Article

AMERICAN MARKETING ASSOCIATION

Journal of Marketing Research
2019, Vol. 56(1) 1-17

DOI: 10.1177/0022243718821660
journals.sagepub.com/home/mrj
SAGE

Frugality Is Hard to Afford

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Abstract

Intertemporal savings strategies, such as bulk buying or accelerating purchase timing to take advantage of a good deal, provide long-term savings in exchange for an increase in immediate spending. Although households with limited financial resources stand to benefit the most from these strategies, they are less likely to make use of them. The authors provide causal evidence that liquidity constraints impede low-income households' ability to use these strategies, above and beyond the impact of other constraints. Exploiting recurring variation in household liquidity, this study shows that when low-income households have more liquidity, they partially catch up to higher-income households' ability to use intertemporal savings strategies. The findings provide guidance to marketing managers and researchers regarding targeted promotional design and measurement of deal-proneness. For policy makers, they suggest a new path for decreasing the higher prices low-income households have been documented to pay for everyday goods. Policies have traditionally focused on increasing financial literacy or access to supermarkets. Our work suggests that providing greater liquidity can help low-income households make better use of savings opportunities already available to them.

Keywords

Intertemporal savings, liquidity constraints, poverty, deal proneness

Online supplement: https://doi.org/10.1177/0022243718821660

Households have several strategies at their disposal to reduce per-unit spending on everyday products. One set of strategies reduces both short-term expenditure and per-unit cost; examples include buying cheaper brands or searching for lower prices. A second set of strategies reduces per-unit cost in exchange for greater short-term expenditure. For example, a household may purchase a12-roll Universal Product Code (UPC) of toilet paper instead of a 4-roll UPC; the 12-roll UPC will typically cost less per roll but requires a larger absolute expenditure on the day of purchase. Consumers commonly use these kinds of intertemporal saving strategies for purchases of everyday goods. Other examples include accelerating purchase incidence to take advantage of a sale and taking advantage of "buy two, get one free" promotions.

Low-income households should have the greatest incentive to use all available strategies that save them money. Indeed, past research has shown that lower-income households are more likely to utilize the first strategy: they tend to purchase cheaper brands (Ailawadi, Neslin, and Gedenk 2001; Akbay and Jones 2005) and make a greater effort to search for lower prices (Aguiar and Hurst 2007) than their higher-income counterparts. However, intertemporal saving strategies require households to have the ability and willingness to increase their short-term expenditure to save money in the long run. We hypothesize that liquidity constraints may inhibit low-income households from utilizing these strategies, even for seemingly low-priced items.

The main objective of this article is to test whether liquidity constraints inhibit low-income households from utilizing intertemporal money-saving strategies for everyday goods, above and beyond other potentially inhibiting factors (e.g., storage constraints, limited access to channels that offer more intertemporal savings opportunities, myopia, financial illiteracy). To this end, we analyze everyday purchase decisions of a large panel of households in the leading nonfood grocery categories over nine years and make use of natural within-household variation in cash constraints. Because low-income households have lower earnings and less access to credit, they are more reliant on paychecks and/or other forms of direct payments (e.g., food stamps) to make purchases, and their liquidity is depleted the further they get from the time they receive these

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payments. For the average low-income household in the panel, liquidity is highest near the start of the month and lowest as the end of the month draws near. In contrast, middle- and high- income households are less likely to lack the liquidity necessary to purchase everyday items. Employing this variation in liquidity constraints, we construct a difference-in-differences specification that compares (1) the difference in low-income households' tendency to utilize intertemporal money-saving strategies 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. We examine two specific examples of intertemporal money-savings strategies that can be readily inferred from households' purchases: buying in bulk and accelerating purchase incidence to take advantage of a sale. We first focus on the use of these strategies in the toilet paper category. As we discuss in detail subsequently, not only is this category the most commonly purchased nonfood grocery item, but it also provides a tightly controlled environment to illustrate the impact of liquidity constraints on the use of intertemporal saving strategies. We then extend our analyses to other commonly purchased nonfood grocery items (paper towels, laundry detergent, and cigarettes) that share many of the features that make the toilet paper category ideal for studying intertemporal substitution (e.g., storability, high frequency of purchase, stable consumption).

The results support the hypothesis that liquidity constraints inhibit low-income households from utilizing intertemporal money-saving strategies. We find that (1) low-income households utilize these strategies less than higher-income households but that (2) low-income households utilize them more during the earlier part of the month than they do during the later part of the month. In short, low-income households utilize intertemporal money-saving strategies more during times of higher liquidity, at least partially catching up to higher-income households' propensity to utilize these strategies. Because we are examining within-household differences in purchase behavior across time, our empirical approach identifies the impact of liquidity constraints on the use of these strategies above and beyond the impact of any household-specific and time-invariant factors. We also demonstrate that our conclusions are robust to several different model specifications that control for changes in the availability, affordability, or desirability of products and channels that may be systematically correlated with time of month.

Our findings shed light on factors that marketers should account for when setting prices and targeting promotions. The results suggest, for example, that low-income households are likely to be more responsive to marketing promotions that offer intertemporal savings at times of higher liquidity. More generally, retailers engaged in heterogeneous targeting of households for promotions would do well to consider measuring the static and intertemporal dimensions of deal-proneness separately, as low-income households may be more responsive to the former than the latter. Our findings also have policy implications. For policy makers aiming to reduce the poverty penalty, the results highlight the potential value of providing greater liquidity over the course of the month to low-income households. While liquidity constraints have long been known to impede larger purchases (e.g., an automobile), our work shows that these constraints can even inhibit the use of money-saving strategies for the purchase of seemingly low-priced, everyday grocery items.

Related Literature

This article investigates the extent to which liquidity constraints inhibit low-income households' ability to utilize intertemporal money-saving strategies. Our work draws from and contributes to the literature on (1) the poverty penalty and (2) the impact of liquidity constraints on purchase behavior.

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 our study, 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 various income groups differ in their propensity to purchase in bulk. The second stream documents ways in which low-income households are disadvantaged by their shopping environments. For example, these households are often located in areas where retail competition is sparse, retail costs are high, and large supermarkets are absent or difficult to get to, and so they tend to pay higher prices (Chung and Myers 1999; Kaufman et al. 1997; Talukdar 2008). The third stream investigates the extent to which differences in household resources, rather than shopping environments, contribute to the poverty penalty. The current study contributes mainly to the last of these streams, as our primary objective is to investigate how liquidity constraints affect low-income households' choices within the shopping environment they face.

Research in this third stream has investigated several resource constraints that may inhibit households from taking advantage of the money-saving opportunities available to them. For example, Aguiar and Hurst (2007) show that consumers with a higher opportunity cost of time are less likely to engage in price search. 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 smaller residences shop more often and purchase smaller quantities, possibly because they have stricter storage constraints. Other researchers have found that the attentional demands of poverty reduce the cognitive resources of low-income households (Mani et al. 2013) and that they may be more present biased (Delaney and Doyle 2012; Griskevicius et al. 2011). Because intertemporal money-saving strategies require planning for the future, the results of this work suggest that lower-income households may be less able or less inclined to utilize these strategies, even when they are available. Some work has even explicitly hypothesized that low-income households may be inhibited from buying in bulk by liquidity constraints (Griffith et al. 2009; Kunreuther 1973). However, the impact of liquidity constraints on lower-income households' ability to take advantage of intertemporal savings strategies has not been empirically tested. Our study contributes to this literature by documenting the impact of liquidity constraints on these behaviors above and beyond the impact of other previously documented factors.

To test for the impact of cash constraints on the use of intertemporal savings strategies, we leverage recurring, anticipated, and relatively small within-household fluctuations in liquidity over the course of the month. Although this approach is closely related to work that studies how overall spending responds to recurring sources of income, such as paychecks (Stephens 2006; Zhang 2017), food stamps (Beatty and Tuttle 2014; Hastings and Shapiro 2017), or Social Security checks (Stephens 2003), our research differs in that we study how shifts in liquidity affect households' utilization of specific, intertemporal money-saving strategies, rather than their overall spending. Other researchers have studied how overall spending (Agarwal, Liu, and Souleles 2007; Bertrand and Morse 2009; Broda and Parker 2014; Johnson, Parker, and Souleles 2006; Misra and Surico 2014; Parker et al. 2013; Shapiro and Slemrod 1995) and the propensity to purchase private labels and redeem coupons (Dube, Hitsch, and Rossi 2018; Nevo and Wong 2015) respond to large and nonrecurring shifts in wealth, such as tax rebates, economic stimuli, and wealth shocks during recessions. Studying the impact of recurring fluctuations in liquidity constraints helps us identify regular changes in the usage of intertemporal savings strategies within a household. In addition, it makes our findings relevant for both (1) policy interventions (e.g., food stamps), as such interventions are likely to provide small, recurring infusions of liquidity, and (2) marketing efforts, as events that households regularly experience can easily be incorporated into promotional planning.

Data and Cross-Sectional Patterns

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

We aim to study categories in which consumers will be incentivized to use intertemporal savings strategies. Erdem, Imai, and Keane (2003) note that categories that provide such incentives are those in which goods are frequently purchased, goods are storable, and opportunities to decrease per-unit costs by front-loading expenditure are frequent. In addition, we find it helpful to focus on purchases for which substitutes from other categories are not common and structural changes in consumption are minimal, such that shifts in purchase patterns can be attributed to intertemporal substitution rather than systematic changes in a household's demand. Finally, as a practical consideration, it is also useful if package sizes across products in the category can be easily converted to a standardized unit of consumption, such that package sizes and consumption rates are comparable across products and households.

