Saving Space: Bulk Buying, Storage Costs, and Inequality

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[*]

Abstract

Bulk discounts help households save money, but they increase inequality and bias our measures of consumption inequality downward by about 10%. I find that bulk purchasing increases with income with households making over $100k being 13% more likely to buy in bulk than households making under $25k. This increases consumption inequality because low-income households are paying higher unit costs for the same goods. Households increase bulk purchases after warehouse clubs open, but the changes are small and limited to middle- and high-income households. Using a structural model of consumer choice, I estimate the relative importance of access, storage costs, transportation costs, and budget constraints on household's ability to buy in bulk.

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1 Introduction

Recent research on household spending has analyzed the ways households save money and how prices can differ even for mostly homogenous goods. These price differences have large implications for both price indices and for understanding consumption inequality.[1] This paper explores how bulk discounts contribute to underlying consumption inequality and bias estimates of expenditure inequality downward. Furthermore, it provides an extensive analysis of how often households take advantage of bulk discounts, what kinds of households utilize bulk discounts, and quantifies what factors prevent poorer households from taking advantage of bulk savings using structural estimation.

I document three key facts about bulk discounting. First, bulk discounting is almost universal, covering 97% of product categories with multiple available sizes. These discounts are steeper for non-perishable items compared to perishable items.[2] For a 10% increase in package size, unit prices can decrease by up to 8% depending on the product category.

Second, bulk discounts cause measures of consumption expenditures to be underestimated by about 10%. While high-income households spend more per unit due to increased product and store quality, the expected increase in price due to those components is offset by savings they get from bulk discounts.

Third, households making over $100k are 6 percentage points more likely to buy in bulk compared to similar households making under $25k. These gaps are particularly large for essential storable items like paper towels (24pp), toilet paper (21pp), and diapers (11pp). For these kinds of items, this presents a puzzle: Why are low-income households not taking advantage of bulk discounts? In the case of toilet paper, I estimate that low-income households are spending 38% more than if they were to purchase the lowest unit-price item available.

To understand this puzzle, I combine reduced-form analysis with structural

[1] See Attanasio and Pistaferri (2016) for an insightful review of consumption inequality research.

[2] I use “storable” and “non-perishable” interchangably as well as “perishable” and “non-storable”.

demand estimation to explain why low-income households do not buy in bulk. This provides guidance for policymakers concerned with alleviating inequality and guidance for improving our measures of consumption inequality.

I test two possible explanations for this bulk discounting gap using reduced-form methods. First, warehouse clubs (large retailers that offer bulk sized items in exchange for a membership fee) may increase this disparity. Using data on warehouse club entry, I find that even though entry increases bulk buying, it can only account for a small portion of the overall gap in bulk purchasing and this effect is limited to middle- and high-income households.

Second, households may not have the funds available to purchase large packages. If this is the case, then if a household's income changes, they may increase their bulk purchasing. To test this hypothesis, I estimate how a household's bulk purchasing changes when their income changes and find significant, but small increases in bulk purchasing after a household's income increases.

Even with these reduced-form facts, a structural model is necessary to obtain a more comprehensive view of the factors that affect a household's decision to buy in bulk. Using household purchases of toilet paper, I estimate a structural demand model to quantify the importance of storage costs, transportation costs, and liquidity constraints to the household's decision of whether or not to buy in bulk.

This paper contributes to two strands of the literature. First, it contributes to the literature on consumer discounting and purchasing behavior. Both marketing and industrial organization have extensively studied how consumers take advantage of a variety of discounts. Griffith et al. (2009) and Nevo and Wong (2018) provide an extensive overview of how often consumers take advantage of sales, coupons, bulk discounts, and generic brands and examines how these behaviors changed during the Great Recession. While much attention has been spent analyzing sales and coupons, bulk discounts have been much less studied from a household standpoint even though they have many desirable properties

(Griffith et al. 2009; Nevo and Wong 2018; Orhun and Palazzolo 2019).[3,4] First, bulk discounts are a standard feature of the shopping environment and are not dynamic (as opposed to sales). Second, search costs are dramatically lower because bulk discounts are available within a store (as opposed searching for coupons or lower prices between stores). Finally, quality trade-offs are virtually non-existent because they apply to different sizes of the same product (as opposed to brand substitution which inherently has quality trade-offs). This paper sheds light on consumer behavior in relation to bulk discounts, which are the most widely available and most substantial discounts that households have access to.

The second strand of the literature concerns consumption inequality and its measurement. Most macro-level research has focused on differences in aggregate spending between households or between various product categories (Krueger and Perri 2006; Heathcote, Perri, and Violante 2010; Attanasio and Pistaferri 2014; Aguiar and Bils 2015). Under the assumption that homogenous goods have the same prices, increased expenditures directly correspond to increased consumption. However, as Kaplan and Menzio (2015) show, prices for homogenous goods are not the same and this has severe consequences for measurement. Most recently, Coibion, Gorodnichenko, and Koustas (2017) prove that consumption inequality is overstated due to bulk buying because households make fewer shopping trips and therefore measured price dispersion increases even if underlying consumption does not.[5] This paper complements

[3]For analyses of consumer responses to sales, see Pesendorfer (2002); Hong, McAfee, and Nayyar (2002); Erdem, Imai, and Keane (2003); Hendel and Nevo (2006a); Hendel and Nevo (2006b); Hendel and Nevo (2013). For analyses of coupons, see Narasimhan (1984); Nevo and Wolfram (2002); Anderson and Song (2004).

[4]Quantity discounts have been studied in other settings such as in operations research, which primarily focuses on business-to-business transactions where large volume orders are being placed. Quantity discounts have also been studied in development economics, but these settings are quite different from the shopping environment of the United States (Rao 2000; Attanasio and Frayne 2006; Dillon, De Weerdt, and O'Donoghue 2017; Gibson and Kim 2018).

[5]This is because the Diary portion of the Consumer Expenditure Survey only records the past 2 weeks of purchases. Bulk buying allows some households to make purchases during those 2 weeks and others will not have to purchase during those 2 weeks.

their analysis by focusing on how bulk discounts can reduce overall expenditures and that avenue will mean our consumption measures are underestimated. Finally, this paper identifies bulk discounts as a factor that increases the "poverty penalty" faced by poor households because they are paying higher prices for the same goods.

2 Data

2.1 Nielsen Consumer Panel Data

I use the Nielsen Consumer Panel Dataset from 2004–2017 available through the Kilts Center for Marketing at the University of Chicago Booth School of Business. This dataset is a longitudinal panel of about 174,000 unique households, of which I observe about 40,000 each year from 2004–2006 and about 60,000 households each year from 2007–2017. This data records all purchases from any outlet intended for personal, in-home use and covers about 30% of consumer expenditures. About 1.5 million unique items (defined by UPC code) are recorded in categories such as groceries, cleaning supplies, health/personal care items, and basic general merchandise.

