Less is More Expensive: Bulk Buying and Inequality

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Updated Version Here*

Abstract

High-income households buy in bulk more often than low-income households, especially for storable, non-food items. By buying in bulk at the same rate as high-income households, low-income households could lower their grocery expenditures by five percent. This paper examines the determinants of consumer heterogeneity in bulk buying behavior. I focus on three factors: cognitive costs, store access, and storage costs. Using data I collected on state-level price regulations, I find that mandated display of per-unit prices, which reduces cognitive costs, increases bulk buying for all households. Using data on warehouse club entry, I find that warehouse club entry increases bulk buying only for middle- and high-income households. I then use a discrete choice model of toilet paper purchases as a case study to quantify how the bulk buying gap changes when regulations, store assortments, and storage costs are changed. Counterfactual simulations find that reducing storage costs would shrink the gap by 40%. A similar effect could be achieved by mandating the display of unit prices, which has only been adopted by 18% of states. I estimate mandated per-unit pricing would reduce the bulk buying gap across household income levels by about 30%.

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1 Introduction

Consumption inequality has grown since the 1980s, even for basic necessities like groceries (Attanasio and Pistaferri 2016). In 2017, the top quintile of households spent 2.5 times more on groceries and housekeeping supplies than the bottom quintile of households (BLS 2019). Even though they spend less in absolute terms, low-income households devote twice as much of their total budget to these items compared to high-income households, making any savings especially valuable. Previous research has found that low-income groups increase home production and time spent shopping to reduce their expenditures (Aguiar and Hurst 2005). Quantity discounts are another way for households to reduce their expenditures, but our empirical understanding of how common these discounts are and who uses them is limited.

This paper presents a new finding that low-income households are less likely to take advantage of quantity discounts than high-income households. Using Nielsen data, I document consumer heterogeneity in bulk buying with regard to household demographics and the implications for consumer expenditures. Second, I explore the reasons for the lower bulk buying rates that I discover among low-income households. I consider three distinct factors: cognitive costs of computing per-unit prices, access to stores that sell bulk packages, and storage or transportation costs. To evaluate the effects of cognitive costs, I exploit the fact that some US states mandate the display of per-unit prices as a consumer protection measure while other states do not. Using a new dataset of state per-unit pricing mandates that I constructed, I show that mandated per-unit pricing is associated with increased bulk buying for all types of households. To control for possible endogeneity in which states adopt such regulations, I examine the bulk buying behavior of households that move between states with different laws. I estimate that there are potentially large consumer welfare gains from per-unit pricing mandates. Another factor that affects a household's bulk buying is its geographic proximity to warehouse clubs. Higher-income households are more likely to live close to clubs. To control for endogeneity in club placement, I analyze the bulk buying behavior of the same households before and after the entry of club stores. I find that middle- and high-income households are the most likely to alter their bulk buying behavior in response to club entry. Third, to assess the importance of storage and transportation costs, I examine the differences in bulk buying relative to the size of a household's home and relative to the physical size of the product being purchased. Finally, I estimate a model of the consumer purchase behavior which incorporates each of these factors and estimates how consumer welfare changes under three counterfactual scenarios: expanding access to bulk sizes, mandating the posting of per-unit prices, and reducing storage and transportation costs.

To conduct this analysis, I exploit a rich combination of datasets, including Nielsen's Consumer

Panel data, a nationally representative panel survey of household grocery purchases, and Nielsen's Retail Scanner data, a national panel of weekly UPC-level sales data from over 30,000 stores. I construct a new dataset of state-level per-unit pricing regulations, including a measure of regulatory stringency. I also use data on entry dates and locations of over 1,400 warehouse clubs in the United States. As a result, I have a comprehensive view of household's choice sets, available information, retail environment, and resulting expenditures

I begin by documenting key facts about quantity discounts, which households use them, and how much households could save. To the best of my knowledge, this is the first paper to estimate the prevalence and magnitude of quantity discounts.[1] Using Nielsen's Retail Scanner data, I find that 91% of product categories have quantity discounts. The median discount is such that a 10% larger package corresponds to a 4.4% lower unit price. Using Nielsen's Consumer Panel data, I find that households differ substantially in their bulk buying. Households making over $100,000 are more likely to buy in bulk than households making under $25,000. This difference is particularly stark for non-food items, with high-income households being 30% more likely to buy in bulk than demographically similar low-income households.[2] This difference in bulk buying has substantial financial consequences. I estimate that low-income households could reduce their grocery expenditures by five percent if they bought in bulk like high-income households, which translates into an aggregate savings of $2.7 billion. Given these savings, I explore three factors that influence a household's decision to buy in bulk, focusing on non-food products since these products display the largest disparity.

First, cognitive costs could affect whether or not households take advantage of quantity discounts because they find it costly to compute unit prices (Mitchell, Lennard, and McGoldrick 2003). Posting unit prices is one way to immediately reduce cognitive costs. Sixteen states have regulations governing the display of unit prices, but to the best of my knowledge, no study has evaluated the impact of these regulations. I provide the first nationwide study of the impact posting unit prices has on bulk purchasing. After controlling for household demographics, Households in states with mandated unit price posting buy in bulk four to nine percent more than households in states without such mandates. To control for possible selection concerns regarding which states adopted these provisions, I examine changes in bulk buying within households that move between states with different regulations. I find that households that move from states with unit price regulations to states without them

[1] I only know of four products for which quantity discounts have previously been estimated. Hendel and Nevo (2006b) reports the average unit price for different sizes of laundry detergent, soft drinks, and yogurt and Orhun and Palazzolo (2019) does the same for toilet paper.

[2] Throughout this paper, "high-income" refers to households making over $100,000 and "low-income" refers to households making under $25,000.

decrease their bulk buying by three to four percent. This decrease is consistent with the idea that computing unit prices is costly. On the other hand, households that move from states without unit price regulations to states with unit price regulations do not significantly change their bulk buying. This is consistent with the idea that consumers should be educated on how to use unit price information. Overall, I show strong evidence that posting unit prices are an effective way to reduce cognitive costs and increase bulk buying.

Second, store access could affect a household's ability to buy in bulk because stores do not stock all possible brands and sizes. After controlling for the types of stores households shop at, the bulk buying gap between high- and low-income households shrinks substantially, but still is significant. This result reveals that a large portion of the difference in bulk buying is related to where households shop. Overall, households shop at a similar mix of stores with the exception of warehouse clubs. Higher-income households spend a larger portion of their budget at warehouse clubs compared to low-income households. Since warehouse clubs tend to be located closer to high-income households than low-income households, geographic proximity to clubs may affect a household's bulk buying. To control for endogeneity in warehouse club locations, I examine differences in a household's bulk buying before and after a warehouse club opens in the household's proximity. I find that only middle- and high-income households increase their bulk buying by five to ten percent, while low-income households do not significantly change their purchasing. Given that the bulk buying gap is still present within stores, the heterogeneous response to warehouse club entry is evidence that clubs may exacerbate pre-existing differences in bulk purchasing due to other factors, such as storage and transportation costs.

Third, storage and transportation costs could affect a household's bulk buying. Using variation in housing size between households, I find that households in single-family homes are more likely to buy in bulk compared to households in apartments. To control for possible selection into housing types, I examine how a household's bulk buying changes when they move to a different type of housing. Bulk buying is three to four percent higher when households live in single-family homes relative to when they live in apartments. As further evidence of storage and transportation costs, I leverage differences in the physical footprint of different product categories. For example, paper towels and toilet paper occupy more space than plastic wrap and detergent. I find that larger product categories have larger differences in bulk purchasing between high- and low-income households.

Each of the previous analyses provides evidence as to the relevance of cognitive costs, store access, and transportation and storage costs to a household's bulk buying decision. However, quantifying the direct effect of reducing storage costs or expanding access to large sizes separate from the other aspects of warehouse clubs (e.g. membership fees, only bulk sizes available, etc.) requires a model. I estimate a model of consumer purchases using toilet paper as a case study. From this demand model, I simulate how households change their purchases when they have access to bulk sizes available at warehouse clubs, when unit prices are posted universally, and when storage costs are reduced, and estimate corresponding welfare changes.

To estimate storage costs, I use a novel approach that leverages cross-sectional variation in product "concentration" instead of relying on purchase histories, which is the standard approach (Hendel and Nevo 2006a, 2006b). The typical challenge is that households with high demand for products are indistinguishable from households with low storage costs because both are more likely to choose large packages. Product concentration breaks this link. The intuition is that a product's yield (e.g. for detergent, the loads of laundry it will wash) can occupy a large volume (e.g. dilute detergent) or a small volume (e.g. concentrated detergent). As an example, for the same number of washes, households may choose between dilute (takes up more fluid volume) or concentrated detergent (takes up less fluid volume). Assuming quality is independent of concentration, households that choose concentrated detergent have higher storage costs than those that choose dilute detergent.

Consistent with my earlier results, I find that increasing access to large sizes has small effects while posting unit prices would reduce the bulk buying gap by about 30% and reducing storage costs narrow the gap by an additional 40%. Given the large storage costs faced by low-income households, they do not change their behavior much when offered a wider assortments of sizes, even if they are more discounted. If policymakers want to encourage households to better utilize quantity discounts, posting unit prices would reduce cognitive costs and increase bulk buying.

Overall, this paper provides new, fundamental facts about the presence and size of quantity discounts. Furthermore, I show that low-income households are less likely to take advantage of them due to a combination of cognitive costs and storage and transportation costs. More work will be needed to examine the importance of quantity discounts along other dimensions, such as age, where it may help retired households reduce expenditures. Finally, how the systematic differences in bulk buying affect our measures of consumption inequality and inflation remains an open question.

1.1 Related Literature

While this paper is one of the first to empirically analyze quantity discounts and who uses them, it builds on the scholarship in public economics, industrial organization, and marketing.

In particular, this paper sits at the intersection of three literatures: (1) How consumers take advantage of discounts in the retail environment; (2) How the retail environment affects inequality; (3) How cognitive costs and information salience affect individual decisions.

First, this paper builds on a long literature documenting how consumers take advantage of various discounts. Griffith et al. (2009) and Nevo and Wong (2019) provide overviews of various discounting behaviors. They find that households use coupons, sales, generic brands, discount stores, and bulk packages to reduce their expenditures and these savings behaviors increased during the Great Recession. Other research has found that households save money by increasing their purchasing during sales (Pesendorfer 2002; Erdem, Imai, and Keane 2003; Hendel and Nevo 2006a, 2006b), switching to lower-quality brands (Argente and Lee 2017), and increasing home production and price search (Aguiar and Hurst 2005, 2007). Overall, the literature has documented a wide range of methods households use to reduce their expenditures. This paper contributes by highlighting key facts about quantity discounts and how often households take advantage of them.

From the firm perspective, these discounts are a way to price discriminate between consumers with different demand elasticities. However, recent research in industrial organization has shown that in the absence heterogeneity in demand elasticity, firms can use nonlinear prices to discriminate between households with varying storage costs (Hendel, Lizzeri, and Roketskiy 2014). Furthermore, hendel2006a uses variation in household purchase frequencies to estimate storage costs. The intuition is that households given households with the same demand for a product, the household with high storage costs will purchase more frequently than the household with low storage costs. I provide a new method for estimating storage costs that does not require observing purchase histories by using differences in product "concentration." Furthermore, I provide evidence that low-income households have high storage costs while high-income households have low storage costs. On balance, this means that firms extract higher rents from low-income households because they have less ability to store for future consumption.

Second, there is a growing literature that examines how the retail environment contributes to inequality. Even though households have a wide array of discounts available to them, not all households may have access to them and this can affect consumption inequality, which has grown substantially over time (Attanasio and Pistaferri 2016). Research has shown that prices tend to be higher and healty foods tend to be scarcer in low-income neighborhoods relative to high-income neighborhoods (Kunreuther 1973; Chung and Myers Jr 1999; Fellowes 2006; Talukdar 2008; Allcott et al. 2019).[3] However, even though there are

[3] There is a large macroeconomic literature that examines how these differences affect price dispersion,

geographic differences in retail environments, Allcott et al. (2019) shows that these differences are only a minor contributor to overall nutritional inequality. Much of this research has documented important differences in price and nutritional quality of food products that households consume. However, little research has examined inequality in essential non-food products. This paper most directly follows the work of Orhun and Palazzolo (2019), which is one of the only analyses of inequality in non-food products. They document that low-income households do not take advantage of bulk discounts available on toilet paper and find that liquidity constraints only explain a minor portion of this difference in bulk buying. This paper contributes by documenting the disparity in take-up of bulk discounts across the full spectrum of food and non-food products and then examines how cognitive costs, store access, and storage and transportation costs contribute to this disparity.

Finally, recent research has demonstrated that cognitive costs can prevent households from making the most economical decisions and these costs may be particularly large for low-income households (Bertrand, Mullainathan, and Shafir 2006; Mani et al. 2013). Even in aggregate, consumers change their behavior when price information becomes more or less prominent (i.e. salient). For example, Chetty, Looney, and Kroft (2009) shows that demand falls by eight percent when sales taxes are added to the shelf price of a product instead of being added at the cash register. Goldin and Homonoff (2013) builds on this finding and shows that while demand for cigarettes falls when taxes affect posted prices, only low-income households respond to tax changes that affect the price paid at the register, but not the posted price. I extend this reasoning to examine how posting per-unit prices affects bulk purchasing. The marketing literature has tried to answer this question, but these studies were generally based on consumer self-reports or small experiments (Bogomolova and Jarratt 2016). Experimental evidence has shown that posting unit prices affects household purchases, but the generalizability of these findings is uncertain for two reasons. First, how retailers or regulators choose to display unit prices may differ substantially from experimental settings. Second, many of these studies were also done before bar codes were universally adopted, and the overall shopping landscape has changed dramatically as a result of bar codes (Basker 2016). To date, no studies have done a large-scale, nationwide evaluation of household response to unit price postings and this paper provides that analysis.

The rest of the paper is structured as follows. Section 2 describes the data used for analysis. Section 3 documents new facts of quantity discounting. Section 4 presents evidence of contributing factors to the bulk-buying gap. Section 5 introduces the model. Section 6

but quantity discounts are often explicitly omitted. See Kaplan and Menzio (2015), Coibion, Gorodnichenko, and Koustas (2017), Kaplan et al. (2019), Hitsch, Hortacsu, and Lin (2019) for discussions.

presents estimation results. Section 7 shows the counterfactual exercises and Section 8 concludes.

2 Data

In this section, I describe the datasets used for my analysis and give a brief overview of their respective features.[4] Nielsen's Consumer Panel data provides information on household's shopping and purchasing decisions. Nielsen's Retail Scanner data provides information on weekly product assortments and prices. Combining the two datasets gives a comprehensive overview of each household's purchasing behavior and choice environment. I also use two new datasets on warehouse club locations and state-level regulations, which provide more information on households' shopping environment.

2.1 Nielsen Consumer Panel Data

I use the Nielsen Consumer Panel Dataset from 2004–2017. This dataset is a panel of about 178,000 unique households, of which I observe about 40,000 households each year from 2004–2006 and about 60,000 households each year from 2007–2017. Households scan all items that they purchase, input quantities, prices, date of purchase, and store. Nielsen retains about 80% of its panel from year to year with the mean and median tenure of a household being four and three years, respectively.

I consider food, drink, and non-food grocery (e.g., paper towels, toilet paper, detergent, etc.) purchases made at grocery stores, discount stores, dollar stores, warehouse clubs, and drug stores. These outlets account for over 90% of household expenditures in these categories. I exclude alcohol, tobacco, health, and general merchandise products from my analysis since these products may have different consumption patterns than food and cleaning products (e.g., cigarettes, painkillers) or are not suited for bulk purchases (e.g., printers, cookware, linens). I also exclude households with a student or military head of household as well as those with an annual income of less than $5,000 and those living in mobile homes. Only about 7% of households are excluded and I use the remaining 166,000 households for my analysis. See Appendix A.1 for further details of sample construction.

Table 1 presents descriptive statistics for households in the sample. The following analysis uses Nielsen's projection weights to be nationally representative unless otherwise stated. Weights

[4]Researcher's own analyses derived based in part 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.

are computed to match moments based on household size, income, age, race, ethnicity, education, occupation, and presence of children.

Table 1: Nielsen Consumer Panel Summary Statistics

Variable	Mean	SD	25th Pctile	75th Pctile
Household income ($000s)	55.82	31.23	27.5	85
Household size	2.55	1.45	1	3
Age	52.68	14.40	41.5	63
College Educated	0.37	0.48	0	1
Child present	0.32	0.47	0	1
Married	0.50	0.50	0	1
N (Household-Years)			770,317	
N (Households)			173,142	

Notes: Data are weighted for national representativeness.

2.2 Nielsen Scanner Data

The Nielsen Scanner Data contains weekly prices and volume sold of individual products at 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. By matching the two datasets, I can recover both the household's choice set and the product it chose to purchase.

2.3 Unit Pricing Regulations

I compile a novel dataset on state-level regulations regarding the display of unit prices. The data is based on annual regulatory updates aggregated in Handbook 130 published by the National Institute of Standards and Technology (NIST 2019). I cross-check this information with state regulatory codes and state officials to ensure accuracy. This data includes information on which states have regulations, when they were adopted, and how stringent these regulations are. More details are discussed in Section 4.1.

2.4 Warehouse Club Data

I also use hand-collected data on all warehouse clubs in the United States between 2004–2015 gathered for Coibion, Gorodnichenko, and Koustas (2017). This data records information on the opening dates, locations, and identity of all warehouse clubs in the United States. It was gathered by combining information available on company websites, annual reports, and by contacting firms.

3 Stylized Facts

In this section, I document two new facts about the shopping landscape. First, I show that quantity discounts apply to 91% of grocery categories. Second, I document that households making over $100,000 are about 30% more likely to buy non-food items in bulk than households making under $25,000, compared to only three percent for food items.

