Bundling to save: Analyzing package size choices in South African grocery stores

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Abstract

Storable goods such as laundry detergent come in different package sizes with different associated unit prices. Buying larger packages is an opportunity to save, but low-income consumers in African countries often appear to forego this opportunity and buy small packages instead. I investigate the determinants of these choices by estimating a model of dynamic consumer demand using scanner data from all stores of South Africa's leading grocery chain. The estimation accounts for "bundling:" due to temporary sales and non-linear pricing of the product, consumers sometimes find it less expensive to purchase multiple small packages instead of a large package. The results show that this phenomenon is quantitatively important in explaining observed patterns in the data. Counterfactual simulations use the model's findings to evaluate the impact of offering different package sizes, which is a relevant consideration for the current expansion of small-format chain stores to low-income areas.

1 Introduction

Storable goods like laundry detergent, bathroom tissue, or non-perishable food items are often sold in the same store in widely different package sizes. The unit price for these goods is typically lower if the consumer buys a larger package. Thus, buying larger packages is a form of saving. In developing countries, low income consumers often appear to forego this opportunity to save and instead buy smaller packages. While buying small packages can have some benefits, if smaller packages have a larger unit price, then households overspend on these storable goods. In this paper, I use a unique dataset on laundry detergents from South Africa to estimate a dynamic demand model that allows quantifying the determinants of these choices. Assuming that a store can carry only one size of laundry detergent, what size would a social planner choose? This question has current relevance in the African context, where grocery store chains are expanding in low-income informal neighborhoods. Traditionally, these areas were served only by a collection of small informal stores, and high travel costs meant that consumers had limited access to formal supermarkets. Now, formal chains are entering these neighborhoods by opening small square-footage stores that do not carry the full selection of package sizes available in their larger stores. Since laundry detergent is a one of the most expensive items a household typically buys in a grocery store, understanding the impact of which size such a store chooses to carry can have large welfare implications.

Studying these questions requires high-frequency purchase data, including market shares and prices, for an entire product category, linked to demographic characteristics of the consumers. While readily available scanner datasets with these features exist for the US, I am not aware of another such dataset from a developing country.

Even with such data, estimating consumers' dynamic decisions about a storable good faces a number of challenges. First, the product inherently features non-linear pricing and, in addition, temporary promotions that often target only specific sizes can substantially change unit prices. These two facts combined can result in situations where consumers are better off buying two smaller packages instead of a larger one. As I show below, ignoring the presence of these "bundling opportunities" can lead to very misleading conclusions regarding consumers' preferences for small package sizes in developing countries.

Second, the identification of dynamic demand for storable goods faces the typical difficulty that even if purchases are observed, individual households' consumption and inventory are not. In this paper I alleviate this issue by fielding an original survey that directly collects information on consumption and inventory (as well as other aspects of detergent use) from a sample of households in my study area.

Cooperating with Unilever South Africa, I have obtained a unique dataset of supermarket scanner data with country-wide coverage for a 16-month period, from July 2011 to October 2012. The data contains monthly information on laundry detergents at the store level from all 330 stores of South Africa's leading grocery chain, Shoprite. In this scanner data, I separately observe all types and brands of Unilever detergents sold. I focus on 3 brands of powdered hand-wash detergent (by far the most common category of laundry detergent sold): Omo, Sunlight, and Sunlight Tropical. These are nationally important brands, comprising 70-85 percent of all detergent sales in Shoprite stores (with a similar market share nationally), and all three are produced by Unilever. These three distinct products are sold in various package sizes, ranging from 250g to 5kg, for a total of 14 brand-size combinations over the period of study.

Using the geo-coded location of the stores, I match the scanner data to household demographics from the South African census. I also use this combined dataset to define local markets for each store. I complement these data with an original survey on detergent use fielded to a sample of consumers in the market area of three selected stores.

I use this dataset to estimate a model of dynamic consumer choice building on Hendel and Nevo (2006). In the model, the consumer chooses which quantity (package size) and brand to purchase, how much to consume, and hence what inventory to hold in a given period.

Applying the estimation strategy in Hendel and Nevo (2006) to my data is not straightforward. First, since I analyze market level data, I estimate the consumer's brand choice conditional on size using BLP. Second, I explicitly take into account the bundling opportunities that arise in some markets when, due to temporary sales, consumers may find it cheaper to purchase multiple small packages instead of a large package. As a result, the econometric model becomes more complex, as these situations violate the discrete choice assumption. I present a method to estimate the share of small packages that were purchased as part of a bundle. This is based on the idea that estimates from markets with no bundling opportunities can be used to infer the counterfactual consumer demand on markets with bundling opportunities if such opportunities were absent.

The estimation of dynamic models with unobserved state variables raises inherent difficulties for the identification of the parameters. Typical applications must address the issue that only households' purchases are observed, while consumption and inventory are unobserved. For example, Hendel and Nevo (2006) simulate an initial distribution of inventories and compute optimal consumption based on the model (see also Erdem, Imai and Keane (2003)).

Here, I use direct information on households' consumption, inventory, and purchase from the survey to help identify the dynamic parameters of the model. Since the solution of the dynamic programming problem requires identifying the dependence between purchased package size, inventory, and consumption, I directly ask households about each of these elements and use this information combined with the scanner data to identify the dynamic parameters.

My first finding is that accounting for bundling opportunities has important effects for the interpretation of observed market shares. I estimate that, on the median market, there are over 3 times as many households who purchase 5 kg of detergent as households who purchase a single 5 kg package. Correspondingly, many of the households buying the smallest package sizes are in fact creating bundles and purchasing a larger total quantity. These findings run against the common belief that due to severe financial constraints, households often purchase products with the lowest package price rather than the lowest unit price. As the case studied here illustrates, looking purely at market shares can be misleading. A consumer might optimally purchase multiple small packages because this bundle is less expensive than a larger package.

Second, I study a counterfactual scenario in which consumers face a decreased fixed cost of purchase (such as lower transportation costs). The results show that the fixed purchase cost is relatively more important in shaping demand compared to the estimated costs of holding inventory at home.

Third, I use the estimated model to evaluate counterfactual scenarios designed to approximate a situation where a small store is constrained to carry only one size of detergent. I simulate consumers' optimal dynamic choices under each of the six package sizes observed in the data, and calculate the expected discounted present value of consumer utility in each case.

In a scenario where a store is restricted to offering a single package size, offering the largest (5 kg) package would provide the highest consumer utility. The 2 kg package yields the second highest consumer utility, and at the same time keeps average inventory (and consumption) closer to what is observed in the data. By contrast, offering the smallest (250 g) package size would deliver one of the lowest values of consumer utility. This is in line with the estimation results which indicate that, in the data, many households only purchased small packages as part of a bundle when buying a larger total quantity. This result may also have implications regarding the most desirable package size offered in grocery chains that are currently expanding in low-income neighborhoods throughout Africa.

This paper continues a line of research on dynamic demand estimation that includes Lal and Rao (1997), Pesendorfer (2002), Erdem, Imai and Keane (2003), Arcidiacono and Miller (2011), Gowrisankaran and Rysman (2012), and Hendel and Nevo (2006, 2013). Unlike earlier studies, I consider a developing country application and explicitly account for the bundling opportunities present in some markets.

This paper also contributes to the development economics literature, where there is long-standing interest in interventions designed to motivate households to save. Even small amounts of savings can contribute to many desirable outcomes, such as enabling households to send their children to school, or to invest in cleaner and healthier cooking equipment. For example, in a series of experiments Karlan et al. (2016) design several interventions to motivate households to make a deposit into their savings accounts each month. In the Philippines (which has the closest mean household income to the South African setting), a door-to-door campaign resulted in 26 USD saved on average. In my data, over a year, a household that consumes the average amount of detergent and always buys the largest package will spend 11.08 USD less than if it always bought the smallest package. These are remarkably high savings on a single product category that typical households regularly purchase in a grocery store. Understanding the determinants of these decisions may thus have important welfare implications.

2 The role of storable goods in developing countries

Commonly studied storable goods in industrial organization, such as laundry detergents, play a special role in developing countries. Most of the time, these are the most expensive items a household buys in a typical grocery store, and in many cases households spend a high fraction of their income on these products. Additionally, these items are difficult to substitute or home-produce. Consequently, almost all households use and purchase these products continuously.

These products are typically sold in many different package sizes and, just as is documented in many studies using US data, they exhibit non-linear pricing. In most cases, the larger package size has a lower unit price, thus purchasing in bulk is a form of saving for households. Because these products are relatively expensive, the potential saving for an average household over a year is significant.

In my data, the average household consumes 1156 grams of laundry detergent per month. Over a year, if a household always buys the smallest package available, it will purchase 55.49 units of 250 gram packages. At the average price for this package size, the household will spend a total of 450.58 Rand. By contrast, if a household purchases only the largest (5kg) package over the year, it will need to purchase 2.77 units, at a total cost of 251.52 Rand using the average price of this package size. This corresponds to a 199.06 Rand or 11.08 USD saving for the household. Using the lowest price of the largest package and the highest price of the smallest package observed in my data, this expenditure gain increases to 23.97 USD per year. This corresponds to 3.1% of the mean or 12.2% of the median monthly household income in South Africa in the same time period. These are remarkably high savings on a single product category purchased by a typical household in a grocery store.