Households scan all items that they purchase, input quantities, prices, date of purchase, and store purchased from. Nielsen retains about 80% of its panel from year to year with the mean and median tenure of a household being 4 and 3 years, respectively.

For my analysis, I exclude households with a student or military head of household as well as any purchases of alcohol, "deferred" modules which Nielsen has stopped tracking, or "magnet" products.[6] Furthermore, I drop any modules for which fewer than 3 unique sizes are purchased or fewer than 100 purchases are recorded in a given year. This leaves me with 957 product modules.[7] My descriptive statistics and reduced-form analysis are generated

[6] Magnet products are typically non-packaged, variable weight products like fresh produce or items ordered from a store's deli counter.

[7] A product module is a narrow product category defined by Nielsen. For example, toilet

from this sample. Table 1 presents descriptive statistics for households in the sample.

[Table 1 about here.]

2.2 Nielsen Retail Scanner Data

I use Nielsen's Retail Scanner Data primarily in my structural estimation. The Nielsen Retail Scanner Data contains weekly pricing and volume of about 35,000 stores from about 90 retail chains between 2006-2016. I match the Retail Scanner Data with the Consumer Panel data based on store identification numbers and purchase dates. Depending on the product, about 45-70% of purchases can be matched. By matching the two datasets, I can see what a household's choice set was and what they ultimately chose to purchase.[8]

3 Stylized Facts

I document 4 stylized facts to motivate my analysis:

1. 97% of product categories with multiple available sizes have quantity discounts and storable items have larger discounts.

2. Households making over $100k are 6 percentage points more likely to buy in bulk compared to households making under $25k. Gaps are particularly large for essential storable items like toilet paper, diapers, and paper towels.

3. Households increase their bulk buying when warehouse clubs open nearby, but this only applies to middle- and high-income households.

4. High-income households use bulk discounts to offset price increases from quality improvement and store choice, resulting in a 10% underestimation

paper, paper towels, and eggs are separate product modules.

[8]The Retail Scanner data only records information on products that have positive sales, so I cannot distinguish between a product was available and did not sell or a product that was unavailable.

of consumption inequality.

3.1 Bulk Discount Prevalence

To understand the importance of bulk discounts, we must first know how common they are. I use purchases recorded in the Nielsen Consumer Panel data from 2004-2017 to estimate their prevalence and magnitude. Bulk discounts are the result of estimating the following regression for each product module m:[9]

$$log(P)^{m}_{ibrdt} = \beta^{m} log(Size)_{ibrdt} + \lambda_{brdt} + \epsilon_{ibrdt}, \quad (1)$$

where P is the real unit price of product i purchased from retailer r of brand b in market d in month t.[10] $Size$ is the amount available in a particular package (measured in the most common units of that product, like ounces for milk). λ is a brand-retailer-market-year-month fixed effect.[11]

Because different retailers might offer different price schedules for different brands and these schedules could potentially vary across markets or over time, I include a brand-retailer-market-year-month fixed effect.[12] This ensures that the bulk discount coefficient is being identified by variation in unit prices between different sizes of the same brand sold at the same retailer in the same market at the same time.

If bulk discounts exist, then β will be negative. To visualize these bulk discounts, I plot the distribution of β in Figure 1. I find that about 97% of all product modules have a significant and negative β and that non-perishable

[9]A product module is a narrowly defined product category. Toilet paper, milk, and eggs are all separate product modules.

[10]Prices are deflated using the CPI to January 2010 dollars.

[11]A market is a Nielsen Designated Market Area which is a non-overlapping county grouping that covers the United States. A map of these DMA regions is available at https://www.thevab.com/wp-content/uploads/2017/06/2016-2017TVDMARegionMap_Small_v4.pdf.

[12]Nielsen records both "retailers" and "stores", where stores correspond to individual locations and retailers are the chain the store belongs to. I use retailer-brand fixed effects because not all individual stores have identifiers and pricing decisions are typically made higher than the store-level.

items generally have larger discounts than perishable items.[13,14] The median β is 0.51 for storable products, which means that a 10 percent increase in package size corresponds to a 5.1 percent decrease in unit costs. This is much larger than the median β for perishable items of 0.39. Given the size and near-universality of bulk discounts, households could use these savings to lower costs without having to sacrifice consumption.

[Figure 1 about here.]

How much could households save by buying in bulk? To find this, I do a similar analysis as Griffith et al. (2009) and estimate the following regression:

$$log(P)_{irb} = \beta_1 Coupon_{irb} + \sum_q \beta_2^q Quintile_{irb}^q + \lambda_{rb} + \epsilon_{irb}, \tag{2}$$

where $log(P)$ is the log real unit price (in January 2010 dollars) of product i of brand b purchased at retailer r. *Coupon* indicates whether that item was purchased with a coupon. $Quintile^q$ is an indicator for whether the product purchased is in quintile q of the size distribution of the product module (with the 2nd quintile being the reference group). λ is a brand-retailer fixed effect. The estimates are weighted by expenditures.

This specification gives the average discount relative to the average unit price of a particular brand (e.g. average per-sheet price of Charmin toilet paper at Target). The coefficient estimates are reported below in Figure 2. Items in the smallest quintile cost more than in the 2nd quintile, but are less popular, and for expositional purposes, I omit the first quintile coefficients from the figure. Overall, bulk savings are substantial and generally larger than those

[13] I restrict my analysis to product categories with more than 3 sizes. One might be concerned that package size is a strategic choice by the manufacturer and in some cases, the manufacturer chose not to produce multiple sizes. This would bias the prevalence of bulk discounts upward. Including all non-deferred, non-alcohol modules reduces this number to 85%, still a vast majority of product categories. Some of these omitted categories are products like hairbrushes and housewares for which there is little need to buy more than a single item at once.

[14] I define an item as "perishable" if it is kept in the refrigerated or frozen section of the store or cannot be kept for extended periods of time, like produce or bread.

provided by coupons. Most notably, bulk savings are larger for storable items compared to perishable items. Hence, not only are bulk discounts on storable items valuable because consumption can be shifted in time, but the actual magnitudes are larger!

[Figure 2 about here.]