3.1 Quantity Discount Prevalence

Simply put, quantity discounts are a specific form of non-linear pricing in which unit prices decrease as package size increases. To establish the prevalence and magnitude of quantity discounts, I use Nielsen's Retail Scanner data from 2016. I estimate quantity discounts using the following regression for each of the 693 product categories.[5]

$$\ln(P)_{ibm} = \beta \ln(Size)_{ibm} + \lambda_{bm} + \epsilon_{ibm}, \tag{1}$$

where P is the unit price (package price divided by package size) of product i from brand b purchased in market m (defined as a store-week). $Size$ is the item's package size, which is the number of units included in a UPC (e.g., quart, square feet, count, pound, etc.). λ is a brand-store-week fixed effect. Variation in unit prices across package sizes within the same brand-store-week identify β. If retailers offer quantity discounts, then β will be negative.

Figure 1 plots the distribution of β across product categories (statistically insignificant betas are zero). I find that 91% of all product categories have a statistically significant and negative β and that non-food items generally have larger discounts than food items. The median β is -0.51 for non-food products, which means that a 10 percent increase in package size is associated with a 5.1 percent decrease in unit price. This discount is larger than the median β for food items (-0.43). The size and near-universality of quantity discounts suggest they offer substantial savings to households without sacrificing consumption.[6]

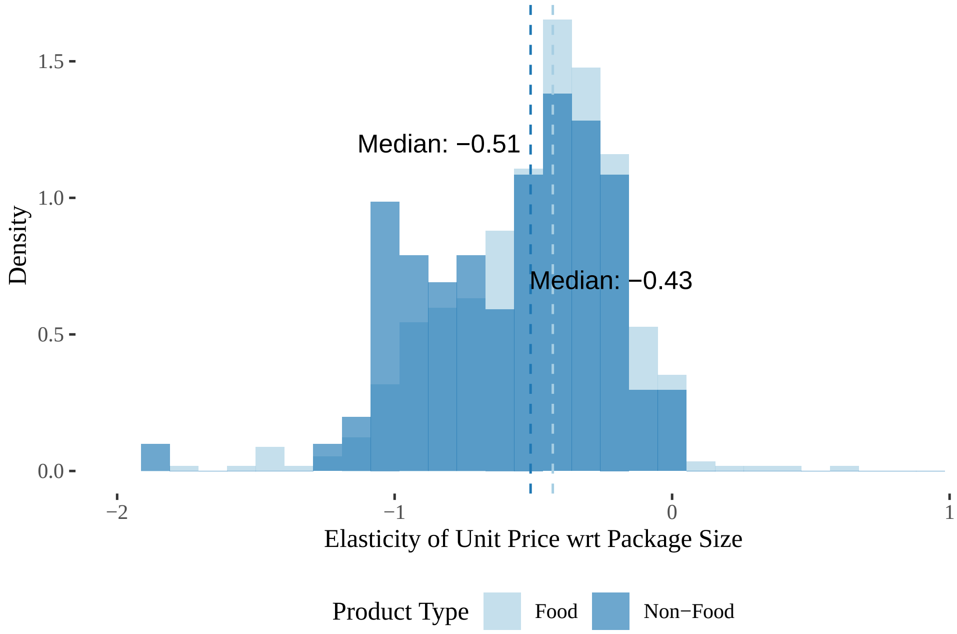
3.2 Bulk Purchasing

Next, I document the take up of quantity discounts among different types of households. Following the literature, I classify a product as "bulk" if it is in the top two quintiles of the size distribution for that product category (Griffith et al. 2009). Then, for each household, I compute the expenditure-weighted share of bulk purchases of food and non-food items. Thus,

[5] 38 categories could not be estimated typically because the data did not have sufficient variation. These were generally uncommon categories like mushroom sauce, canned grapes, and canned chow mein.

[6] For a comparison of quantity discounts with coupons, see Appendix A.2.

Figure 1: Distribution of Bulk Discounts by Product Type



Notes: Using Nielsen Retail Scanner data from 2016, this figure plots the distribution of coefficients from a regression of log unit price on log package size (Equation (1)) for individual product categories. "Unit Price Change" denotes the percent reduction in a product's unit price for a one percent increase in the package size. Regression controls for store-brand-week fixed effects. Histogram plots 645 product categories.

for each household, I have the share of purchases that were bulk purchases. I then regress this "bulk share" on household income and other household characteristics that could affect consumption patterns and may be correlated with income, and plot the income coefficients. The equation below is estimated on food and non-food purchases separately.

$$BulkShare_{imt} = \sum_q \beta^q Income_{imt} + \gamma X_{imt} + \lambda_m + \lambda_t + \epsilon_{imt}, \quad (2)$$

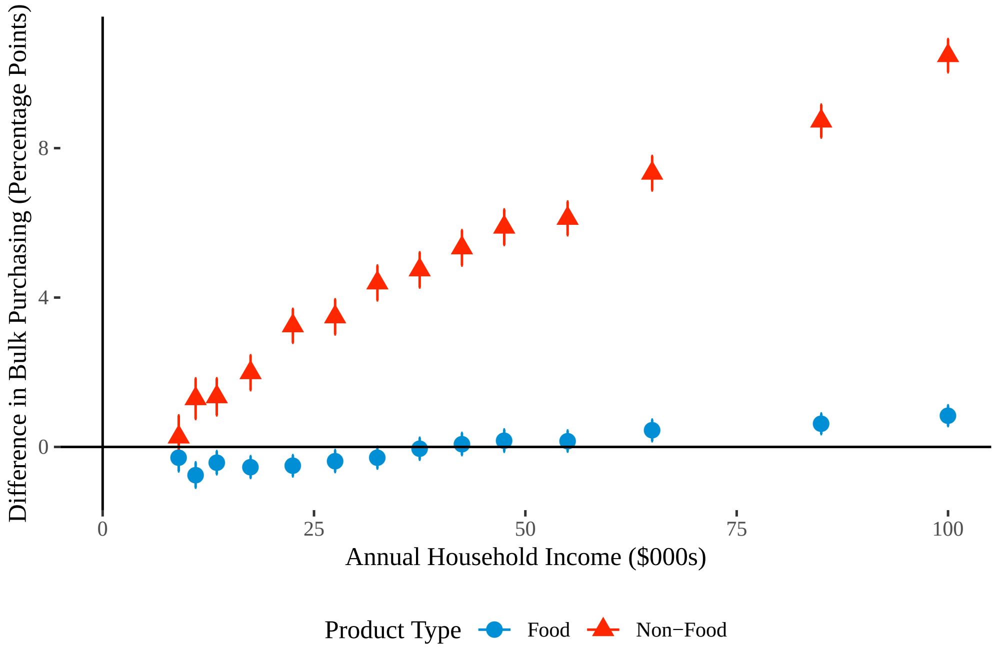
where $BulkShare$ is household i's share of bulk purchases in market m in year t.[7] $Income$ consists of dummies for each income bin q. X consists of household demographics (age, household composition, marital status, and education).[8] Year and market fixed effects are captured by λ.

Figure 2 illustrates that bulk purchases compose a ten percentage point larger share of non-food expenditures for households making over \$100,000 compared to those making \$5,000–\$8,000. As income increases, bulk purchases comprise an increasing share of expenditures.

[7] I define a market as a Designated Market Area (DMA), which are non-overlapping groups of counties originally defined by Nielsen to measure television audience share. DMA's provide a finer geographic aggregation than MSA's while capturing markets that are bigger than single counties.

[8] See Data Appendix for details of demographic variables and how they are collected.

Figure 2: Bulk Purchasing by Household Income and Product Type



Notes: Using 2004–2017 Nielsen Consumer Panel data, this figure plots the income bin coefficients from Equation (2), which regresses the share of annual purchases that were bulk packages on income, household composition, age, marital status, and education, as well as market and year fixed effects. Nielsen projection weights are used to ensure national representativeness. Households making $5–8k are the reference group. Coefficient values are reported in Appendix Tables 17 and 18.

For food items, there is a more muted increase of one percentage point across income groups.

The ten percentage point gap is quite large. For the average household making between $5,000-8,000, 33.4% of their non-food grocery spending is on bulk packages. Hence, households making over $100,000 are 30% more likely to buy in bulk relative to the lowest-income group.

These patterns are consistent with high-income households buying in bulk, obtaining low unit prices, and consuming out of storage. Given the existence of quantity discounts, larger packages correspond to lower unit prices. The fact that low-income households are less likely to buy these storable items in bulk suggests that some obstacles may prevent them from buying and storing large packages.[9]

Because the bulk buying gap is largest for non-food products, the rest of this paper focuses on non-food products. These products are ideal for analyzing bulk purchasing because they isolate the key features that make bulk buying and quantity discounts attractive for households. Primarily, households can store items for future consumption. Additionally, these products generally do not have substitutes and they cannot be produced at home (e.g.,

[9]Appendix A.3 provides the same analysis across popular product categories.

toilet paper, diapers, etc.). My findings carry over to food products, but one must be careful to account for perishability, which counteracts product storability. Additionally, many food products have close substitutes (e.g., soda, juice, water, etc.) and home production can substitute for many products (Aguiar and Hurst 2005, 2007).

3.3 Savings from Bulk Buying

In this subsection, I calculate the savings that households could achieve from buying in bulk using estimates from Sections 3.1 and 3.2 to predict savings if low-income households purchased the same size packages as high-income households. For each product category, I compute the average difference in package sizes by estimating the following regression:

$$\ln(AvgSize)_{imt} = \sum_q \beta^q Income_{imt} + \gamma X_{imt} + \lambda_m + \lambda_t + \epsilon_{imt}, \tag{3}$$

where $AvgSize$ is the quantity-weighted average package size purchased by household i in market m in year t.[10] $Income$ is an indicator for a household's income quartile. X consists of household demographics (household composition, age, marital status, education). Market and year fixed effects are included through λ.

In this regression, β^q gives the average difference between the package size purchased by a household in income quartile q and the lowest-income household (making less than \$25,000). To compute savings, I multiply this average difference in package size purchased by the quantity discount estimated in Section 3.1. For example, high-income households buy 30% larger package of toilet paper which has a quantity discount of 0.216. Therefore, low-income households could save $0.3 * 0.216 = 0.0648$ or about 6% from buying big packages like high-income households do. Aggregating across all categories where high-income households buy larger packages gives an estimated savings of 5%.[11,12]

Saving 5% on these common household purchases is substantial for low-income households. For the bottom quintile of the income distribution, these items account for 12% of total household spending compared to 7% for the top quintile of the distribution.[13] If the about

[10] Average package size is weighted by quantity to account for the fact that an unweighted average would favor small packages.

[11] This averages only across categories where high-income households buy larger packages. There are some categories, such as septic tank cleaners, clothespins, and soda which high-income households buy in smaller packages. Imposing that low-income households buy the same average size across *all* categories reduces projected savings to 2.3%.

[12] See Appendix A.4 for an alternate method of computing savings using all choices available to households on their shopping trip.

[13] Based on expenditure data on food at home and housekeeping supplies from Table 1 of the 2017 Consumer

11 million households making under $25,000 were to obtain these savings, that would be an overall savings of $2.7 billion. For context, this is equal to 4% of the $65 billion federal Supplemental Nutrition Assistance Program budget in 2018 (United States Department of Agriculture 2019). Buying in bulk does not necessarily change how much households *consume*, it just changes how much they *buy* at one time.

4 Factors Affecting Bulk Buying

In this section, I provide evidence for the importance of *cognitive costs*, *store access*, and *storage costs* to the bulk-buying gap. To do this, I use plausibly exogenous variation and natural experiments to estimate the causal impact of warehouse club entry and unit pricing regulation on bulk purchasing.

4.1 Cognitive Costs

Cognitive costs are the first possible contributor to the bulk-buying gap. Consumers may not be aware of the quantity discount because they do not compute unit prices when making purchases. To test this hypothesis, I utilize a novel hand-collected dataset of state-level unit-price, which substantially reduce the cognitive costs of computing unit prices so households can compare products and pick the best value.

Unit price labeling dates back to the late 1960s and early 1970s. During this period, there was a large consumer protection movement pushed for unit prices to be posted so consumers could compare different brands and sizes of products (Miyazaki, Sprott, and Manning 2000). While this provision was not incorporated into federal law, some states passed laws requiring that retailers post unit prices. These laws varied widely with some giving retailers discretion over how to display unit prices and other states specifying formatting requirements, such as minimum font sizes and background colors to aid readability and clarity (Rose 2000).

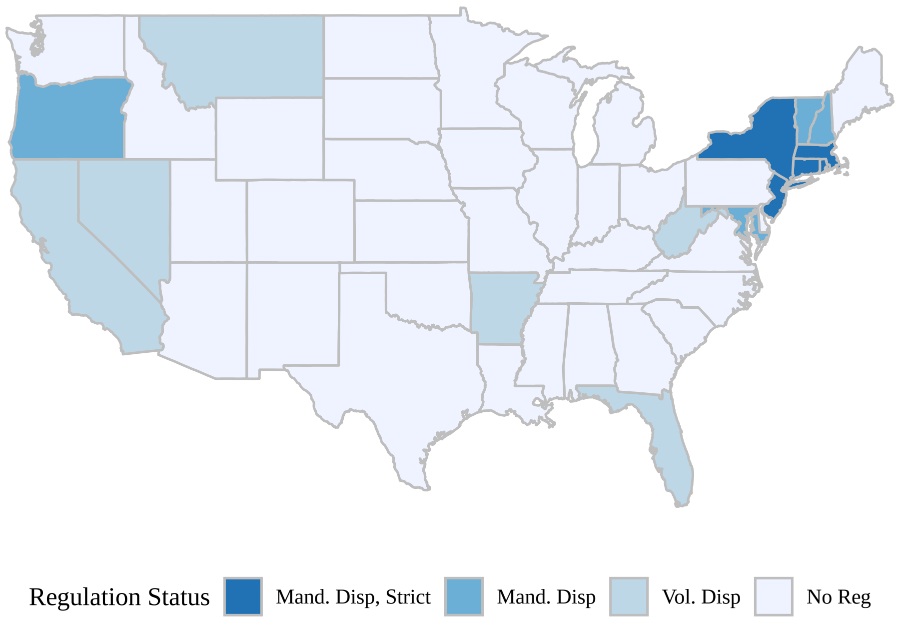
Using annual regulatory updates published by the National Institute of Standards and Technology (NIST), I compile a time series of state-level regulations on unit pricing (NIST 2019). For states with regulations, I cross-checked NIST's designation with state regulatory codes and consulted with state officials to ensure accuracy. Figure 3 shows that, as of 2017, 16 states have regulations on the display of unit prices and 34 have no regulations.[14]

If these regulations affect household decisions, then bulk buying should differ between states

Expenditure Survey available at https://www.bls.gov/opub/reports/consumer-expenditures/2017/home.htm

[14] Summary statistics of these groups are reported in Appendix Table 22.

Figure 3: Unit Price Regulations by State (2017)



Notes: Using data from NIST Handbook 130, this figure plots whether or not a state has regulations in place governing the display of unit prices as of August 1, 2017.

with and without these regulations. To test this hypothesis, I estimate the differences in bulk purchasing between states with and without unit pricing regulations using the following regression:

$$BulkShare_{it} = \beta_1 Reg_{it} + \gamma X_{it} + \lambda_t + \epsilon_{it}, \tag{4}$$

where $BulkShare$ is the annual share of expenditures that were bulk purchases for household i in year t. Reg is an indicator for whether or not unit-price regulations are in effect. X controls for household composition, income, age, marital status, and education. I control for time fixed effects through λ. If there are different patterns across income groups within states that have unit pricing regulations, then the interaction term will pick them up. Standard errors are clustered by state because these regulations are at the state level.

Since 2004, no state has modified its regulations on unit prices, so the coefficient on unit pricing regulation is identified from cross-sectional variation between states that have regulations and those that do not. Table 2 reports the results. Columns (1) and (2) reveal that bulk purchasing is three to four percentage points higher in states with unit price regulations compared to states without unit price regulation, even after controlling for household demographics and year fixed effects. Column (3) demonstrates that unit price regulation corresponds to an increase of at about two percentage points in bulk buying for the lowest income households, and there is some evidence that this effect is increasing in income. However, estimating at this level of detail is likely under-powered, so I only focus on differences between states for the remaining estimations.

Table 2: Unit Price Regulations and Bulk Buying

	(1)	(2)	(3)	(4)	(5)
Regulation	0.035**	0.032**	0.021**		
	(0.017)	(0.015)	(0.010)		
. : 25-50k			0.007*		
			(0.004)		
. : 50-100k			0.016*		
			(0.009)		
. : >100k			0.020*		
			(0.012)		
Vol. Disp				0.046*	0.009
				(0.026)	(0.009)
Mand. Disp				0.035***	0.035***
				(0.009)	(0.009)
Mand. Disp, Strict				0.021***	0.021***
				(0.006)	(0.006)
Demographics	N	Y	Y	Y	Y
Omit California	N	N	N	N	Y
Observations	767,195	767,195	767,195	767,195	700,722
Adjusted R^2	0.006	0.056	0.056	0.041	0.034

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Using Nielsen 2004–2017 Consumer Panel data combined with state-level regulations, this table shows the results of estimating Equation 4. The dependent variable is the annual share of bulk purchases made by households and the independent variables are measures of regulation as well as household demographics (household composition, age, marital status, and education). Columns (1)-(3) show the relationship between bulk buying and the presence or absence of regulation. Columns (4) and (5) show the relationship between bulk buying and the stringency of regulation. Column (6) omits California because it is the only state that has voluntary unit price, but strict requirements on how unit prices are displayed. Standard errors are clustered by state.

I then analyze these unit pricing regulations at a higher level of detail. In particular, the regulations vary across two dimensions: Posting and Formatting. Table 3 shows the breakdown of states along these dimensions. First, states can opt to have unit price posting be voluntary (seven states) or mandatory (nine states). Second, states can specify how unit prices are formatted when they are displayed.[15] Formatting regulations specify features including minimum font sizes, background colors, and label positioning. With the exception of California, only states that mandate unit price posting have formatting requirements.

[15]All states with these regulations standardize how unit prices are to be calculated, which is what makes the voluntary states different from states without regulations.

Excluding California, regulations are naturally ordered: no regulation, voluntary posting, mandatory posting (no formatting requirements), and mandatory posting (with formatting requirements).

Table 3: Unit Price Regulations by State

	No Formatting Rules		Strict Formatting Rules	
Voluntary Posting	Arkansas	Montana	California	
	Florida	Nevada		
	Hawai'i	West Virginia		
Mandatory Posting	Maryland	Vermont	Connecticut	New York
	New Hampshire		Massachusetts	Rhode Island
	Oregon		New Jersey	

Notes: Based on state regulatory codes, the above table reports whether unit price posting is mandatory or voluntary for retailers and whether or not there are strict formatting requirements on how unit prices should be displayed (minimum font size, color, etc.).