In the development literature, there is long-standing interest in interventions designed to motivate households to save. Even small amounts of savings can contribute to many desirable outcomes, such as enabling households to send their children to school, or to invest in cleaner and healthier cooking equipment. For example, in a series of experiments Karlan et al. (2017) design several interventions to motivate households to make a deposit into their savings accounts each month. Their experiments span 3 countries, and some of them last for 24 months. They find that in the Philippines, which has the closest mean household income to the South African setting studied here, a door-to-door marketing campaign resulted in 26 USD saved on average. In this sense, the potential savings that can be achieved by changing what size products households buy are larger than those produced by a typical information campaign. Consequently, understanding the determinants of how households choose among different package sizes can have widespread implications.

3 Data and background

3.1 Background

In 2011-12, Unilever's market share in the laundry detergent category was approximately 80-90 percent, with some fluctuation in this range attributed to temporary promotions, but no permanent shifts or trend over the period (Figure A.2 in the Appendix, left panel).[1]Among laundry care products, standard powdered detergents continued to experience the fastest value and volume growth, reaching R8 billion in 2011. Powdered detergents have consistently taken market share away from bar soap and other low-cost cleaning agents.

The laundry detergent market has two distinct types of product: hand-wash and automatic washing detergents. These products do not substitute each-other. Around 20% of South African households owned washing machines in 2011. The majority of these were in urban areas: 27% of urban households owned a washing machine, compared to only 4% of rural households. Many of these washing machines are low efficiency, where the machine drains into a bathtub or is used outside the house. These machines require *hand-wash* detergents. Detergents labeled as automatic detergent are considered a niche product used

[1]The second largest producer, Procter & Gamble, entered the market in 2013, after the end of my data, with up to 10 percent share of the entire market.

for high efficiency machines. Hand-wash detergents account for about 90 percent of all sales during my period of study. Among hand-wash detergents, Unilever has a 80-95 percent share (Figure A.3 in the Appendix). The remaining products on this market are small brands, none of them with more than 2 percent of the market. These are mostly specialty detergents (such as detergents advertised for baby clothes or dark clothes, or with extra fabric softener incorporated), or other generic store brands (the latter have a combined markets share of 4 percent on average).

3.2 Scanner data

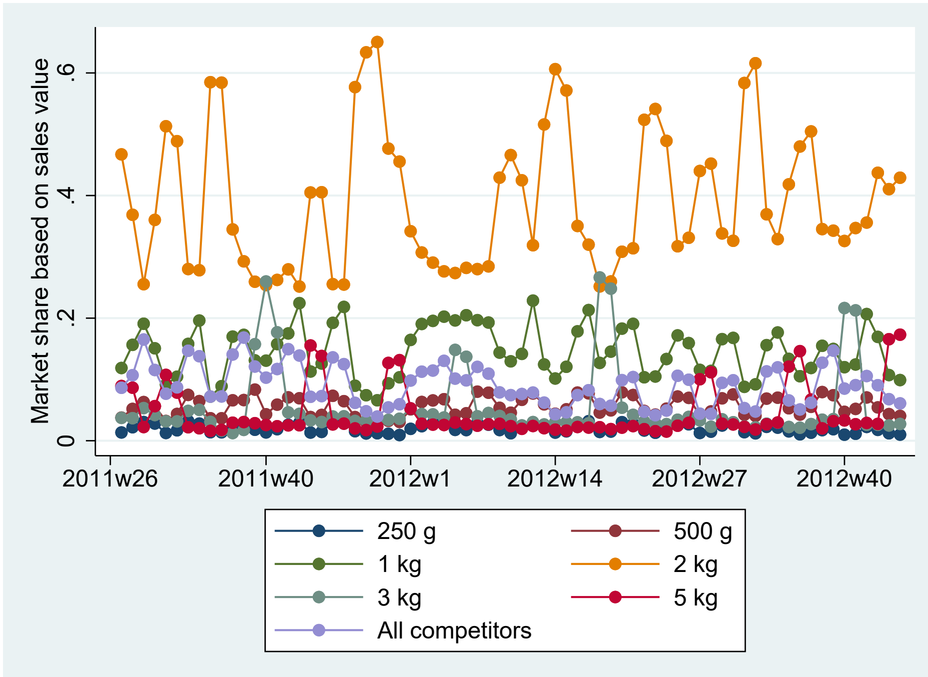
Cooperating with Unilever South Africa, I have obtained a unique dataset of supermarket scanner data with country-wide coverage for a 16 month period, from July 2011 to October 2012. The data contains monthly information at the store level based on scanner data from all Shoprite stores in South Africa (330 stores), separately for all types and brands of Unilever detergents sold. The data includes sales, (sales weighted) price per package, (sales weighted) price per volume, sales revenue, and total volume sold. I also observe weekly scanner data (aggregated across all Shoprite stores) on each brand and variant of any laundry detergent sold, including competitors (this data includes sales value and volume, as well as price per item). Lastly, I also observe weekly scanner data on promotional activities of each of these products. This includes both the sales weighted regular price and the sales weighted promotional price, as well as the percentage of volume sold during the promotion. I describe these datasets in more detail below.

3.2.1 Products and package sizes in the sample

The sample used in this paper includes 3 powdered hand-wash detergent brands: Omo, Sunlight, and Sunlight Tropical Scent. These are nationally important brands (Sunlight alone has about 60 percent of the entire market) and all three are sold by Unilever.

These three distinct products are sold in various package sizes, ranging from 250g to 5kg, for a total of 14 brand-size combinations over the period of study. This group of products comprises 70-85 percent of all detergent sales across Shoprite stores, and a similar market share nationally. Considering only the markets studied here (16 months for 330 stores), Sunlight has 56 percent of the total market share. Omo, which is considered to be a higher-performance detergent with better cleaning ability, has 27 percent. This brand is more popular in urban areas. Sunlight Tropical is a variation of the Sunlight brand - it is perceived to have a stronger, longer lasting scent. Perhaps because of this feature this is more popular in low-income and rural areas. Table 1 shows the summary statistics of these

Figure 1: Market share of Unilver products by package size



Notes: Market shares based on sales value for all 14 Unilver products by package size. "All competitors" contain all sizes of all non-Unilver products.

market shares for all 14 products in my main sample. The most popular size (both in sales value and volume) is the 2 kg package, which has 50 percent market share. In contrast to popular belief, packages smaller than 1 kg are not very popular. None of the products below 1kg has a market share larger than 4 percent, and the six products in this group have only 9 percent market share combined. The two largest sizes have 14 percent combined market share, despite the fact that these can only be purchased from one brand, Sunlight.

Figure 1, plots market shares based on sales value for the main sample brands versus all the other competitor and additional Unilever brands, aggregated across all Shoprites. There are a total of 57 additional such products sold in Shoprites, and one of them has more than 5 percent market share (most of them has less than 0.2 percent).

Table 1: Market shares and prices

	Sunlight regular				Sunlight tropical				OMO			
	Market share	Regular price per package	Quantity sold on sale (%)	Sale price (%)	Market share	Regular price per package	Quantity sold on sale (%)	Sale price (%)	Market share	Regular price per package	Quantity sold on sale (%)	Sale price (%)
250g	0.01	7.923	0.5	23.1	0.007	7.939	0.2	-3.3	0.006	8.456	13.3	5.2
500g	0.038	15.3	10.7	10.5	0.014	15.35	11.9	23.4	0.016	16.659	14.5	11.1
1kg	0.125	24.659	24.6	14.5	0.051	24.824	23.6	16.2	0.057	26.254	14.0	10.6
2kg	0.244	39.413	37.8	13.1	0.099	39.501	37.3	14.5	0.191	40.688	45.1	12.7
3kg	0.078	54.999	32.5	11.0	x	x	x	x	x	x	x	x
5kg	0.063	90.663	33.6	14.3	x	x	x	x	x	x	x	x

Notes: Market share is fraction of total quantity sold over the entire 71 week period. Regular price is in Rand. Quantity sold on sale is fraction of total quantity sold of given brand/size that was sold on sale. Sale price is (1 - (sales weighted promotional price / sales weighted regular price))*100 averaged across weeks.

Table A.1 in the Appendix shows the availability of the sample products. Not all sizes are available at all times, and not all stores carry all available sizes, although there is no substantial variation in the availability of the products across stores and time. Twelve out of the 14 products are available in at least 90 percent of the stores during the entire period. Some products have temporary dips in availability. I cannot distinguish whether the product was physically in the store, but had no sales for an entire month, or it was not available. Nevertheless, I observe a few products where availability temporarily declines by more than 30 percentage points (for example Sunlight 250 g or Sunlight Tropical 1 kg). This suggests that there is some variability in the consumers' choice sets.