Toilet paper is the most frequently purchased nonfood grocery category in the Nielsen data set and most closely satisfies the aforementioned criteria: it is nonperishable; it has no close substitutes; consumption is unlikely to change structurally within a household; and the size of each UPC can easily be characterized by a few attributes readily available in the data (rolls, sheets per roll, and ply), which we can use to generate a standardized measure of size: standardized rolls (275 sheets of two-ply toilet paper).[2] Moreover, many opportunities are available to utilize intertemporal money-saving strategies in this category, as both bulk and temporary discounts are common and substantial. Table 1 documents the magnitude of bulk discounts by comparing prices across major brands and sizes.[3]

The data sample used for our analyses contains 3.2 million purchases in the toilet paper category made by more than 104,000 households purchasing from 2006 to 2014.[4] These purchases occurred primarily at grocery (47% of purchases), discount (29%), warehouse (8%), drug (6%), and dollar (6%) stores. The average household purchase pattern indicates a consumption rate of slightly less than a roll of toilet paper per capita, per week. Using households' reported annual income, we sort them into five annual household income groups that closely mirror the income quintiles in the United States: (1) <\$20,000, (2) \$20,000–\$40,000, (3) \$40,000–\$60,000, (4) \$60,000–\$100,000, and (5) >\$100,000.[5] Table 2 reports

[1] Researchers' own analyses calculated (or derived) based on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[2] The average UPC in our data set contains the equivalent of 275 two-ply sheets.

[3] 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 74% of purchases, and private labels account for another 20%.

[4] It is important to account for recording discrepancies in this data set (Einav, Leibtag, and Nevo, 2010), so we make a conservative effort to clean the data, correcting or removing entries that are obviously incorrect. For example, some package sizes are clearly erroneous (one UPC was reported to contain 1,296 rolls of toilet paper), and a few households seem to have not reported all their purchases (some do not report purchasing toilet paper for several years). We retain 89% of observations for our primary analyses, and our conclusions are not sensitive to the removed entries. Part 1 of the Web Appendix details our cleaning approach.

[5] Actual quintiles in 2011 were \$0–\$25,000, \$25,000–\$45,000, \$45,000–65,000, \$65,000–105,000, and >\$105,000. Although Nielsen's income brackets do not perfectly match these quintiles, the panel data set provides fairly good coverage of each income group, although it slightly

Table 1. Price, Bulk Discounts, and Temporary Discounts.

	Nonsale Price	Magnitude of Bulk Discount (Unit Price vs. 4-Roll Unit Price)			
	4-Roll UPCs	12 Roll	24 Roll	30/36 Roll	Percentage of Purchases on Sale
Angel Soft	\$1.62	−17.4%	−19.2%	−25.3%	29.3%
Charmin	\$3.06	−21.8%	−30.4%	−32.6%	40.8%
Kleenex Cottonelle	\$2.82	−26.9%	−34.5%	−45.5%	53.4%
Quilted Northern	\$2.97	−25.9%	−32.5%	−40.0%	38.7%
Scott	\$3.47	−22.7%	−47.4%	−29.2%	36.7%
Store Brands	\$2.00	−15.4%	−22.6%	−32.7%	18.4%

This table provides (1) the average nonsale price for 4-roll UPCs of the given brand in the data, (2) the bulk discount (price per standardized roll) offered by 12-, 24-, and 30-/36-roll products relative to the product's 4-roll equivalent, and (3) the percentage of each brand's purchases made on sale.

Table 2. Summary Statistics of Size and Interpurchase Time.

UPC Size (Standardized Rolls)						
Income Group	25th Percentile	50th Percentile	75th Percentile	M	SD	N
1	3.84	7.28	13.10	9.48	8.49	340,253
2	4.37	7.69	13.45	10.58	9.30	833,299
3	5.02	8.65	15.36	11.47	10.08	759,887
4	5.76	8.73	15.37	12.92	11.42	858,607
5	6.72	10.81	17.47	14.72	12.65	375,497
Interpurchase Time (Days)						
Income Group	25th Percentile	50th Percentile	75th Percentile	M	SD	N
1	13	26	49	37.4	38.2	326,449
2	13	26	49	38.2	39.4	799,535
3	14	27	50	39.2	40.3	728,143
4	14	28	56	42.3	43.0	820,044
5	16	33	63	47.9	47.3	357,223

summary statistics of the number of days between purchases and the package size purchased by each income group in this category. The raw data indicate an increasing relationship between income and both package size and interpurchase time, though a causal relationship between income and intertemporal savings strategies cannot be inferred merely from cross-sectional differences.

As mentioned previously, consumers have many savings opportunities available to them (e.g., buying in bulk, accelerating purchases to buy on sale, buying store brands, choosing cheaper options). Griffith et al. (2009) show that these strategies provide comparable savings. Because low-income households are more price sensitive (Ailawadi, Neslin, and Gedenk 2001), we might expect them to be more motivated to utilize all savings strategies available to them, both those that provide immediate savings (e.g., purchasing the cheapest option or the store brand) and those that provide savings over time (e.g., bulk buying, accelerating purchases to take advantage of a deal). To test how low-income households differ in their propensity to buy the store brand, to buy the cheapest option, or to take advantage of bulk discounts, we perform the following cross-sectional regression on three independent variables (Y_{hpt}):

$$Y_{hpt} = \beta_1 + \sum\nolimits_{i=2}^{5} \beta_i I[INC_{ht} = i] + \sum\nolimits_{j=1}^{3} \mu_j [Consumption]_h^j + \varepsilon_{ht},$$

where Y_{hpt} represents one of multiple dependent variables. First, we let $Y_{hpt} = 1$ if household h's purchase p during trip t was the cheapest brand in the household's designated market area (DMA), given the size purchased.[6] 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 trip t. $[Consumption]_h$ refers to the household h's consumption rate. We center this variable at the median consumption rate of low-income households and include a third-order polynomial of it to flexibly control for heterogeneity in shopping behavior that

overrepresents the middle-income groups. The Web Appendix presents some basic statistics about other household demographics for the interested reader.

[6] The cheapest brand for each size is identified as the one with the lowest average price paid in a DMA for a given quarter.

Table 3. Cross-Sectional Differences in Savings Strategies.

	(1) Cheapest Brand	(2) Store Brand	(3) UPC Size		(4) Interpurchase Time	(5) Interpurchase Time$_{post}$
Intercept	.167***	.243***	8.293***	δ_1 (I[sale])	−1.22***	6.76***
	(.001)	(.001)	(.018)		(.204)	(.226)
β_2 (Income Group 2)	−.017***	−.046***	.772***	δ_2 (× Inc 2)	−.28	−.79**
	(.001)	(.001)	(.021)		(.225)	(.244)
β_3 (Income Group 3)	−.032***	−.068***	1.494***	δ_3 (× Inc 3)	−.89***	−1.50***
	(.001)	(.001)	(.021)		(.233)	(.255)
β_4 (Income Group 4)	−.036***	−.088***	2.837***	δ_4 (× Inc 4)	−1.41***	−2.38***
	(.001)	(.001)	(.021)		(.235)	(.258)
β_5 (Income Group 5)	−.037***	−.098***	4.654***	δ_5 (× Inc 5)	−1.52***	−2.42***
	(.001)	(.001)	(.024)		(.287)	(.310)
Observations	3,175,064	Observations	2,974,335			

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

is driven by differences in consumption rates that may otherwise be attributed to differences in income.[7]

Column 1 of Table 3 presents the results from this regression: households in the lowest-income group are 3.7% more likely to buy the cheapest brand in the DMA than the highest-income group (β_5). Second, we repeat the analysis using another dependent variable indicating whether the purchased item was a store brand. Column 2 of Table 3 shows these results: low-income households are 9.8% more likely to buy store brands (β_5). These findings are in line with prior work that documents income differences across different categories in the propensity to buy cheaper brands (Ailawadi, Neslin, and Gedenk 2001; Kalyanam and Putler 1997). In contrast, low-income households are less likely to purchase large packages. Column 3 of Table 3 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 4.65 fewer standardized rolls than higher-income households with similar consumption rates.[8]

Because low-income households are more price sensitive than other households, it is noteworthy that they use one money-saving strategy (buying cheaper brands) more than other households but use another strategy (bulk buying) less. Importantly, 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% per standardized roll if they purchased larger sizes to the degree that the highest-income households do (holding their brand choice constant). Importantly, these forgone savings are comparable to the savings they accrue by purchasing cheap brands, as low-income households save 11% per standardized roll by purchasing cheaper brands than the highest-income households (holding their size choice constant).[9] What explains the gap between low- and high-income households' propensity 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.[10] Herein, we examine the liquidity constraints hypothesis: low-income households do not utilize intertemporal money-saving strategies as much as they would if they were less constrained because they cannot afford the increase in the up-front expenditures that these strategies require.