3.2 Discounting Behavior

Given the substantial savings given by bulk discounts, do households take advantage of them? To answer this question, I calculate the expenditure-weighted share of each household's shopping basket that is purchased in bulk (defined as a purchase in the largest 2 quintiles of the size distribution for that product category). I then regress this "bulk share" on household income after controlling for other household characteristics that could affect how much a household purchases or are correlated with income and plot the income coefficients.

$$Y_{idt} = \beta_1 Income_{idt} + \beta_2 Age_{idt} + \beta_3 HHSize_{idt} + \beta_4 Child_{idt} + \lambda_d + \lambda_t + \epsilon_{idt}, \quad (3)$$

where Y_i is household i's basket share of bulk purchases in market d in year t. *Income* is a dummy for a household i's income bin, *Age* is the head of household's age, *HHSize* is the number of people in the household, and *Child* is an indicator for whether the household has any children.[15] λ is a year and a market fixed effect.

The results are plotted in Figure 3 and they show that overall, richer households are 4 percentage points more likely to buy in bulk. Additionally, these differences are primarily driven by non-perishable items. The gap for non-perishable items is 6 percentage points compared to virtually no difference for perishable items.

One explanation is that richer households consumer more and therefore, they

[15]I control for these covariates because household income varies with household size, age, and children for reasons outside of socio-economic status. These covariates are also likely to affect how much a household purchases.

buy larger packages. While that is likely true for certain product categories, it should be seen in purchases of "perishable" items because by definition, they must be consumed within a short period of time. However, there is little difference in bulk purchasing of perishable items after adjusting for important household characteristics. Increased consumption could also explain the gap in non-perishable items, but this is less obvious because these goods do not have to be consumed immediately and therefore, households could be deferring consumption to a later date, but incurring the costs now. However, for products where this is unlikely, such as toilet paper, paper towels, and diapers, these patterns persist, suggesting low-income households are paying more for the same basket simply because they are buying smaller quantities per trip.

Across popular spending categories, the biggest gaps are in storable categories like paper towels (24 pp), toilet paper (21 pp), and diapers (11 pp), while perishable categories show little relationship (See Figure 4).

[Figure 3 about here.]

[Figure 4 about here.]

3.3 Missed Bulk Savings

Given that low-income households are less likely to buy in bulk and bulk savings can be substantial, how much money are they "leaving on the table"? The easiest way to compute this would be to see what alternatives the household had when they were shopping and compare the unit price they could have paid with the unit price they actually paid. Fortunately, linking the Nielsen Consumer Panel with the Nielsen Scanner data allows me to do just that.

Due to storage limitations, I can only do this analysis on only a few product categories. To capture both perishable and non-perishable items with relatively fixed demand, I focus on toilet paper, diapers, milk, and eggs. For each category, I do the following to compute the average "missed" savings. First, for each shopping trip, I compute the "first-best" unit price the household would have paid if they had obtained the lowest unit price given their brand

and store choice. Then, to get the average "missed" savings for a household, I expenditure-weight each of these missed savings and aggregate to the household level. Based on this measure, we get the following average missed savings by income group (averages computed for a family of 4).

[Table 2 about here.]

Overall, missed savings are quite substantial and it appears that most households could realize savings from buying larger packages. We can estimate the differences in "missed" savings between households by using the following regression:

$$Y_{idt} = \beta Income_{idt} + \gamma X_{idt} + \lambda_{dt} + \epsilon_{idt}, \tag{4}$$

where Y is the "missed" savings of household i in market d in year t. $Income$ is the household's income bin and X consists of demographic measures (age, household size, presence of children). λ is a market-year fixed effect. Table 3 shows that low-income households miss out on more savings than high-income households and this is primarily in non-perishable categories like toilet paper and diapers as opposed to perishable categories like milk and eggs.

[Table 3 about here.]

3.4 Price Decomposition

One underlying assumption of expenditure measures is that increased expenditures reflect a combination of increased consumption and increased quality. Bulk discounts violate this assumption because they induce a nonlinear price schedule. Because of their nature, it is possible for households to record increased expenditures even with the same underlying quality and quantity of goods. As an example, consider a homogenous product that comes in 2 different sizes and has a bulk discount. Households have a fixed demand for the product, but may vary in their expenditure path to satisfy their demand. "Bulk" households only buy big sizes and "Budget" households only buy small sizes. Because of discounts, "bulk" households record lower expenditures than "budget" households and an analysis of only aggregates might infer that the "bulk" buying household was obtaining a lower quality or quantity of the purchased goods. This example illustrates how bulk discounts bias inequality measures downward.

The same intuition carries over into a setting with differing product qualities. If the "bulk" household buys premium products in bulk and the "budget" household buys small, economy products, the "bulk" household might spend more for the same underlying quantity and achieve a higher quality. However, the bulk discounts would offset some of the predicted cost increases associated with the premium brand.

I focus on the underestimation of quality induced by bulk discounts. To do this, I examine unit price differences instead of overall expenditure differences. Ideally, unit price differences should only reflect differences in underlying product quality or, possibly, shopping amenities. In reality, high-income households tend to pay higher unit costs for items because they are more likely to purchase higher quality items or shop at premium stores. However, because of bulk discounts, we are likely underestimating their actual realized increase in quality or shopping amenities.

In order to separately identify these factors, I decompose the unit price of each product module into store, brand, and size components using a hedonic regression. The contribution of each component is then aggregated up to the household level based on that module's basket share and these are aggregated across households using Nielsen's projection weights. The hedonic regression is shown in Equation 5.

$$unitPrice_{brq}^{m} = \lambda_b + \lambda_r + \lambda_q + \epsilon_{brq} \tag{5}$$

The hedonic regression decomposes the unit price of a product purchased in module m of brand b at retailer r in size quintile q into brand, retailer, and size components. All coefficients are relative to the reference category which is the second-smallest generic brand product sold at the most popular discount retailer. Figure 5 shows that the contribution of brand and retailer components increase the price for high-income households, but that size components offset a large portion of this increase. Most importantly, the figure illustrates the large importance of size components in determining an item's unit costs.

[Figure 5 about here.]

4 Reduced-Form Analysis

4.1 Warehouse Club Entry on Bulk Purchasing

One possible explanation for this "bulk buying gap" is that low-income households may not have access to large, bulk sizes that high-income households do. Warehouse club stores offer access to large packages with low unit prices in exchange for an annual membership fee. The largest warehouse club chains are Costco, Sam's Club, and BJ's. If access is the primary driver of this gap, then warehouse club entry should correspond with an increase in bulk purchasing.

