior of interest, we hypothesize that ϕ_i will be indistinguishable from zero.

$$Y_{htp} = \alpha_h + \phi_1 I[LiqHi]_t + \sum_{i=2}^{5} \phi_i I[INC = i] I[LiqHi]_t + \sum_{i=2}^{5} \nu_i I[INC = i] + \varepsilon_{htp}$$

Table 11 reports results from these placebo tests.[21] The results show that low-income households are not more likely to use coupons, purchase store brands, or purchase the cheapest brand during periods of higher liquidity. These results lend support to the assumption that our liquidity instrument is uncorrelated with structural changes that lead low-income households to be more likely to use money-saving strategies in general.

[Insert Table 11 about here]

Inability to Take Advantage of Bulk Discounts May Affect the Ability to Wait for Sales

We examined the ability to purchase in bulk and the ability to accelerate purchases to take advantage of sales separately. But does a household's ability to buy in bulk affect its ability to take advantage of sales? Such a relationship may exist if the following two conjectures hold: (1) The purchase of a large UPC provides a bigger boost to inventory and therefore provides the household with more time until it is forced to purchase again, and (2) having a longer time before inventory runs out increases the likelihood that the household will be able to wait to take advantage of a sale.

The data lend support to both of these conjectures. As we expected, higher-income households typically have larger inventories. Moreover, sale purchases are likely to be made when a household has higher inventory levels (Online Appendix), consistent with the notion

[21] In the interest of space, only the results using the first liquidity shifter–the first seven days of the month–are presented here. The results using the other liquidity shifters are consistent with those in Table and are available from the authors upon request.

that purchases at low inventory levels are more likely to be induced by necessity. Given this evidence, we conclude that increased ability to buy in bulk may indirectly help a household better time its purchases to take advantage of sales. This discussion highlights yet another way in which low-income households are at a disadvantage in utilizing money-saving opportunities, and it points to additional implications of increased liquidity.

Conclusion

This paper provides evidence that liquidity constraints hinder the ability of low-income households to buy in bulk and accelerate their purchase timing to take advantage of sales. The consequent financial losses are best understood in comparison to other hard-earned savings: low-income households' limited ability to utilize savings strategies that require up-front investments forces them to forfeit the vast majority of the savings they accrue by purchasing cheaper brands. In times of greater liquidity, however, low-income households can make up a considerable portion of these losses.

Our work contributes to an important debate regarding the financial decisions low-income households make. As Carvalho, Meier, and Wang (2014) note, "The debate about the reasons underlying [differences in financial decision-making behavior across income groups] has a long and contentious history in the social sciences; the two opposing views are that either the poor rationally adapt and make optimal decisions for their economic environment or that a 'culture of poverty' shapes their preferences and makes them more prone to mistakes." In support of the latter view, researchers have suggested that the attentional demands of poverty reduce the cognitive capacity of the poor (Mani, Mullainathan, Shafir, and Zhao 2013), and that low-income households may be more myopic or present-biased (Delaney and Doyle 2012; Griskevicius, Tybur, Delton, and Robertson 2011). However, the finding that low-income households behave more like higher-income households when their liquidity constraints are relaxed provides support for the former view.

At a broader level, this paper is also related to previous literature documenting cross-sectional differences across households of different income groups in their coupon usage (Bawa and Shoemaker 1987) and deal-proneness (Blattberg, Buesing, Peacock, and Sen 1978; Lichtenstein, Burton, and Netemeyer 1997). Our research shows that liquidity constraints can inhibit the ability of low-income households to trade off current expenditure for future savings, and therefore suggests that liquidity constraints may also be a relevant and important driver of differences in deal proneness.