Given this hypothesis, we should also expect low-income households to be less likely to accelerate purchase incidence to take advantage of temporary discounts. If a household buys earlier than it otherwise would to take advantage of sales, then the household' s average interpurchase time preceding sale purchases should be shorter than the household's average interpurchase time preceding nonsale purchases (Hendel and Nevo 2006; Neslin, Henderson, and Quelch 1985). To check whether low-income households are less likely to accelerate their purchase timing to take advantage of a sale than other households, we evaluate whether the difference between sale and nonsale interpurchase times is less pronounced for low-income households than for higher-income households using the following regression:

$$\mathrm{IPT_{ht}} = \alpha_h + \delta_{ht}\mathrm{I[sale]_{ht}} + \sum\nolimits_{i=2}^{5} \nu_i \mathrm{I[INC_{ht} = i]} + \varepsilon_{ht},$$

where $\delta_{ht} = \delta_1 + \sum\nolimits_{i=2}^{5} \delta_i \mathrm{I[INC_{ht} = i]} + \sum\nolimits_{j=1}^{3} \mu_j [\mathrm{Consumption}]_h^j.$

Here, we regress the interpurchase time preceding a trip to the store, $\mathrm{IPT_{ht}}$, on household fixed effects, α_h, to account for households' baseline, nonsale interpurchase times; an indicator

[7] The Appendix details calculation of consumption rate, and household consumption rates are summarized in Table A1. Consumption rate differences across the income groups are mainly driven by differences in household-size distributions within these groups.

[8] Some prior work has also found that low-income households are less likely to purchase larger-sized packages in other categories (Attanasio and Frayne 2006; Frank, Douglas, and Polli 1967; Kunreuther 1973; Rao 2000), but others have concluded the opposite (Beatty 2010; Griffith et al. 2009).

[9] The Appendix explains how we calculate these savings numbers and provides a more thorough discussion.

[10] In Part 2 of the Web Appendix, we report estimates from other specifications that include controls for geographic access and other household characteristics for the interested reader. These results show that while these factors matter, they cannot fully explain the gap.

for whether any purchase made during this trip was for a sale ($I[\text{sale}]_{ht}$) item; and household income group dummies, which account for variations in household income over time. We let δ_{ht}, household h's response to sale during trip t, vary with the household's income group and a third-order polynomial of its consumption rate. A negative estimate for δ_{ht} indicates purchase acceleration in response to sale. Parameters δ_i ($i \geq 2$) capture whether higher-income households accelerate more ($\delta_i < 0$) or less ($\delta_i > 0$) than low-income households (whose purchase acceleration is captured by δ_1). The consumption controls account for consumption differences across households that may otherwise be misattributed to income differences.

Column 4 of Table 3 shows that higher-income groups accelerate purchases more than low-income households when they encounter a sale ($\delta_i < 0$ for $i \geq 2$).[11] Specifically, the interpurchase time for low-income households' sale purchases is only 1.22 days (δ_1) shorter than that for their nonsale purchases, while the difference for the highest-income households is 2.74 ($\delta_1 + \delta_5$) days.[12] To check whether this difference in interpurchase times is due, at least in part, to purchase acceleration (rather than merely an increase in consumption), we test whether the time until the next purchase occasion (IPTpost_{htp}) increases in response to purchasing on sale during the current purchase occasion using the previously used specification. The final column of Table 3 presents the results of the regression with this dependent variable. The data show that households wait longer before purchasing again following sale purchases than they did following nonsale purchases ($\delta_1 > 0$). This finding supports the notion that households are not merely buying earlier to consume more in the current period but are storing for future consumption.

The results presented here show that low-income households utilize intertemporal savings strategies less often than higher-income households do, even though they are more likely to take advantage of static money-saving strategies. In the next section, we test whether and to what degree liquidity constraints inhibit low-income households' use of these strategies.

Empirical Analysis: Liquidity Constraints

Identification Strategy: Natural Variance in Liquidity

Our central hypothesis is that liquidity constraints inhibit low-income households from utilizing intertemporal money-saving strategies. To assess this hypothesis, we leverage natural variation in the liquidity of households over the course of the month. Previous research has indicated that low-income households are more likely to have higher liquidity at the beginning of the month (e.g., Stephens 2003), and that households respond to temporary liquidity increases by increasing their total spending (Stephens 2006; Zhang 2017). Consistent with this notion, low-income households in the Nielsen data experience significant increases in their average daily expenditures early in the month, but high-income households do not.[13] For each income group, Figure 1 displays the percentage deviation of the group's average trip incidence and expenditure for a given day of the month from the group's average (across all days of the month) daily trip incidence and expenditure; for all categories (left panel) and the toilet paper category (right panel). The figure shows a clear decline in propensity to shop and in daily expenditure for low-income households over the course of the month, a more modest decline for the second income group

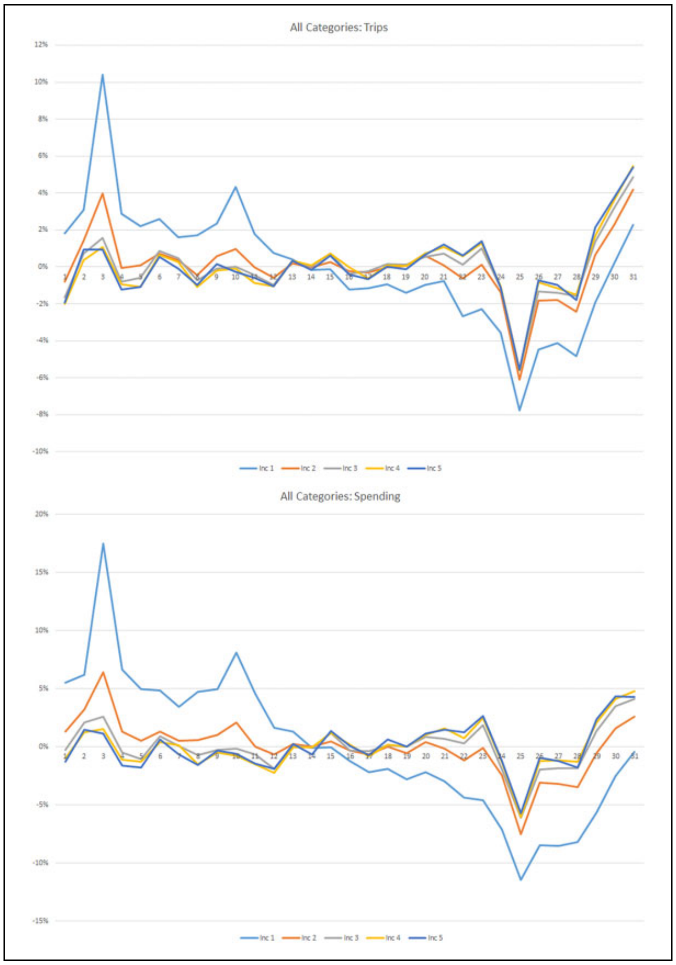

Figure 1. Percentage deviation of average daily store visit and spending patterns from monthly average, by income group. X-axis: Day of month. Y-axis: Day of month's percentage deviation from monthly average.

[11] Neslin, Henderson, and Quelch (1985) test for but do not find any significant differences in purchase acceleration between income groups, potentially due to a much smaller sample (N = 2,293).

[12] Not all sale purchases involve acceleration; at times, sales will coincide with a planned purchase. These estimates should therefore be interpreted as lower bounds on the magnitude of purchase acceleration.

[13] Part 4 of the Web Appendix provides additional evidence that low-income households are more constrained at the start of the month from a survey of 413 households. Low-income residents are the most likely to report being cash constrained for necessities. Among those that report feeling cash constrained for necessities at least once a month, low-income households are more likely than others to feel most constrained at the end of the month. Respondents from the second-lowest income group feel less cash-constrained than the lowest income group for necessities but feel similarly constrained for large-ticket items.

($20,000–$40,000 annual salary), and virtually no change for the other income groups after accounting for patterns that affect all income groups.[14] Given these patterns, we expect liquidity depletion over the course of the month to primarily restrain choices of the lowest-income group in the toilet paper category.

We define a purchase to take place during a high-liquidity period if it was made during the first week of the month and if it occurred during the household's first or second trip of that month (to purchase from any category).[15] This definition relies on the premises that low-income households have greater liquidity at the start of the month and that each subsequent shopping trip reduces the household's liquidity.

Using this definition of high-liquidity periods, our difference-in-differences analyses compare (1) the difference between low-income households' tendency to utilize intertemporal money-saving strategies in high-liquidity periods with (2) the difference between higher-income households' tendency to utilize these strategies during those periods. Because we expect liquidity constraints to bind only low-income households' purchases of low-priced, everyday goods like toilet paper, our main hypothesis implies that low-income households should have larger differences in purchase behavior between high- and low-liquidity periods than other households. We caution the reader that the instrument for high-liquidity periods is noisy: Although low-income households are most constrained at the start of the month on average, each household has its own unique cash-flow schedule; payments (e.g., earnings, Social Security, food stamps) may arrive at different times, and financial demands (e.g., rent, bills) may vary across households.[16] These idiosyncrasies lead to considerable noise in the liquidity shifter; therefore, the magnitude of our estimates should be treated as conservative. However, the difference-in-differences identification approach is valid as long as during the high-liquidity periods (as defined by the proxy), liquidity increases for low-income households more than it does for higher-income households, a data pattern Figure 1 confirms.

Two important features of the difference-in-differences analyses are worth highlighting. First, household-specific and time-invariant differences across households (e.g., storage constraints, transportation constraints, access to different stores, myopia, financial literacy) do not contribute to the estimates of interest, because inferences are based on within-household variation. Second, we also control for systematic differences in the shopping environment of a household from week to week to the extent that they are common to high- and low-income households. In the "Discussion and Robustness Checks" section, we provide additional analyses to show that controlling for variation in the shopping environment within a particular geographic area, or for variation in the desirability of options available to households does not change our conclusions.