3.2.2 Prices, quantity discount and promotional activity

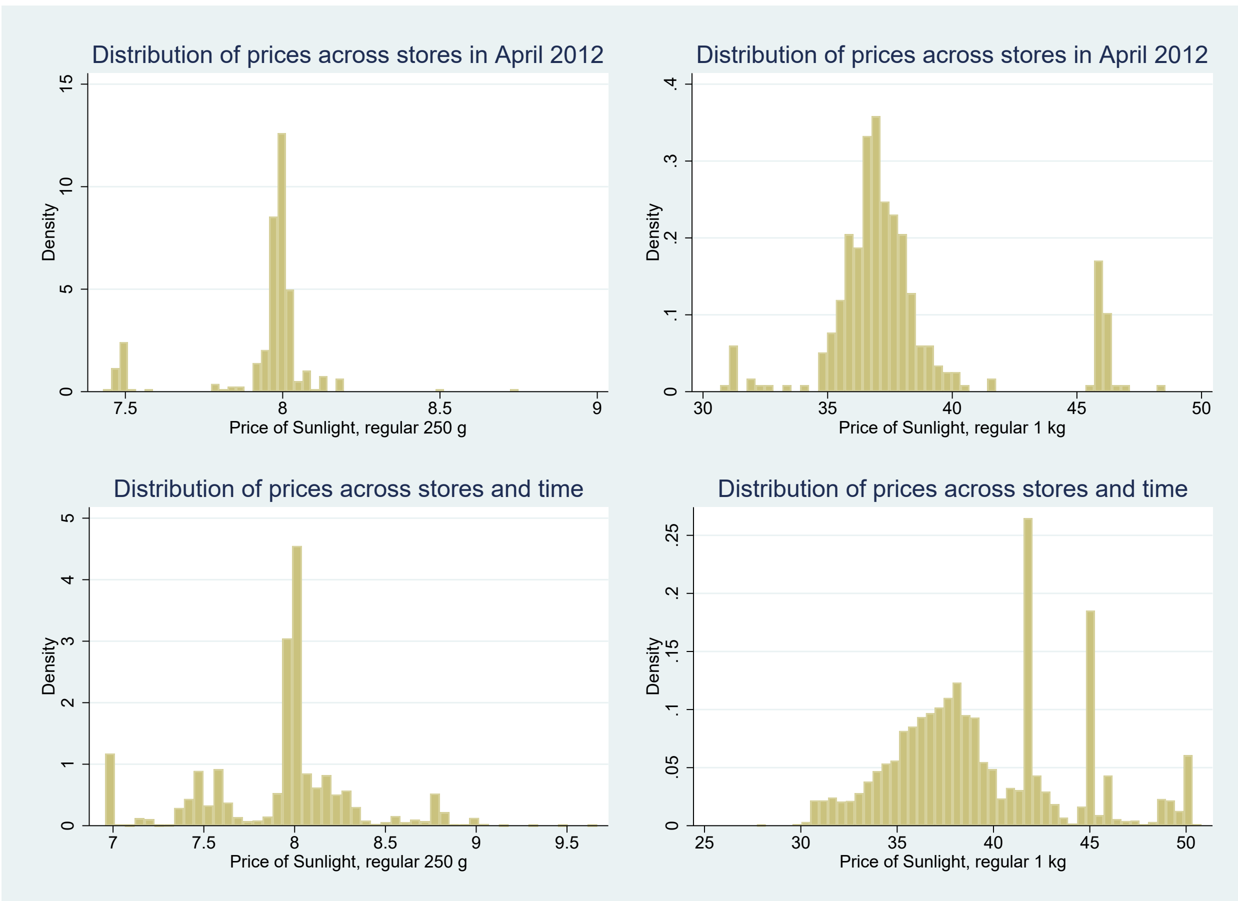
Table 1 shows the summary statistics of the products. There are three features worth mentioning: (1) prices are not uniform among stores even though all stores belong to the same chain, (2) there is a substantial quantity discount embedded in the prices, and (3) promotions affect different package sizes at different times. I describe each of these features below.

Non-uniform prices across stores from the same chain. The average price of a given package size is similar across brands. However, these similar average prices mask significant price variation both across stores and across time. This is in contrast to patterns documented in US data, for example in DellaVigna and Gentzkow (2019). On the top panel of Figure 2, I display the distribution of prices for selected products for a specific month to illustrate price dispersion of the same product across the 330 stores. The lower panel displays the same two product prices across all markets (time $\times$ stores), which shows even more dispersion. Generally, smaller sizes have lower price variance than larger sizes. It is also important to note that the most common small size is priced differently across neighborhoods with different income levels, while larger sizes seem to exhibit price variation across stores, but not across areas based on income levels.

Figure 3 shows the three specific products with the highest market shares in selected stores over the study period. These graphs further illustrate the differences between the price per package of the same product among selected stores. Both the relative prices of the products and the evolution of prices over time seem to be different, which provides the variation necessary to identify price elasticities.

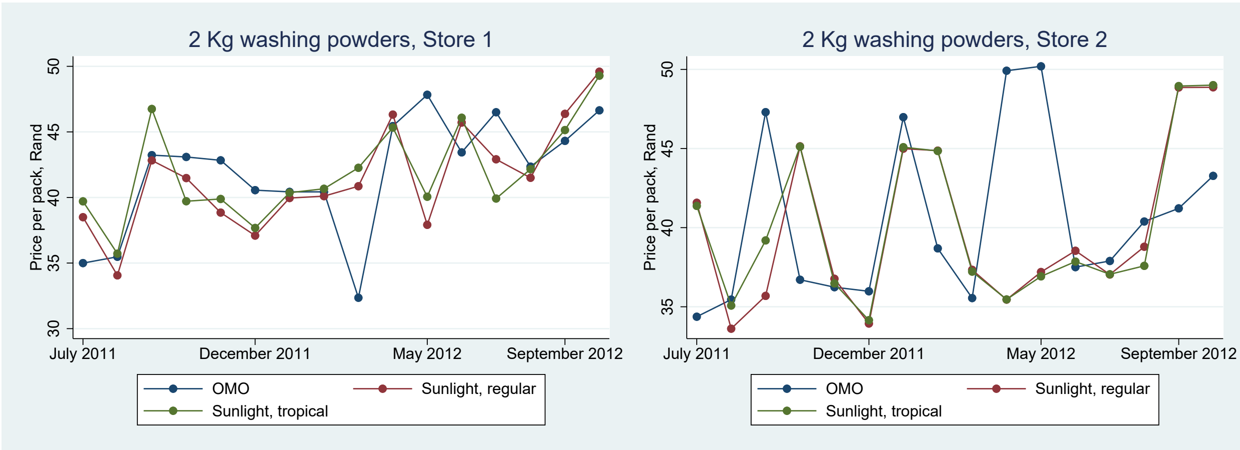
Non-linear pricing. Table 2 shows the price of buying 1 kg of the product for each package size, relative to a 1 kg package of the same brand. The figures shown are average across store-months, computed using regular (non-sale) prices. For example, based on the first column, purchasing 1 kg of Sunlight detergent as four 250 g packages is 25% more expensive than

Figure 2: Distribution of prices of selected products



Notes: Store level monthly sales weighted prices in Rand. The upper panels show the price distribution across stores for two products in April 2012 (the middle of the sample period). The lower panels show the corresponding distributions over the entire sample (16 months, 330 stores).

Figure 3: Prices of 2 kg packages in selected stores



Notes: Store level monthly sales weighted prices in Rand.

Table 2: Quantity discounts

	Sunlight regular	Sunlight tropical	OMO
250g	1.30	1.29	1.30
500g	1.25	1.24	1.27
1kg	1	1	1
2kg	0.80	0.80	0.78
3kg	0.74	x	x
5kg	0.74	x	x