Over my sample period, I observe 419 warehouse club openings. Since the Nielsen data has a panel structure, I can observe the changes in purchases within a household before and after a warehouse club opens nearby. I estimate the following regression:

$$Y_{imt} = \beta S_{it} + \gamma X_{it} + \lambda_{im} + \lambda_{mt} + \epsilon_{imt}, \tag{6}$$

where Y is the expenditure-weighted share of bulk purchases made by houeshold i in market m in quarter t. S is the number of warehouse clubs that have entered within 30 kilometers of the household as of month t.[16] X is a vector of household characteristics including income, household size, age, and presence of children. λ are fixed effects for household-markets (to ensure identification is from club entry and not household moves) and market-quarter. Standard errors are clustered at the household-market level.

[16]Distance is measured between the centroids of the household ZIP code and the store ZIP code.

Before estimating Equation 6, I graphically illustrate the event study by plotting the coefficients of a modified version of Equation 6.

$$Y_{imt} = B_{it}\left(\sum_t \beta_t E_{it} + \alpha\right) + \gamma X_{it} + \lambda_{im} + \lambda_{mt} + \epsilon_{imt}, \tag{7}$$

where B is an indicator for whether a household was continuously located in a market with a warehouse club opening and was there during the 4 quarters prior to the opening and 8 quarters after the opening. E is a dummy for each of the 4 quarters prior to opening and each of the 8 quarters after opening. The β coefficients are plotting in Figure 6

[Figure 6 about here.]

The event study shows that warehouse clubs increase a household's bulk purchasing, but this effect is primarily concentrated in higher-income households, with households making under \$25k having no significant change in their purchasing behavior. Households making over \$100k exhibit the largest increase in bulk purchasing, but I cannot definitively say if their change is larger than the change for other households making over \$25k.

The estimation results for Equation 6 are reported in Table 4 and after a warehouse club opens, bulk purchasing increases by about 1 percentage point overall, but when this analysis is run separately on each quartile, we see that this effect is primarily on the upper end of the income distribution with households making under \$25k exhibiting no significant difference in their bulk purchasing.

One reason why low-income households may not change their bulk purchasing is that they cannot afford the warehouse club membership fee and therefore still do not have access to the club even if it is nearby. Even if that was not the case, the coefficient estimates on wealthier households suggest that increased access to bulk sizes is unlikely to substantially close the 6 percentage point gap in bulk purchasing behavior.

[Table 4 about here.]

4.2 Income Changes on Bulk Purchasing

About 49% of households in the Nielsen Consumer Panel experience a change in income. As a result, we can get a first-look as to whether income changes affect bulk purchasing. The hypothesis is that increased income will alleviate some of the factors that prevent households from buying in bulk. With increased income, households may have more access to bulk sizes (e.g. households can afford a Costco membership) or reduced budget constraints.

To see how bulk buying changes when a household's income changes, I estimate a modified version of Equation 3:

$$Y_{idt} = \beta_1 Income_{idt} + \beta_2 Age_{idt} + \beta_3 HHSize_{idt} + \beta_4 Child_{idt} + \lambda_i + \lambda_d + \lambda_t + \epsilon_{idt}, \tag{8}$$

where Y_i is household i's basket share of bulk purchases in year t in market d. $Income$ is a dummy for a household i's income bin, Age is the head of household's age, $HHSize$ is the number of people in the household, and $Child$ is an indicator for whether the household has any children. λ consists of fixed effects. In order to capture any household-specific, time-invariant features, I use a household fixed effect.

The regression results are reported in Table **??**. While there is a statistically significant increase in bulk buying as a household increases their income, the effect is at most 1 percentage point. The gap in bulk purchasing was about 6 percentage points. This suggests that while income may help reduce some barriers to buying in bulk, the largest barriers will not be fixed through income changes. These other factors include transportation and storage costs (i.e. car and home ownership are unlikely to change unless a household experiences an extremely large income shock).

5 References

Aguiar, Mark, and Mark Bils. 2015. "Has Consumption Inequality Mirrored Income Inequality?" *American Economic Review* 105 (9): 2725–56.

Anderson, Eric T, and Inseong Song. 2004. "Coordinating Price Reductions and Coupon Events." *Journal of Marketing Research* 41 (4). American Marketing Association: 411–22.

Attanasio, Orazio, and Christine Frayne. 2006. "Do the Poor Pay More?" Mario Einaudi Center for International Studies.

Attanasio, Orazio, and Luigi Pistaferri. 2014. "Consumption Inequality over the Last Half Century: Some Evidence Using the New Psid Consumption Measure." *American Economic Review* 104 (5): 122–26.

Attanasio, Orazio P, and Luigi Pistaferri. 2016. "Consumption Inequality." *Journal of Economic Perspectives* 30 (2): 3–28.

Coibion, Olivier, Yuriy Gorodnichenko, and Dmitri Koustas. 2017. "Consumption Inequality and the Frequency of Purchases." Working Paper 23357. Working Paper Series. National Bureau of Economic Research. http://www.nber.org/papers/w23357.

Dillon, Brian, Joachim De Weerdt, and Ted O'Donoghue. 2017. "Paying More for Less: Why Don't Households in Tanzania Take Advantage of Bulk Discounts?"

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

Gibson, John, and Bonggeun Kim. 2018. "Economies of Scale, Bulk Discounts, and Liquidity Constraints: Comparing Unit Value and Transaction Level Evidence in a Poor Country." *Review of Economics of the Household* 16 (1). Springer: 21–39.

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.

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L Violante. 2010. "Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967–2006." *Review of Economic Dynamics* 13 (1). Elsevier: 15–51.

Hendel, Igal, and Aviv Nevo. 2006a. "Measuring the Implications of Sales and Consumer Inventory Behavior." *Econometrica* 74 (6). Wiley Online Library: 1637–73.

———. 2006b. "Sales and Consumer Inventory." *The RAND Journal of Economics* 37 (3). Wiley Online Library: 543–61.

———. 2013. "Intertemporal Price Discrimination in Storable Goods Markets." *American Economic Review* 103 (7): 2722–51.

Hong, Pilky, R Preston McAfee, and Ashish Nayyar. 2002. "Equilibrium Price Dispersion with Consumer Inventories." *Journal of Economic Theory* 105 (2). Academic Press: 503–17.

Kaplan, Greg, and Guido Menzio. 2015. "The Morphology of Price Dispersion." *International Economic Review* 56 (4). Wiley Online Library: 1165–1206.

Krueger, Dirk, and Fabrizio Perri. 2006. "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory." *The Review of Economic Studies* 73 (1). Wiley-Blackwell: 163–93.

Narasimhan, Chakravarthi. 1984. "A Price Discrimination Theory of Coupons." *Marketing Science* 3 (2). INFORMS: 128–47.

Nevo, Aviv, and Catherine Wolfram. 2002. "Why Do Manufacturers Issue Coupons? An Empirical Analysis of Breakfast Cereals." *RAND Journal of Economics*. JSTOR, 319–39.