How Do Liquidity Constraints Affect the Ability to Buy in Bulk?

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. Our regressions take the following form:

$$\mathrm{S_{htp}} = \alpha_\mathrm{h} + \psi_\mathrm{ht}\mathrm{I[LiqHi]_{ht}} + \sum_{\mathrm{i}=2}^{5}\nu_\mathrm{i}\mathrm{I[INC_{ht} = i]} + \varepsilon_\mathrm{htp}$$
$$\text{where } \psi_\mathrm{ht} = \psi_1 + \textstyle\sum_{\mathrm{i}=2}^{5}\psi_\mathrm{i}\mathrm{I[INC_{ht} = i]} + \sum_{\mathrm{j}=1}^{3}\phi_\mathrm{j}\mathrm{[Consumption]_h^j}, \tag{1}$$

where $\mathrm{S_{htp}}$ is the package size of product p purchased by household h during shopping trip t, $\mathrm{I[LiqHi]_{ht}}$ is equal to 1 if trip t was made during the first week of the month and was the first or second shopping trip taken that month, and $\mathrm{[Consumption]_h^j}$ is a third-order polynomial of the daily consumption rate of household h. A household's response to higher liquidity (ψ_h) is a function of both its consumption rate (which may influence its propensity to stockpile for future consumption) and income. 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. We include them to account for changes in household income over time. In this difference-in-differences specification, the proper test of our hypothesis is whether $\psi_\mathrm{i}<0$ for $\mathrm{i} \geq 2$. That is, we test whether, relative to the sizes purchased by higher-income households, the sizes purchased by low-income households increase during high-liquidity periods, reducing the gap between low- and high-income households ($\psi_\mathrm{i}<0$). Although ψ_1 might be greater than 0, the model cannot establish whether this result is due to low-income households choosing to buy in bulk more often or to changes in the shopping environment that affect all households at the beginning of the month (e.g., bulk items being more readily available).

Columns 1 and 2 of Table 4 present the results from the preceding specification, as well as an alternate specification without consumption controls. They indicate that low-income households, compared with their higher-income counterparts,

[14] There are two noticeable spikes in all income groups' behavior. The first is a dip on the 25th of the month, explained by decreased spending on the Christmas holiday. 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] Our results are robust to several other specifications of the high-liquidity period that extend the period to the first ten days of the month and/or consider a different set of purchases than the first two. Our results are also robust to specifications that do not assume binary "high" and "low" liquidity periods. These results can be found in Part 2 of the Web Appendix.

[16] Social Security payments are often distributed on the last day or the first week of the month. Most low-income households in our panel live in states where distribution of food stamps occurs near the beginning of the month. Monthly or biweekly paychecks also boost liquidity at the beginning of the month.

Table 4. Bulk Buying: Changes During Times of High Liquidity.

	Primary		Robustness Checks				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High-liquidity period (ψ_1)	.18***	.17***	.17***	.17**	−.05	.10**	.12***
	(.030)	(.030)	(.027)	(.026)	(.031)	(.029)	(.029)
× Income Group 2 (ψ_2)	−.17***	−.17***	−.13***	−.14***	−.16***	−.13***	−.14***
	(.036)	(.036)	(.032)	(.031)	(.037)	(.032)	(.031)
× Income Group 3 (ψ_3)	−.17***	−.17***	−.13***	−.14***	−.17***	−.13***	−.13***
	(.038)	(.038)	(.033)	(.032)	(.038)	(.033)	(.032)
× Income Group 4 (ψ_4)	−.15***	−.16***	−.12***	−.13***	−.15***	−.12**	−.12***
	(.038)	(.038)	(.033)	(.032)	(.038)	(.034)	(.033)
× Income Group 5 (ψ_5)	−.17***	−.17***	−.071	−.10*	−.16**	−.07	−.08*
	(.048)	(.048)	(.040)	(.039)	(.047)	(.041)	(.039)
N				3,167,543			
Controls							
Consumption		Yes	Yes	Yes	Yes	Yes	Yes
Brand + Chan			Yes	Yes		Yes	Yes
Brand × Chan				Yes			Yes
SaleFreq × W1					Yes		
(Br + Ch)× W1						Yes	Yes
Br × Ch × W1							Yes

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

purchase larger package sizes at the start of the month when they have more liquidity. For example, the estimates reported in Column 1 show that low-income households increase their average package size purchased, relative to higher-income households, by .15 to .17 more standardized rolls (ψ_i for $i \geq 2$) during the first week of the month than during the rest of the month. This value represents 3%–4% of the previously identified 4.65-roll deficit compared with highest income group and 22% of the .772-roll deficit compared with the second income group (Table 3). Estimates from the specification that includes consumption controls, reported in Column 2, are virtually the same, ruling out the concern that consumption differences across income groups could be driving these results. In summary, our findings show that low-income households buy in bulk more when they have more liquidity available to them.

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:

$$\mathrm{IPT}_{ht} = \alpha_h + \delta_{ht}\mathrm{I[sale]}_{ht} + \gamma_{ht}\mathrm{I[LiqHi]}_{ht} + \psi_{ht}\mathrm{I[LiqHi]}_{ht}\mathrm{I[sale]}_{ht} + \sum_{i=2}^{5}\nu_i\mathrm{I[INC}_{ht} = i] + \varepsilon_{ht}, \quad (2)$$

where

$$\delta_{ht} = \delta_1 + \textstyle\sum_{i=2}^{5} \delta_i \mathrm{I[INC}_{ht} = i] + \sum_{j=1}^{3} \mu_j [\mathrm{Consumption}]_h^j$$
$$\gamma_{ht} = \gamma_1 + \textstyle\sum_{i=2}^{5} \gamma_i \mathrm{I[INC}_{ht} = i] + \sum_{j=1}^{3} \kappa_j [\mathrm{Consumption}]_h^j$$
$$\psi_{ht} = \psi_1 + \textstyle\sum_{i=2}^{5} \psi_i \mathrm{I[INC}_{ht} = i] + \sum_{j=1}^{3} \phi_j [\mathrm{Consumption}]_h^j.$$

The variable $\mathrm{I[sale]}_{ht}$ is equal to 1 if at least one UPC purchased by household h on trip t was purchased on sale.[17] The other variables are defined as in Equation 1. The baseline impact of I[sale], estimated by δ_1, captures the difference between low-income households' sale and nonsale interpurchase times outside the high-liquidity period (where $\delta_1<0$ indicates that interpurchase times preceding sale purchases are shorter, signaling purchase acceleration). The parameter δ_i captures the degree to which the difference between sale and nonsale interpurchase times for income group i differs from δ_1 (the difference for the low-income group). The parameter ψ_1 captures the degree to which the difference in sale and nonsale interpurchase times changes for low-income households during times of relatively high liquidity (where $\psi_1<0$ suggests relatively shorter interpurchase times preceding sale purchases), while ψ_i captures whether income group i differs from Income Group 1 in this regard. As with Equation 1, the proper test of whether high liquidity has a causal impact on low-income households' purchase acceleration rests with the parameters ψ_i. If the ability of low-income households to accelerate their purchase incidence in response to sales increases during times of higher liquidity, after controlling for differences in the

[17] Households typically only purchased a single toilet paper UPC, doing so on 98% of their trips.

Table 5. Purchase Acceleration: Changes During Times of High Liquidity.

	Primary		Robustness Checks				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sale (δ_1)	−.78***	−1.01***	−.60**	−.65**	−.71**	−.61**	−.66**
	(.208)	(.216)	(.214)	(.214)	(.217)	(.214)	(.214)
× Income Group 2 (δ_2)	−.45	−.50	−.37	−.33	−.52	−.37	−.34
	(.238)	(.238)	(.235)	(.235)	(.238)	(.235)	(.235)
× Income Group 3 (δ_3)	−.98***	−1.05***	−.77**	−.69**	−1.08***	−.77**	−.70**
	(.245)	(.246)	(.242)	(.242)	(.246)	(.242)	(.242)
× Income Group 4 (δ_4)	−1.53***	−1.63***	−1.17***	−1.02***	−1.66***	−1.17***	−1.02***
	(.246)	(.247)	(.243)	(.243)	(.247)	(.243)	(.243)
× Income Group 5 (δ_5)	−1.76***	−1.85***	−1.29***	−1.05***	−1.90***	−1.29***	−1.05***
	(.301)	(.302)	(.296)	(.295)	(.302)	(.296)	(.295)
High liquidity × Sale (ψ_1)	−1.09**	−1.13**	−1.14**	−1.15**	−1.06**	−1.03**	−1.06**
	(.342)	(.353)	(.353)	(.353)	(.353)	(.355)	(.355)
× Income Group 2 (ψ_2)	1.18**	1.15**	1.16**	1.16**	1.15**	1.18**	1.17**
	(.411)	(.411)	(.411)	(.410)	(.411)	(.411)	(.410)
× Income Group 3 (ψ_3)	.91*	.87*	.85*	.85*	.87*	.86*	.85*
	(.414)	(.415)	(.415)	(.415)	(.415)	(.415)	(.415)
× Income Group 4 (ψ_4)	1.21**	1.15**	1.10**	1.11**	1.15**	1.12**	1.10**
	(.409)	(.412)	(.411)	(.411)	(.412)	(.411)	(.411)
× Income Group 5 (ψ_5)	1.85***	1.79***	1.78***	1.76**	1.79***	1.76**	1.72**
	(.502)	(.504)	(.503)	(.503)	(.504)	(.504)	(.504)
N				2,974,335			
Controls							
Consumption		Yes	Yes	Yes	Yes	Yes	Yes
Brand + Chan			Yes	Yes		Yes	Yes
Brand × Chan				Yes			Yes
SaleFreq × W1					Yes		
(Br + Ch)× W1						Yes	Yes
Br × Ch × W1							Yes

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

shopping environment that affect all households, then it should be the case that $\psi_i > 0$ for $i \geq 2$.