Columns (4) and (5) continue the earlier analysis, but leverage the stringency of the regulations. Column (4) shows that mandatory posting is associated with significantly higher bulk buying, but states with voluntary requirements may have higher rates of bulk buying. However, as Table 3 shows, California is an outlier in this regulatory environment because is is the only state with the unique combination of voluntary posting and strict formatting requirements. Because of this, I exclude California and re-estimate the regression. Column (5) reveals that California is the primary driver of this effect and states with voluntary posting do not have significantly higher bulk purchasing. On the other hand, mandatory unit price posting is associated with a two to four percentage point increase in bulk buying. The point estimates for bulk buying in states with strict formatting requirements are lower than those in states without formatting requirements, but these estimates are not significantly different from each other. This pattern supports the intuition that standardized unit price presentation reduces cognitive costs, increase the *salience* of unit prices, and facilitate comparisons for consumers.

This estimation provides strong evidence of a relationship between unit pricing regulations and bulk purchasing. However, there is a risk of selection bias since these regulations were primarily adopted in the Northeast and West Coast regions of the United States. Given the results, the selection would have to be such that states with households pre-disposed to buy in bulk were more likely to pass these regulations. This implication contradicts the narrative that these regulations were primarily focused on increasing consumer protection, so these states would likely have been ones focused on consumer protection and populations that may actually have been less likely to buy in bulk without this information provision.

To avoid this possible selection issue and provide causal evidence, I examine the 2,219 households that move between states with different regulatory regimes. To estimate the effect of unit-price regulations on these movers, I use the following regression:

$$BulkShare_{it} = \beta_1 Reg_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \epsilon_{it}, \tag{5}$$

where the variables are the same as in Equation (4), but I control for household fixed effects and standard errors are clustered at the household level.[16] With this specification, β_1 is identified by changes in bulk purchases for households that move from a state with unit-price regulations to a state without unit-price regulations (or vice versa).[17]

Table 4: Event Study of Movers to Different State Regulatory Regimes

	(1)	(2)	(3)
Regulation	0.011***	0.011***	
	(0.004)	(0.004)	
Law to No Law			−0.016***
			(0.005)
No Law to Law			0.003
			(0.006)
Household FE	Y	Y	Y
Year FE	Y	Y	Y
Demographics	N	Y	Y
Observations	16,204	16,204	16,204
Adjusted R^2	0.604	0.607	0.607
Note:	*p<0.1; **p<0.05; ***p<0.01		

Notes: Using 2004–2017 Nielsen Consumer Panel data and state-level regulations, this table shows estimates of Equation 5 which regresses household bulk buying on unit price regulation after controlling for household fixed effects. "Regulation" denotes the estimated effect of moving from a state without regulation to a state with regulation. Column (3) allows for different types of moves. "Law to No Law" specifies a move from a state with unit price regulation to a state without unit price regulation. "No Law to Law" specifies a move from a state without unit price regulations to a state with unit price regulations. Standard errors are clustered at the household level.

Table 4 reports the results of estimating Equation (5). Columns (1) and (2) show that moving to a state with unit price regulation increases bulk buying by about one percentage point. This specification implicitly assumes that the effect of moving to a state with unit price regulations will be the same as moving to a state without regulations (i.e. the effect is symmetric). Column (3) treats the different directions of moving differently and shows that moving to a state without unit price regulations significantly decreases bulk buying, by

[16]Household fixed effects are actually household-income fixed effects to ensure that the interaction term is identified by differences in regulation and not by changes in a household's income.

[17]Projection weights are not used because the weights are not designed for this subsample of movers.

1.4 percentage points while moving to a state with regulations does not change bulk buying significantly.

To illustrate this effect graphically, I plot an event study by estimating a modified version of Equation (5):

$$Y_{it} = \sum_{T} \beta_1^t E_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \epsilon_{it}, \tag{6}$$

where E is a dummy for each year before or after a household moves to a state with a different unit pricing regime. The reference group is $t = -1$ so all effects are relative to the year before the household moves. I estimate this equation separately for different types of moves and plot the annual coefficients in Figure 4. Moves from states without regulations to states with regulations may have different effects than moves from states with regulations to states without regulations. Figure 4 shows that households decrease their bulk buying by about two percentage points when they move from a state with unit-price regulations to a state without unit-price regulations. On the other hand, households that move from states without unit-price regulations to states with unit pricing regulations do not significantly change their bulk buying.

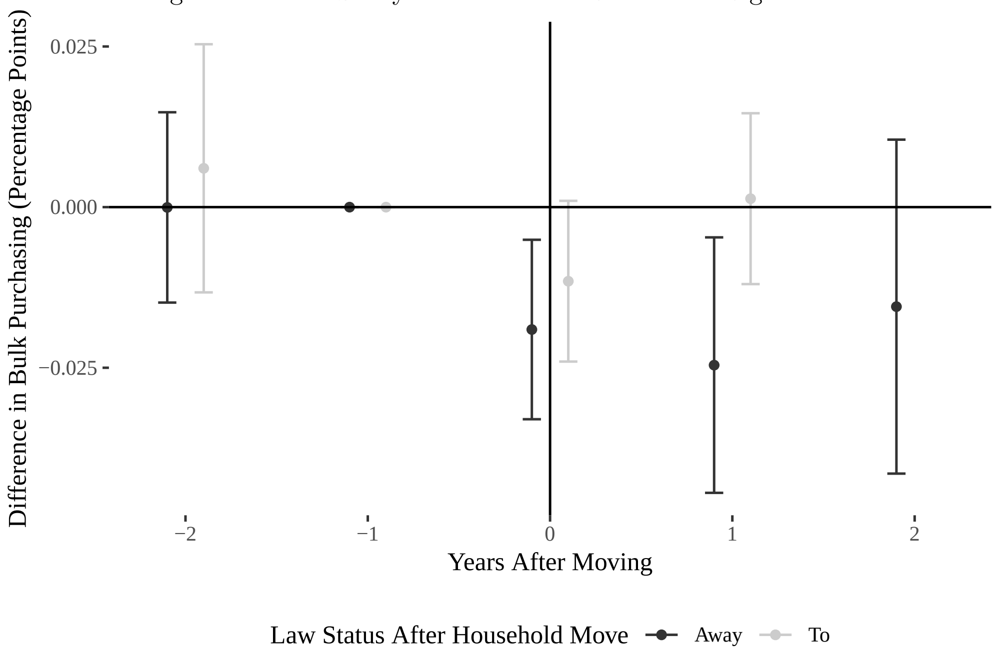
Overall, this shows that unit-price regulations, which reduce cognitive costs and increase the *salience* of unit prices have an effect on bulk purchasing. The effect is similar to warehouse club entry, but more equitably spread across households. Because unit-price regulation increases bulk buying for all households with slightly larger increases for high-income households, this is strong evidence that improving education and messaging around understanding unit prices and how to utilize them will encourage more households to buy in bulk and lower their total shopping bill.

Unit pricing regulations are relatively simple to implement for both policymakers and retailers. Retailers will bear some initial setup costs of redesigning their price labels, but ongoing costs will likely be similar to current menu costs that firms bear. Adopting unit pricing policies (like those recommended by the National Conference on Weights and Measures) would encourage bulk buying while imposing few costs. These findings support the broader assertion that increasing price transparency allows households to improve their decision-making.

4.2 Store Access

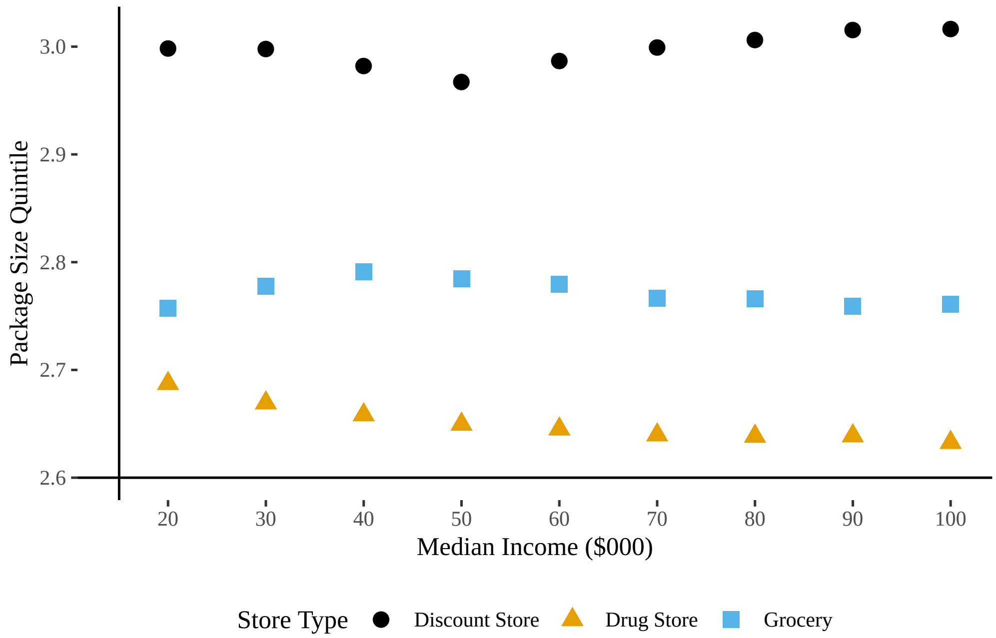
The second potential contributor to the bulk buying gap is *store access*; low-income households may not live in areas where bulk sizes are available or may not shop at stores that offer bulk sizes. In this subsection, I provide evidence that the bulk buying gap persists within neighborhoods and within store types. Then, I show that warehouse club entry increases bulk

Figure 4: Event Study of Movers and Unit Price Regulations



Notes: Using 2004–2017 Nielsen Consumer Panel data, this figure plots the β_1^t coefficients and 95% confidence intervals from Equation (6), which regresses household bulk purchasing on dummies for years before and after a household moves to a state with a different unit pricing regime than the state it moves from. The regression controls for household composition, age, marital status, and education as well as household and year fixed effects. Standard errors are clustered at the household level. "To" reports estimates for households that move from a state without unit price regulations to a state with unit price regulations. "Away" reports estimates for households that move from a state with unit price regulations to a state without regulations.

Figure 5: Average Package Quintile By Zip Code Median Income



Notes: Using 2016 Nielsen Retail Scanner data, this figure plots the average size quintile offered within a store type within categories of ZIP code median income. The $100,000 income bin includes all ZIP codes with incomes greater than $100,000.

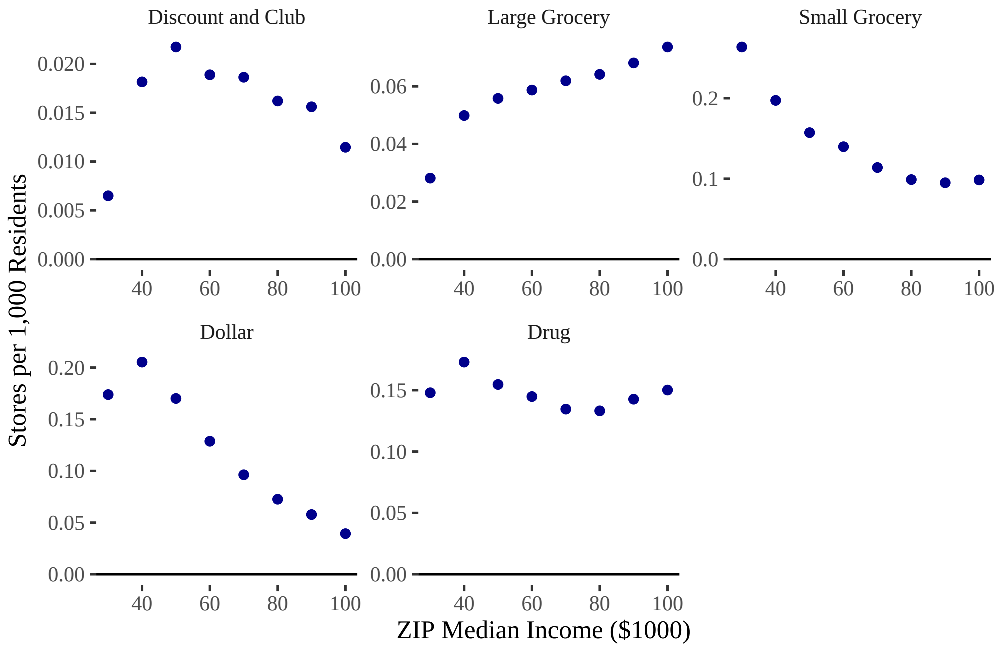
buying by five to nine percent, but these increases hold only for middle- and high-income households.

4.2.1 Inequality Within Markets and Retail Chains

The first possibility is that store assortments differ between high- and low-income neighborhoods. This hypothesis is similar to the literature on food deserts, which analyzes whether supply differences contribute to nutritional inequality (Allcott et al. 2019). To measure the average size offered by each store, I map each available package to its corresponding size quintile in its product category and then average across all products offered by the store. Figure 5 shows the relationship between the average size quintile offered in Retail Scanner stores and ZIP code median income. Within store types, there is little relationship between the average size offered and a ZIP code's median income. However, there are substantial differences in the sizes offered by different types of stores.

Using ZIP Code Business Patterns data, Figure 6 illustrates that there are substantial differences in the types of stores available in various neighborhoods. Richer ZIP codes have more large grocery stores per capita while poorer ZIP codes have more small grocery and dollar stores. Drug stores are more evenly distributed and discount and club stores tend to

Figure 6: Store Counts by ZIP Code Median Income



Notes: Using 2016 ZIP Code Business Patterns data, this figure plots the number of stores per 1,000 residents for the (population-weighted) average ZIP code in each income bin. The lowest income bin includes all ZIP codes with median incomes of $30,000 or less and the highest income bin includes all ZIP codes with median incomes of greater than $100,000. "Large" denotes a grocery store with 50 or more employees. The stores types correspond to the following 2012 NAICS codes: Discount and Club Stores – 452910 (Warehouse Clubs and Supercenters); Grocery Stores – 445110 (Supermarkets and Other Grocery (except Convenience) Stores); Dollar Stores – 452990 (All Other General Merchandise Stores); Drug Stores – 446110 (Pharmacies and Drug Stores).

occupy middle-income ZIP codes.

If supply factors are the primary driver of the bulk buying gap, then the gap should disappear when comparing households in the same location since they have access to the same set of stores. I show that the bulk buying gap still persists within ZIP codes. This remaining gap corresponds to the amount that *cannot* be explained by differences in access, at least as approximated by geography.

The ideal experiment would randomly assign households to various shopping environments and compare the bulk buying behavior of each. However, the Nielsen data only reveals shopping choices after households have selected into neighborhoods. To the extent that households that live in the same neighborhood are unobservably similar, I interpret any differences between cross-sectional bulk buying and within-ZIP bulk buying as an upper bound on the share of the bulk buying gap that is attributable to store access.

Even within ZIP codes, there may be other factors affecting where households shop, such as whether or not a household has a vehicle, access to public transit, or a warehouse club membership. To account for possible differences, I examine how much of the bulk buying gap persists within chains. This exercise assumes that within a chain, households have access to the same assortment of goods (DellaVigna and Gentzkow 2019). I also examine the bulk buying gap within store types (i.e. "channel") to account for the fact that bulk buying differences may primarily be between channels (discount versus dollar) instead of between retailers within a channel (Walmart versus Target).

I estimate within-ZIP and within-chain bulk buying gaps using a modified form of Equation 2:

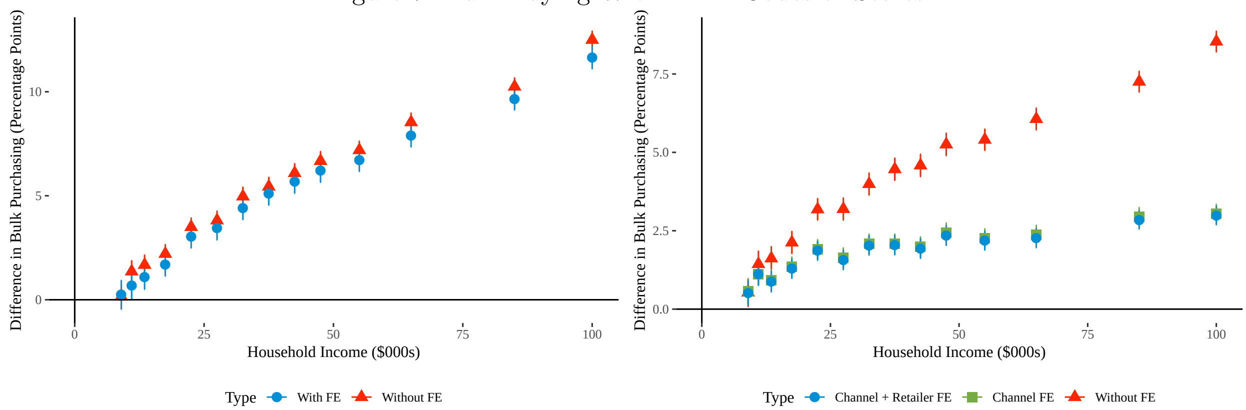
$$BulkShare_{imt} = \sum_{q} \beta^q Income_{imt} + \gamma X_{imt} + \lambda_{mt} + \epsilon_{imt}, \tag{7}$$

where $Income$ is an indicator for the income bin of household i in market m in year t. X consists of household demographics (household composition, age, marital status, and education). For the analysis of bulk buying within ZIP code, $BulkShare$ is the share of bulk purchases made by household i in ZIP code m in year t and λ_{mt} is a ZIP-year fixed effect. For the analysis of bulk buying within retail chains, $BulkShare$ is the share of bulk purchases made by household i in retail chain m in year t and λ_{mt} is a retail chain-year fixed effect and/or a channel fixed effect.