Nevo, Aviv, and Arlene Wong. 2018. "The Elasticity of Substitution Between Time and Market Goods: Evidence from the Great Recession." *International Economic Review (Forthcoming)*.

Orhun, A. Yeşim, and Michael Palazzolo. 2019. "Frugality Is Hard to Afford." *Journal of Marketing Research* 56 (1). American Marketing Association.

Pesendorfer, Martin. 2002. "Retail Sales: A Study of Pricing Behavior in Supermarkets." *The Journal of Business* 75 (1). JSTOR: 33–66.

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). Wiley Online Library: 201–11.

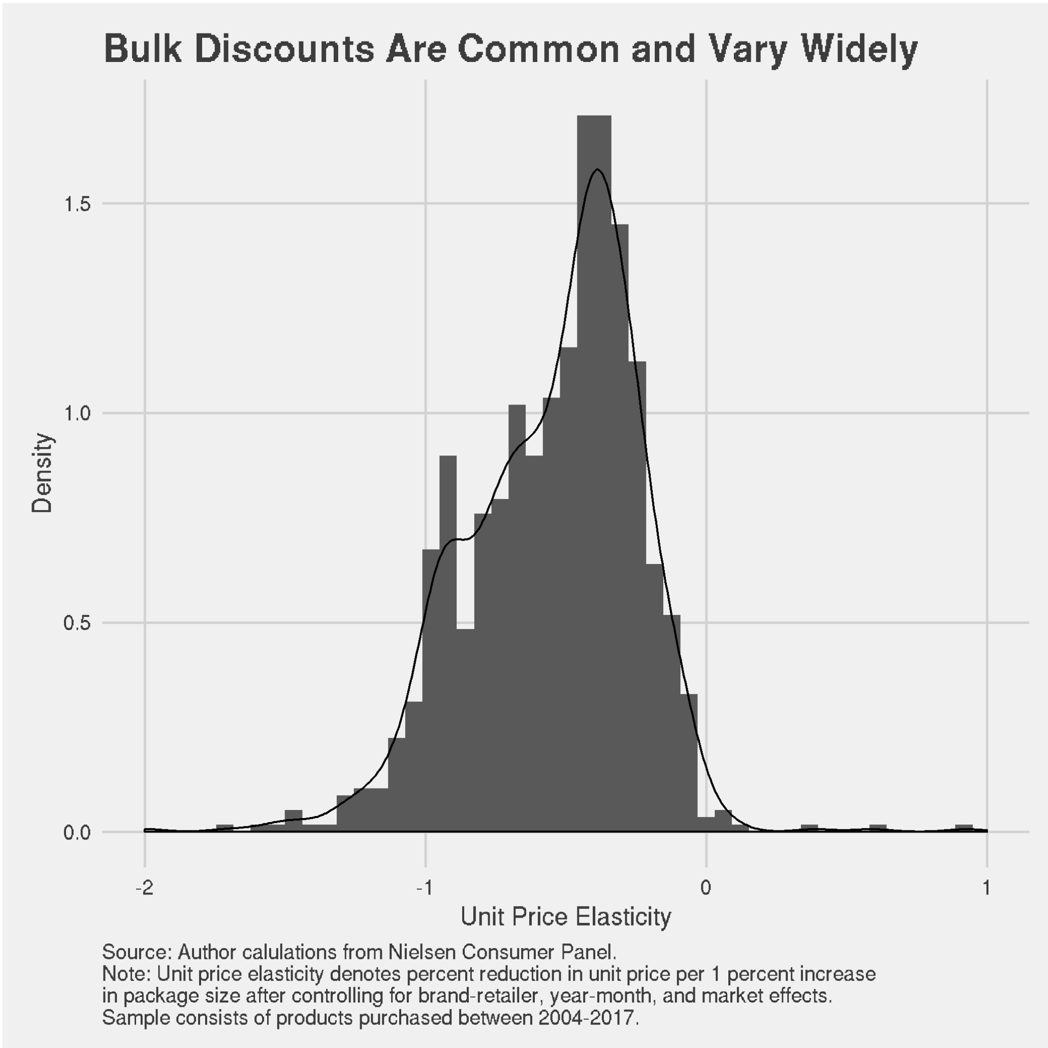

Bulk Discounts Are Common and Vary Widely
Density
1.5
1.0
0.5
0.0
-2
-1
0
1
Unit Price Elasticity
Source: Author calulations from Nielsen Consumer Panel.
Note: Unit price elasticity denotes percent reduction in unit price per 1 percent increase
in package size after controlling for brand-retailer, year-month, and market effects.
Sample consists of products purchased between 2004-2017.