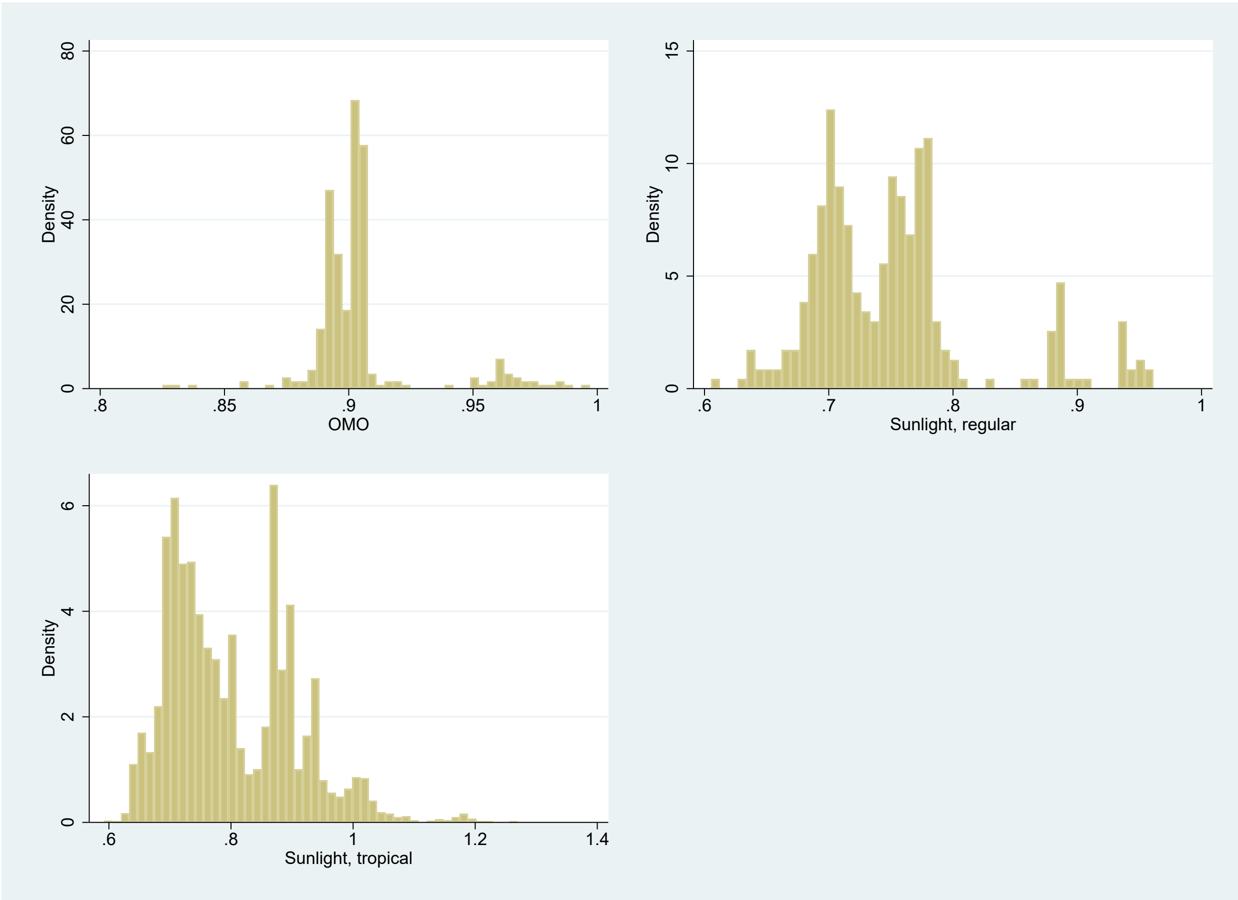
Notes: Unit prices (per 1 kg) relative to a 1 kg package of the same brand. Based on regular (non-promotional) prices.

purchasing a single 1 kg package. Table 2 indicates that quantity discounts across brands are very similar. In addition, although there are up to 5 different sizes from the same brand, there seem to be only three groups of percentage discounts. Smaller products are on average 25-30 percent more expensive, and larger products are 20-25 percent cheaper compared to a 1 kg package. Even though there are 2, 3 and 5 kg packages, they are all offered on average at the same quantity discount.[2] I also computed the same figures separately for different areas based on living standard measures, and I do not find any noticeable differences compared to Table 2.

There appears to be some variation in quantity discounts over time and across stores as well. To illustrate this, Figure 4 plots the quantity discount of a 2 kg package versus buying

[2]This pricing behavior by the firm could be caused by price discrimination or cost differences across sizes - see, e.g., Cohen (2008).

Figure 4: Store level variation in quantity discounts



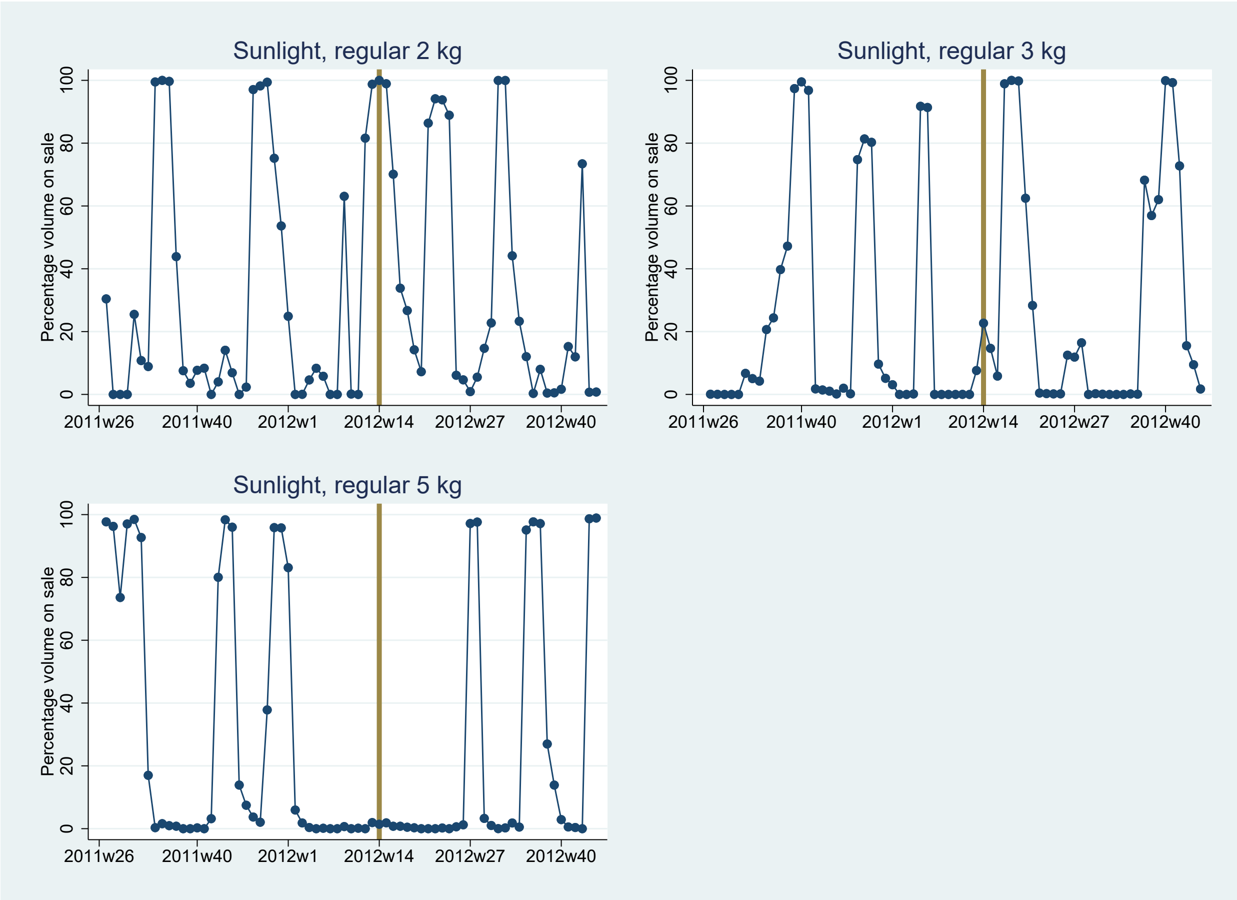
Notes: Price of one 2 kg vs two 1 kg packages of the same brand. Based on data from 330 stores for April 2012 (middle of sample period).

two 1 kg packages across the 330 stores for April 2012 (the middle of the period). The x-axis shows the relative prices (price of a 2 kg package divided by the price of two 1 kg packages). There are substantial (up to 35 percent) differences in the amount of quantity discount for this month. In most cases, these measures are below 1, as one would expect. There are some values above 1, where purchasing two 1 kg packages is less expensive than one 2 kg package. This feature arises because of temporary discounts (see below) and is extensively discussed in Section 4.

Temporary sales. I observe store level prices, but I do not know whether those store level prices are promotional or regular prices. I do know, for each week, the percentage of total volume sold on promotion, aggregated across all stores. I also know both the average regular and promotional prices.[3] As shown in Table 1, smaller sizes are less frequently on sale. The

[3]Note that store level prices alone would be sufficient to estimate demand.

Figure 5: Percentage of volume on sale for selected products

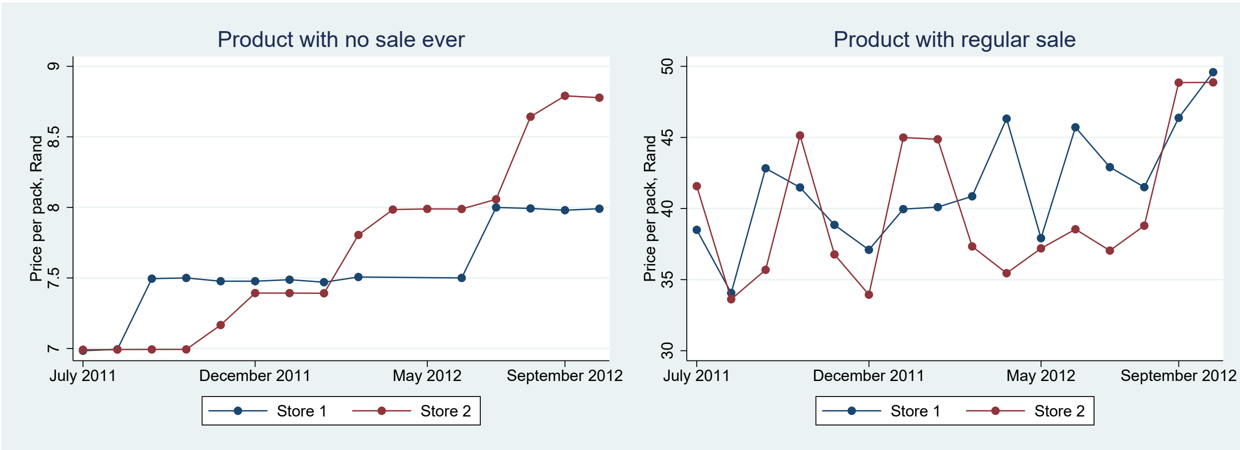


Notes: Data for all stores. The vertical line indicates the same week on each panel.