Columns 1 and 2 of Table 5 present the results from the preceding specification and an additional specification without consumption controls, respectively. 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 .9 to 1.85 days; ψ_i for $i \geq 2$ in Columns 1 and 2). Importantly, these estimates are comparable to the degree to which higher-income households exceed low-income households in their purchase acceleration during times of low liquidity (.98 to 1.85 days; δ_i for $i \geq 3$ in Columns 1 and 2 of Table 5).[18] Therefore, we conclude that the liquidity boost that low-income households receive at the beginning of the month helps them almost completely close the gap between their ability to accelerate purchase incidence in response to sales and higher-income households' ability to do so.

[18] The magnitude of the estimates are also comparable to the low-income households' disadvantage documented by the cross-sectional analysis in the data section (.89 to 1.52 days; δ_i for $i \geq 3$ in Column 4 of Table 3), providing additional evidence that higher liquidity allows low-income households to catch up to higher-income households in their ability to accelerate purchases in response to a sale.

Discussion and Robustness Checks

We show that low-income households utilize two common intertemporal money-saving strategies—buying in bulk and accelerating purchase incidence to take advantage of sales—more often when they have greater 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 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, present evidence from other categories, explore the extent to which liquidity constraints affect channel and brand choices, and present several robustness analyses that support our identifying assumptions.

A Caution Regarding the Estimated Magnitude of the Impact of Liquidity

The results provide evidence that liquidity constraints have a causal effect on shopping behavior in everyday product categories. However, we caution 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 it is likely that these inflows only partially relax low-income households' liquidity constraints and would not allow us to observe fully unconstrained behavior. 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 estimates 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.

Robustness Check 1: Changes in Store and Brand Preferences

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 how liquidity affects store or brand choice. 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. Therefore, we repeat our main analyses with brand and channel controls ($[\text{BrandChannel}]_{htp}$); indicator variables for (1) the brand of purchase p made by household h during trip t and (2) the channel at which trip t was made.[19] We estimate two specifications, one in which $[\text{BrandChannel}]_{htp}$ includes brand and channel fixed effects separately (i.e., $[\text{BrandChannel}]_{htp} = \text{I}(\text{Brand})_{htp} + \text{I}(\text{Channel})_{ht}$) and one in which fixed effects for each brand-channel pair are included (i.e., $[\text{BrandChannel}]_{htp} = \text{I}(\text{Brand}_{htp}) \cdot \text{I}(\text{Channel}_{ht})$).[20] These regressions capture both (1) the direct impact of liquidity relaxation on the household's size choice given the store it visited (via the parameters associated with the liquidity shifter $\text{I}[\text{LiqHi}]_{ht}$) and (2) the indirect effect arising from the fact that the household visited a store in which bulk options are more readily available (via brand and channel fixed effects).

Columns 3 and 4 of Table 4 present the estimates from the bulk buying regressions with the two $[\text{BrandChannel}]_{htp}$ controls. The results suggest that while low-income households are slightly more likely to visit stores and purchase brands that offer bulk buying opportunities during times of higher liquidity, this shift in behavior is small; the estimates suggest low-income households increase their average package size by about .13 rolls (ψ_i for $i \geq 2$), down slightly from the estimates in Columns 1 and 2. We observed no meaningful change in purchase acceleration with the new specification.

Robustness Check 2: Supply-Side Changes During Times of Greater Liquidity

An implicit assumption of our main analyses is that the availability, affordability, or desirability of products or channels does not change over the course 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 consumers prefer. Such changes over time within a channel or brand would not be accounted for by the brand and channel fixed effects in the previous specification. Therefore, we extend those specifications to account for systematic temporal changes in the availability, affordability, and desirability of brands or channels.

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 calculate the average sale frequency (percentage of UPCs purchased on sale) of each product and size combination in each channel within a DMA during the first week of the month ($\text{I}[\text{Week1}]_t = 1$) and during the rest of the month ($\text{I}[\text{Week1}]_t = 0$) in a given calendar year.[21] 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 liquidity (first week, $\text{I}[\text{Week1}]_t = 1$), $[\text{SaleFreqHi}]_{htpk}$, or low liquidity (after first week, $\text{I}[\text{Week1}]_t = 0$), $[\text{SaleFreqLo}]_{htpk}$.[22] If more large package sizes (e.g., 24-roll UPCs) are on sale during high-liquidity periods, including these variables will absorb any change in package size due to such changes

[19] Fixed effects are included for (1) the five primary channels (grocery, drug, discount, dollar, and warehouse stores) plus a sixth "other" conglomerate category and (2) the six primary brands purchased (Angel Soft, Charmin, Kleenex Cottonelle, Quilted Northern, Scott, and store brands) plus a seventh "other" conglomerate brand.

[20] For the interpurchase time regression, $[\text{BrandChannel}]_{ht}$ is specified in the same manner if only one UPC was purchased on the trip. Otherwise, the fixed effects in $[\text{BrandChannel}]_{ht}$ are equal to 1 for each brand purchased.

[21] We use $\text{I}[\text{Week1}]_t$ instead of $\text{I}[\text{LiqHi}]_{ht}$ because features of the shopping environment are independent of the number of times a household has purchased during the month.

[22] For IPT_{ht} regressions, we include overall sale frequency for the product purchased (irrespective of size). If more than one UPC was purchased on a trip, we use the average of their sale frequencies.

at the DMA level. Specifically, we estimate the following:

$$
\begin{aligned}
S_{htp} = \alpha_h + \psi_{ht} I[LiqHi]_{ht} + \sum_{i=2}^{5} \nu_i I[INC = i] \\
+ \sum_{k=1}^{K} \tau_k ([SaleFreqHi]_{htpk} I[Week1]_t \\
+ [SaleFreqLo]_{htpk} (1 - I[Week1]_t)) + \varepsilon_{htp}
\end{aligned}
\quad \text{and} \quad (3)
$$

$$
\begin{aligned}
IPT_{ht} = \alpha_h + \delta_{ht} I[sale]_{ht} + \gamma_{ht} I[LiqHi]_{ht} + \psi_{ht} I[LiqHi]_{ht} I[sale]_{ht} \\
+ \sum_{i=2}^{5} \nu_i I[INC = i] + \tau([SaleFreqHi]_{ht} I[Week1]_t \\
+ [SaleFreqLo]_{ht} (1 - I[Week1]_t)) + \varepsilon_{ht}
\end{aligned}
\quad (4)
$$

Second, in an alternative specification, we include the interaction of brand and channel controls with the variable $I[Week1]_t$ to control for any systematic supply-side changes in the affordability, desirability, or availability of products and channels:

$$
\begin{aligned}
S_{htp} = \alpha_h + \psi_{ht} I[LiqHi]_{ht} + \sum_{i=2}^{5} \nu_i I[INC_{ht} = i] \\
+ \lambda [BrandChannel]_{htp} + \kappa [BrandChannel]_{htp} I[Week1]_t \\
+ \varepsilon_{htp}
\end{aligned}
\quad \text{and} \quad (5)
$$

$$
\begin{aligned}
IPT_{ht} = \alpha_h + \delta_{ht} I[sale]_{ht} + \gamma_{ht} I[LiqHi]_{ht} + \psi_{ht} I[LiqHi]_{ht} I[sale]_{ht} \\
+ \sum_{i=2}^{5} \nu_i I[INC = i] + \lambda [BrandChannel]_{ht} \\
+ \kappa [BrandChannel]_{ht} I[Week1]_t + \varepsilon_{ht}
\end{aligned}
\quad . \quad (6)
$$

In both sets of specifications, δ_{ht}, γ_{ht}, and ψ_{ht} are again specified as they were in Equation 2:

$$\delta_{ht} = \delta_1 + \sum\nolimits_{i=2}^{5} \delta_i I[INC_{ht} = i] + \sum\nolimits_{j=1}^{3} \mu_j [Consumption]_h^j,$$

$$\gamma_{ht} = \gamma_1 + \sum\nolimits_{i=2}^{5} \gamma_i I[INC_{ht} = i] + \sum\nolimits_{j=1}^{3} \kappa_j [Consumption]_h^j \text{ , and}$$

$$\psi_{ht} = \psi_1 + \sum\nolimits_{i=2}^{5} \psi_i I[INC_{ht} = i] + \sum\nolimits_{j=1}^{3} \phi_j [Consumption]_h^j$$

Note that these two sets of specifications represent different sets of assumptions. The first approach, including DMA-level sale frequency 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 occurring, 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 and purchase a 36-roll UPC).

We present the estimates from these specifications in Columns 5–7 of Tables 4 (for bulk buying) and 5 (for purchase acceleration). Given the minor changes in the estimates of interest compared with the previous specifications, we conclude that supply-side changes do not confound our conclusions; they have minimal impact, if any.