Figure 1

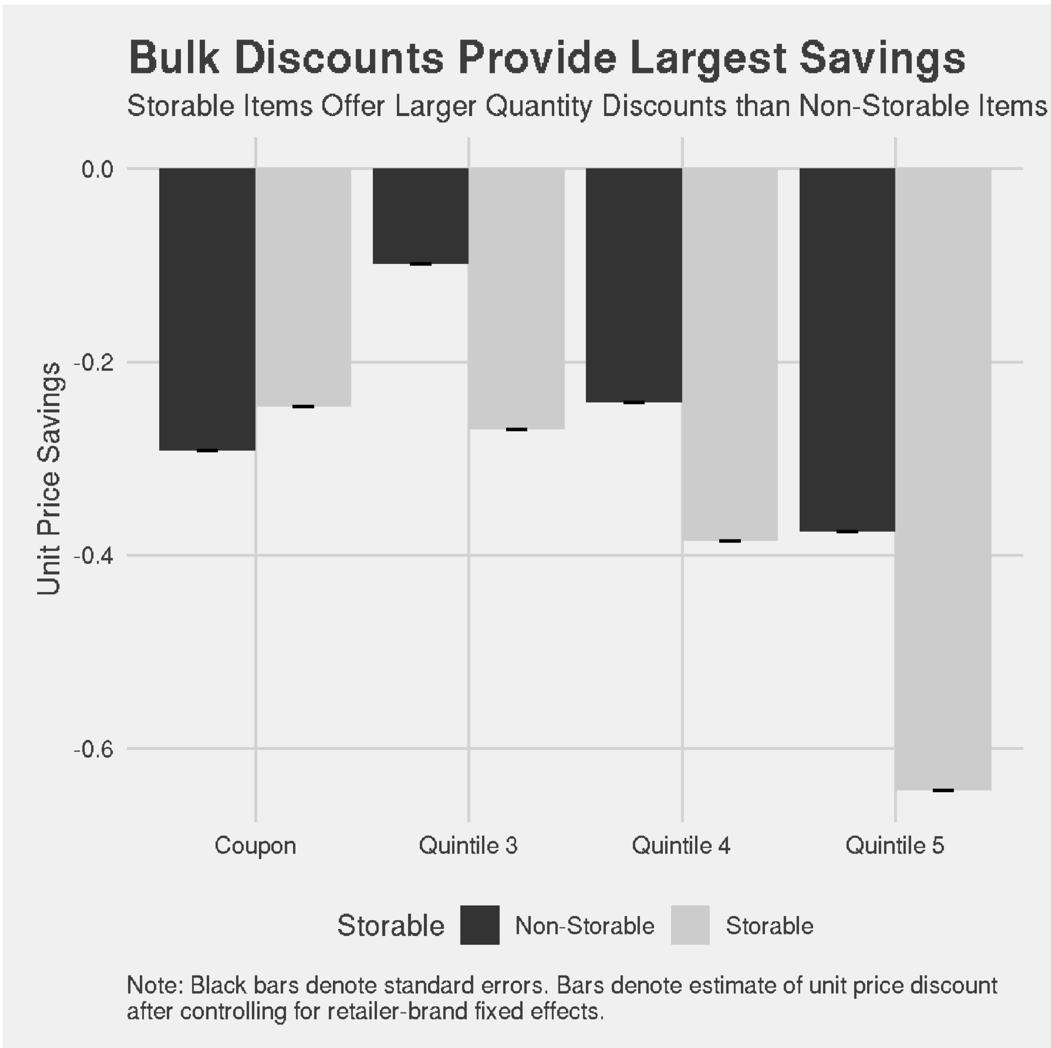

Bulk Discounts Provide Largest Savings
Storable Items Offer Larger Quantity Discounts than Non-Storable Items
Unit Price Savings
0.0
-0.2
-0.4
-0.6
Coupon
Quintile 3
Quintile 4
Quintile 5
Storable
Non-Storable
Storable
Note: Black bars denote standard errors. Bars denote estimate of unit price discount after controlling for retailer-brand fixed effects.

Figure 2

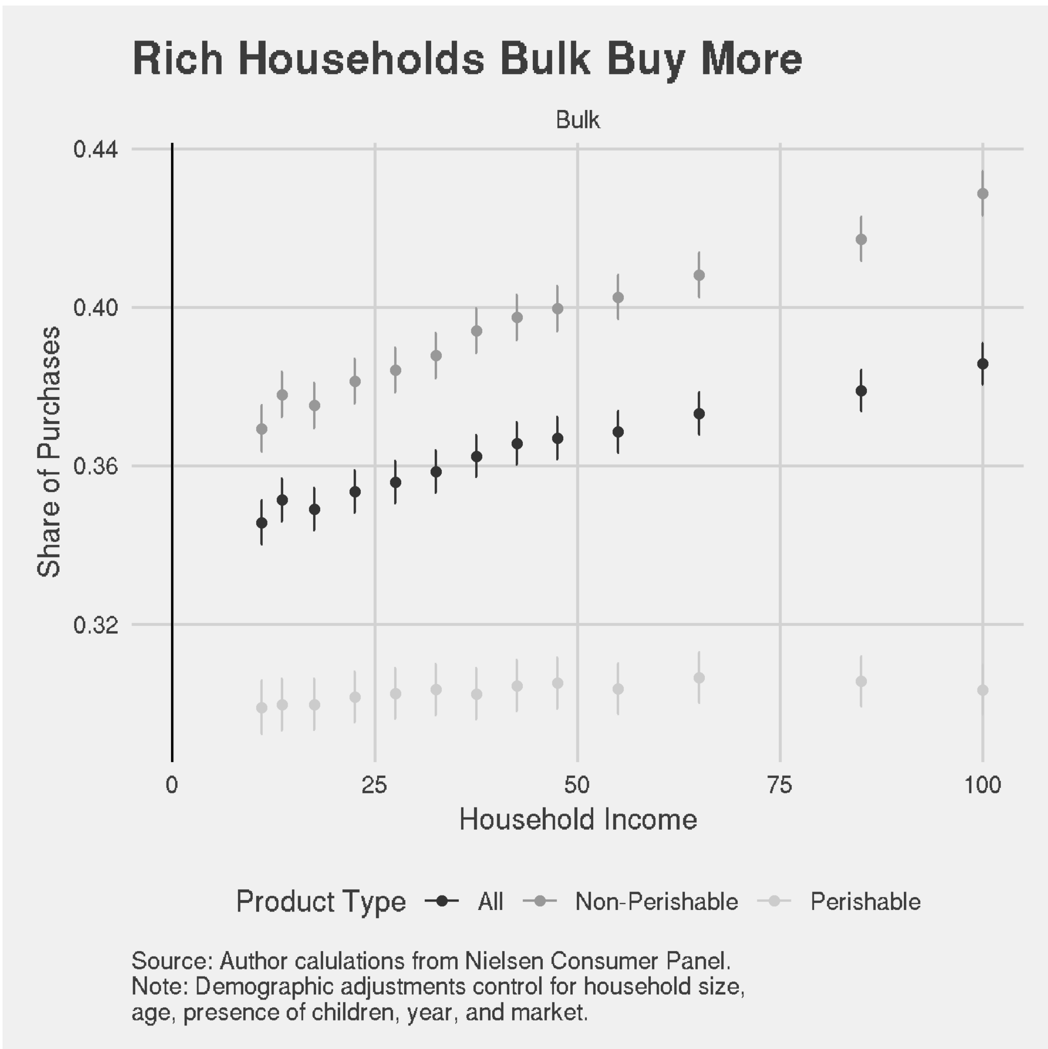

Rich Households Bulk Buy More
Bulk
0.44
0.40
0.36
0.32
Share of Purchases
0
25
50
75
100
Household Income
Product Type
All
Non-Perishable
Perishable
Source: Author calulations from Nielsen Consumer Panel.
Note: Demographic adjustments control for household size,
age, presence of children, year, and market.