250 g Sunlight package was on sale in my sample period only for 1 week, while the 2 kg OMO package was on sale for 59 weeks, and 45.1% of the total volume sold during the 16 month period was during these sale periods. On Figure 5, I plot the percentage of volume on sale over time for the most popular brand. This shows that in almost all cases, either zero or 100 percent of the volume was sold at promotional prices, which strongly suggests that promotions were conducted nationally by the chain, rather than individually at the store level. This also suggests that the price variation I observe across stores cannot be explained by promotions taking place in some stores but not others.

Next, I compute the percentage promotional discount as $(1-(\textit{promotional price} \,/\, \textit{regular price})) \times 100$. The magnitude of the average percentage promotional discount is similar across brands. Larger sizes tend to have larger percentage discounts than smaller sizes. This measure can be negative as well, if the stores that implement the promotion still have higher prices than stores that do not have a promotion. This happens in the data for the smallest

Figure 6: Evolution of prices with and without frequent promotions



Notes: Store level monthly sales weighted prices in Rand. Left panel shows Sunlight, regular 250 g. Right panel shows Sunlight, regular 1 kg.

size Sunlight Tropical, mostly in city centre stores, where the regular price of this item is substantially higher than its national average price.

Figure 6 shows the evolution of prices for two distinct products over time in two selected stores. The first product (Sunlight 250 g) had only 1 week of temporary promotion during the study period and the second (Sunlight 1 kg) had the most frequent promotions. The left panel of Figure 6 shows that prices of the product with little promotion stay steady over a longer period in a given store, but they can be more than 10 percent higher in a different store. In both stores, we see an increasing price trend over the 16 month period, although the timing of the price increases is different. Figure 2 above showed the distribution of prices for these same two products. The product with little temporary promotion has a smaller variation both across stores in a given month (upper panels) and over the period (lower panels).

Appendix Figure A.4 plots the market shares over time for the most common (2 kg) size for each brand. This is also a size which is regularly subject to temporary promotions. I observe large variation in the market shares. Sunlight and Sunlight Tropical mostly move together, suggesting common promotions. The large temporary market share gains cannot be explained by changes in the third product's (OMO) market share or by changes due to the competitor products (Figure A.4, right panel). Instead, changes might be due to consumers' dynamic purchase behavior and/or substitution among different package sizes.

3.2.3 Stores

I have data on 330 Shoprite stores across the country. Shoprite is a South-African supermarket chain that has grown considerably in the past decades and is known for expanding in all areas of the county, including low income neighborhoods.[4] This last feature sets it aside from all other formal grocery store chains in the country. I know the exact location of the stores, which allows me to use Census data at a very low level of aggregation to complement store-level data with demographics. I collected the GPS coordinates for each store using Google Maps. The data covers all nine South African provinces. Table A.9 in the Appendix shows both the distribution of the population and the number of stores by province, which reveals that the number of stores follows the population distribution except for Western Cape, where the Shoprites are overrepresented on a per capita basis compared to other provinces. Figure A.5 shows the location of all stores in my sample and Figure A.6 illustrates that these stores are located in both urban, suburban and rural areas.

Unilever uses a Living Standard Measure (LSM) to categorize stores based on their location for internal marketing purposes. This measure is designed to approximate consumers' purchasing power, and places each store into one of three main categories.[5] For simplicity, in the rest of the paper I refer to low, middle and high income areas based on this LSM definition. In my data, 17 percent of the stores fall into the low-income category, 43 percent into the middle-income category, and 40 in the high-income category.[6] Average household income in the lowest category is 2285 Rand (310 USD) per month, which makes this population representative of low-income households elsewhere in Africa.

Since I know the identity of each store, I was able to collect store characteristics from individual stores' websites. I collected the following information: store is located in a shopping mall, store is located in a city center, and Sunday opening hours (Tables A.10 and A.11 in the Appendix). Approximately 9 percent of the grocery stores are in a shopping mall. There is large variation in Sunday opening hours across stores, ranging from closed all day to open until 9 pm. I use these variables to proxy for unobservable market characteristics, such as popularity or accessibility of the store.

[4]The Shoprite group started in Cape Town with 8 supermarkets in 1979.

[5]The Living Standard Measure is created by the South African Audience Research Foundation and is used widely by companies for marketing purposes. Based on multiple measures, it divides the population into 10 LSM groups, from 10 (highest) to 1 (lowest). In the data, stores are categorized into low LSM (1-4), medium LSM (5-6) and high LSM (7-10) areas. More details about LSM are available at http://www.saarf.co.za/lsm/lsms.asp

[6]The share of the adult population in South Africa in each of these categories is 32, 18 and 50 percent, respectively.

3.3 Demographic data

I have two additional sources of data which I combine with the store level scanner data. First, I use the full version of the latest South African Census (2011) Community Profile dataset. The Census was undertaken exactly in the time period covered by the scanner data, and it contains a detailed geographical identifier called small area codes. This geographic identifier covers only 100-500 households (typically 2-3 street blocks), which allows me to work with a very precise market definition. Specifically, since I know the GPS coordinates of each store, I can define markets based on distance to the store. Shoprite presumably opened stores to maximize access: about 1 million households live less than 1 km from a Shoprite store. I describe my detailed market size definition in Section 6.1.

The Census contains household level information on annual income, type of main dwelling, population group (ethnicity) and gender of the household head, and ownership of various appliances. Since I observe individual households rather than census layer averages, I can directly sample individual households for estimation. Even though Shoprite stores are over-represented in and around larger urban areas, 15% of the sample population live in rural areas and 13% of them live in informal dwellings.

In the demand estimation I found it useful to include ownership of a washing machine and ownership of a car. Ownership of a car can be important in explaining whether households choose larger package sizes that are more difficult to transport. It is interesting to note that 10% of the households own a car but do not own a washing machine. Table 3 provides summary statistics on these variables.

3.4 Survey data

The second source of information on households is from two rounds of a survey I conducted specifically for this paper to gather information on (i) how households purchase laundry detergents, (ii) the amount of laundry detergent they keep at home (i.e., their inventory), and (iii) their storage costs. The survey asks the households where and how frequently they usually buy laundry detergent, and what kind of transportation they use. The surveyors also ask households to show us the detergent they currently have at home, and they record the package size and how much is left in the package (e.g., half empty, almost gone, etc), which allows me to determine the household's exact inventory.

The literature using US data typically relies on house size or urban/suburban location of the household to proxy the (physical) cost of storage. In a developing country setting there might be other considerations. For example, a larger package may get ruined or stolen, or invite neighbors asking to use it. These are potentially important determinants of whether

Table 3: Household demographics

	South Africa	Sample markets
Mean income	8801.476	11621.32
Median income	2262.75	4525.5
Urban area	68.03	85.42
Male household head	57.61	66.95
Owns a car	32.17	42.77
Owns a washing machine	34.42	47.77
Owns no car or washm	55.81	42.48
Owns washm only	12.02	14.76
Owns car only	9.77	9.75
Population group of household head		
Black African	77.71	62.58
White	10.96	17.76
Other	11.33	19.66
Type of dwelling		
House	66.97	66.34
Flat/apartment	12.44	20.49
Other (Informal dwelling, shack in backyard)	20.59	13.17
N	11,643,451	3,765,101

Notes: Based on 2011 South African Census. Income is annual household income in Rand. Other variables are percentages of total.

a household decides to keep a large package at home, and I therefore collect information on all these factors.

For the survey, I randomly selected 3 stores, one in each LSM income category, and sampled 100 households around each of these stores. In total, through the two rounds of the survey, I have 600 inventory observations for 300 households. The first round of the survey took place in December 2020 and the second in March 2022, about 16 months apart, which also corresponds to the length of my data, although in a different time period.

4 Savings due to bundling

As documented in the previous sections, the product features non-linear pricing, with similar unit prices within each of three broad size categories, small, medium and large. At the same time, temporary promotions, which usually target only some sizes, can substantially decrease prices.[7] In many markets, these two facts combined result in situations where consumers are better off buying two smaller packages instead of a larger one. That is, the relatively flat

[7]From the firm's point of view, the use of promotions on some package sizes but not others of a given product is consistent with Aguirregabiria (1999).

quantity discount within size groups combined with temporary promotions that affect only one or two sizes per brand induce non-monotonicity in the nonlinear pricing schedule.