Robustness Check 3: Placebo Tests

To further test the causal interpretation of our results and to rule out concerns about supply-side changes systematically occurring during 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 (relative to higher-income households) to use static money-saving strategies that do not require up-front investments, such as using coupons, searching for lower prices, or purchasing store brands during times of higher liquidity. Thus, in the following regression, where the dependent variable Y_{htp} is an indicator variable for the behavior of interest, we hypothesize that ψ_i will be indistinguishable from 0.

$$Y_{htp} = \alpha_h + \psi_{ht} I[LiqHi]_t + \sum_{i=2}^{5} \nu_i I[INC = i] + \varepsilon_{htp}, \quad (7)$$

where $\psi_{ht} = \psi_1 + \sum_{i=2}^{5} \psi_i I[INC_{ht} = i] + \sum_{j=1}^{3} \phi_j [Consumption]_h^j$. The results, reported in Table 6, show that, indeed, low-income households are not more likely to use coupons, purchase store brands, or purchase the cheapest brand during periods of higher liquidity; if anything, it appears that households may be using some of their increased liquidity to purchase brands other than store brands. 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.

Robustness Check 4: Evidence from Other Categories

We replicate our analyses in three other leading nonfood grocery categories: paper towels, laundry detergents, and cigarettes. Recall the criteria categories must satisfy to provide controlled environments to test our hypotheses: (1) products are storable and there are opportunities to decrease per-unit costs by front-loading expenditure; (2) category substitutes are not common; (3) systematic changes in consumption are minimal, such that changes in purchases can be attributed to intertemporal substitution; and (4) package sizes across products in the category can be easily converted to a standardized unit of

Table 6. Placebo Tests: Changes During Times of High Liquidity.

	Coupon Use	Store Brand	Cheap Brand
High-liquidity period (ψ_1)	−.003	−.004*	.002
	(.001)	(.002)	(.002)
× Income Group 2 (ψ_2)	.000	.003	−.003
	(.002)	(.002)	(.002)
× Income Group 3 (ψ_3)	−.001	.004*	−.003
	(.002)	(.002)	(.002)
× Income Group 4 (ψ_4)	−.001	.003	.000
	(.002)	(.002)	(.002)
× Income Group 5 (ψ_5)	−.001	.004	−.002
	(.002)	(.002)	(.002)
N		3,175,064	

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

Table 7. Bulk Buying: Evidence from Other Categories.

	Paper Towels		*Cigarettes*		*Detergent*	
	(1)	(2)	(1)	(2)	(1)	(2)
High-liquidity	.09***	.08***	1.99***	1.66***	1.01***	.98**
period (ψ_1)	.014	.014	.341	.342	.283	.284
× Income Group	−.05**	−.06**	−1.02*	−1.07**	−.44	−.45
2 (ψ_2)	.017	.017	.404	.402	.332	.333
× Income Group	−.07***	−.07***	−1.27**	−1.32**	−.36	−.39
3 (ψ_3)	.017	.017	.439	.436	.336	.337
× Income Group	−.05**	−.06**	−1.14*	−1.14*	−.21	−.25
4 (ψ_4)	.017	.017	.446	.446	.330	.331
× Income Group	−.06**	−.07**	−1.52*	−1.48*	.32	.28
5 (ψ_5)	.020	.020	.630	.632	.374	.376
Consumer Controls	No	Yes	No	Yes	No	Yes
N	3,175,064		1,513,242		2,142,248	

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

consumption. The paper towel category comes closest to the toilet paper category in satisfying these criteria, although substitutes are less rare for paper towels than for toilet paper (e.g., hand towels, sponges, tissue paper). Cigarettes do not have close substitutes, but some households may have structural changes in their consumption if they try to quit smoking or if they are intermittent social smokers.[23] The laundry detergent category does not meet the criteria for studying intertemporal purchase behavior as well as the other two categories: although it satisfies the first three criteria, package sizes are typically reported in ounces, and the number of ounces needed per load washed varies considerably by product. This additional noise is nontrivial, making it difficult to compare sizes or accurately define household consumption rates.

Tables 7 and 8 report, for each of these three categories, the estimates from regressions 1 (bulk buying) and 2 (purchase acceleration), both with and without consumption controls. Our previous findings generalize to these categories: low-income households accelerate their purchase timing to a greater degree during periods of high liquidity in all three categories and increase their bulk buying behavior during periods of high liquidity in both the paper towel and cigarette categories.[24] These results provide additional evidence that liquidity constraints inhibit low-income households from utilizing intertemporal savings strategies, showing the generalizability of our results across several categories.

Table 8. Purchase Acceleration: Evidence from Other Categories.

	Paper Towels		*Cigarettes*		*Detergent*	
	(1)	(2)	(1)	(2)	(1)	(2)
Sale × High-	−2.64*	−2.44	−1.34***	−1.37**	−3.09*	−3.38**
liquidity (ψ_1)	(1.263)	(1.328)	(.372)	(.429)	(1.450)	(1.507)
× Income	3.02*	3.05*	1.50**	1.50**	3.10	2.97
Group 2 (ψ_2)	(1.451)	(1.452)	(.483)	(.484)	(1.639)	(1.637)
× Income	3.24*	3.30*	1.50**	1.52**	3.25*	3.05
Group 3 (ψ_3)	(1.442)	(1.444)	(.506)	(.508)	(1.622)	(1.621)
× Income	3.62*	3.68**	1.11*	1.15*	3.39*	3.16*
Group 4 (ψ_4)	(1.411)	(1.412)	(.558)	(.559)	(1.593)	(1.592)
× Income	3.71*	3.79*	.38	.39	5.46**	5.23**
Group 5 (ψ_5)	(1.606)	(1.609)	(.811)	(.810)	(1.780)	(1.785)
Consumer Controls	No	Yes	No	Yes	No	Yes
N	2,974,335		1,351,032		1,939,081	

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

Conclusion

This article provides evidence that liquidity constraints hinder low-income households' ability to utilize money-saving strategies that require an increase in up-front expenditure—specifically, buying in bulk and accelerating purchase timing to take advantage of sales. The consequent financial losses are best understood in comparison to other hard-earned savings: by underutilizing these strategies, low-income households forfeit the majority of the savings they accrue by purchasing cheaper brands. Our results demonstrate that liquidity constraints shape shopping behavior even for seemingly low-priced, everyday purchases. Although the number of categories that provide controlled environments suitable to examine households' use of intertemporal money-saving strategies is limited, we find no reason to believe the documented effects are limited only to

[23] We make a conservative effort to focus on regular smokers by studying the purchase decisions of the top 99% of households in terms of total number of cigarette purchases. Doing so eliminates households that purchase eight times or fewer. Our conclusions are not sensitive to the dropped observations. All data cleaning steps are detailed in Part 3 of the Web Appendix.

[24] The lack of evidence that low-income households buy larger sizes in periods of high liquidity may be due to the noise in the size variable, or it may be a genuine result driven by category-specific factors (e.g., the fact that laundry detergents are heavy and low-income households are less likely to have cars).

these categories. Furthermore, these findings are likely to extend to other forms of intertemporal money-saving strategies that were not readily measurable in the Nielsen data set, such as "buy two, get one free" deals.

Our work contributes to an important debate about the financial decisions low-income households make. As Carvalho, Meier, and Wang (2016) 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 et al. 2013) and that low-income households may be more present biased (Delaney and Doyle 2012; Griskevicius et al. 2011). We find that low-income households behave more like higher-income households when their liquidity constraints are relaxed, utilizing intertemporal money-saving strategies more often. This finding provides support for the view that the poor would be able to make intertemporal trade-offs that save them money but lack the resources that would allow them to do so.[25]

This finding has both policy and marketing implications. From a policy perspective, it suggests a loss of welfare due to a lack of liquidity, even holding income constant. Public policy makers and researchers studying the costs that low-income households face often focus on factors that limit the accessibility of supermarkets (e.g., Chung and Myers 1999; Kaufman et al. 1997; Talukdar 2008) or that impede the development of financial literacy (Fernandes, Lynch, and Netemeyer 2014). While 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. Moreover, the fact that these households utilize these strategies more often at the start of the month suggests that some low-income households have sufficient financial literacy to utilize liquidity when they have it.

However, it is important to emphasize that any policy intervention designed to help ameliorate low-income households' loss in overall welfare should also consider other behaviors related to intertemporal substitution that have been documented in the literature. For example, in some product categories, research has shown that increases in inventory lead to greater consumption (Ailawadi, Ma, and Grewal 2018; Ailawadi and Neslin 1998; Ailawadi et al. 2007; Chandon and Wansink 2002). If consumption increases and this increase is not offset by a decrease in consumption of other goods, stockpiling may not save households money. In addition, increases in consumption may have undesirable health consequences, especially for unhealthy items such as cigarettes or high-caloric snacks.

The marketing implications of our work are related, albeit indirectly, 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 et al. 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. Broadly speaking, our work contributes to our understanding households' intertemporal substitution patterns, which is an important factor in promotion planning (Silva-Risso, Bucklin, and Morrison 1999). Our findings highlight the importance of separately accounting for households' heterogeneous responsiveness to different types of deals. They suggest that low-income households are likely to be less responsive than higher-income households to deals that require intertemporal substitution (e.g., bulk discounts, "buy two, get one free" promotions). Moreover, our findings suggest that low-income households are likely to be more responsive to these types of deals during periods of higher liquidity than lower liquidity (e.g., at the start of the month), whereas higher-income households' responsiveness to deals that require up-front investment is effectively time invariant. Therefore, our work also highlights the importance of taking into account how different consumer segments' deal-responsiveness may vary over the course of the month when making a promotional plan.