Figure 7 plots the income coefficients with and without fixed effects for each regression. Adding ZIP-year fixed effects reduces the gap between the highest and lowest income quartile by 5% (from 10.1 percentage points to 9.6 percentage points). Results are unchanged if I use county-year fixed effects instead of ZIP-year fixed effects. Using channel-year fixed effects reduces the bulk buying gap by a more substantial 72% (from 6.4 percentage points to 1.8 percentage points). Adding retail chain-year fixed effects on top of channel-year fixed effects does not significantly affect the bulk buying gap. This implies that a large share of the bulk buying gap is related to the *types* of stores households shop at, but not the specific chain they choose within a particular store type.

Overall, within ZIP codes, the bulk buying gap between high- and low-income households persists. However, within store type (or retail chain), the bulk buying gap is substantially reduced. Two important conclusions can be drawn from these patterns. First, in an accounting sense, the type of store a household shops at accounts for almost three-quarters of the bulk buying gap. This is likely an overestimate given that there is endogeneity in store choice by households because many factors influence where households choose to shop. Second, the bulk buying gap *still persists* within channels and retail chains. These patterns suggest that where a household shops and what they choose within a store are much more important than where a household is located. The next section explores how store preferences are related to

Figure 7: Bulk Buying Within ZIP Codes or Stores



(a) ZIP-Year Fixed Effects

(b) Retailer/Channel-Year Fixed Effects

Notes: Using 2004–2017 Nielsen Consumer Panel data, this figure plots the income bin coefficients from Equation (7), which regresses the share of annual purchases that were bulk packages on income, household composition, age, marital status, and education as well as either ZIP code-year, retailer-year, or channel-year fixed effects (a "channel" is a type of store). Nielsen projection weights are used to ensure national representativeness. Households making $5–8k are the reference group. Coefficient values are reported in Table 19.

income and how warehouse clubs affect bulk buying.

4.2.2 Store Preferences by Income

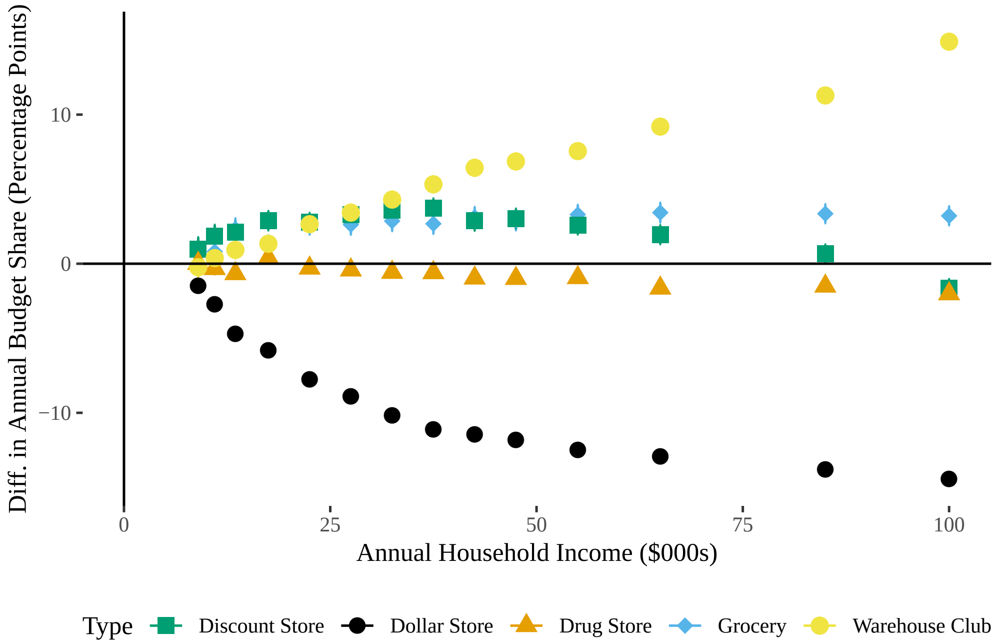
The previous section shows that while the bulk buying gap persists within ZIP codes, it is substantially moderated within store types and retail chains. In this section, I document differences in store preferences between income groups and then estimate the effect of warehouse club entry on bulk buying.

To demonstrate differences in store preference by household income, I examine the association of annual non-food purchase shares at various outlets while controlling for household characteristics:

$$ChannelShare_{imt} = \sum_q \beta^q Income_{imt} + \gamma X_{imt} + \lambda_m + \lambda_t + \epsilon_{imt}, \quad (8)$$

where $ChannelShare$ is the share of annual spending that household i in market m in year t made in a particular channel (grocery store, discount store, dollar store, drug store, or warehouse club). $Income$ is an indicator for a household's income bin. X captures other household demographics (household composition, age, marital status, and education). Finally, market and year fixed effects capture differences in spending shares across markets and over time.

Figure 8: Annual Spending By Store Type, Relative to Low-Income Households



Notes: Using 2004–2017 Nielsen Consumer Panel data, this figure plots the income bin coefficients from Equation (8), which regresses the share of annual purchases at each store type on income, household composition, age, marital status, and education as well as year and market fixed effects. Nielsen projection weights are used to ensure national representativeness. Households making $5–8k are the reference group.

Figure 8 reveals that while there are small differences in the share of annual expenditures at grocery, drug, and discount stores, there are dramatic differences in whether households shop at warehouse clubs or dollar stores: households making over $100,000 spend about 13 percentage points more of their non-food expenditures at warehouse clubs than households making under $25,000.

Because the biggest differences are in warehouse clubs and these stores almost solely stock bulk sizes, I focus on how warehouse clubs affect bulk buying. The following analysis of warehouse clubs uses hand-collected data on over 1,400 warehouse club locations between 2004–2015.[18] The first possibility is that high-income households shop at warehouse clubs because they are closer. Table 5 shows that low-income households are about 15 miles away from the nearest warehouse club compared to only 8 miles away for high-income households.

The ideal experiment would randomly assign warehouse clubs to neighborhoods and then their effect on bulk buying could easily be calculated. However, store locations are not randomly assigned. Within a household, it is exceedingly unlikely that a club opening could be co-incident with a shift in bulk buying, so any observed changes are likely causal.

[18]Data provided by the authors of Coibion, Gorodnichenko, and Koustas (2017) and covers BJ's, Costco, and Sam's Club.

Table 5: Average Distance to Warehouse Club by Income (Miles)

Household Income	Mean	SD	25th Pctile	75th Pctile
<25k	14.79	18.98	3.26	20.53
25-50k	12.79	17.51	3.03	15.94
50-100k	10.61	15.16	2.85	12.01
>100k	7.92	12.08	2.51	8.45

Notes: Using Nielsen Consumer Panel data from 2004–2015 and warehouse location data, this table reports the distance between ZIP code centroids of warehouse locations and household locations. Nielsen projection weights are used to ensure national representativeness.

Leveraging the panel structure of the Nielsen Consumer Panel, I estimate how a household's bulk purchasing changes after a warehouse club opens using the following equation:

$$BulkShare_{imt} = \beta Entry_{imt} + \gamma X_{imt} + \lambda_{im} + \epsilon_{imt}, \tag{9}$$

where $BulkShare$ is the share of bulk purchases made by household i in market m in quarter t. $Entry$ is an indicator for whether or not a club entered within 15 miles of household i in quarter t.[19,20] I include a household-market fixed effect λ to ensure that β is identified by within-household changes in bulk buying before and after a club opens instead of households that may move to areas closer to warehouse clubs. X controls for possible demographic changes within the household (household composition, age, marital status, and education).

Table 6 shows the regression results. Overall, households that experienced a warehouse club entry increased their bulk purchasing by about two percentage points. However, when I interact household income with club entry, the increase in bulk buying is due to changes for households making over \$25,000 and is increasing in income, with households making over \$100,000 increasing their bulk buying by four percentage points. Households in the lowest quartile do not have any significant change in their bulk buying. One likely reason that low-income households do not change their bulk buying is that even after a warehouse club enters, households do not purchase a membership (fees range from \$45-\$120 depending on the chain and membership level). Other possible reasons are that low-income households do not have access to transportation that can carry items home, do not have the space to store the items, or even if they had a membership, they still would not purchase extremely

[19] In cases where a household is located near multiple warehouse clubs, I use the earliest entry date since the first warehouse club would generate the largest supply shock.

[20] According to the 2017 National Household Travel Survey, the average household traveled about seven miles to buy goods, with low-income households traveling about one or two miles less than higher-income households (Federal Highway Administration 2017). Allowing for the possibility that households might travel farther to shop at a warehouse club, I use a cutoff of 15 miles. Appendix Table 23 shows that this pattern is robust to other cutoffs.

large sizes available at warehouse clubs due to budget constraints.[21]

Table 6: Effect of Warehouse Club Entry on Bulk Buying

	(1)	(2)	(3)
Post-Entry	0.017^{***}	0.017^{***}	-0.005
	(0.004)	(0.004)	(0.007)
Post-Entry : 25-50k			0.022^{***}
			(0.008)
Post-Entry : 50-100k			0.028^{***}
			(0.009)
Post-Entry : >100k			0.039^{***}
			(0.012)
Household-ZIP FE's	Y	Y	Y
Year-Quarter FE's	Y	Y	Y
Demographic Controls	N	Y	Y
Observations	2,520,129	2,520,129	2,520,129
Adjusted R^2	0.427	0.427	0.427
Note:	*p<0.1; **p<0.05; ***p<0.01		

Notes: This table uses 2004–2015 Nielsen Consumer Panel data at the household-quarter level. Coefficients are reported for Equation (9) which regresses households' quarterly bulk purchase shares on an indicator for warehouse club entry, an indicator for whether the household shops at a warehouse club, and an interaction term as well as household demographics (household size, age, presence of children, and marital status). Household-ZIP code and year-quarter fixed effects are included. Projection weights are not used.

To illustrate the effect of club entry on bulk buying and check for pre-trends, I estimate Equation 9, but replace the entry indicator with dummies for each quarter pre- and post-entry:

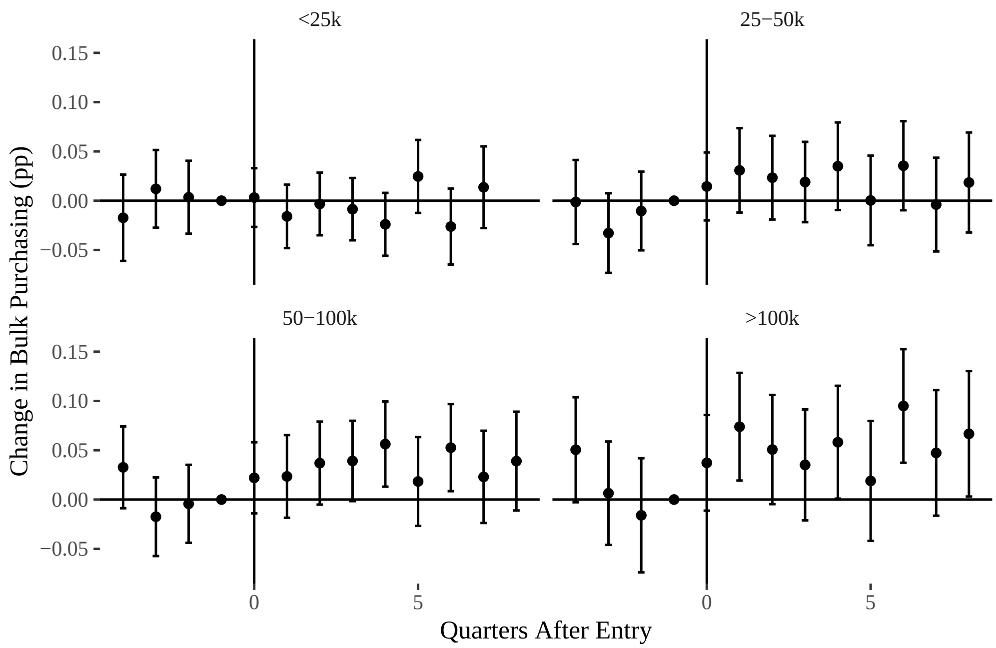
$$BulkShare_{imt} = \sum_{q} \beta^{q} Qtr_{imt} + \gamma X_{imt} + \lambda_{im} + \epsilon_{imt}, \tag{10}$$

where Qtr is a dummy for each quarter prior to entry and after entry, with the quarter immediately before entry ($q = -1$) as the reference group. Figure 9 plots the quarterly coefficients and shows that there are no significant pre-trends and post-entry, there are significant increases in bulk buying for higher income households with households making over \$100,000 increasing their bulk buying by four to seven percentage points. These effects are persistent up to eight quarters after a warehouse club has opened.

This analysis estimates the intent to treat effect since not all households shop at the entrant warehouse club after it opens. As a result, this is a conservative lower bound on the actual

[21] As an example, Philadelphia provides public transit access to a warehouse club. However, carrying club-sized items on a bus is infeasible for more than two or three items. A personal vehicle would be necessary.

Figure 9: Event Study of Warehouse Club Entry



Notes: This figure plots the quarterly coefficients from Equation (10)—the effects of warehouse club entry on bulk purchasing of households before and after club store entry—using 2004–2015 household-by-quarter Nielsen Consumer Panel data. The regression controls for household composition, age, marital status, and education as well as household-ZIP code fixed effects. All coefficients are relative to bulk purchasing in the quarter before entry ($q = -1$). Error bars denote 95% confidence intervals.

treatment effect on households that shop at warehouse clubs.[22] The effect is quite substantial even given how conservative it is.

4.3 Storage Costs

Storage costs are the third contributing factor that I examine. Intuitively, households that buy in bulk need a place to store a large quantity, which could be in a basement, pantry, or cabinets. Households without available storage space may want to realize the savings of buying in bulk, but choose not to because they have limited space to store the large package.

The ideal experiment would randomly assign households to various home sizes and then observe their bulk purchasing behavior to identify storage costs. However, exogenously changing a household's living situation is infeasible for a variety of reasons. The next best option is to test some intuitive implications of storage costs. First, while I cannot randomly assign households to different home sizes, there are many households that move while they are in the Nielsen panel. I observe whether households live in single-family homes or apartments, which generates variation in available storage space. According to the American Housing Survey, the median single-family home is about twice as large as the median apartment. Since at least 1999, new single-family homes have had a median size of 2,000-2,400 square feet while the median apartment is only 1,000-1,100 square feet and this holds true within Census regions as well. Therefore, households that move between single-family homes and apartments likely experience a large change in their available storage space and this will impact their ability to buy in bulk.

I already estimated this bulk buying change in Section 4.1 when I estimated the effect of unit price regulations for households that moved between regulatory regimes. Below I reproduce Equation 5 that I estimate as well as the results, highlighting bulk buying differences due to changes in housing:

$$BulkShare_{it} = \beta_1 Reg_{it} + \beta_2 Single-Family_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \epsilon_{it}, \qquad (11)$$

where Reg is the indicator for whether household i is in a state with unit price regulations in year t. $Single-Family$ is a dummy for whether a household lives in a single-family home (apartments are the reference group). X controls for changes in other household demographics (household size, marital status, age, education, etc.). Household and year fixed effects, λ,

[22] Even though low-income households do not change their bulk buying, other research suggests that they may be worse off because existing retailers are more likely to increase prices for storable products as a competitive response (Bauner and Wang 2019).

ensure that β is identified off of within-household changes in housing. Standard errors are clustered at the household level. Table 4 is reproduced below with housing information included (it was suppressed in the previous table for expository purposes).

Table 7: Relationship Between Bulk Buying and Housing

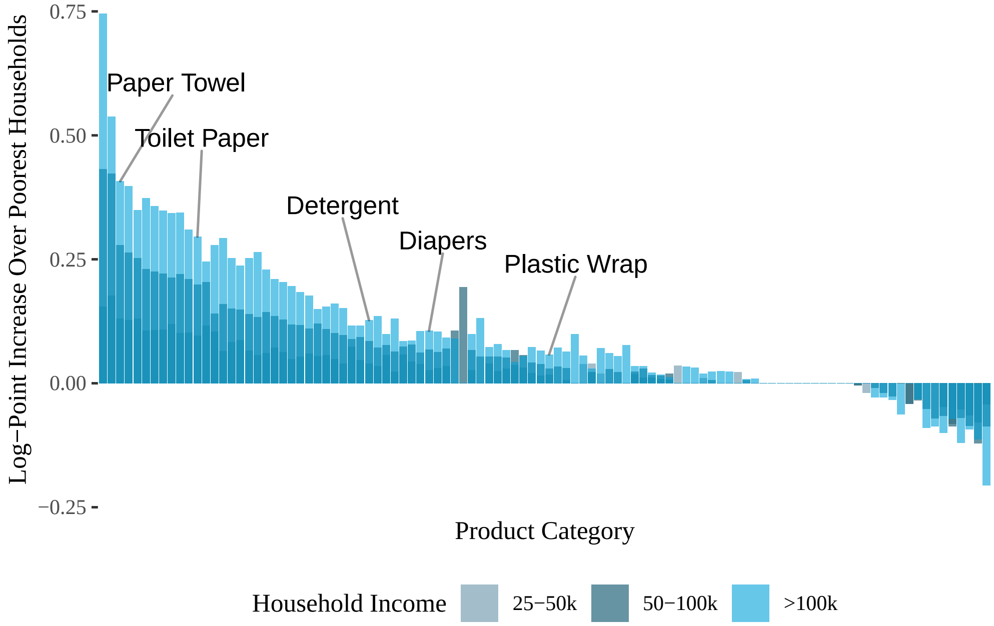
	(1)	(2)	(3)
Regulation	0.011^{***}	0.011^{***}	
	(0.004)	(0.004)	
Law to No Law			-0.016^{***}
			(0.005)
No Law to Law			0.003
			(0.006)
Single-Family Home		0.015^{**}	0.015^{**}
		(0.007)	(0.007)
Household FE	Y	Y	Y
Year FE	Y	Y	Y
Demographics	N	Y	Y
Observations	16,204	16,204	16,204
Adjusted R^2	0.604	0.607	0.607
Note:	*p<0.1; **p<0.05; ***p<0.01		

Notes: Using 2004–2017 Nielsen Consumer Panel data and state-level regulations, this table shows estimates of Equation 5 which regresses household bulk buying on unit price regulation after controlling for household fixed effects. "Regulation" denotes the estimated effect of moving from a state without regulation to a state with regulation. Column (3) allows for different types of moves. "Law to No Law" specifies a move from a state with unit price regulation to a state without unit price regulation. "No Law to Law" specifies a move from a state without unit price regulations to a state with unit price regulations. "Single-Family Home" indicates that household lives in a single-family home with the reference category being an apartment. Standard errors are clustered at the household level.