Our results demonstrate that liquidity constraints shape shopping behavior even for seemingly low-priced, everyday purchases. We show that low-income households do use intertemporal savings strategies relatively more often when they have more liquidity, even when other money-saving strategies are available. Overall, this finding may seem discouraging from a social-welfare point of view. However, we caution the reader against drawing broad claims about welfare from these results. At least two related issues are left for further research to examine. First, in some product categories, research has shown that increases in inventory lead to greater consumption (Ailawadi and Neslin 1998; Ailawadi, Gedenk, Lutzky, and Neslin 2007; Chandon and Wansink 2002). If the increased consumption of the good at lower unit prices does not replace consumption of other goods, stockpiling may not save households money. In categories in which self-control issues may cause households to consume a lot more of the good when they have more of it on hand, the question of overall savings must be studied carefully. Second, while our results show that low-income households are inhibited from using intertemporal saving strategies, our analyses are not intended to determine whether using these money-saving strategies is the best use of their liquidity.

Our work can be useful to managers, as understanding households' intertemporal substitution patterns is valuable for promotion planning (Silva-Risso, Bucklin, and Morrison 1999). Retailers that hope to appeal to low-income consumers may generate greater sales lift if they schedule temporary discounts during times of higher liquidity. The results also suggest that retailers could potentially increase the responsiveness of households to price promotions and bulk discounts and, in turn, potentially increase their share of these households' wallets by offering liquidity assistance. Although some retailers have offered financing programs in the past, these programs are typically targeted at households looking to make large purchases (e.g., televisions) but not the everyday purchases that make up such a large share of low-income households' expenses. For many everyday product categories, only a small amount of liquidity assistance would be needed. Thus, exposure to risk might be low for retailers. Clearly, retailers will be incentivized to fine-tune their pricing strategies to enable low-income households to make better use of intertemporal savings strategies only when doing so will increase profits from these segments. Therefore, any such changes can be expected only in markets in which retailers are competing for the business of low-income consumers.

In situations in which lowering the unit cost of consumption is desirable, our work also higlights the need to enact policies that provide liquidity relief. Public policy makers and researchers studying the costs that low-income households face (e.g., Kaufman et al. 1997; Chung and Myers 1999; Talukdar 2008) often focus on factors that limit the accessibility of supermarkets, or factors that impede the development of financial literacy (Fernandes, Lynch, and Netemeyer 2014). While providing greater access to stores that offer bulk and temporary discounts might increase the utilization of these strategies, policies that help provide liquidity to low-income households may assist them in saving money in the shopping environment already available to them. We hope that our results contribute to the conversation on how society can help alleviate the additional financial burdens shouldered by low-income households.

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Tables and Figures

Table 1: Price, Bulk Discounts, and Temporary Discounts

	Non-sale price	Magnitude of Bulk Discount			Percentage of
	4-Roll	(Unit Price vs. 4-Roll Unit Price)			Purchases
	UPCs	12 Roll	24 Roll	30/36 Roll	on Sale
Angel Soft	\$1.61	–17.5%	–19.3%	–26.5%	29.8%
Charmin	\$3.06	–22.8%	–30.4%	–32.8%	41.1%
Kleenex Cottonelle	\$2.80	–28.8%	–34.7%	–46.7%	53.7%
Quilted Northern	\$2.97	–26.7%	–32.1%	–40.3%	39.0%
Scott	\$3.47	–24.3%	–47.6%	–31.6%	37.5%
Store Brands	\$1.99	–15.6%	–23.8%	–32.6%	19.1%

Column 2 provides the average price for 4-roll UPCs of the given brand in the data. Columns 3–5 provide the price difference per standardized roll offered by 12-, 24-, and 30-/36-roll products relative to the product's 4-roll equivalent. Column 6 lists the percentage of each brand's purchases made on sale.