Figure 3

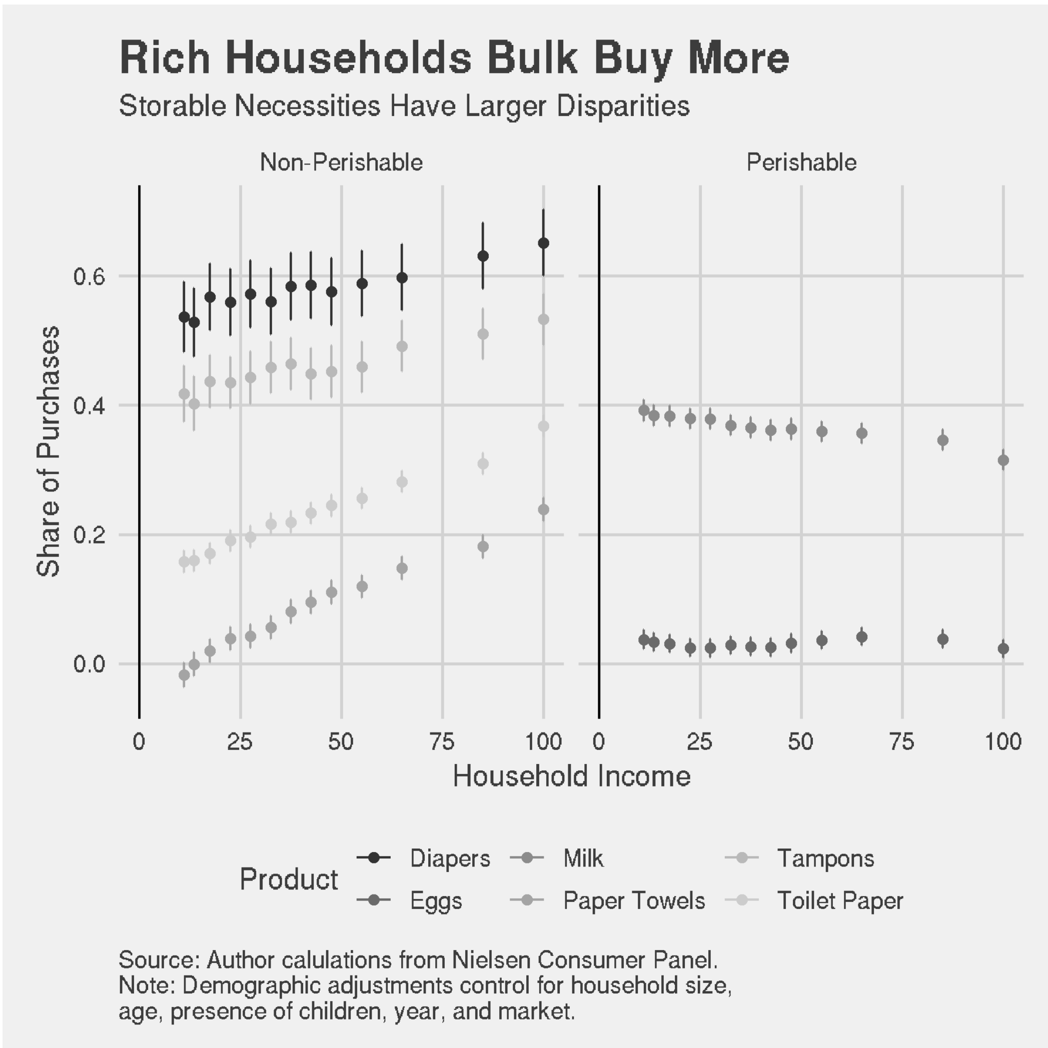
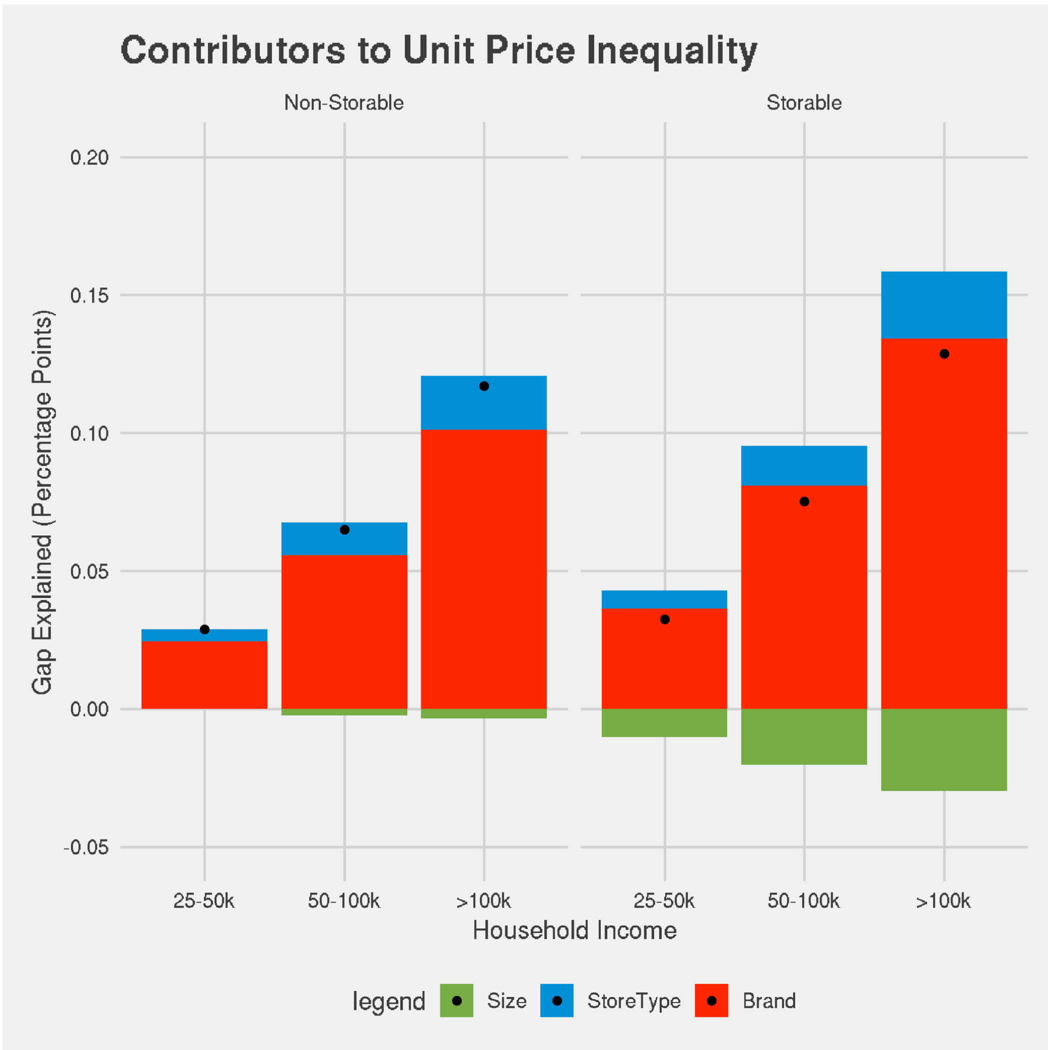
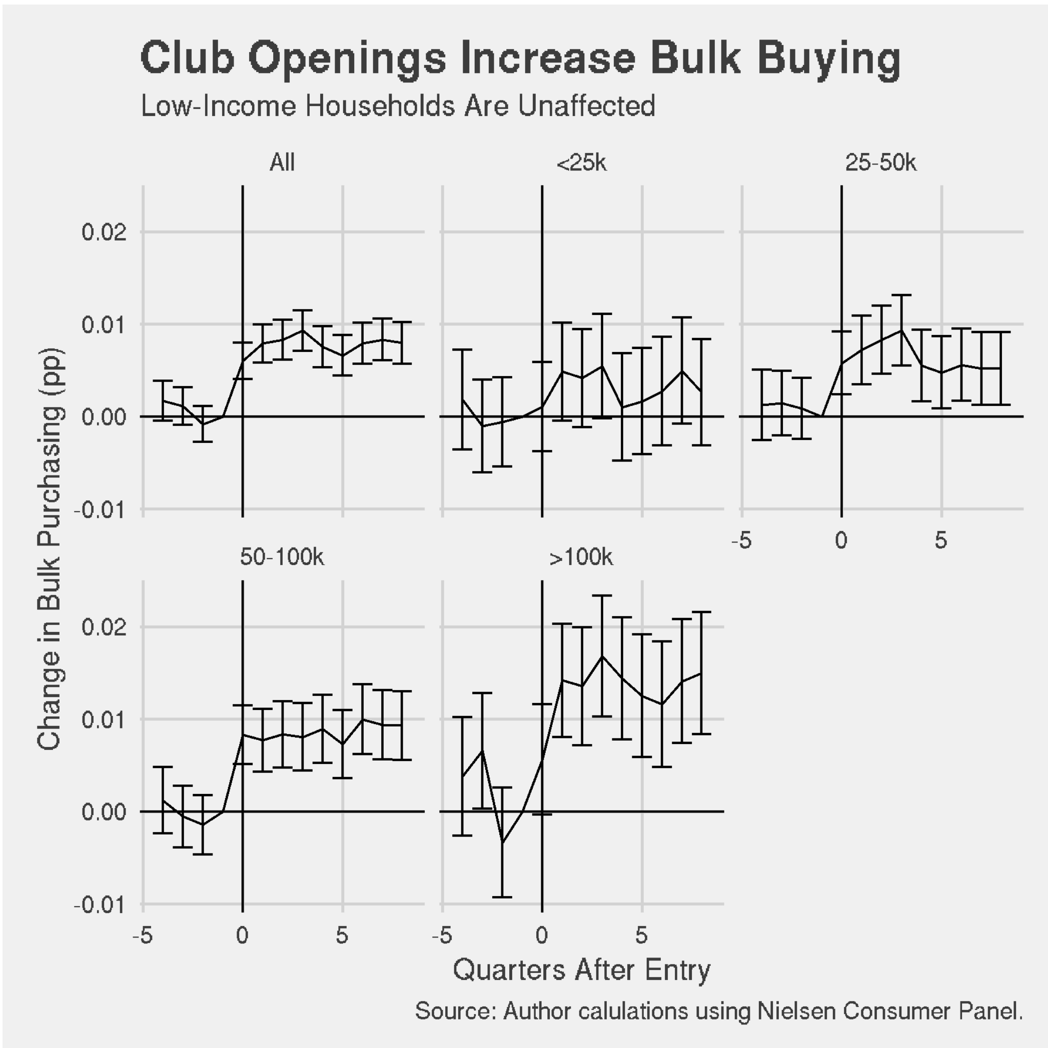