The housing coefficient reveals that moving to a single-family home is associated with a 1.5 percentage point increase in bulk buying, which matches the intuition that when households have more storage space, they are more able to buy in bulk. Interestingly, the increase in bulk buying is of a similar magnitude to the change in bulk buying due to cognitive costs of computing unit prices.

One other implication of storage costs are that products with a smaller "footprint" (physical volume) have lower storage costs. Therefore, if storage costs influence bulk buying, there should be a smaller gap in bulk buying for smaller products (like plastic wrap) relative to large, cumbersome products (like paper towels and toilet paper). To test this implication, I estimate Equation 3 (reproduced below) that relates average package sizes with household

Figure 10: Bulk Buying Gap For Non-Food Grocery Products



Notes: Using 2004–2017 Nielsen Consumer Panel data, these figures plot the β coefficients from Equation (3), which regresses average package size purchased on household income. The regression controls for household composition, age, marital status, and education as well as market and year fixed effects. Values are reported in Appendix Table 21.

income:

$$\ln(AvgSize)_{imt} = \sum_q \beta^q Income_{imt} + \gamma X_{imt} + \lambda_m + \lambda_t + \epsilon_{imt},$$

where $AvgSize$ is the average package size purchased by household i in market m in year t. $Income$ consists of dummies for each income quantile q. X consists of household demographics (age, household composition, marital status, and education). Year and market fixed effects are captured by λ.

Figure 10 plots the income coefficients from the regression for all non-food grocery categories. I have highlighted some popular product categories. The bulk buying gap is largest for the physically biggest products such as paper towels and toilet paper while the gap is smaller for less bulky items such as liquid detergent and plastic wrap. This pattern supports the hypothesis that storage costs contribute to the bulk buying gap, but the persistence of the gap even for smaller products suggests that other factors are at play.

Overall, these results provide evidence that storage costs and bulk buying are related. When households move to larger homes (relative to apartments), they buy more in bulk. Similarly, product categories with larger physical footprints exhibit larger bulk buying gaps relative to product categories with smaller footprints. To more precisely quantify storage costs, I estimate a simple model of the consumer purchase decision.

5 Model

The previous analyses show that cognitive costs and store access (especially warehouse clubs) affect bulk buying. To decompose the contribution of each explanation and account for storage costs, I embed these factors into a discrete choice model of the household's purchase decision. The ideal setting would include a homogeneous good where demand is uncorrelated with income. Given a wide range of prices and sizes and different regulatory regimes, differences in large and small purchases between high-income and low-income households would identify storage costs and differences in buying between regulatory regimes would identify cognitive costs. This setting is approximated by one where products have limited dimensions of differentiation and storage costs can be separately identified from demand.

A discrete choice model of toilet paper purchases closely approximates this ideal setting. Toilet paper is ideal for this analysis because it is a necessity item with easily observable dimensions of differentiation, namely price, quality, quantity, and package size. It is offered in a wide range of package sizes and stores stock numerous brands and sizes (grocery and mass merchandise stores usually stock 35–40 unique brand-sizes). The top five brands and private-label store brands account for 86% of sales. I focus on the most common package sizes, which range from 4- to 24-roll packages. I define a product as a unique brand-size combination.[23] Additionally, underlying toilet paper consumption is primarily a function of household composition and age, not income.[24] High-income households consume a similar amount as low-income households but make fewer purchases (Orhun and Palazzolo 2019). Finally, toilet paper cannot be easily substituted for another product nor can it be obtained through home production.[25]

The biggest identification challenge is separately identifying storage costs from underlying demand (i.e. households may buy large quantities because they have high consumption or because they have low storage costs). To separate storage costs from demand, I use variation induced by differences in product concentration. Product concentration breaks the direct link between volume and consumption. In the detergent category, the same number of washes

[23] Specifically, this is a unique brand-roll count-sheet count because packages can differ in their "concentration" due to "double," "mega," and "super mega" rolls.

[24] A 100-fold cross-validated lasso regression of annual purchases on household characteristics rules out income as significantly predictive. See Appendix A.5 for details.

[25] While a bidet is a possible alternative, this is more likely a lifestyle choice instead of a situation where households switch between toilet paper and bidets. Furthermore, in the United States, 98% of households report that they use toilet paper (the remainder either said no or did not respond) (Statista 2019).

could be covered with a large diluted package or a smaller concentrated package. Both packages support the same underlying demand, but households with higher storage costs will prefer the smaller, more concentrated package over the larger one.

The same reasoning holds true for toilet paper. Households do not demand a particular number of rolls (the primary determinant of package size), but choose how long they want their supply to last (i.e. purchase enough to last for two weeks, a month, two months, etc.).[26] Toilet paper comes in a variety of concentrations with "mega" rolls being more concentrated than "regular" rolls. Therefore, households that purchase 24 "regular" rolls have the same demand for toilet paper uses as households that purchase six "mega" rolls, but the former household has lower storage costs since they can store the bigger package.

To illustrate the varying concentrations of toilet paper, Figure 11 plots the distribution of quantity (measured in number of days the supply will last for a single person) against package sizes (measured in rolls) for toilet paper products in the Nielsen data. As expected, there is an increasing relationship between how long the package will last and the number of rolls in a package, but there is substantial variation within packages containing the same number of rolls. The dashed lines denote the 25th and 75th percentiles of the average days' supply purchased by households. A wide range of package sizes fall within this range for each brand.[27] For example, a household demanding a 60-day supply of Charmin could purchase a package containing anywhere from 8 to 24 rolls. This overlap generates the necessary variation to separate storage costs from underlying demand.[28]

5.1 Model Setup

I model a household's purchase decision using a static discrete choice framework. When making a purchase, households consider the unit price, quality, and size of each package and choose the package that maximizes their utility. These features are captured in the household i's indirect utility function:

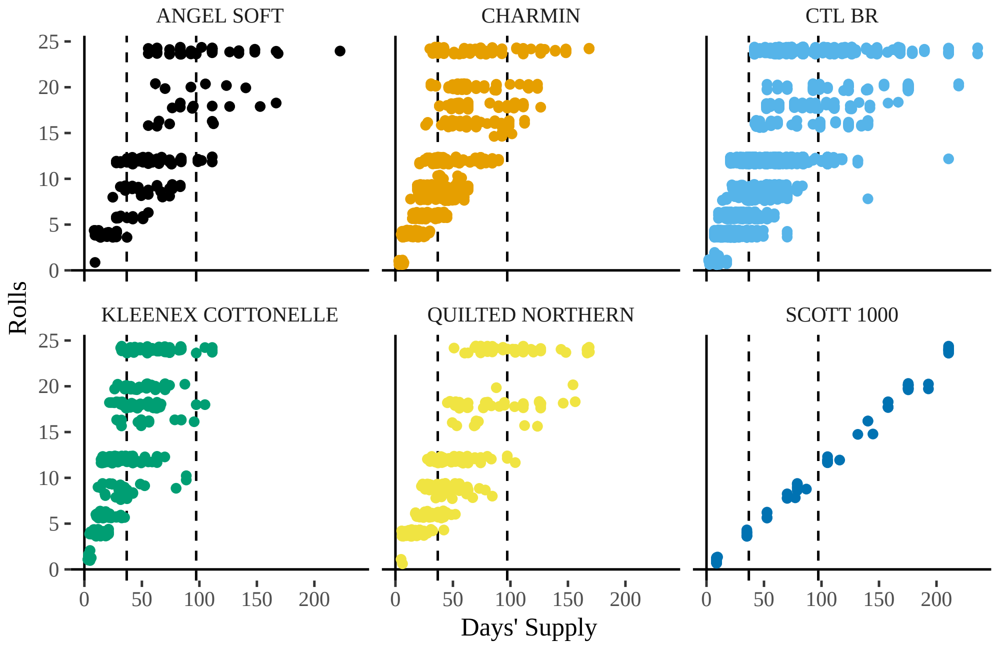
$$
\begin{aligned}
U_{ijt} = & \beta_1 Price_{jt} + \beta_2 Price_{jt} \times Reg_{jt} + && (12) \\
& \beta_3 UnitPrice_{jt} + \beta_4 UnitPrice_{jt} \times Reg_{jt} + && (13) \\
& \beta_5 \log(Days_j) + \beta_6 BigPack_j + \beta_7 SmallPack_j + \theta_{b(j)} + \epsilon_{ijt}, && (14)
\end{aligned}
$$

[26]According to a 2007 Charmin survey, the average person uses 57 sheets per day. I assume this consumption rate when computing how long a product will last (Jaffe 2007).

[27]Scott toilet paper is an exception because it does not offer different roll types. All rolls have 1000 sheets.

[28]This reasoning can be generalized to allow for cross-category comparisons based on the physical "footprint" of different product categories. See Appendix **??** for a discussion of how the bulk buying gap varies across categories with different "footprints."

Figure 11: Scatter-plot of Toilet Paper Package Size and Quantity



Notes: Using 2004–2017 Nielsen Consumer Panel data, this figure plots the package sizes and quantities of the top five toilet paper brands and private-label products. The x-axis represents the number of toilet paper rolls contained in a package while the y-axis represents the number of days a product will last a single person household assuming a consumption rate of 57 two-ply sheets per day (Jaffe 2007). Noise is added vertically to better illustrate the number of products available within package sizes since roll counts are discrete. Dashed lines indicate the 25th and 75th percentiles of the average days' supply purchased by a household.

where *Price* is the total price of product j at time t. *Reg* is an indicator for whether unit price regulations are in effect. *Days* is the number of days the package will last (a function of the number of total sheets in the package). *UnitPrice* is the per-day price of the package, since the yield of a package is how many days it will last. *BigPack* is a dummy for the package having more than 12 rolls, *SmallPack* is a dummy for less than 12 rolls, and θ is a brand fixed effect.[29] Brand fixed effects capture quality differences between products. I assume ϵ is iid Type 1 extreme value.

This simple model incorporates the key features necessary to decompose the bulk buying gap. Preferences for package size (a measure of storage costs) are captured by β_6 and β_7 while the salience of unit pricing is captured by β_3, but I allow it to differ based on regulations (β_4).

The price coefficient is identified using price variation across shopping trips due to shopping at different stores or sales. The size coefficient is identified by variation in the product "concentration" as illustrated in Figure 11. That is, given their preferred days' supply (x-value), some households choose large packages and some choose small packages (y-value).

Given these assumptions and the structure of the error term, the probability that household i chooses product j on trip t has a closed form:

$$P_{ijt} = \frac{e^{\beta' x_{ijt}}}{\sum_j e^{\beta' x_{ijt}}}, \tag{15}$$

As a result, the log-likelihood function can be written as:

$$LL(\beta) = \sum_t \sum_i \sum_j y_{ijt} \log(P_{ijt}), \tag{16}$$

where y indicates whether household i chose product j on shopping trip t. The preference parameters β can then be estimated using MLE.

6 Estimation Results

I estimate this model separately for each income quartile and year. The coefficients for 2016 are reported in Table 8. I observe about 45,500 toilet paper purchases across about 14,800 households at grocery and mass merchandisers.

The estimation results show that both the price and unit price coefficients are negative,

[29] Households bunch at 12-roll packages, so this allows for different package preferences around this bunching point.

Table 8: Multinomial Logit Estimation Results (2016)

	<25k	25-50k	50-100k	>100k
	(1)	(2)	(3)	(4)
Total Price	-0.188^{***}	-0.181^{***}	-0.158^{***}	-0.139^{***}
	(0.009)	(0.006)	(0.005)	(0.007)
. : Reg	0.036^{***}	0.019^{***}	0.019^{***}	0.022^{***}
	(0.010)	(0.006)	(0.005)	(0.006)
Unit Price	-8.127^{***}	-7.914^{***}	-9.583^{***}	-8.385^{***}
	(0.439)	(0.272)	(0.244)	(0.376)
. : Reg	-2.388^{***}	-2.897^{***}	-1.703^{***}	-0.812^{**}
	(0.489)	(0.297)	(0.239)	(0.321)
Log(Days)	0.268^{***}	0.384^{***}	0.268^{***}	0.308^{***}
	(0.051)	(0.034)	(0.030)	(0.051)
Large Size	-0.595^{***}	-0.639^{***}	-0.414^{***}	-0.589^{***}
	(0.096)	(0.070)	(0.068)	(0.126)
. : Home	0.163	0.105	0.004	0.309^{**}
	(0.113)	(0.078)	(0.072)	(0.129)
Small Size	-0.231^{***}	-0.279^{***}	-0.254^{***}	-0.427^{***}
	(0.057)	(0.044)	(0.048)	(0.091)
. : Home	-0.241^{***}	-0.136^{***}	-0.239^{***}	-0.110
	(0.065)	(0.047)	(0.050)	(0.094)
Brand FE's	Y	Y	Y	Y
Observations	4,968	12,950	17,875	7,942
Log Likelihood	$-15{,}751.570$	$-40{,}778.780$	$-55{,}801.250$	$-24{,}757.150$

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Using 2016 Nielsen Consumer Panel and Retail Scanner data, this table presents MLE estimates of price and package size coefficients from Equation 12. "Large" indicates packages that are larger than 12 rolls and "small" indicates packages that are smaller than 12 rolls. A 12-roll package is the reference group.

implying that all else equal, households prefer lower prices. Lower income households are more price sensitive than high-income households, but higher-income households are more sensitive to unit prices. The interaction terms reveal that when unit prices are posted, all households are less sensitive to total prices and are more sensitive to unit prices with low-income households being affected the most. All households prefer to have more days' supply of toilet paper compared to less. Finally, in terms of storage costs, all households have a preference against large sizes, but this dislike decreases with income suggesting that high-income households have lower storage costs than high income households. On the other hand, all households also have a preference against small sizes, but this dislike is smallest for low-income households. Under a pure storage costs story, the small packages might have been expected to have a positive sign for low-income households. However, as mentioned in the model specification section, there is a lot of bunching at 12-roll packages across households of all types, so this negative sign on the small size is likely a result of that bunching.

Figure 12 plots the distribution of price elasticities (own-price) for each brand. The majority of elasticities fall between -0.5 and -2.5 with poorer households having larger elasticities (in magnitude).[30]

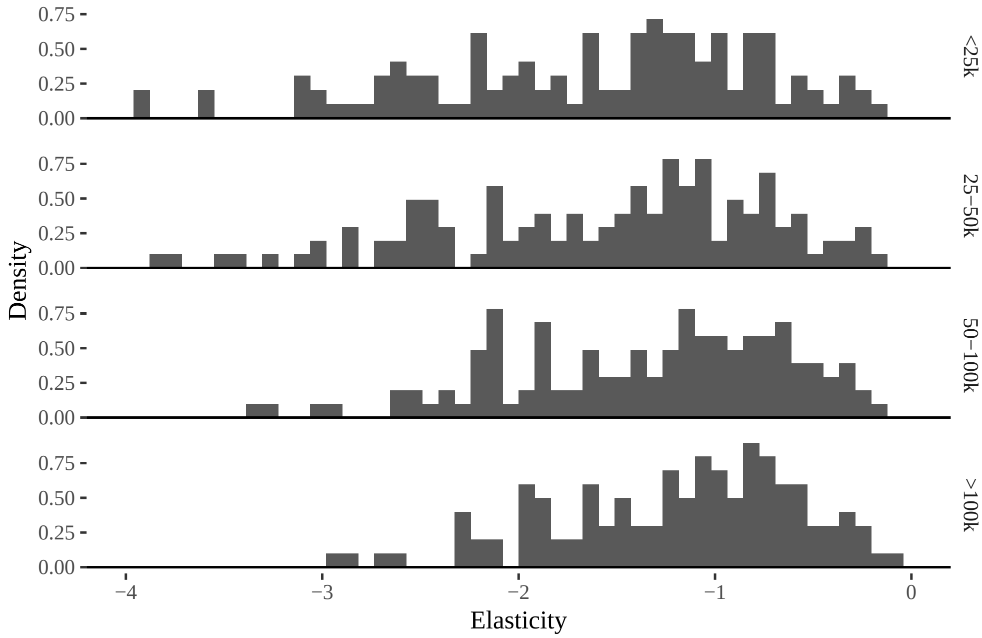
To check the reasonableness of the estimates, I compute the willingness-to-pay measure for each coefficient by dividing each coefficient by the price coefficient. Households are willing to pay between \$0.42 and \$0.62 for a \$0.01 reduction in the unit price of the package, which is reasonable given that a wide range of packages will last for one to two months (See Figure 11).

Turning to storage costs, all households prefer 12-roll packages, but households in the lowest quartiles of the income distribution are willing to pay more to avoid large packages than higher income households, which supports the hypothesis that they face higher storage costs. While low-income households also dislike smaller packages, they are more willing to accept a smaller package relative to higher income households.

These results support my earlier findings that unit price regulations affect a household's bulk buying decision. Storage is more costly for low-income households compared to high-income households. These estimates show that low-income households are more price-sensitive, but their high storage costs counteract this preference. In the counterfactuals, I predict how the bulk buying gap changes in response to regulatory changes and reductions in storage costs.

[30]Table 4 of Cohen (2008) reports elasticities ranging from -1.94 to -2.54 for paper towels. My estimates cover this range, but are generally much lower with a large mass between -0.5 and -1.5. Demand for toilet paper is likely less elastic than toilet paper since kitchen towels or paper napkins can substitute for paper towels. Toilet paper does not have any similar, readily available, substitutes.

Figure 12: Distribution of Price Elasticity by Household Income



Notes: Using 2016 Nielsen Consumer Panel and Retail Scanner data, this figure plots the distribution of price elasticities resulting from the estimation of Equation 12.

6.1 Model Fit

Table 9 compares the overall model predictions to the actual data. The model fits the data quite well, even given its parsimony. It slightly over-predicts purchasing for all households, but this is primarily because it does not capture some products are disproportionately popular (or unpopular) relative to what would be expected based on their characteristics. For example, a particular Charmin 6-pack has a 9-10% share for each income group, but based on its characteristics, the model only predicts a 6-7% share. Including a product-specific effect would ensure a better fit, but at the cost of reducing the interpretability and intuition of the model. I opt to maintain the parsimony and interpretability of the model and simulate counterfactuals using this specification.