In the data, 14 products are being sold, where a product is a particular package size of a particular brand. By bundling smaller packages, the quantities corresponding to these package sizes can be purchased in a total of 30 different combinations. For example, 1 kg of Sunlight Tropical could be purchased as four 250 g packages or two 500 g packages (as well as a non-bundled 1 kg package). Table 4 below shows all these possible product bundles.[8]

[8]Since substituting a larger package with a mixture of *different* small packages can never be optimal (e.g., buying two 250g and one 500g package instead of one 1kg package), such combinations are not listed in the table.

Table 4: Possible bundles

	Unique stores	Unique month	Markets (store × month)
Sunlignt, tropical			
Buy 2x250g instead of 500g	265	16	988
Buy 2x500g instead of 1kg	54	1	54
Buy 4x250g instead of 1kg	0	0	0
Buy 2x1kg instead of 2kg	137	7	214
Buy 4x500g instead of 2kg	2	1	2
Buy 8x250g instead of 2kg	0	0	0
All Sunlight, tropical	287	16	1207
Sunlight, regular			
Buy 2x250g instead of 500g	290	16	974
Buy 2x500g instead of 1kg	13	1	13
Buy 4x250g instead of 1kg	0	0	0
Buy 2x1kg instead of 2kg	140	6	220
Buy 4x500g instead of 2kg	0	0	0
Buy 8x250g instead of 2kg	0	0	0
Buy 1x2kg and 1x1kg instead of 3kg	308	7	967
Buy 3x1kg instead of 3kg	4	3	5
Buy 6x500g instead of 3kg	0	0	0
Buy 12x250g instead of 3kg	0	0	0
Buy 1x2kg and 2x500g instead of 3kg	11	1	11
Buy 1x2kg and 1x3kg instead of 5kg	329	16	2005
Buy 2x1kg and 1x3kg instead of 5kg	312	14	1076
Buy 2x2kg and 1x1kg instead of 5kg	309	14	1068
Buy 5x1kg instead of 5kg	5	2	5
Buy 10x500g instead of 5kg	0	0	0
Buy 20x250g instead of 5kg	0	0	0
Buy 2x2kg and 2x500g instead of 5kg	0	0	0
All Sunlight, regular	330	16	3355
OMO			
Buy 2x250g instead of 500g	283	16	1849
Buy 2x500g instead of 1kg	0	0	0
Buy 4x250g instead of 1kg	0	0	0
Buy 2x1kg instead of 2kg	3	1	3
Buy 4x500g instead of 2kg	0	0	0
Buy 8x250g instead of 2kg	0	0	0
All OMO	283	16	1852

Notes: Total number of stores is 330, total number of months is 16. Total number of markets is 5255.

Out of the 30 possible bundles, 16 are cost-minimizing at least once in the data, i.e., the consumer is better off purchasing a bundle instead of a single package. The most common cost-minimizing bundle is to purchase a 1 kg and a 2 kg package instead of a 3 kg package. This is the case in 2005 out of the 5255 markets in the data. There are markets where bundling can be cost-minimizing for multiple sizes and/or brands at the same time. For example, I see 363 markets where buying two 250 g packages of OMO instead of one 500 g package *and* buying a 3 kg and a 2 kg package of Sunlight instead of one 5 kg are both cost-minimizing bundles. In total, there are 57 possible combinations of these bundling opportunities in the data. The online Appendix lists all these cases.

The opportunity to bundle small packages is common for all brands. For example, in 19% (resp. 35%) of the markets, it is cheaper to purchase two 250 g packages of Sunlight (resp. OMO) instead of one 500 g package.[9] This is especially interesting in the context of African countries, where the common belief is that due to severe financial constraints, households often purchase products with the lowest package price rather than the lowest unit price. This appears to be supported by the large market shares of small packages. However, looking purely at market shares can be misleading, as the case studied here illustrates. A consumer might optimally purchase multiple small packages because this bundle is less expensive than a larger package.

I investigate any potential correlation between bundling opportunities and market characteristics, including whether the store is in a city center or shopping mall, area income and other average household characteristcs. The Online Appendix shows the adjusted R^2 from regressions when store and market characteristics are added separately or jointly to explain bundling opportunities for each package size. These 14 characteristics explain no more than 1 percent of the variation on top of the basic controls such as state and month fixed effects. Variables such as area income or store location appear to have little to no correlation with bundling opportunities.

In the next section, I first address this issue in the context of demand estimation. I present a method to estimate the share of small packages that may have been purchased as part of a bundle instead of a large package. The estimation relies on the fact that I observe a large number of markets. For each size, I have over 1000 markets where there are no bundling opportunities, so that one can proceed with a conventional discrete choice demand model. I use these estimates to infer counterfactual consumer demand on markets with bundling opportunities if such opportunities were absent.

[9] This accounts for the fact that some sizes are not available in a store in a given month.

Table 5: Markets with no bundling opportunities

	Unique stores	Unique month	Markets (store $\times$ month)
250g	326	16	1064
500g	326	16	1088
1kg	326	16	1088
2kg	326	16	1088
3kg	324	16	1049
5kg	325	16	1029
All	330	16	5255

Notes: Total number of stores is 330, total number of months is 16. Total number of markets is 5255.

5 Model and estimation

Since laundry detergent is a storable product and prices change over time because of temporary discounts, the consumer may purchase the product in a dynamic manner. Besides these obvious features, the demand model should also incorporate the fact that laundry detergent is a differentiated product. The estimation needs to take into account of the fact that purchase is observed at the market level rather than the individual level, and that there are bundling opportunities present on some, but not all markets. The model and estimation below incorporate all these features.

5.1 Model setup

The main model is based on Hendel and Nevo (2006). On a given market, consumer h makes monthly choices between brands $j = 1, ..., J$ sold in different sizes x. Utility from consumption is not dependent on brand. The good is storable, any quantity not consumed is stored as inventory. Brand and quantity decisions are modeled separately. The brand decision is a static decision of the consumer, while quantity choice is dynamic.

The per period utility from buying size x_{jt} of brand j is

$$\begin{aligned} U(c_{ht}, x_{hjt}, i_{h,t+1}) \quad &= \quad u(c_{ht}, v_{ht}, x_{hjt}, \gamma) - C(i_{h,t+1}, \boldsymbol{\theta}^C) - F(x_{hjt}) \\ &\quad\quad + \boldsymbol{\beta}_x \mathbf{a}_{jxt} + \xi_{jxt} + \boldsymbol{\mu}(\mathbf{a}_{jxt}, \mathbf{D}_h, \boldsymbol{\theta}^\mu) + \varepsilon_{hjxt} \end{aligned}$$

where c_{ht} is the quantity consumed (from all brands) by the consumer at time t, v_t is randomness in the consumer's needs, $C(.)$ is the storage cost of inventory i, $F(.)$ is the fixed cost of purchase, $\mathbf{a}_{jxt}$ are observed product characteristics, including prices, ξ_{jxt} is the valuation of unobserved characteristics, $\mu(.)$ is the valuation of product characteristics as a function of consumer demographics, γ, $\boldsymbol{\theta}^C$, $\boldsymbol{\theta}^\mu$ and $\boldsymbol{\beta}_x$ are parameters, and ε_{hjxt} is a Logit error.

The inventory transition is given by

$$i_{h,t+1} = i_{ht} - c_{ht} + x_{ht} \tag{1}$$

The consumer's problem is:

$$V(\sigma_1) = \max_{\{j, x_{hjt}|\sigma_t\}} \sum_{t=1}^{\infty} \delta^{t-1} E\left[U(c_{ht}, x_{hjt}, i_{h,t+1})|\sigma_1\right] \tag{2}$$

s.t. $0 \leq i_{ht}, 0 \leq c_{ht}, 0 \leq x_{hjt}$ and (1), where the state variables are $\sigma_t = \{i_{ht}, v_{ht}, \mathbf{a}_{jxt}, c_{ht}, \xi_{jxt}, \varepsilon_{hjxt}\}$.

I make similar assumptions regarding the distribution and evolution of $v_{ht}, \varepsilon_{hxt}$, and prices as Hendel and Nevo (2006). Namely, v_{ht} is independently distributed over time and across consumers, prices follow a first-order Markov process, and ε_{hjxt} is i.i.d. Type-I extreme value. See that paper for discussion and justification of these assumptions.

5.2 Towards estimation

The estimation builds on Hendel and Nevo (2006), which in turn builds on the nested algorithm of Rust (1987). The objective of the dynamic model is to describe the choice among different package sizes. Briefly, to reduce the dimensionality problem, the dynamic decision is based on a summary measure ("inclusive value") of the factors that enter the static demand estimation. In other words, given package size, the choice of which brand of detergent to buy is not part of the consumer's dynamic problem.