Rich Households Bulk Buy More
Storable Necessities Have Larger Disparities
Non-Perishable
Perishable
Share of Purchases
0.0
0.2
0.4
0.6
0
25
50
75
100
Household Income
Product
Diapers
Eggs
Milk
Paper Towels
Tampons
Toilet Paper
Source: Author calulations from Nielsen Consumer Panel.
Note: Demographic adjustments control for household size,
age, presence of children, year, and market.

Figure 4



Contributors to Unit Price Inequality
Non-Storable
Storable
Gap Explained (Percentage Points)
0.20
0.15
0.10
0.05
0.00
-0.05
25-50k
50-100k
>100k
25-50k
50-100k
>100k
Household Income
legend
Size
StoreType
Brand

Figure 5



Club Openings Increase Bulk Buying
Low-Income Households Are Unaffected
All
<25k
25-50k
50-100k
>100k
Change in Bulk Purchasing (pp)
0.02
0.01
0.00
-0.01
-5
0
5
Quarters After Entry
Source: Author calulations using Nielsen Consumer Panel.

Figure 6

Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation
Household income ($000s)	57.36	30.50
Household size	2.58	1.45
Hispanic	1.89	0.32
Age	52.59	14.39
College Educated	0.38	0.49
White	0.77	0.42
Child present	0.33	0.47
Married	0.51	0.50

Table 2: Missed Savings

	Non-Perishable		Perishable	
Income	Toilet Paper	Diapers	Milk	Eggs
<$25k	0.36	0.33	0.31	0.17
$25-50k	0.35	0.33	0.30	0.17
$50-100k	0.34	0.33	0.31	0.17
>$100k	0.33	0.31	0.33	0.18

Table 3: Rich Households Miss Out on Less Savings

	Diapers	Toilet Paper	Eggs	Milk
	(1)	(2)	(3)	(4)
25-50k	-0.010^{**}	-0.005^{***}	0.001	-0.002
	(0.005)	(0.001)	(0.001)	(0.001)
50-100k	-0.015^{***}	-0.013^{***}	0.004^{***}	0.002^{**}
	(0.005)	(0.001)	(0.001)	(0.001)
>100k	-0.018^{***}	-0.017^{***}	0.018^{***}	0.010^{***}
	(0.005)	(0.002)	(0.002)	(0.001)
Demographics	Y	Y	Y	Y
Market-Year FE	Y	Y	Y	Y
Observations	36,903	182,415	194,413	247,451
Adjusted R^2	0.012	0.071	0.117	0.231

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4: Warehouse Club Opening

	All	<25k	25-50k	50-100k	>100k
	(1)	(2)	(3)	(4)	(5)
<20 km	0.010***	0.0003	0.009***	0.012***	0.013***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
20-40km	0.007***	−0.001	0.008***	0.008***	0.012**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
Household-Market FE	Y	Y	Y	Y	Y
Market-Quarter FE	Y	Y	Y	Y	Y
Observations	3,027,655	424,285	963,860	1,182,324	457,186
Adjusted R^2	0.673	0.642	0.671	0.689	0.694

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at the household-market level.