7 Counterfactuals

Using the parameter estimates from the previous section, I predict how households respond to lower storage costs and universal unit price regulation. For these counterfactual exercises, I compare all counterfactual results to a "base case" of predicted purchases given their current shopping environment. I consider two counterfactual scenarios:

1. **Unit-Price Regulation:** Unit-price regulations are adopted everywhere.

Table 9: Multinomial Logit Model Fit (Days' Supply Purchased)

Income	Data	Model
<25k	48.54	49.38
25-50k	49.09	50.13
50-100k	51.24	52.18
>100k	53.63	54.24

Notes: Using 2016 Nielsen Consumer Panel and Retail Scanner data, this table compares the average days' supply of toilet paper purchased in the data with the predicted purchase from the model. I assume an average daily consumption rate of 57 two-ply sheets per day (Jaffe 2007).

2. **Reduced Storage Costs:** All households have the same storage costs (i.e. size preferences) as high-income households.

For the unit-price regulation scenario, I set each household's price coefficients (both total and unit prices) to the sum of their coefficient and the regulation interaction term. For households making under \$25,000, their price coefficient becomes $-0.193 + 0.032 = -0.161$. For the reduced storage cost scenario, I set all size coefficients equal to the coefficients for households making over \$100,000.

Table 10 reports the counterfactual predictions. When unit price regulations are adopted, all households increase their purchasing, with lower income groups increasing the most. As a result, the gap between the top and the bottom quartiles closes by 30%. Equalizing storage costs closes another 42% of the gap and almost closes it completely for all but the poorest households.

Table 10: Predicted Effects on Bulk Purchasing

Income	Base	+ Unit Price Regs	+ Rich Storage
<25k	49.38	52.35	54.45
25-50k	50.13	53.20	55.53
50-100k	52.18	54.24	55.23
>100k	54.24	55.97	55.97

Notes: This table reports predicted package quantities purchased by households using model estimates of Equation (12). Units are number of days the chosen package will last assuming average daily consumption rate of 57 two-ply sheets (Jaffe 2007). The "Unit Price Regs" scenario imposes unit price regulations everywhere. The "Rich Storage" scenario imposes that all households have the same preferences for "large" packages as households making over \$100k. Scenarios are cumulative.

These counterfactuals support the main findings from Section 4 which showed that unit price regulations increase bulk buying and that storage costs are a substantial factor preventing households from buying in bulk. Since the earlier sections examined bulk purchasing across all non-food products, I repeat the earlier analysis on mover households specifically for toilet paper purchases. I estimate a modified version of Equation 5 which replaces share of bulk purchases with log days' supply of toilet paper:

$$Log(DaysSupply)_{it} = \beta_1 Reg_{it} + \beta_2 SingleFamily_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \epsilon_{it}, \qquad (17)$$

Table 11 shows that households increase the days' supply purchased by 3.5% when unit prices are posted and by 2.6% when they move into a single-family home. The model predictions are in line with these changes. The model predicts that purchasing increases by 3-6% when unit prices are posted and by 2-4% when storage costs are reduced. Overall, reducing cognitive costs and increasing the salience of unit prices helps households make better value decisions, and generate a similar boost to bulk buying as reducing storage costs.

Table 11

	(1)	(2)
Regulation	0.029*	0.035**
	(0.015)	(0.015)
Single-Family Home		0.026***
		(0.006)
Household FE	Y	Y
Year FE	Y	Y
Demographics	N	Y
Observations	4,553,957	4,553,957
Adjusted R^2	0.507	0.508
Notes:	*p<0.1; **p<0.05; ***p<0.01	

Notes: Using 2004–2017 Nielsen Consumer Panel data and state-level regulations, this table shows estimates of Equation 5 which regresses household bulk buying on unit price regulation after controlling for household fixed effects and changes in household characteristics. "Regulation" denotes the estimated effect of moving from a state without regulation to a state with regulation. Standard errors are clustered at the household level.

8 Conclusion

This paper documents a new dimension of inequality, the bulk-buying gap in which high-income households buy in bulk more often than low-income households, thereby paying lower unit prices for the same goods. This gap is especially large for storable, necessity items like toilet paper and paper towels. Because they do not take advantage of quantity discounts, low-income households spend 5% more on grocery items than if they bought in bulk like high-income households. I provide evidence that *cognitive costs*, *store access*, and *storage costs* contribute to this gap.

I show that *where* a household shops accounts for a large portion of this disparity and that warehouse clubs increase bulk buying, but only for middle- and high-income households. Low-income households are unlikely to shop at warehouse clubs, even if they are nearby. Furthermore, using between-state variation in regulations on posting unit prices, I find that regulations that reduce cognitive costs and increase the salience of unit prices increase bulk buying.

Combining these features into a discrete choice model of toilet paper purchases, I predict how households' bulk purchasing changes if unit-price regulations are adopted universally and if storage costs are removed. I find that unit-price regulations close the bulk buying gap by about 30% and reducing storage costs closes the gap an additional 40%.

This paper is one of the first to focus on consumer's take-up of quantity discounts and explore the factors that contribute to this decision. It provides evidence that differences in bulk buying are due to *cognitive costs*, *store access*, and *storage costs*. Furthermore, this paper demonstrates that inequality persists even within everyday shopping trips because high-income households are more likely to take advantage of quantity discounts than low-income households. These differences have substantial financial consequences for the poorest households and are likely to generate systematic underestimates of consumption inequality if quantity discounts offset quality differences between products. Additionally, if the prices of large and small packages evolve differently, then households may experience substantial changes in their buying power. Future work will determine the extent to which inequality and inflation measures are underestimated because of quantity discounts.

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A Appendix

A.1 Data Appendix

The Nielsen Consumer Panel consists of about 40,000–60,000 US households that provide information on their shopping purchases using in-home scanners or Nielsen's mobile app. Panelists are geographically dispersed and demographically balanced. Households are recruited based on key demographic characteristics, primarily household size, income, age, education, presence of children, race, ethnicity, and occupation. To generate national averages, Nielsen assigns each household a projection factor.

Households are recruited through direct mail and online invitations. To incentivize households to remain in the panel, Nielsen provides monthly prize drawings, sweepstakes, points, and regular communication and support to panelists. Nielsen tries to ensure that incentive methods are non-biasing and regularly tests for its correlation with retention rates.

To ensure data quality, Nielsen filters out any households that are poor reporters and do not meet minimum spending thresholds based on their household size. All households in the sample meet this threshold for the full year.

Demographic variables are recorded and updated annually. For my analysis, I collapse some of the demographic variables into more aggregate categories. Household composition measures the number of adult men, adult women, and children under the age of 18 residing in the home. Marital status is an indicator for whether the head of household is married or not (I do not distinguish between single, divorced, or widowed). Presence of children is an indicator for whether or not there is at least one child under the age of 18 present in the household. Education is an indicator for whether at least one head of household completed college. Finally, age is the age of the head of household. In the case of two heads, I average the two ages.

To construct my analysis sample, I remove any households where the head of household is a student or a member of the military because these households likely have different living arrangements that are not representative of a typical household's decision (i.e. on campus housing or barracks are different than traditional homes and apartments). I drop any households living in mobile homes as well because this type of housing could include a wide range of house types including RVs and manufactured homes. I also remove any households making less that $5,000 and those that could not be geocoded based on their ZIP code and the 2017 Census Gazetteer which provides a correspondence between ZIP codes and the latitude and longitude of the centroid of the ZIP code. Finally, some households were dropped because they could not be matched to tract-level car ownership data. Table 12 reports how many households were removed based on this cleaning procedure.

Table 12: Homescan Sample Construction

Step	HH
Starting HH:	178,232
Exclude military and students:	175,102
Exclude Households under 5k:	174,106
Exclude Mobile Homes:	167,065
Drop ZIPs Not Geocoded:	166,366
Cannot Be Matched to Car Access:	166,164

Notes: Using 2004–2017 Nielsen Consumer Panel data, this table reports the number of unique households in the sample after each step of data refinement.

In the purchase data, I exclude alcohol, tobacco, pet items, health and beauty items, general merchandise, "magnet," and "deferred" product categories from my analysis. Alcohol and tobacco are excluded because of their addictive qualities, which may induce peculiar purchase patterns. For example, a smoker may choose to only buy one pack of cigarettes with the intention of quitting even though a full carton may deliver a better value. Pet items are excluded to focus on products intended for human consumption. I exclude health and beauty items and general merchandise because these products such as trash cans, printers, eye shadow, and antacids are unlikely to be bought in bulk or have irregular consumption patterns. "Deferred" categories are categories that Nielsen has stopped tracking, so to maintain a consistent sample of products, these are excluded from my analysis. Finally, "magnet" purchases are items which do not have a UPC codes such as fresh fruits and vegetables, deli counter items, or bakery items. Because these items are only recorded for a subset of Nielsen households and are not standardized, I also exclude them from my analysis. This process leaves me with 721 unique product categories. Because this paper focuses on bulk purchases, I also exclude 28 categories that have five or fewer sizes across all products.[31] Overall, the products analyzed are common household staples including almost all food categories, basic toiletry items, and non-food essentials like toilet paper, soaps/detergents, and diapers. See Table 13 for summary statistics of the top 20 product categories by annual spending.

[31] These excluded categories are: jelled aspic salad, sour cream sauce mix, canned roast beef, canned roast beef hash, retort pouch bags, prepared sandwiches, canned rice, canned dumplings, canned bread, frozen vegetables in pastry, frozen grapefruit juice, frozen grape juice, frozen orange juice, frozen cream substitutes, canned ham patties, bathroom accessory, packaged soap, borateem, dry starch, grease relief, bathroom brushes, miscellaneous brushes, thermometers, dustpans, feather dusters, laundry baskets, sanitary belts, gift package with candy or gum.

Table 13: Summary Statistics of Top 20 Product Categories in Nielsen Homescan Data (2017)

Product	Annual Spending	SD	Avg. Price	SD	Avg. Size	SD
Soft Drinks	79.38	139.02	4.75	4.17	85.87	53.81
Diet Soft Drinks	74.82	132.79	4.73	5.07	84.18	65.06
Milk	65.65	77.02	3.11	1.79	97.79	35.00
Cereal	57.97	68.37	4.06	2.10	18.05	8.17
Toilet Paper	56.15	49.47	11.44	7.09	17.09	10.51
Yogurt	55.00	75.68	3.28	2.17	17.25	15.22
Coffee	53.97	61.69	8.60	5.74	21.84	11.05
Bread	50.03	47.09	2.88	1.52	20.54	4.64
Cookies	46.97	57.60	3.59	3.44	13.02	6.39
Fresh Meat	46.96	62.86	7.75	5.03	30.48	24.97
Frozen Pizza	44.48	60.64	5.99	3.67	20.69	12.48
Bottled Water	44.06	73.46	4.21	3.75	261.91	181.39
Fresh Fruit	42.68	64.91	4.28	2.06	1.93	1.31
Chocolate Candy	41.05	53.83	3.91	3.67	8.64	9.15
Detergent	40.17	45.29	10.05	7.85	99.52	61.23
Shredded Cheese	39.16	42.80	4.21	2.45	13.37	10.98
Bacon	37.63	45.44	6.87	4.67	17.42	11.88
Ice Cream	37.36	50.34	4.43	2.03	46.80	24.47
Potato Chips	35.99	41.71	3.04	1.89	8.87	3.81
Canned Soup	32.39	38.36	3.21	2.22	22.07	17.33

Notes: Using 2004–2017 Nielsen Consumer Panel data, this table reports summary statistics for the top 20 product categories by total spending. Annual spending is the average spending in that product category among households that purchased in that product category over the course of the year. Average price and average size are the average prices and sizes of products purchased in their corresponding category. All estimates are weighted using Nielsen's projection weights. Prices are in nominal 2017 dollars. Sizes are reported in common units for for that category (e.g. ounces for milk).

To compare sizes across different product categories, I assign each product to its quintile in the size distribution for that product category. I assign quintiles based upon the sample quintiles of product sizes to ensure that each quintile has 20% of available products in its support. An alternative strategy would assign quintiles based on cutting the range of product sizes into equal intervals. However, in some product categories, this risks generating quintiles with sparse support when there is an especially large package available. As an example, consider eggs. Most packages contain 6, 12, or 18 eggs, but there are some products that offer up to 15-dozen eggs (180 eggs). Generating quintiles by cutting the available range into equal intervals would generate quintiles of 1-36, 37-72, 73-108, 109-144, 145-180 which would assign almost all packages to the first quintile and the fifth quintile. Using the sample quintiles generates a more even distribution ensuring better support of each quintile. For products with a narrow range of sizes, I assign the product to the minimum quintile. For example, over 60% of egg products are dozens, which covers three quintiles. I assign all products with 12 or fewer eggs to the first quintile.

A.2 Quantity Discounts and Coupon Savings

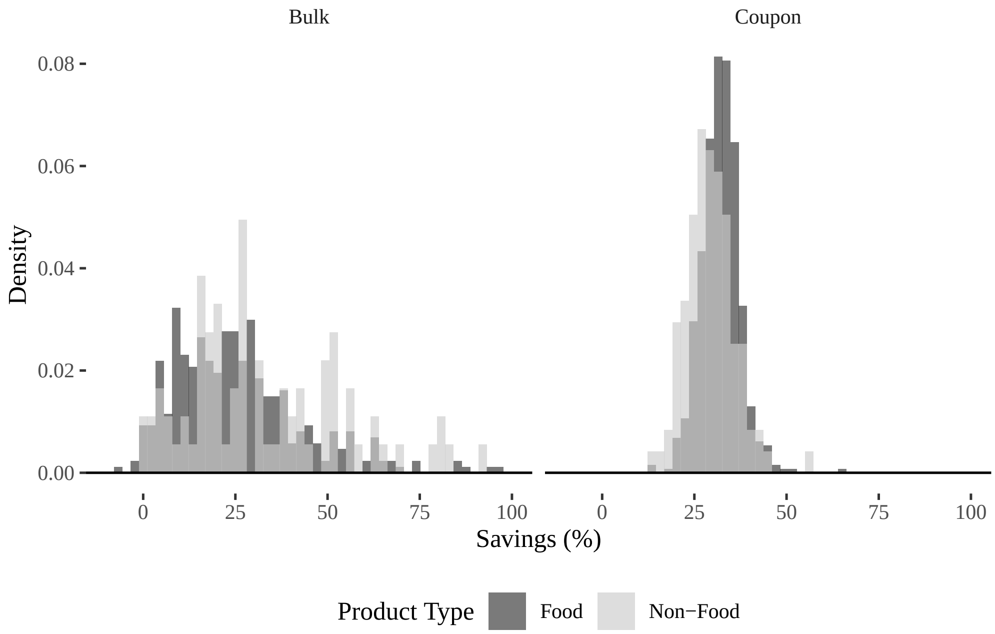
This section compares savings from quantity discounts to savings from coupons. To be conservative, I compare the savings from redeemed coupons (likely higher than the average savings of all coupons offered) to savings offered by quantity discounts (likely lower than quantity discounts actually redeemed). For each product purchased in the Consumer Panel data, households can input the value saved if they used a coupon. For each product category, I compute the average discount across all products in that category.

I then estimate quantity discount savings based on moving from a product in the second quintile to the fourth quintile of the size distribution. This leaves out small product sizes that may have high unit prices due to convenience (e.g., a 20-oz soda bottle at the checkout counter) and especially large sizes that may not be widely available at all stores. This range covers sizes that households are likely to consider when making their purchase decision.

Figure 13 plots the distribution of coupon savings and estimated bulk savings for food and non-food products. Coupon savings are narrowly clustered with a median savings of 31% for non-food products and 33% for food products. Bulk discounts have lower median savings for non-food and food products of 27% and 23%, respectively, but are more widely dispersed, even exceeding 50% savings for some non-food products.[32] Coupon savings are similar across product categories while there is substantial variation in quantity discounts with non-food

[32] Smaller shifts, such as from the second to third quintile or third to fourth quintile generate smaller savings, but still preserve the long right tail primarily for non-food products.

Figure 13: Percent Savings from Coupons and Bulk Discounts



Notes: Using 2004–2017 Consumer Panel and 2016 Retail Scanner data, this figure plots the distribution of savings from coupons and quantity discounts. For each coupon redemption, the percent savings are the ratio of the coupon value to the product's price. These savings are then averaged across all purchases in that product category. Bulk discounts are computed using coefficient estimates obtained from Equation (1) relating log unit prices to log package sizes. Bulk savings are the estimated savings obtained from moving from the second to the fourth quintile of the size distribution for each product category.

products offering higher savings.

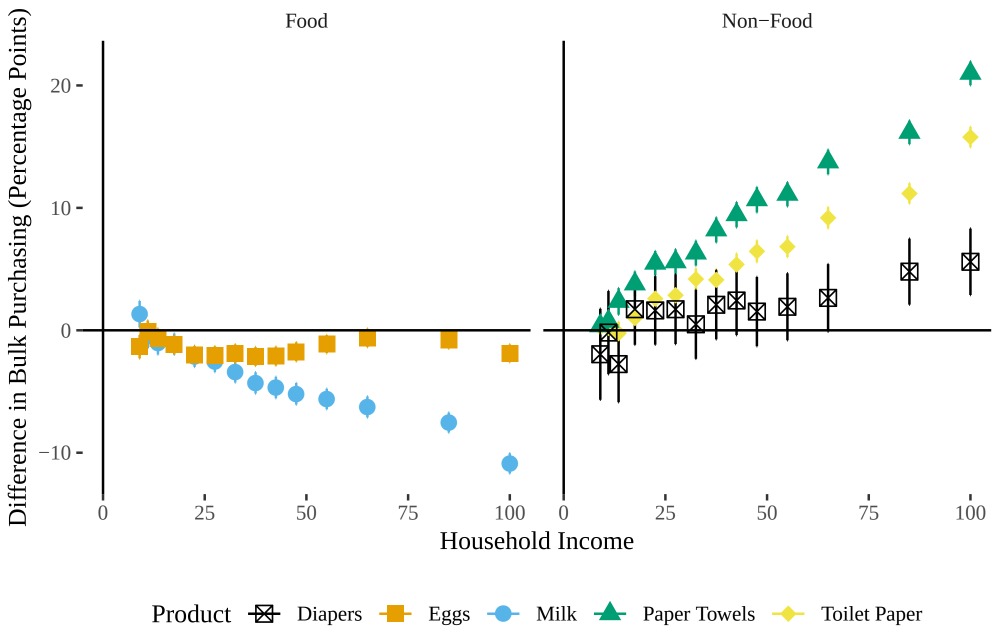
A.3 Bulk Buying Across Popular Categories

Across popular spending categories, these gaps are particularly large in storable, non-food categories like paper towels and toilet paper, where households making over $100,000 are more than twice as likely to buy in bulk compared to households making under $25,000. In popular food categories like milk and eggs, there is little relationship or even a negative relationship between income and bulk buying (See Figure 14).