Table 2: Cross-Sectional Differences in Savings Strategies: Buying Store Brands, Buying the Cheapest Brand, and Bulk Buying

	Buy Store Brand	Buy Cheapest Brand	Package Size
β_2 (Inc Grp 2)	-0.044***	-0.019***	0.82***
	(0.005)	(-0.003)	(0.093)
β_3 (Inc Grp 3)	-0.066***	-0.030***	1.53***
	(0.005)	(0.003)	(0.099)
β_4 (Inc Grp 4)	-0.088***	-0.035***	2.87***
	(0.005)	(0.003)	(0.102)
β_5 (Inc Grp 5)	-0.099***	-0.040***	4.64***
	(0.006)	(0.003)	(0.125)
Number of Observations	3,250,995	3,250,995	3,243,202

Standard errors are clustered at the household level and reported in parentheses. *** p<.001, ** p<.01, * p<.05

Table 3: Cross-Sectional Differences in Savings Strategies: Purchase Acceleration

Variable	I[sale]	Inc 2 * I[sale]	Inc 3 * I[sale]	Inc 4 * I[sale]	Inc 5 * I[sale]
Coefficient	δ_1	δ_2	δ_3	δ_4	δ_5
Inter-purchase time	-0.997***	-0.223	-.865***	-1.324***	-1.508***
	(0.208)	(0.234)	(0.242)	(0.243)	(0.297)
Number of Obs.			3,092,089		

Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

Table 4: Percentage of Trips Made During High-Liquidity Periods, by Liquidity Shifter

Liquidity Shifter:	1	2	3	4	5
Inc Grp 1 (<\$20K)	26.4%	13.0%	20.0%	14.5%	23.9%
Inc Grp 2 (\$20–40K)	24.0%	11.6%	18.0%	12.9%	21.5%
Inc Grp 3 (\$40–60K)	23.5%	11.5%	17.7%	12.9%	21.3%
Inc Grp 4 (\$60–100K)	23.3%	11.5%	17.7%	12.9%	21.3%
Inc Grp 5 (> \$100K)	23.2%	11.5%	17.6%	13.0%	21.3%

Table 5: Bulk Buying: Changes During Times of High Liquidity

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity Shifter	0.168***	0.158***	0.168***	0.169***	0.182***
	(0.027)	(0.035)	(0.030)	(0.033)	(0.028)
$\times$ Inc Grp 2	-0.163***	-0.164***	-0.159***	-0.170***	-0.159***
	(0.033)	(0.042)	(0.036)	(0.040)	(0.034)
$\times$ Inc Grp 3	-0.145***	-0.160***	-0.155***	-0.162***	-0.143***
	(0.034)	(0.043)	(0.037)	(0.042)	(0.035)
$\times$ Inc Grp 4	-0.156***	-0.151***	-0.152***	-0.149***	-0.142***
	(0.034)	(0.044)	(0.038)	(0.042)	(0.035)
$\times$ Inc Grp 5	-0.146***	-0.193***	-0.167***	-0.185***	-0.157***
	(0.043)	(0.056)	(0.048)	(0.054)	(0.045)
N	3,243,202	3,243,202	3,243,202	3,243,202	3,243,202

Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

Table 6: Purchase Acceleration: Changes During Times of High Liquidity

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Sale	-0.718**	-0.836***	-0.764***	-0.830***	-0.768***
	(0.228)	(0.216)	(0.221)	(0.216)	(0.222)
× Inc Grp 2	-0.530*	-0.375	-0.474	-0.371	-0.478***
	(0.257)	(0.243)	(0.249)	(0.244)	(0.251)
× Inc Grp 3	-1.051***	-1.038***	-1.086***	-1.054***	-1.122***
	(0.263)	(0.251)	(0.256)	(0.251)	(0.258)
× Inc Grp 4	-1.585***	-1.487***	-1.561***	-1.498***	-1.581***
	(0.265)	(0.252)	(0.258)	(0.252)	(0.259)
× Inc Grp 5	-1.790***	-1.734***	-1.819***	-1.725***	-1.862***
	(0.322)	(0.307)	(0.313)	(0.308)	(0.315)
Sale × Liquidity Shifter	-1.076***	-1.319**	-1.223***	-1.234**	-1.007**
	(0.319)	(0.435)	(0.358)	(0.420)	(0.342)
× Inc Grp 2	1.197**	1.266*	1.334**	1.134*	1.153**
	(0.381)	(0.527)	(0.431)	(0.508)	(0.410)
× Inc Grp 3	0.681	1.485**	1.166**	1.490**	1.174**
	(0.384)	(0.529)	(0.434)	(0.513)	(0.414)
× Inc Grp 4	0.996**	1.386**	1.251**	1.358**	1.168**
	(0.378)	(0.517)	(0.426)	(0.499)	(0.406)
× Inc Grp 5	1.088*	1.924**	1.687**	1.671**	1.647***
	(0.465)	(0.632)	(0.525)	(0.611)	(0.497)
N	3,092,089	3,092,089	3,092,089	3,092,089	3,092,089

Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

Table 7: Change in Bulk Buying, using Channel and Brand Controls

Using Brand+Channel Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity Shifter	0.190***	0.144***	0.170***	0.153***	0.173***
	(0.025)	(0.031)	(0.027)	(0.030)	(0.025)
× Inc Grp 2	-0.147***	-0.121**	-0.127***	-0.130***	-0.119***
	(0.029)	(0.037)	(0.032)	(0.036)	(0.030)
× Inc Grp 3	-0.124***	-0.109**	-0.119***	-0.115**	-0.107***
	(0.030)	(0.038)	(0.032)	(0.037)	(0.030)
× Inc Grp 4	-0.125***	-0.106**	-0.114***	-0.111**	-0.104***
	(0.030)	(0.038)	(0.033)	(0.037)	(0.031)
× Inc Grp 5	-0.082*	-0.071	-0.067	-0.065	-0.058
	(0.036)	(0.047)	(0.040)	(0.045)	(0.037)

Using Brand+Channel + Brand×Channel Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity Shifter	0.182***	0.148***	0.167***	0.154***	0.170***
	(0.024)	(0.030)	(0.026)	(0.029)	(0.024)
× Inc Grp 2	-0.154***	-0.137***	-0.141***	-0.145***	-0.134***
	(0.028)	(0.036)	(0.031)	(0.035)	(0.029)
× Inc Grp 3	-0.130***	-0.118**	-0.130***	-0.121***	-0.119***
	(0.029)	(0.037)	(0.032)	(0.036)	(0.030)
× Inc Grp 4	-0.136***	-0.120**	-0.126***	-0.123***	-0.115***
	(0.029)	(0.037)	(0.032)	(0.036)	(0.030)
× Inc Grp 5	-0.110**	-0.107*	-0.098*	-0.097*	-0.083*
	(0.035)	(0.046)	(0.038)	(0.044)	(0.036)
N	3,243,202	3,243,202	3,243,202	3,243,202	3,243,202

Standard errors are clustered at the household level and reported in parentheses.
*** $p<.001$, ** $p<.01$, * $p<.05$

Table 8: Change in Purchase Acceleration, using Channel and Brand Controls

Using Brand+Channel Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity×Sale	-1.085***	-1.324**	-1.235***	-1.250**	-1.026**
	(0.318)	(0.434)	(0.358)	(0.420)	(0.342)
× Inc Grp 2	1.217**	1.243*	1.340**	1.119*	1.162**
	(0.381)	(0.526)	(0.430)	(0.508)	(0.409)
× Inc Grp 3	0.686	1.440**	1.151**	1.450**	1.150**
	(0.383)	(0.528)	(0.434)	(0.512)	(0.413)
× Inc Grp 4	0.998**	1.299*	1.210**	1.288**	1.134**
	(0.378)	(0.516)	(0.426)	(0.498)	(0.406)
× Inc Grp 5	1.122*	1.912**	1.688**	1.672**	1.660***
	(0.464)	(0.631)	(0.524)	(0.610)	(0.496)