In conclusion, this article contributes to a better understanding of both consumer behavior and the financial burdens shouldered by low-income households. We encourage future research to address several important related topics. First, researchers should examine how to comprehensively incorporate households' heterogeneous, time-varying deal-proneness into a promotion-planning framework. It should also characterize equilibrium outcomes for retailers and consumers if all retailers utilize knowledge of liquidity schedules to target consumers. It is important to note that the marketing and welfare implications of our work may not be independent of each other; if firms schedule deals at times of high liquidity, when low-income households are better able to take advantage of them, both the retailers and the customers may be better off. Therefore, we hope that our study encourages future research to explore the conditions under which firms might find it profitable to plan promotions in a manner that would benefit low-income customers.

Appendix

Calculating Consumption

A household's daily consumption rate is calculated as the total volume purchased—excluding their volume purchased on their

[25] Note that we do not claim that intertemporal savings strategies are the very best use of their finances or the best way to save money. Such claims are beyond the scope of this study.

final day purchasing from the category—divided by the total time in the panel that they were actively purchasing in the category.[26] We calculate the household's consumption rate using all but the last purchase of each of the household's "active periods" (consecutive purchases without a missing observation) and the length of each active period, as follows:

$$\text{Consumption}_h = \frac{\sum_{a=1}^{A}\sum_{p=1}^{P_a-1} V_{hpa}}{\sum_{a=1}^{a=A} T_a}. \quad (8)$$

Here, V_{hpa} is the volume of toilet paper for purchase p during active period a, P_a is the total number of purchases made during period a, and T_a is the time between the first and last purchase during active period a. We sum all volume purchased by a household except that of the last purchase and divide that sum by the total number of days across all active periods. The logic behind this approach is that a household' s consumption rate should reflect the relationship between volume purchased and the time over which the purchased volume was consumed. A household's time in panel ends with the last purchase; therefore, that last purchase should not be included, as it clearly would not be consumed during that time. An implicit assumption is that inventory at the time of the household's last purchase is equal to what the household's inventory was at the time of its first purchase (or, alternatively, that a household consumed exactly as much as it purchased between the day of its first purchase and the day before its last purchase).[27]

Income groups differ noticeably in their average daily consumption of toilet paper (Row 1 of Table A1). However, this difference is primarily driven by differences in household size, as low-income households in the panel are smaller than wealthier households. Single-person households tend to have similar consumption patterns irrespective of income, as do multi-person households (Rows 2 and 3 of Table A1).

Table A1. Household Average Daily Consumption (Standardized Rolls).

	INC_1	INC_2	INC_3	INC_4	INC_5
Average daily consumption, all households	.270	.294	.315	.322	.327
Single-person households[a]	.215	.200	.214	.215	.191
Multi-person households[b]	.331	.331	.334	.333	.334
25th percentile	.136	.157	.171	.182	.189
50th percentile	.213	.240	.261	.269	.277
75th percentile	.331	.367	.390	.400	.405
N (number of households)	8,682	19,465	15,792	21,617	11,576
Percent single-person	53%	28%	16%	9%	5%
Percent multi-person	47%	72%	84%	91%	95%

Data in this table exclude households that changed income groups during the panel
[a]Households that never had more than one person during their time in the panel
[b]Households that always had at least two or more people during their time in the panel

Forgone Savings Calculations

In the "Data" section, we note the potential savings from buying cheaper brands and buying in bulk are comparable. We provide the calculations behind this conclusion next. We calculate two values: how much low-income households would pay, per standardized roll of toilet paper, if they (1) kept their brands purchased constant but purchased the same package sizes that higher-income households do when buying that brand or (2) kept their package size purchased constant but purchased the same brands that higher-income households do when buying that size. We calculate these values as follows. First, for each brand (major brands, plus a conglomerate "other" brand) b and package size (in rolls) s, we calculate the average price per standardized roll paid by low-income households in each quarter q ($PPSR_{bsq}$). Because the number of standardized rolls in any given package size s differs across brands, we also calculate the number of standardized rolls for each brand and package size in each quarter q ($SRoll_{bsq}$). Finally, for each quarter q, for each income group $i = 1, 2, 3, 4, 5$, we calculate the frequency with which households purchase (1) a given brand b (π_b^{qi}), (2) a given package size s (π_s^{qi}), (3) a given brand b conditional on purchasing a given package size s ($\pi_{b|s}^{qi}$), and (4) a given package size s conditional on purchasing a given brand b ($\pi_{s|b}^{qi}$).

To calculate the average price per standardized roll paid by low-income households, given their size and brand purchases and given the proportion of our observations from each quarter ($\pi_{q|i}$), we simply calculate the low-income households' frequency of purchasing each brand–size combination in each quarter ($\pi_b^{qi} \times \pi_{s|b}^{qi}$, or, equivalently, $\pi_s^{qi} \times \pi_{b|s}^{qi}$) and calculate a weighted average (across quarters, sizes, and brands) of price per standardized roll:

$$\sum_b\sum_s\sum_q \pi_{q|(i=1)}\left(\pi_b^{q(i=1)} \times \pi_{s|b}^{q(i=1)}\right)\left(\frac{PPSR_{bsq} \times SRoll_{bsq}}{SRoll_{bsq}}\right).$$

This calculation gives us our baseline, against which we compare calculations 1 and 2 outlined in the preceding paragraph. To calculate the first value, we simply remove the conditional size purchase frequencies for income group 1 in the preceding equation ($\pi_{s|b}^{q(i=1)}$) and replace them with the corresponding

[26] The Homescan data indicate that some households may have failed to scan at least one purchase during their time in the panel. These missing value issues are likely to have occurred randomly with respect to our research interests; however, they will bias consumption rates downward. We take a conservative approach in identifying missing trips by flagging unreasonably long interpurchase times. Active periods for a household correspond to the set of consecutive purchases that are likely to be reported without missing values. If we conclude that the likelihood of a missing trip between t and t + 1 is high (due to an extremely long interpurchase time), trip t marks the end of one "active period" and t + 1 marks the beginning of a new active period. See Part 1 of the Web Appendix for further details on how we construct the threshold that flags unreasonably long interpurchase times.

[27] Note that a household must have at least two consecutive purchases in an active period to calculate consumption rate. If consumption rate cannot be calculated due to the pattern of missing values, the household is not included in the sample, as detailed in Part 1 of the Web Appendix.

Table A2. Prices Paid and Potential Savings.

Holding Brand Purchased Constant	Size (SR)	Price / SR	Potential Savings
Actual sizes purchased (first income group)	8.71	$.577	—
If they purchased sizes like Income Group 2	9.43	$.569	1.3%
If they purchased sizes like Income Group 3	10.04	$.562	2.5%
If they purchased sizes like Income Group 4	11.46	$.544	5.6%
If they purchased sizes like Income Group 5	12.98	$.531	7.9%
If they purchased largest size available	34.22	$.443	23.1%
Holding Size Purchased Constant			
		Price / SR	Realized Savings
Actual brands purchased (first income group)		$.577	—
If they purchased brands like Income Group 2		$.597	3.6%
If they purchased brands like Income Group 3		$.608	5.4%
If they purchased brands like Income Group 4		$.622	7.8%
If they purchased brands like Income Group 5		$.640	11.0%
		Price / SR	Potential Savings
If they purchased store brands only		$.438	24.1%

conditional size purchase frequencies for a higher income group. For example, if we want to see how much low-income households would save if they purchased the sizes that the highest-income households (i = 5) do, we would substitute $\pi_{s|b}^{q(i=5)}$ for $\pi_{s|b}^{q(i=1)}$. A similar logic applies to calculating the second value. To control for differences in consumption across income groups, we calculate these values for single- and multi-person households and present weighted averages in Table A2 (where the weight applied to each is the percentage of the lowest-income group purchases made by single- and multi-person households).

Table A2 presents the average price per standardized roll paid by low-income households given their size and brand choices ($.577) and how much they would pay if they purchased the sizes and brands that higher-income households do. The potential savings from bulk discounts is on par with (though slightly lower than) the potential savings from buying cheaper brands: low-income households save 11% by purchasing cheaper brands than the highest-income households and could save 8% by purchasing the same sizes as those households. Table A2 also provides related calculations: how much low-income households could save if they always purchased the largest size available for a given brand (23.1%) or always purchased store brands (24.1%).

Acknowledgments

The authors thank Dan Ackerberg, John Lynch, attendees of the 2015 Ross School of Business Marketing Camp, attendees of the 2016 Boulder Summer Conference on Consumer Financial Decision Making, and the marketing faculty at the Leavey School of Business for their assistance and suggestions. They are grateful to the Kilts Center for Marketing at Chicago Booth for providing the data.

Associate Editor

Russell Winer served as associate editor for this article.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

A. Yeşim Orhun gratefully acknowledges research funding provided by the 3M Company.

References

Agarwal, Sumit, Chunlin Liu, and Nicholas S. Souleles (2007), "The Reaction of Consumer Spending and Debt to Tax Rebates—Evidence from Consumer Credit Data," *Journal of Political Economy*, 115 (6), 986–1019.

Aguiar, Mark, and Erik Hurst (2007), "Life-Cycle Prices and Production," *American Economic Review*, 97 (5), 1533–59.

Ailawadi, Kusum L., Karen Gedenk, Christian Lutzky, and Scott A. Neslin (2007), "Decomposition of the Sales Impact of Promotion-Induced Stockpiling," *Journal of Marketing Research*, 44 (3), 450–67.