A.4 Alternative Calculation of Missed Quantity Discounts

An alternative way of calculating savings from quantity discounts is to calculate first-best savings obtained from purchasing the lowest unit-priced item available, since even high-income households may not be buying at the lowest unit price. I compute this by taking the difference between the unit price paid by each household and the lowest unit price available in the store, given the household's brand preference. I get this information through linking the Nielsen

Figure 14: Bulk Purchasing by Household Income and Product Type



Notes: Using 2004–2017 Nielsen Consumer Panel data, this figure plots the income bin coefficients from Equation (2), which regresses the share of annual purchases that were bulk packages on income, household composition, age, and marital status as well as market and year fixed effects. This regression is estimated for milk, eggs, diapers, toilet paper, and paper towels. Nielsen projection weights are used to ensure national representativeness. Households making $5–8k are the reference group. Standard errors are clustered at the DMA level. Coefficient values are reported in Appendix Table 20

Consumer Panel with the Nielsen Retail Scanner data.

I compute the first-best savings a household could obtain for toilet paper, diapers, milk, and eggs using the following approach.[33] First, for each shopping trip, I compute the lowest unit price the household could have paid given its brand and store choice in that week. The difference in unit prices relative to the unit price chosen is a household's first-best savings for that purchase. Then, to get the average savings for a household, I compute the expenditure-weighted average savings across all purchases for each household. Based on this measure, Table 14 reports average excess spending by income group, computed for a family of four.

Table 14: First-Best Savings by Household Income and Product

	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

Notes: This table uses 2006–2016 Nielsen Retail Scanner and Consumer Panel data to compute average savings a household could achieve given its brand and store choice. Average savings for a family of four is reported above. For example, a household making <$25k could save 36% by purchasing at the lowest unit price available.

Overall, households could save over 30% by buying in bulk and low-income households could save even more. I estimate the differences in savings between households from the following regression:

$$Y_{imt} = \sum_q \beta^q Income_{imt} + \gamma X_{imt} + \lambda_{mt} + \epsilon_{imt}, \tag{18}$$

where Y is the excess spending of household i in market m in year t. $Income$ is the household's income bin and X consists of demographic measures (age, marital status, household composition, education). λ is a market-year fixed effect. Table 15 shows that low-income households miss out on two percentage points more savings than high-income households and the excess spending is primarily in non-food categories like toilet paper (36% savings) and diapers (33% savings) as opposed to food categories like milk (31% savings) and eggs (17% savings). Given the perishability of food items, these savings may not be realized if the product perishes before it can be consumed.

Overall, low-income households could benefit substantially from buying in bulk and obtaining lower unit prices. Furthermore, these savings are likely to be more important for low-income

[33] Due to computing and data storage constraints, I cannot do this for more than a few categories.

Table 15: Regression Results of First-Best Savings Across Household Income and Products

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

Notes: This table uses 2006–2016 Nielsen Retail Scanner and Consumer Panel data and reports the income coefficients of Equation (18), which regresses savings on household demographics (household income, composition, age, education, and marital status) as well as a market and year fixed effect. Units are percentage points. For example, a household making over $100k have 2 percentage points lower excess spending than households making under $25k. Nielsen's projection weights are used for national representativeness.

households since the marginal utility of an additional dollar of savings is likely to be higher than for high-income households. This analysis also provides evidence that all households could benefit from purchasing at the lowest unit price.

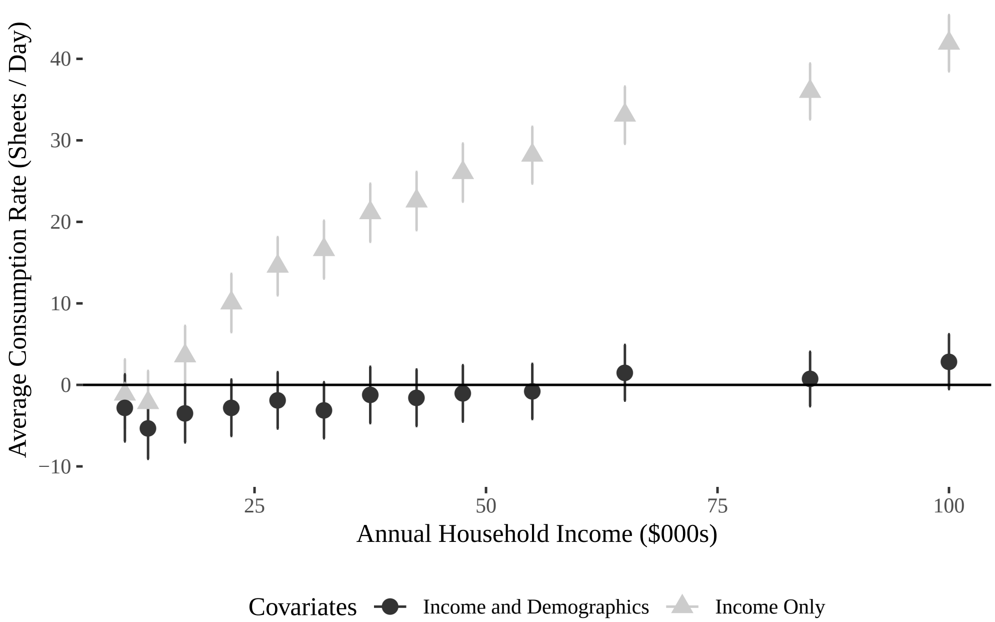
A.5 Annual Consumption Analysis

I show that income is not predictive of a household's toilet paper consumption rate first using basic OLS regressions. I then formalize the result using a 100-fold cross-validated elastic net regression to select the most predictive variables. If income and toilet paper consumption are related, then an OLS regression will extract the correlation.

First, I compute a household's daily consumption by aggregating the total number of sheets purchased by a household in a given year, excluding the final purchase of the year since it may not be consumed within the year. I divide this total by the number of days between the first and last purchase of the year to get a household's average daily consumption rate. This method avoids complications where end of the year inventory may be carried over to the following year or a household may start the year with some inventory.

Given a household's average daily consumption rate, I estimate an OLS regression of con-

Figure 15: Average Daily Consumption by Household Income



Notes: Using 2004–2017 Nielsen Consumer Panel data, this figure plots the income bin coefficients from Equation (19), which regresses average daily household toilet paper consumption on household demographics (household composition, age, marital status, and education). Average daily consumption is computed by dividing total quantity purchased in a year by the number of days a household was active in the panel.

sumption on household characteristics:

$$Y_i = \beta X_i + \epsilon_i, \tag{19}$$

where Y is household i's average daily consumption and X is a vector of household characteristics. Figure 15 plots the income coefficients of an OLS regression including only income covariates and the coefficients when household composition, age, marital status, and education are included. The graph illustrates that after controlling for covariates that plausibly cause increased consumption, income is not significantly correlated with consumption.

The above specification omits many other possible covariates that could be correlated with average daily consumption. When there are many possible variables that can be included, there is a risk of over-fitting. Elastic net regularization is a machine learning method that penalizes over-fitting and selects only the most predictive variables.

The elastic net solves the following minimization problem:

$$\min_{\beta} \|y - X\beta\|^2 + \lambda \left(\alpha \|\beta\|_1 + (1-\alpha)\|\beta\|_2^2 \right), \tag{20}$$

where $\|\cdot\|_1$ is the L1 norm and $\|\cdot\|_2$ is the L2 norm. The OLS estimate is the β that solves the minimization problem with only the first term. The second term and third term provide penalties to shrink and select for the most predictive variables.

I set the mixing parameter α to be 0.5. When covariates are correlated in groups, lasso regression ($\alpha = 1$) tends to only select one and discard all other members of the group while ridge regression ($\alpha = 0$) tends to shrink correlated coefficients towards each other (Zou and Hastie 2005). Because some of the possible covariates form natural groups (e.g., all income bins or all markets), I chose $\alpha = 0.5$ since this tends to include or exclude groups together.

I estimate a 100-fold cross-validated elastic net regression to select the most predictive covariates. The resulting estimates selects many household characteristics including household composition, age, marital status, and race, but excludes almost all income and geographic coefficients.[34]

A.6 Implications for Inequality

Because quantity discounts are disproportionately taken up by high-income households, consumption inequality is persistently understated. In this section, I quantify the extent of this underestimation.

I quantify consumption inequality in terms of unit prices since this is a more natural way of capturing quantity discounts. This approach abstracts away from consumption inequality attributable to differences in quantity consumed. For normal goods, adding this dimension will serve to further increase consumption inequality since high income households will consume larger quantities of the goods, compounding the inequality generated by lower unit prices. Unit prices are a conceptually simple way to approach consumption inequality. In the absence of quantity discounting, unit price differences would logically be attributed to differences in quality, such as brand or store amenities.

However, quantity discounts complicate this measurement. Consider the following example: a homogeneous product has a quantity discount. If some households buy large packages with low unit prices ("bulk" buyers) and some buy small packages with high unit prices ("budget" buyers), then the quantity discount would generate a difference in the underlying unit price. Even more troublingly, the inequality would be of the wrong sign. If one did not account for the quantity discount and only assumed unit price differences reflected differences in quality, then one would conclude that the "budget" buyers were better off than the "bulk" buyers, which is untrue since the "bulk" buyers obtain the same good more cheaply.

[34] Elastic net results are available upon request.

To quantify how much consumption inequality is underestimated, I decompose the unit price of each product category into store, brand, and size components using the following regression (estimated separately for each product category and year):

$$\log(unitPrice)_{ibr} = \beta \log(pkgSize)_{ibr} + \lambda_b + \lambda_r + \epsilon_{ibr}, \tag{21}$$

where *unitPrice* is the unit price of a product purchased by household i of brand b at retailer r. *pkgSize* is the quantity contained within the package. Brand and retailer components are captured by λ. All coefficients are relative to the reference category which is the generic brand product sold at the most popular discount retailer.

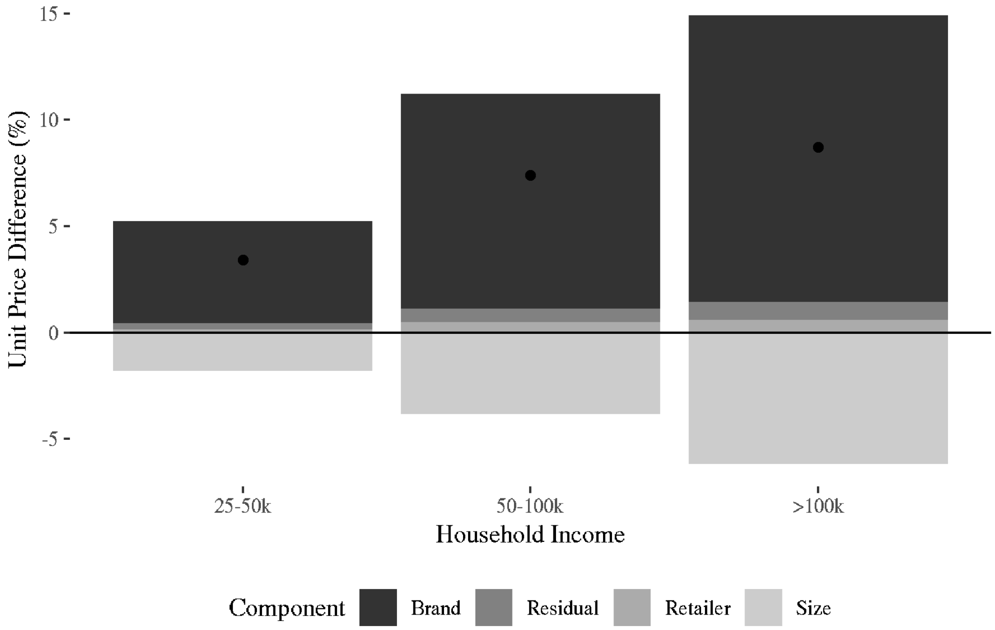
Using the estimates from Equation (21), I decompose each purchase into a brand, retailer, and size component. I then aggregate these components to the household level by taking the expenditure-weighted average of the components across all purchases made by a particular household. I then regress each of these components on household income and other demographics (household composition, age, marital status, and education) to determine which components contribute to the difference in unit prices paid by different income groups.

$$Y_{it} = \beta Income_{it} + \gamma X_{it} + \lambda_t + \epsilon_{it}, \tag{22}$$

where Y is the average brand/retailer/size component for household i's purchases made in year t. X consists of household composition, age, marital status, and education. Year fixed effects are captured by λ. The regression is weighted using Nielsen's projection weights. Figure 16 plots the income group coefficients for each component on all toilet paper purchases. First, the plotted points show that the average unit price paid increases with household income. The decomposition shows that this increase is overwhelmingly due to brand composition with a small, but significantly positive contribution from retailer composition. Excluding a residual component, households making over \$100,000 would pay 14% higher unit prices based on brand and store choices (13% from brand choice and 1% from store choice). Bulk discounts are estimated to reduce unit costs by six percentage points. As a result, consumption inequality in this category would be understated by 43% (unit prices for high-income households would be 8% compared to the "true" difference of 14%). Due to a residual factor, the measured difference in unit prices is 9%, so the "true" difference is understated by a still-substantial 36%.

Bulk discounts have large implications for price 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

Figure 16: Decomposition of Unit Price Differences



Notes: Using 2004–2017 Nielsen Consumer Panel data, this figure plots the contribution of brand, store, and package size choices to the differences in unit prices paid for toilet paper for different income groups relative to households making less than $25,000. Dots denote difference in average unit price paid by each income group relative to households making under $25,000. See Appendix Table 16 for values.

Table 16: Unit Price Decomposition (Toilet Paper)

	Unit Price	Brand	Retailer	Size	Residual
	(1)	(2)	(3)	(4)	(5)
25-50k	0.034***	0.048***	0.001***	−0.018***	0.003***
	(0.001)	(0.001)	(0.0002)	(0.0004)	(0.001)
50-100k	0.074***	0.101***	0.005***	−0.038***	0.006***
	(0.001)	(0.001)	(0.0002)	(0.0004)	(0.001)
>100k	0.087***	0.135***	0.006***	−0.062***	0.009***
	(0.002)	(0.001)	(0.0002)	(0.0005)	(0.001)
Observations	710,647	710,647	710,647	710,647	710,647
Adjusted R^2	0.031	0.212	0.064	0.684	0.001

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Using 2004–2017 Nielsen Consumer Panel data, this table reports the contribution of brand, retailer, and package size to the average log unit price obtained by each household income group. Log unit prices were decomposed using Equation (21). Each household's component composition is the expenditure-weighted average of each component applied to each of its purchases. Household-level components were then regressed on household income, size, age, marital status, and presence of children. Income coefficients are reported above.

and Pistaferri 2014; Aguiar and Bils 2015). Under the assumption that homogeneous goods have the same prices, increased expenditures directly correspond to increased consumption. However, as Kaplan and Menzio (2015) show, prices for homogeneous goods are not the same and this non-uniformity 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.[35]

Using hedonic regression, I find that unit prices are underestimated by about 10% due to quantity discounts, but this underestimation varies widely across product categories. See Appendix for analysis.

Previous research has documented that this "spikiness" has strong implications for measuring consumption inequality (Coibion, Gorodnichenko, and Koustas 2017). Furthermore, quantity discounts could have implications for inflation measurement as well. Given the prevalence of quantity discounts, if a basket price is computed using the largest package available, measured prices may underestimate the price faced by consumers that cannot afford that package, or buy the same amount in smaller shopping trips. For example, the BLS uses unit-prices when computing the price of the CPI market basket. Therefore, the choice of package size can strongly influence this price. If the prices of different package sizes fluctuate differently, quantity discounts could systematically affect our measurement of inflation. Further research would be necessary to determine if inflation rates differ across product sizes is the case and what the magnitude could be.[36]

A.7 Appendix Tables

[35]This dispersion results 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.

[36]The BLS specifically deals with multi-unit discounts buy using the "first multiple-unit price" as the price measured. However, the method for dealing with different package sizes is less well defined. Per correspondence with the BLS: "In general, price-per-unit calculations are the standard practice in calculating items with quantity changes. For example if a loaf of bread is $1 and you a second loaf for $0.50, you have two loaves for $1.50, and then depending on the weight of the two loaves, you divide the $1.50 by number of ounces and get a price per ounce. Due to sample rotation, there is no guarantee that any specific item and specific size – toilet paper, olive oil, etc. – will be in the sample at a given time. If it is, and the economic assistant can't find the specified size and has to substitute to a different size, price change is calculated on a per unit basis, as illustrated in the above example." Given that the BLS uses unit-prices to compute market basket prices, the choice of package size could strongly influence the computed price of the market basket.