Using Brand+Channel + Brand×Channel Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity×Sale	-1.101***	-1.343**	-1.251***	-1.263**	-1.037**
	(0.318)	(0.434)	(0.358)	(0.420)	(0.342)
× Inc Grp 2	1.216**	1.259*	1.350**	1.133*	1.170**
	(0.381)	(0.526)	(0.430)	(0.507)	(0.409)
× Inc Grp 3	0.686	1.446**	1.158**	1.455**	1.156**
	(0.383)	(0.528)	(0.434)	(0.512)	(0.413)
× Inc Grp 4	1.008**	1.314**	1.221**	1.298**	1.139**
	(0.378)	(0.516)	(0.426)	(0.498)	(0.406)
× Inc Grp 5	1.111*	1.894**	1.677**	1.648**	1.639**
	(0.464)	(0.631)	(0.523)	(0.610)	(0.496)
N	3,092,089	3,092,089	3,092,089	3,092,089	3,092,089

Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

Table 9: Change in Bulk Buying, controlling for supply-side variation

Using Sale Frequency Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity Shifter	-0.141***	-0.100**	-0.119***	0.033	0.022
	(0.028)	(0.035)	(0.030)	(0.034)	(0.028)
× Inc Grp 2	-0.134***	-0.144***	-0.130***	-0.158***	-0.135***
	(0.033)	(0.042)	(0.036)	(0.041)	(0.034)
× Inc Grp 3	-0.121***	-0.147***	-0.131***	-0.158***	-0.128***
	(0.035)	(0.044)	(0.037)	(0.042)	(0.035)
× Inc Grp 4	-0.104**	-0.122**	-0.109**	-0.135**	-0.119***
	(0.035)	(0.044)	(0.038)	(0.042)	(0.035)
× Inc Grp 5	-0.084*	-0.146**	-0.109*	-0.159**	-0.125**
	(0.043)	(0.055)	(0.047)	(0.053)	(0.044)

Using Brand×Liquidity and Channel×Liquidity Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity Shifter	0.148***	0.069*	0.096**	0.056	0.062*
	(0.033)	(0.032)	(0.029)	(0.031)	(0.027)
× Inc Grp 2	-0.145***	-0.122**	-0.126***	-0.130***	-0.116***
	(0.029)	(0.037)	(0.032)	(0.036)	(0.030)
× Inc Grp 3	-0.122***	-0.110**	-0.118***	-0.115**	-0.105***
	(0.030)	(0.038)	(0.033)	(0.037)	(0.031)
× Inc Grp 4	-0.123***	-0.108**	-0.114***	-0.110**	-0.100**
	(0.030)	(0.039)	(0.033)	(0.037)	(0.031)
× Inc Grp 5	-0.082*	-0.075	-0.070	-0.067	-0.058
	(0.037)	(0.048)	(0.040)	(0.046)	(0.038)

Using Brand×Channel×Liquidity Shifter Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity Shifter	0.235***	0.089***	0.116***	0.075**	0.084**
	(0.039)	(0.031)	(0.029)	(0.030)	(0.026)
× Inc Grp 2	-0.149***	-0.134**	-0.136***	-0.141***	-0.128***
	(0.028)	(0.036)	(0.031)	(0.035)	(0.029)
× Inc Grp 3	-0.123***	-0.113**	-0.123***	-0.115**	-0.110***
	(0.029)	(0.037)	(0.032)	(0.036)	(0.030)
× Inc Grp 4	-0.125***	-0.112**	-0.117***	-0.113**	-0.101***
	(0.029)	(0.037)	(0.032)	(0.036)	(0.030)
× Inc Grp 5	-0.094**	-0.097*	-0.087*	-0.085	-0.068
	(0.036)	(0.046)	(0.039)	(0.044)	(0.037)
N	3,243,202	3,243,202	3,243,202	3,243,202	3,243,202

Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

Table 10: Change in Purchase Acceleration, controlling for supply-side variation

Using Sale Frequency Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity×Sale	-1.044**	-1.308**	-1.210***	-1.252**	-1.019**
	0.318	0.434	0.358	0.421	0.342
× Inc Grp 2	1.207**	1.262*	1.346**	1.136*	1.165**
	0.381	0.526	0.431	0.508	0.410
× Inc Grp 3	0.680	1.479**	1.162**	1.485**	1.167**
	0.383	0.529	0.434	0.513	0.414
× Inc Grp 4	0.992**	1.375**	1.249**	1.353**	1.161**
	0.378	0.517	0.426	0.499	0.406
× Inc Grp 5	1.106*	1.947**	1.703**	1.692**	1.666***
	0.464	0.631	0.524	0.611	0.497

Using Brand×Liquidity and Channel×Liquidity Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity×Sale	-1.083***	-1.239**	-1.125**	-1.201**	-0.938**
	0.322	0.436	0.361	0.421	0.344
× Inc Grp 2	1.224**	1.265*	1.370**	1.138*	1.190**
	0.381	0.526	0.430	0.508	0.409
× Inc Grp 3	0.699	1.464**	1.179**	1.474**	1.179**
	0.383	0.528	0.434	0.512	0.413
× Inc Grp 4	1.018**	1.322*	1.236**	1.311**	1.159**
	0.378	0.516	0.426	0.499	0.406
× Inc Grp 5	1.149**	1.914**	1.684**	1.676**	1.652***
	0.464	0.631	0.524	0.610	0.497

Using Brand×Channel×Liquidity Shifter Controls

	Liq 1	Liq 2	Liq 3	Liq 4	Liq 5
Liquidity×Sale	-1.102***	-1.280**	-1.167**	-1.238**	-0.985**
	(0.322)	(0.436)	(0.361)	(0.421)	(0.344)
× Inc Grp 2	1.223**	1.266*	1.367**	1.141*	1.188**
	(0.381)	(0.526)	(0.430)	(0.507)	(0.409)
× Inc Grp 3	0.686	1.449**	1.165**	1.462**	1.166**
	(0.383)	(0.528)	(0.434)	(0.512)	(0.413)
× Inc Grp 4	1.011**	1.314*	1.228**	1.309**	1.153**
	(0.378)	(0.516)	(0.426)	(0.498)	(0.406)
× Inc Grp 5	1.113*	1.872**	1.649**	1.636**	1.616**
	(0.465)	(0.631)	(0.524)	(0.610)	(0.497)
N	3,092,089	3,092,089	3,092,089	3,092,089	3,092,089

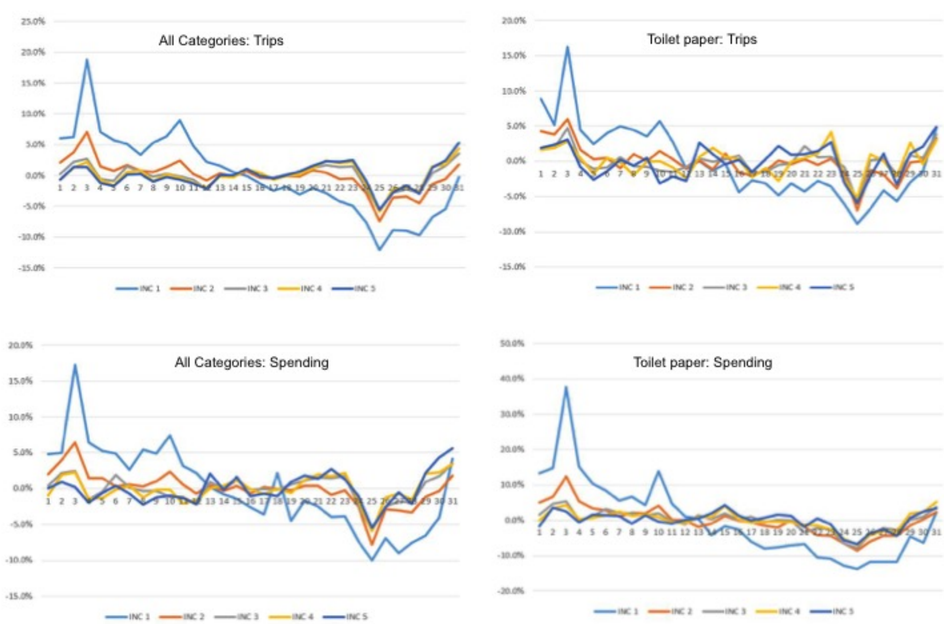
Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