For each size sold, define

$$\widetilde{\omega}_{hxt} = \log\left[\sum_j \exp(\boldsymbol{\beta}_x \mathbf{a}_{jxt} + \xi_{jxt} + \boldsymbol{\mu}(\mathbf{a}_{jxt}, \mathbf{D}_h, \boldsymbol{\theta}^\mu))\right], \tag{3}$$

as the inclusive value (quality adjusted price index) for all brands of size x. The sum is over brands which come in size x. To use these inclusive values in the dynamic problem of the consumer an adjustment must be made to account for a different interpretation of the outside options. In the dynamic problem, the interpretation is standard, the value of buying a given package size compared to not buying anything. Since the static demand estimation is a series of BLP exercises, one for each package size, the inclusive value in (3) is interpreted as a the value of buying a specific size compared to anything else, which can be either a different size or not buying any detergent. This is discussed in Section 6.5. Using these adjusted inclusive values (ω_{hxt}), I can rewrite the dynamic programming problem as

$$\begin{aligned} V(i_{ht}, v_{ht}, c_{ht}, \boldsymbol{\omega}_{ht}, \boldsymbol{\varepsilon}_{ht}) \quad = \quad & \max_{x_{ht}|\sigma_t} u(c_{ht}, v_{ht}, \gamma) - C(i_{h,t+1}, \boldsymbol{\theta}^C) - F(x_{ht}) + \omega_{hxt} + \varepsilon_{hxt} \\ & + \delta E\left[V(i_{h,t+1}, v_{h,t+1}, \boldsymbol{\omega}_{h,t+1}, \boldsymbol{\varepsilon}_{h,t+1}) | i_{ht}, v_{ht}, \boldsymbol{\omega}_{ht}, \boldsymbol{\varepsilon}_{ht}, x_{ht}\right], \end{aligned} \tag{4}$$

with the additional assumption about the transition process

$$\Pr(\omega_{hx,t+1} | \boldsymbol{a}_t, \boldsymbol{\xi}_t, \mu_{ht}) = \Pr(\omega_{hx,t+1} | \boldsymbol{\omega}_{ht})$$

For estimation, I need to specify functional forms for the objects defined above. Following Hendel and Nevo (2006), I specify

$$u(c_{ht}, v_{ht}, \gamma) = \gamma \log(c_{ht} + v_{ht})$$

$$C(i_{ht}, \boldsymbol{\theta}^C) = \theta_1^C i_{ht} + \theta_2^C i_{ht}^2 + \theta_3^C i_{ht}^3$$

The distribution of ω_{hxt} is assumed to be Normal, with standard deviation σ_x and mean

$$\iota_0 + \sum_{x'} \iota_{x'} \omega_{hx',t-1}.$$

To proceed with the dynamic estimation, one needs to compute inclusive values for all markets. The inclusive values (3) contain marginal utilities of the prices and product characteristics from the static demand. Since individual purchase data is not available, a BLP (1995) type discrete choice estimation is the natural approach to recover these marginal utilities. However, the discrete choice assumption is violated in markets where there is a potential bundling opportunity. I now describe a possible solution to this issue.

5.3 Estimating static parameters and correcting the market shares

First, consider markets with no bundling opportunities (i.e., where based on the observed prices it is not optimal to purchase multiple smaller packages instead of a bigger package). For these markets, I estimate β_x,ξ_{jxt} and $\mu_h(\mathbf{a}_{jxt})$ (that is, all the ingredients for the inclusive values in (3)) using BLP. Since the consumer's static brand choice is conditional on size, a separate BLP estimation is run for each set of products of a given size x. In each case, the interpretation of the outside option is "a choice other than size x."

Next, I consider markets with bundling opportunities. On these markets, I first need to estimate the share of packages that were purchased as part of a bundle. Next, I use these estimates to "correct" the market shares, and compute all necessary ingredients to compute inclusive values and proceed with the estimation of a dynamic demand of the consumer.

I begin by computing the total price of buying each profitable bundle (for example, the price of buying a 2 kg and a 3 kg package instead of a 5 kg package of the same brand when the latter is more expensive). Call this the "effective price" of the given total quantity (in this example, the effective price of 5 kg of the product).

Using these effective prices together with the BLP parameter estimates, it is possible to compute the "corrected" market share of, say a 2 kg package - the share of 2 kg packages that were not purchased as part of a bundle. To do this, I use the parameter estimates to compute the demand increase for a 5 kg package when its price drops to the effective price. This is the extra demand for 5 kg of the product that will be fulfilled through the purchase of bundles. In this example, if the observed market share of the 5 kg packages is $S_{jt}^{(5)}$ and their predicted market share under the effective price is $\hat{s}_{j5t}$, then the corrected market share of the 2 kg and 3 kg packages will be $\hat{s}_{j2t} = S_{jt}^{(2)} - (\hat{s}_{j5t} - S_{jt}^{(5)})/2$ and $\hat{s}_{j3t} = S_{jt}^{(3)} - (\hat{s}_{j5t} - S_{jt}^{(5)})/2$, respectively.

To compute $\hat{s}_{j5t}$, I simulate 1000 values of the ξ_{j5t} estimated for the markets with no bundling, compute the market shares $\hat{s}_{j5t}$ for each simulation (using the actual observed prices and the effective prices), and take the average across simulations. Note that this procedure retains that attractive feature of BLP that no distributional assumptions are made on ξ.[10]

What remains is the computation of the ξ's. To obtain these, I use the BLP parameter estimates β_x and $\mu_h(\mathbf{a}_{jxt})$ and solve systems of equation of the form

$$s_{jxt}(\mathbf{a}_{jxt}, \beta_x, \xi_{xt}, \mu_h(\mathbf{a}_{jxt})) = S_{jt}^{(x)},$$

i.e., equating the model-predicted market shares to those observed in the data. For brands/-sizes involved in bundling (for example, the 2, 3, and 5 kg packages in the example above), I use the corrected market shares $\hat{s}_{jxt}$ obtained above.

5.4 Estimation of the dynamic parameters

As described above, the inclusive values in (3) allow simplifying the dynamic problem, which now requires keeping track only of the expected utility conditional on size. Since the (simulated) households have specific characteristics, the inclusive values will be household-specific

[10]In robustness checks, I extend the support of ξ_{j5t} used in these simulations in multiple ways, such as adding +/- 2 standard deviations. See the detailed results in the Appendix.

as well. Below, I start by estimating a single process for all households; I then relax this assumption and allow separate processes for household groups by income area.

The estimation proceeds by solving the consumer's dynamic programming problem for each trial of the dynamic parameters. Consumers choose package size as a function of their state variables. These state variables include inventory, consumption shocks, random shocks to the consumer's size choice, and inclusive values. Consumption is assumed to be exogenously given. The consumer trades off the cost of holding an inventory with its benefits. The benefits arise on the one hand from the quantity discount embedded in purchasing a larger size, and on the other from the ability to exploit temporary price discounts. The consumer's inventory is an endogenous state variable which is determined by the previous level of inventory, purchased size and current consumption.

The Bellman equation used in the estimation is given by equation (4). The value function is approximated by a polynomial function of the state variables (inventory, consumption shocks, random shocks to the consumer's size choice, and inclusive values). The estimated value function is an input to compute the dynamic choice probabilities of each simulated consumer.

The model implies a set of choice probabilities of each package size for each (simulated) consumer and market:

$$\Pr(x_{ht} = x) = \frac{\exp(\omega_{hxt} + M(c_{ht}, i_{h,t+1}, v_{ht}, \boldsymbol{\omega}_{ht}, x))}{\sum_{x'} \exp(\omega_{hx't} + M(c_{ht}, i_{h,t+1}, v_{ht}, \boldsymbol{\omega}_{ht}, x'))}$$

where

$$\begin{aligned} M(c_{ht}, i_{h,t+1}, v_{ht}, \boldsymbol{\omega}_{ht}, x) \quad &= \quad u(c_{ht}, v_{ht}, \gamma) - C(i_{h,t+1}, \theta^C) - F(x) \\ &\quad\; +\delta E\left[V(i_{h,t+1}, v_{h,t+1}, \boldsymbol{\omega}_{h,t+1}, \boldsymbol{\varepsilon}_{h,t+1}) | i_{ht}, v_{ht}, \boldsymbol{\omega}_{ht}, x\right] \end{aligned}$$

Since in the current application data is at the store level, simulated consumers are aggregated across markets. Parameters are computed using a simple simulated minimum distance estimator, minimizing the squared distance of model-predicted and observed market shares. Let N_H denote the number of simulated consumers on a market, and define

$$Q(\boldsymbol{\theta}) = \sum_x \left(S^x - \frac{1}{N} \sum_{h=1}^{N} \Pr(x_{ht} = x) \right)^2$$

The estimator minimizes $Q(\boldsymbol{\theta})$ summed across markets.

6 Estimation details

6.1 Market definition

There are two important practical implications of how one defines the market (i.e., of choosing the market size). First, the market size plays a role in determining the market share of the outside good. If the market size chosen is too small (smaller than the quantity of laundry detergents actually sold), estimation becomes impossible. If the chosen market size is too large, that also has undesirable consequences. In a typical static demand estimation, the outside good is a normalization. The case considered here is different: the outside market shares need to accurately reflect the probability that the consumer does not buy any laundry detergent in a given month to be consistent with the dynamic part of the demand estimation. I will discuss this issue in more details in Section 6.3.