Table 17: Correlation of Bulk Buying and Demographics (Food Products)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
8-10k	−0.003	−0.002	−0.002	−0.002	−0.002	−0.003	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
10-12k	−0.001	−0.002	−0.002	−0.004**	−0.004**	−0.005	−0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
12-15k	0.0001	−0.002	−0.0005	−0.003**	−0.003*	−0.004	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
15-20k	0.001	−0.003**	−0.002	−0.006***	−0.005***	−0.006	−0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
20-25k	0.007***	−0.0002	0.001	−0.004***	−0.003**	−0.005	−0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
25-30k	0.013***	0.003**	0.004**	−0.004***	−0.003**	−0.004	−0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
30-35k	0.015***	0.004***	0.004***	−0.004***	−0.003**	−0.003	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
35-40k	0.020***	0.006***	0.006***	−0.002	−0.001	−0.001	−0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
40-45k	0.022***	0.008***	0.008***	−0.001	0.0004	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
45-50k	0.026***	0.009***	0.009***	−0.001	0.001	0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
50-60k	0.027***	0.008***	0.008***	−0.002	0.0004	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
60-70k	0.032***	0.012***	0.012***	0.001	0.004***	0.005	0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
70-100k	0.036***	0.013***	0.012***	0.002	0.005***	0.007*	0.008**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
>100k	0.038***	0.013***	0.012***	0.001	0.007***	0.009**	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Married		0.043***	0.042***	0.018***	0.017***	0.016***	0.017***
		(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.001)	(0.001)
Age			−0.0003***	0.0002***	0.0001***	0.0002**	0.0002**
			(0.00001)	(0.00001)	(0.00001)	(0.0001)	(0.0001)
Men				0.033***	0.033***	0.031***	0.031***
				(0.0003)	(0.0003)	(0.001)	(0.001)
Women				0.005***	0.004***	0.004***	0.004***
				(0.0002)	(0.0002)	(0.001)	(0.001)
Children				0.018***	0.018***	0.017***	0.017***
				(0.0002)	(0.0002)	(0.001)	(0.001)
College					−0.010***	−0.008***	−0.008***
					(0.0004)	(0.002)	(0.002)
Market FE's	N	N	N	N	N	N	Y
Year FE's	N	N	N	N	N	N	N
Observations	769,430	769,430	769,430	769,430	769,430	769,430	769,430
Adjusted R^2	0.009	0.029	0.029	0.059	0.059	0.103	0.104

Note: *p<0.1; **p<0.05; ***p<0.01
Source: Author calulations from Nielsen Consumer Panel. Columns (7) and (8) cluster standard errors at the market level

Table 18: Correlation of Bulk Buying and Demographics (Non-Food Products)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
8-10k	0.008***	0.008***	0.008***	0.008***	0.008***	0.005	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
10-12k	0.022***	0.022***	0.021***	0.020***	0.020***	0.016**	0.013*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.007)
12-15k	0.024***	0.022***	0.021***	0.020***	0.020***	0.019***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
15-20k	0.033***	0.030***	0.029***	0.027***	0.026***	0.024***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
20-25k	0.050***	0.044***	0.043***	0.041***	0.040***	0.037***	0.034***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
25-30k	0.055***	0.047***	0.047***	0.043***	0.042***	0.039***	0.037***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
30-35k	0.069***	0.060***	0.060***	0.056***	0.054***	0.050***	0.048***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
35-40k	0.075***	0.065***	0.065***	0.061***	0.058***	0.054***	0.052***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
40-45k	0.083***	0.072***	0.072***	0.068***	0.064***	0.060***	0.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
45-50k	0.093***	0.080***	0.080***	0.075***	0.071***	0.066***	0.063***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
50-60k	0.099***	0.085***	0.085***	0.080***	0.075***	0.071***	0.068***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
60-70k	0.116***	0.101***	0.101***	0.096***	0.090***	0.084***	0.080***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
70-100k	0.136***	0.118***	0.119***	0.113***	0.105***	0.098***	0.096***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
>100k	0.172***	0.152***	0.152***	0.146***	0.135***	0.123***	0.115***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
Married		0.033***	0.034***	0.022***	0.024***	0.029***	0.028***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Age			0.0002***	0.0004***	0.0005***	0.0004***	0.0004***
			(0.00002)	(0.00002)	(0.00002)	(0.0001)	(0.0001)
Men				0.016***	0.017***	0.014***	0.015***
				(0.0004)	(0.0004)	(0.002)	(0.002)
Women				0.003***	0.005***	0.003**	0.003**
				(0.0004)	(0.0004)	(0.001)	(0.001)
Children				0.008***	0.008***	0.006***	0.007***
				(0.0003)	(0.0003)	(0.001)	(0.001)
College					0.020***	0.018***	0.017***
					(0.001)	(0.002)	(0.002)
Market FE's	N	N	N	N	N	N	Y
Year FE's	N	N	N	N	N	N	N
Observations	767,195	767,195	767,195	767,195	767,195	767,195	767,195
Adjusted R^2	0.050	0.054	0.055	0.057	0.059	0.083	0.090

Note: *p<0.1; **p<0.05; ***p<0.01
Source: Author calulations from Nielsen Consumer Panel. Columns (7) and (8) cluster standard errors at the market level

Table 19: Bulk Buying Within ZIP Codes, Store Types, or Retail Chains by Income

	ZIP Code		Channel/Retailer Type		
	(1)	(2)	(3)	(4)	(5)
8-10k	0.002	0.002	0.001	0.002	0.001
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
10-12k	0.014***	0.007**	0.012***	0.009***	0.009***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
12-15k	0.017***	0.011***	0.014***	0.008***	0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
15-20k	0.022***	0.017***	0.018***	0.010***	0.010***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
20-25k	0.035***	0.030***	0.028***	0.015***	0.015***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
25-30k	0.038***	0.034***	0.029***	0.013***	0.013***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
30-35k	0.050***	0.044***	0.037***	0.019***	0.018***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
35-40k	0.054***	0.051***	0.042***	0.018***	0.018***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
40-45k	0.061***	0.057***	0.043***	0.018***	0.017***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
45-50k	0.067***	0.062***	0.049***	0.021***	0.020***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
50-60k	0.072***	0.067***	0.052***	0.021***	0.020***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
60-70k	0.085***	0.079***	0.058***	0.022***	0.020***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
70-100k	0.102***	0.097***	0.071***	0.028***	0.026***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
>100k	0.125***	0.116***	0.083***	0.029***	0.028***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Demographics	Y	Y	Y	Y	Y
ZIP-Year FE	N	Y	N	N	N
Channel-Year FE	N	N	N	Y	Y
Chain-Year FE	N	N	N	N	Y
Observations	767,195	767,195	3,978,987	3,978,987	3,978,987
Adjusted R^2	0.088	0.267	0.012	0.221	0.238
Note:	*p<0.1; **p<0.05; ***p<0.01				

Notes: Using 2004–2017 Nielsen Consumer Panel data, this table displays the regression coefficients from estimating Equation eq:discountingBehaviorFE which regresses a household's annual share of bulk purchases of non-food products on household characteristics (household composition, age, marital status, and education) and includes a DMA and year fixed effect (Columns 1, 3, 5). Columns 2, 4, and 6 also include a ZIP code-year, store type-year, or retail chain-year fixed effect.

Table 20

	Toilet Paper	Paper Towels	Diapers	Eggs	Milk
	(1)	(2)	(3)	(4)	(5)
8-10k	0.001	0.003	−0.011	−0.015	0.014
	(0.010)	(0.010)	(0.033)	(0.009)	(0.012)
10-12k	0.009	0.009	0.005	−0.002	0.001
	(0.009)	(0.011)	(0.030)	(0.010)	(0.012)
12-15k	0.007	0.026***	−0.009	−0.004	−0.008
	(0.008)	(0.009)	(0.027)	(0.009)	(0.011)
15-20k	0.018**	0.042***	0.027	−0.009	−0.012
	(0.008)	(0.009)	(0.024)	(0.008)	(0.010)
20-25k	0.034***	0.060***	0.019	−0.017**	−0.020**
	(0.007)	(0.009)	(0.026)	(0.008)	(0.010)
25-30k	0.040***	0.062***	0.029	−0.017*	−0.024**
	(0.008)	(0.009)	(0.025)	(0.010)	(0.011)
30-35k	0.056***	0.073***	0.016	−0.014	−0.036***
	(0.008)	(0.009)	(0.025)	(0.008)	(0.009)
35-40k	0.057***	0.095***	0.032	−0.015*	−0.042***
	(0.008)	(0.010)	(0.025)	(0.008)	(0.009)
40-45k	0.069***	0.108***	0.031	−0.015*	−0.046***
	(0.008)	(0.010)	(0.025)	(0.009)	(0.010)
45-50k	0.080***	0.122***	0.022	−0.010	−0.050***
	(0.008)	(0.009)	(0.023)	(0.009)	(0.010)
50-60k	0.088***	0.129***	0.029	−0.005	−0.055***
	(0.007)	(0.009)	(0.024)	(0.009)	(0.010)
60-70k	0.112***	0.157***	0.036	0.001	−0.059***
	(0.008)	(0.010)	(0.024)	(0.009)	(0.009)
70-100k	0.135***	0.185***	0.059**	0.001	−0.071***
	(0.008)	(0.009)	(0.023)	(0.009)	(0.009)
>100k	0.185***	0.237***	0.067***	−0.009	−0.102***
	(0.008)	(0.010)	(0.021)	(0.009)	(0.010)
Married	0.053***	0.047***	0.022***	0.031***	0.062***
	(0.004)	(0.004)	(0.007)	(0.003)	(0.003)
Age	0.00001	0.002***	−0.003***	−0.001***	−0.002***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Men	0.012***	0.014***	0.009**	0.056***	0.096***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)
Women	0.024***	0.012***	0.008*	0.057***	0.045***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
Children	0.012***	0.004*	−0.014***	0.041***	0.093***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
College	0.029***	0.019***	0.046***	−0.047***	−0.033***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Market FE's	Y	Y	Y	Y	Y
Year FE's	Y	Y	Y	Y	Y
Observations	704,311	627,266	116,886	716,563	716,881
Adjusted R^2	0.090	0.080	0.040	0.133	0.170

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Using Nielsen Consumer Panel data from 2004–2017, this table reports the coefficients plotted in Figure 14. Standard errors are clustered at the market level.

Table 21: Package Size Differences by Income (Non-Food Products)

Category	25-50k	50-100k	>100k
POOL AND SPA CHEMICALS AND TREATMENT	0.155	0.432	0.746
BAGS - PAPER	0.177	0.423	0.538
PAPER TOWELS	0.131	0.278	0.407
BAGS - TALL KITCHEN	0.128	0.263	0.397
ALUMINUM FOIL	0.107	0.230	0.373
BAGS - TRASH/TRASH COMPACTOR	0.108	0.225	0.358
SOAP - BAR	0.131	0.253	0.349
BAGS - LAWN AND LEAF	0.108	0.222	0.349
FABRIC SOFTENERS-DRY	0.102	0.220	0.345
CLOTH-POLISHING/CLEANING	0.120	0.213	0.343
DISPOSABLE CUPS	0.102	0.210	0.310
TOILET TISSUE	0.096	0.199	0.296
BAGS - FREEZER	0.065	0.160	0.293
FIREPLACE LOGS	0.104	0.141	0.279
FACIAL TISSUE	0.057	0.134	0.264
TOILET BOWL - CLEANERS	0.066	0.140	0.252
WATER CONDITIONERS FILTERS AND UNITS	0.083	0.151	0.252
DETERGENTS-PACKAGED	0.116	0.204	0.246
FABRIC WASHES - SPECIAL	0.087	0.148	0.238
BAGS - SANDWICH	0.061	0.144	0.230
BAGS - FOOD STORAGE	0.072	0.136	0.210
CHARCOAL	0.063	0.129	0.204
DISHWASHER RINSING AIDS	0.049	0.118	0.196
SANITARY NAPKINS	0.054	0.118	0.184
CLEANERS - DISINFECTANTS	0.060	0.111	0.177
FABRIC SOFTENERS-LIQUID	0.049	0.101	0.161
CLEANERS - BATHROOM	0.057	0.109	0.155
TAMPONS	0.040	0.098	0.151
RUG CLEANERS	0.055	0.120	0.149
CHARCOAL/WOOD LIGHTERS	0.035	0.072	0.135
LAUNDRY AND IRONING ACCESSORIES	0	0.054	0.132
DRAIN PIPE OPENERS	0.023	0.064	0.131
DETERGENTS - HEAVY DUTY - LIQUID	0.040	0.085	0.127
AUTOMATIC DISHWASHER COMPOUNDS	0.047	0.094	0.117
MOTH PREVENTATIVES	0.074	0.089	0.117
DISPOSABLE DIAPERS	0.027	0.068	0.106
SOAP - SPECIALTY	0.039	0.062	0.105
MILDEW REMOVERS AND PREVENTATIVES	0.031	0.063	0.105
CLEANERS - POWDERS	0	0	0.100
DETERGENT BOOSTERS	0.057	0.077	0.100
DISPOSABLE DISHES	0.027	0.067	0.099
RUG AND ROOM DEODORIZERS	0.035	0.070	0.093
DYE AND DYE REMOVER	0	0.106	0.090
BAGS - OVEN	0.044	0.078	0.086
SOAP - LIQUID	0.058	0.074	0.085
CLEANERS - WINDOW	0.024	0.054	0.079
BATH ADDITIVES - DRY	0	0	0.077
DETERGENTS - LIGHT DUTY	0.020	0.042	0.073
ABRASIVE CLEANSERS-LIQUID	0.039	0.054	0.073
PAPER NAPKINS	0	0.034	0.072
POLISHES	0.019	0	0.072
DISINFECTANTS	0.030	0.052	0.067
STARCH - AEROSOL AND SPRAY	0.016	0.039	0.066
FURNITURE POLISH	0.006	0.031	0.064
CLEANERS-METAL	0	0.029	0.061
PLASTIC WRAP	0.018	0.030	0.058
UPHOLSTERY CLEANERS	0.039	0	0.056
RUST REMOVERS	0.032	0.057	0.055
AIR/SPECIALTY FRESHNERS - AEROSOL SPRAY AND PUMP	0	0.023	0.055
SPOT AND STAIN REMOVERS	0.037	0.067	0.043
AMMONIA	0.012	0.030	0.035
AIR/SPECIALTY FRESHENERS - SOLID	0.018	0.023	0.035
SODA STRAWS	0	0	0.034
FLOOR CARE - WAXES	0	0	0.032
BLEACH - DRY	0.040	0.023	0.030
HAND CLEANERS AND HAND SANITIZERS	0	0	0.024
CLEANERS - NON-DISINFECTANT	0	0.006	0.024
FLOOR CARE-CLEANERS	0	0	0.023
OVEN CLEANERS	0.012	0.017	0.022
WATER FILTRATION STORAGE CONTAINER	0.011	0	0.020
WAX PAPER	0.009	0.015	0.017
ABRASIVE CLEANSERS-POWDERED	0.008	0.020	0.013
SALT-WATER SOFTENING	0	0	0.009
BROOMS/ MOPS AND WAX APPLICATORS	0	0.007	0.008
BATH OIL - LIQUIDS	0	0.194	0
BLEACH - LIQUID/GEL	0	0	0
BLUINGS	0	0	0
BRUSHES-KITCHEN AND SCRUB	-0.005	-0.004	0
CLEANERS-HUMIDIFIERS/VAPORIZERS	0	0	0
CLEANERS-PASTE AND JELLY	0	0	0
DISPOSABLE LIDS	0	0	0
FABRIC FINISHERS	0	0	0
FABRIC PROTECTORS	0	0	0
FOOD WRAP - REMAINING	0	0	0
HEAT-CANNED	0	0	0
HOUSEHOLD AREA ALLERGEN CONTROL	0	0	0
MATCHES	0	0	0
SCOURING PADS	-0.041	-0.042	0
STARCH - LIQUID	0.036	0	0
TOILET BOWL - DEODORIZERS	-0.019	0	0
WATER SOFTENERS AND CONDITIONERS	0.023	0	0
COFFEE AND TEA FILTERS - DISPOSABLE	0	-0.009	-0.028
BAGS - WASTE	0	-0.020	-0.029
SPONGES AND SQUEEGEES - HOUSEHOLD	-0.033	-0.035	-0.032
LAUNDRY TREATMENT AIDS	0	-0.027	-0.034
CLOTHESPINS	0	0	-0.062
FABRIC SOFTENERS-AEROSOL	-0.083	-0.087	-0.072
LAUNDRY BAR SOAP	0	-0.071	-0.087
WOOD CHIPS-COOKING	0	-0.052	-0.090
PRE-MOISTENED TOWELETTES	-0.065	-0.086	-0.093
BAKING CUPS AND LINERS	-0.048	-0.066	-0.100
AIR/SPECIALTY FRESHENERS - REMAINING	-0.079	-0.121	-0.113
BATH ADDITIVES - LIQUID	-0.053	-0.070	-0.121
CLEANERS-SEPTIC TANK	-0.043	-0.088	-0.206
BATH OIL - DRY	0	0	-1.258

Table 22: Nielsen Consumer Panel Summary Statistics for States With and Without Unit Price Regulation

	Without Regs		With Regs	
Variable	Mean	SD	Mean	SD
Household income ($000s)	55.64	28.20	59.49	29.52
Household size	2.39	1.29	2.33	1.28
Age	56.07	12.94	57.07	13.08
College Educated	0.50	0.50	0.54	0.50
Child present	0.23	0.42	0.21	0.41
Married	0.64	0.48	0.60	0.49
Households	117,128		58,233	

Notes: Unweighted means and standard deviations are reported.

Table 23: Robustness Test: Warehouse Club Entry on Bulk Buying (Different Radii)

	5 Mi	10 Mi	15 Mi	20 Mi
	(1)	(2)	(3)	(4)
Post-Entry	0.003	−0.001	0.001	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Post-Entry : 25-50k	0.018***	0.020***	0.022***	0.007
	(0.004)	(0.005)	(0.005)	(0.005)
Post-Entry : 50-100k	0.019***	0.031***	0.030***	0.016***
	(0.004)	(0.005)	(0.005)	(0.005)
Post-Entry : >100k	0.026***	0.041***	0.040***	0.040***
	(0.005)	(0.006)	(0.007)	(0.008)
Household-ZIP FE's	Y	Y	Y	Y
Year-Qtr FE's	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y
Observations	2,519,594	2,520,936	2,520,129	2,519,937
Adjusted R^2	0.426	0.426	0.426	0.426
Note:	*p<0.1; **p<0.05; ***p<0.01			

Notes: This table uses 2004–2015 Nielsen Consumer Panel data at the household-quarter level. Coefficients are reported for Equation (9) which regresses households' quarterly bulk purchase shares on an indicator for warehouse club entry, an indicator for whether the household shops at a warehouse club, and an interaction term as well as household demographics (household size, age, presence of children, and marital status). Different distance cutoffs defining an "entry" are used for each regression. Household-ZIP code and year-quarter fixed effects are included. Projection weights are not used.