Table 11: Placebo Tests: Changes During Times of High Liquidity

	Coupon Use	Store Brand	Cheap Brand
Liquidity Shifter (first 7 days)	-0.0006	-0.0050***	0.0020
	(0.0012)	(0.0015)	(0.0014)
× Inc Grp 2	-0.0009	0.0026	-0.0007
	(0.0014)	(0.0017)	(0.0016)
× Inc Grp 3	-0.0014	0.0045**	-0.0004
	(0.0015)	(0.0017)	(0.0016)
× Inc Grp 4	-0.0011	0.0046**	-0.0011
	(0.0015)	(0.0017)	(0.0016)
× Inc Grp 5	-0.0032	0.0045*	-0.0018
	(0.0018)	(0.0019)	(0.0018)
N	3,250,995	3,250,995	3,250,995

Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

Figure 1: Percentage Deviation of Average Daily Store Visit and Spending Patterns from Monthly Average, by Income Group



Appendix

Exploring Changes in Cross-sectional Results with Demographics and Location Controls

As Table 12 illustrates, income groups also vary in other demographics. For example, low-income households also tend to be the most likely to live in multi-family homes, which are associated with smaller living spaces and therefore may help proxy for storage constraints.

Table 12: Demographic Summary Statistics

	INC_1	INC_2	INC_3	INC_4	INC_5
Income Group:	10.1%	24.8%	23.1%	28.0%	14.0%
Household Size					
One person	54.1%	31.3%	18.3%	10.2%	5.3%
Two people	29.0%	43.1%	47.4%	47.2%	46.5%
Three people	9.0%	12.4%	14.9%	17.7%	19.5%
Four people	4.7%	7.8%	11.8%	15.8%	19.0%
Five or more people	3.1%	5.4%	7.6%	9.2%	9.8%
Average household size	1.75	2.16	2.47	2.71	2.86
Marital Status					
Married	27.0%	52.4%	69.1%	80.0%	87.1%
Widowed	20.6%	12.7%	5.5%	3.0%	1.7%
Divorced	31.7%	20.1%	13.4%	8.1%	4.9%
Single	20.7%	14.8%	12.1%	8.9%	6.3%
Race					
White/Caucasian	85.0%	86.2%	85.1%	83.9%	81.7%
Highest Education Attained in HH					
Less than high school	5.4%	2.0%	0.7%	0.2%	0.1%
High school grad	69.6%	64.9%	52.5%	37.2%	18.4%
College grad	20.5%	26.7%	34.6%	41.8%	42.1%
Post-college education	4.4%	6.4%	12.3%	20.7%	39.3%
Type of Residence					
Single-family home	58.3%	71.1%	79.9%	87.4%	91.2%

For some demographic categorical variables, we reduce the number of categories for use in our cross-sectional analyses. Specifically, (1) we condense the Type of Residence variable to a binary variable indicating whether each household resides in a single-family home (the source variable broke multi-family homes down into several, smaller sub-categories that each made

Table 13: Cross-Sectional Differences in Different Saving Strategies: Additional Controls