Ailawadi, Kusum L., Yu Ma, and Dhruv Grewal (2018), " The Club Store Effect: Impact of Shopping in Warehouse Club Stores on Consumers' Packaged Food Purchases," *Journal of Marketing Research*, 55 (2), 193–207.

Ailawadi, Kusum L., and Scott A. Neslin (1998), "The Effect of Promotion on Consumption: Buying More and Consuming It Faster," *Journal of Marketing Research*, 35 (3), 390–8.

Ailawadi, Kusum L., Scott A. Neslin, and Karen Gedenk (2001), "Pursuing the Value-Conscious Consumer: Store Brands Versus National Brand Promotions," *Journal of Marketing*, 65 (1), 71–89.

Akbay, Cuma, and Eugene Jones (2005), "Food Consumption Behavior of Socioeconomic Groups for Private Labels and National Brands," *Food Quality and Preference*, 16 (7), 621–31.

Attanasio, Orazio, and Christine Frayne (2006), "Do the Poor Pay More?" in *Proceedings from Eighth Bureau of Research and Economic Analysis of Development Conference*. Ithaca, NY: Cornell University.

Bawa, Kapil, and Robert W. Shoemaker (1987), "The Coupon-Prone Consumer: Some Findings Based on Purchase Behavior Across Product Classes," *Journal of Marketing*, 51 (4), 99–110.

Beatty, Timothy K. M. (2010), "Do the Poor Pay More for Food? Evidence from the United Kingdom," *American Journal of Agricultural Economics*, 92 (3), 608–21.

Beatty, Timothy K. M., and Charlotte J. Tuttle (2014), "Expenditure Response to Increases in In-Kind Transfers: Evidence from the Supplemental Nutrition Assistance Program," *American Journal of Agricultural Economics*, 97 (2), 390–404.

Bell, David R., and Christian AL Hilber (2006), "An Empirical Test of the Theory of Sales: Do Household Storage Constraints Affect Consumer and Store Behavior?" *Quantitative Marketing and Economics*, 4 (2), 87–117.

Bertrand, Marianne, and Adair Morse (2009), "What Do High-Interest Borrowers Do with Their Tax Rebate?" *The American Economic Review*, 99 (2), 418–23.

Blattberg, Robert, Thomas Buesing, Peter Peacock, and Subrata Sen (1978), "Identifying the Deal Prone Segment," *Journal of Marketing Research*, 15 (3), 369–77.

Broda, Christian, and Jonathan A. Parker (2014), "The Economic Stimulus Payments of 2008 and the Aggregate Demand for Consumption," *Journal of Monetary Economics*, 68, S20–36.

Carvalho, Leandro S., Stephan Meier, and Stephanie W. Wang (2016), "Poverty and Economic Decision-Making: Evidence from Changes in Financial Resources at Payday," *American Economic Review*, 106 (2), 260–84.

Chandon, Pierre, and Brian Wansink (2002), "When Are Stockpiled Products Consumed Faster? A Convenience-Salience Framework of Postpurchase Consumption Incidence and Quantity," *Journal of Marketing Research*, 39 (3), 321–35.

Chung, Chanjin, and Samuel L. Myers (1999), "Do the Poor Pay More for Food? An Analysis of Grocery Store Availability and Food Price Disparities," *The Journal of Consumer Affairs*, 33 (2), 276–96.

Delaney, Liam, and Orla Doyle (2012), "Socioeconomic Differences in Early Childhood Time Preferences," *Journal of Economic Psychology*, 33 (1), 237–47.

Dubé, Jean-Pierre, Günter J. Hitsch, and Peter E. Rossi (2018), "Income and Wealth Effects on Private-Label Demand: Evidence from the Great Recession," *Marketing Science*, 37 (1), 22–53.

Einav, Liran, Ephraim Leibtag, and Aviv Nevo (2010), "Recording Discrepancies in Nielsen Homescan Data: Are They Present and Do They Matter?" *Quantitative Marketing and Economics*, 8 (2), 207–239.

Erdem, Tülin, Susumu Imai, and Michael P. Keane (2003), "Brand and Quantity Choice Dynamics Under Price Uncertainty," *Quantitative Marketing and Economics*, 1 (1), 5–64.

Fernandes, Daniel, John G. Lynch Jr., and Richard G. Netemeyer (2014), " Financial Literacy, Financial Education, and Downstream Financial Behaviors," *Management Science*, 60 (8), 1861–83.

Frank, Ronald E., Susan P. Douglas, and Rolando E. Polli (1967), "Household Correlates of Package-Size Proneness for Grocery Products," *Journal of Marketing Research*, 4 (4), 381–4.

Griffith, Rachel, Ephraim Leibtag, Andrew Leicester, and Aviv Nevo (2009), "Consumer Shopping Behavior: How Much Do Consumers Save?" *Journal of Economic Perspectives*, 23 (2), 99–120.

Griskevicius, Vladas, Joshua M. Tybur, Andrew W. Delton, and Theresa E. Robertson (2011), "The Influence of Mortality and Socioeconomic Status on Risk and Delayed Rewards: A Life History Theory Approach," *Journal of Personality and Social Psychology*, 100 (6), 1015–26.

Hastings, Justine S., and Jesse M. Shapiro (2017), "How are SNAP Benefits Spent? Evidence from a Retail Panel," Working Paper No. w23112, National Bureau of Economic Research.

Hendel, Igal, and Aviv Nevo (2006), "Sales and Consumer Inventory," *RAND Journal of Economics*, 37 (3), 543–61.

Johnson, David S., Jonathan A. Parker, and Nicholas S. Souleles (2006), "Household Expenditure and the Income Tax Rebates of 2001," *The American Economic Review*, 96 (5), 1589–610.

Kalyanam, Kirthi, and Daniel S. Putler (1997), "Incorporating Demographic Variables in Brand Choice Models: An Indivisible Alternatives Framework," *Marketing Science*, 16 (2), 166–81.

Kaufman, Phil R., James MacDonald, Steve M. Lutz, and David Smallwood (1997), "Do the Poor Pay More for Food? Item Selection and Price Differences Affect Low-Income Household Food Costs," Economic Research Service No. 34065, United States Department of Agriculture, http://purl.umn.edu/34065.

Kunreuther, Howard (1973), "Why the Poor May Pay More for Food: Theoretical and Empirical Evidence," *Journal of Business*, 46 (3), 368–83.

Lichtenstein, Donald R., Scot Burton, and Richard G. Netemeyer (1997), "An Examination of Deal Proneness Across Sales Promotion Types: A Consumer Segmentation Perspective," *Journal of Retailing*, 73 (2), 283–97.

Mani, Anandi, Sendhil Mullainathan, Eldar Shafir, and Jiaying Zhao (2013), "Poverty Impedes Cognitive Function," *Science*, 341 (6149), 976–80.

Misra, Kanishka, and Paolo Surico (2014), "Consumption, Income Changes, and Heterogeneity: Evidence from Two Fiscal Stimulus Programs," *American Economic Journal: Macroeconomics*, 6 (4), 84–106.

Neslin, Scott A., Caroline Henderson, and John Quelch (1985), "Consumer Promotions and the Acceleration of Product Purchases," *Marketing Science*, 4 (2), 147–65.

Nevo, Aviv, and Arlene Wong (2015), "The Elasticity of Substitution Between Time and Market Goods: Evidence From the Great Recession," Working Paper No. w21318, National Bureau of Economic Research.

Parker, Jonathan A., Nicholas S. Souleles, David S. Johnson, and Robert McClelland (2013), "Consumer Spending and the Economic Stimulus Payments of 2008," *American Economic Review*, 103 (6), 2530–53.

Rao, Vijayendra (2000), "Price Heterogeneity and 'Real' Inequality: A Case Study of Prices and Poverty in Rural South India," *Review of Income and Wealth*, 46 (2), 201–11.

Shapiro, Matthew D., and Joel Slemrod (1995), "Consumer Response to the Timing of Income: Evidence from a Change in Tax Withholding," *The American Economic Review*, 85 (1), 274–83.

Silva-Risso, Jorge M., Randolph E. Bucklin, and Donald G. Morrison (1999), "A Decision Support System for Planning Manufacturers' Sales Promotion Calendars," *Marketing Science*, 18 (3), 274–300.

Stephens, Melvin Jr. (2003), "'3rd of Tha Month': Do Social Security Recipients Smooth Consumption Between Checks?" *The American Economic Review*, 93 (1), 406–22.

Stephens, Melvin Jr. (2006), "Paycheque Receipt and the Timing of Consumption," *The Economic Journal*, 116 (513), 680–701.

Stilley, Karen M., J. Jeffrey Inman, and Kirk L. Wakefield (2010), "Spending on the Fly: Mental Budgets, Promotions, and Spending Behavior," *Journal of Marketing*, 74 (3), 34–47.

Talukdar, Debabrata (2008), "Cost of Being Poor: Retail Price and Consumer Price Search Differences Across Inner-City and Suburban Neighborhoods," *Journal of Consumer Research*, 35 (3), 457–71.

Zhang, Yiwei (2017), "Consumption Responses to Pay Frequency: Evidence from 'Extra' Paychecks," in *NA—Advances in Consumer Research*, Vol. 45, Ayelet Gneezy, Vladas Griskevicius and Patti Williams, eds. Duluth, MN: Association for Consumer Research, 170–74.