	Buy Store Brand			Buy Cheapest Brand			Package Size		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Income Grp 2	-0.04***	-0.04***	-0.04***	-0.02***	-0.02***	-0.01***	0.9***	0.7***	0.5***
	(0.006)	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)	(0.10)	(0.11)	(0.08)
Income Grp 3	-0.07***	-0.06***	-0.06***	-0.03***	-0.04***	-0.02***	1.6***	1.2***	0.9***
	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.002)	(0.11)	(0.12)	(0.09)
Income Grp 4	-0.09***	-0.08***	-0.09***	-0.03***	-0.05***	-0.02***	2.9***	2.2***	1.7***
	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.002)	(0.11)	(0.13)	(0.10)
Income Grp 5	-0.10***	-0.10***	-0.10***	-0.03***	-0.05***	-0.01***	4.7***	3.5***	2.7***
	(0.006)	(0.007)	(0.005)	(0.003)	(0.004)	(0.003)	(0.13)	(0.15)	(0.13)
Controls									
Consumption	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Location	No	No	Yes	No	No	Yes	No	No	Yes
N	2,898,666			2,898,666			2,891,525		

Note: We report results from 4-digit zipcodes that include at least 10 reporting panelists.
Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

up a small percentage of observations in the Nielsen data set), (2) for the male and female head of a household's education (two separate variables), we divide households by whether they graduated from high school and graduated from college (rather than distinguishing, for example, between a high school graduate with no college and one with a little bit of college), (3) we condense the Race variable into a binary variable indicating whether the household head is caucasion or not, since the vast majority of household heads were caucasian, and (4) combine all households of size greater than or equal to five into a single category, since there were very few households with more than five occupants.

Table 13 introduces additional controls to the cross-sectional results presented in Table 2. For each dependent variable, column 1 repeats the main cross-sectional specification that has consumption rate controls. Column 2 includes levels of all demographics summarized in Table 12 as indicator variables. Column 3 adds fixed effects for each 4-digit zipcode with more than 10 reporting households. All specifications are run on a subsample that includes only observations from panelists living in 4-digit zipcodes with a minimum of 10 reporting households for ease of comparison across three specifications. We see that the degree of cross-

Table 14: Difference in Duration after Purchase for Sale and Non-sale Purchases

Variable	I[sale]	Inc 2 * I[sale]	Inc 3 * I[sale]	Inc 4 * I[sale]	Inc 5 * I[sale]
Coefficient	δ_1	δ_2	δ_3	δ_4	δ_5
Inter-purchase time	4.753***	-0.860***	-1.680***	-2.561***	-2.680***
	(0.236)	(0.257)	(0.267)	(0.269)	(0.321)
Number of Obs.			3,133,108		

Standard errors are clustered at the household level and reported in parentheses.
*** p<.001, ** p<.01, * p<.05

sectional differences across income groups in buying store brands does not change with added controls. On the other hand, the differences in the propensity to purchase the cheapest brand respond significantly to the addition of location controls. The extent to which households differ in their bulk-buying habits also responds to the addition of demographics and location controls, although large cross-sectional differences in this behavior remain even after we control for these factors.

Duration After Purchase

To check whether the difference in interpurchase timing across households is due, at least in part, to purchase acceleration, rather than an increase in consumption, we test whether the time until the next purchase occasion ($Duration_{htp}$) increases in response to purchasing on sale using the following specification:

$$Duration_{htp} = \alpha_h + \delta_h I[sale]_{htp} + \textstyle\sum_{i=2}^{5} \nu_i I[INC_{ht} = i] + \sum_{j=1}^{3} \mu_j [Consumption]_h^j + \epsilon_{htp}$$

$$\text{where } \delta_h = \delta_1 + \textstyle\sum_{i=2}^{5} \delta_i I[INC_{ht} = i] + \sum_{j=1}^{3} \mu_j [Consumption]_h^j.$$

Consistent with stockpiling behavior, the results in Table 14 illustrate that households waited longer before purchasing again following sale purchases than they did following non-sale purchases ($\delta_0 > 0$). Interestingly, this difference is greatest for low-income households ($\delta_i < 0$ for $i > 2$), even though high income households display greater purchase acceleration.