Second, the market definition affects which demographic characteristics should be included in the estimation. In South Africa, many areas are segregated, but substantially different populations live in relatively close proximity to each other. Thus, a more precise market definition helps match the actual households that use particular stores. Similarly, having the right market definition can be important to know which characteristics may affect consumers' product size choices. For example, it is common for the households considered here to walk to the store, which makes the cost of carrying a large package an important consideration in the dynamic model.

I define markets based on both time period and geography. The scanner data is at the store-month level, which is the right frequency to model laundry detergent purchase. Based on my survey, 93.7 percent of households said that they purchased detergent once a month, and only 2 percent said that they made more frequent purchases. Since I know the exact location of the stores, I can define the market based on distance. Stores are in areas with different population density. Even though I do not know the location of all possible supermarket chains in South Africa, I know the distance to the nearest store of the same chain. This distance varies substantially in my data, which suggests that using a simple definition of the market is not useful. For example, it is not useful to define the entire metropolitan area of Tshwane (the area around the capital city of Pretoria) as a market, since there are are 26 stores in this area and almost all stores have a neighbor within 2 kilometers.

I define the market size for each store as follows. Based on the Census, for each store, I compute the number of households N_r who live within r km, where $r = 1, 2, ..., 50$. I also compute the maximum number of laundry products the store sells in a given month over the time period observed in the data, L. I set the market size to be $\min_r \{N^r | L \cdot 1.1 \leq N^r\}$, i.e., the radius where the number of households exceeds the total number laundry products sold, plus 10 percent. Using this definition, the average market size is 11,432 households. The market is defined as a radius of 5 km or less from the store for 94.8 percent of the stores. The radius is 1 km for 43.9% of the stores, and it is 2 km for 32.7%. The distribution of the market radius is shown on Figure A.8. I also use this market definition to create control variables in the estimation, specifically, the number of stores from the same chain in a given market, and the distance from the store to its nearest neighboring store.[11]

6.2 Details of the static demand estimation

Estimation of the static demand parameters follows the Generalized Method of Moments (GMM) algorithm proposed by Berry, Levinsohn and Pakes (1995). Detailed treatments of the procedure can be found in Berry, Levinsohn and Pakes (1995) and Nevo (2001). Briefly, consider a dataset with information on product and market characteristics $\mathbf{a}_{jxt}$ and actual product shares $S^{(x)}_{jt}$. Berry et al. (1995) show that, for given $\mu_h(.)$, it is possible to numerically solve for $\psi_{jxt} \equiv \beta_x \mathbf{a}_{jxt} + \xi_{jxt}$ from the equations $s_{jxt}(\mathbf{a}_{jxt}, \beta_x, \xi_{xt}, \mu_h(\mathbf{a}_{jxt})) = S^{(x)}_{jt}$, i.e., equating the model-predicted market shares to those observed in the data. Using the resulting values of ψ_{jxt}, one can express the unobserved product characteristics as $\xi_{jxt} = \psi_{jxt} - \beta_x \mathbf{a}_{jxt}$, a nonlinear function of the model parameters. Identification relies on moment conditions $E[\xi_{jxt}|\mathbf{Z}_{jxt}] = 0$ where the $\mathbf{Z}_{jxt}$ are suitable instruments, and estimation is via GMM.

Linear variables. The linear part of the utility, $\beta_x \mathbf{a}_{jxt}$, includes price, brand dummies, store characteristics and demographics. Store characteristics are included as they are likely to be correlated with consumer choices as well as prices and/or the violability of a given package size. For example, if stores located in city centers are more likely to offer smaller package sizes, then we need to control for the location of the stores. Similarly, I control for whether the store is in a larger shopping mall, opening hours on Sunday, and the distance to the nearest store to control for popularity and accessibility. For example, stores closed on Sunday and located in the city center might be used by people returning home from work and looking for smaller package sizes.

The linear part of the utility also includes a set of market-level average household demographics that exhibit little to no variation within markets. This lack of variation in some demographic variables is due to features of the South African setting combined with the relatively small markets I consider. In this application, perhaps uniquely among similar discrete choice demand applications, I see very segregated markets. This arises from the segregation

[11] The median distance to the nearest store is 4.7 km, the mean is 17.8 km.

of South African neighborhoods, and it implies that there is little to no variation in, e.g., population groups across individuals within markets. In addition, as described above, markets are defined as relatively small areas around each store, and consequently characteristics such as "urban" or "rural" do not change across individuals within markets. The full set of variables included are shown in Table 7 under "Linear parameters."

Nonlinear variables. To model individual level heterogeneity among simulated consumers, I use demographic characteristics that vary within market and are relevant in the current context. I use household income, a binary variable indicating whether the household head is male, and four categories based on whether the household owns a washing machine and/or a car. Table 3 illustrates the variation in these variables. For example, there is a meaningful portion of the population that owns a car but does not own a washing machine. Since I am able to draw individuals from the Census, I do not need to estimate the covariance of the different demographics and can instead use their empirical distribution.

The nonlinear part of the utility, $\mu_h(\mathbf{a}_{jxt})$, interacts these household demographics with price and with a constant. Interactions with the constant capture heterogeneity in the valuation of the outside good among individuals. The interpretation of the outside good in each BLP estimation is that the consumer decides to purchase no product (or a product not modelled here), or a different size. For example, the fact that a household has a car is probably an important determinant of which size they purchase.

I do not include interactions between brand dummies and household demographics. Including these would only be useful if there was variation in either the availability of brands across markets, or market shares, correlated with the demographics included in the model. Here, there is little variation in the availability of brands across markets. In addition, all the products I consider are powdered hand-washing detergents, and the biggest differences between them (other than the brand) are likely to be factors such as scent. Preference for these factors is unlikely to be explained by the demographic variables that are typically available in Census data. For the full set of nonlinear variables included, see Table 7 under "Non-linear parameters."

Instruments. To identify the model, instruments are needed for two reasons: to control for price endogeneity, and to identify the nonlinear parameters. Some of the previous attempts to instrument for price are not feasible in the current context. There are no product characteristics in $\mathbf{a}_{jxt}$, only brand dummies. None of the product characteristics change across markets (either across months or across stores) and there is little variation in the availability of different brands conditional on size across stores. This prevents the use of instruments based on exogenous product characteristics. Instead, similar to Nevo (2000), I construct instruments using the prices of the same product in different markets. Specifically, I identify the 15 closest neighbors of each store.[12] I regress stores' price on these 15 prices and rank neighbors based on the size of these correlations. To determine the number of neighboring prices used as instrument, I compute F statistics and include neighbors until there is no further increase in the F statistic.

To identify the nonlinear parameters, I use the market-level average of the demographic characteristics that enter the nonlinear part of the utility. This includes household income, male household head, and the fraction of households owning cars/washing machines. In some specifications, I found it useful to add the interaction of some of these instruments and the most relevant price instrument.

Other considerations. Demand specifications are the same across all sizes. For each market, I simulate 400 individuals, and the same individuals are used in estimating the demand for each size. Standard errors reported below are clustered at the store-month level, to allow for both heteroskedasticity and correlation of the shocks ξ_{jxt} across products within a market. For each specification, I report the J overidentification statistic, and the Newey-West D-test for the null hypothesis that the nonlinear parameters are jointly 0. The numerical stability of the estimates is ensured through the choice of optimizer, convergence criterion, and by eliminating a source of instability in the typical codes used to implement the procedure following Ujhelyi, Chatterjee and Szabó (2021), Appendix D.5.

6.3 Details of the dynamic model

Inventory and consumption. The solution of the dynamic programming problem requires identifying the dependence between purchased package size, inventory, and consumption. Typical applications must address the issue that only households' purchases are observed, while consumption and inventory are unobserved. For example, Hendel and Nevo (2006) generate an initial distribution of inventories and compute optimal consumption based on the model (see also Erdem, Imai and Keane (2003)). In my survey, I directly ask households about each of these elements, and use this information combined with the scanner data to identify the dynamic parameters. I use three variables from the survey: consumption, quantity of detergent in inventory, and the package size(s) in inventory.

For consumption, I ask households how often they typically do laundry (daily/weekly/-monthly), and I separately ask how many loads of laundry they typically do each time. Based on these, I compute how many loads of laundry a household typically does in a month, and the associated consumption of detergent (one load of laundry requires about 100 gram of

[12] If that particular brand is not sold in that particular store in a month, than the next store prices are used. Thus I select the 15 closest store where the particular product was actually sold.

powdered detergent, based on the directions on the package). Table 6 shows the summary statistics.

Table 6: Detergent consumption by income area in the survey

	Mean	Median	St.dev.	Min	Max	N
Low-income area	1229	1200	589.01	200	3200	100
Middle-income area	1106.06	1200	535.82	400	3200	99
High-income area	1133	1200	459.7	400	2400	100

Notes: Powdered detergent consumption in the survey by income area. Values are in gram.

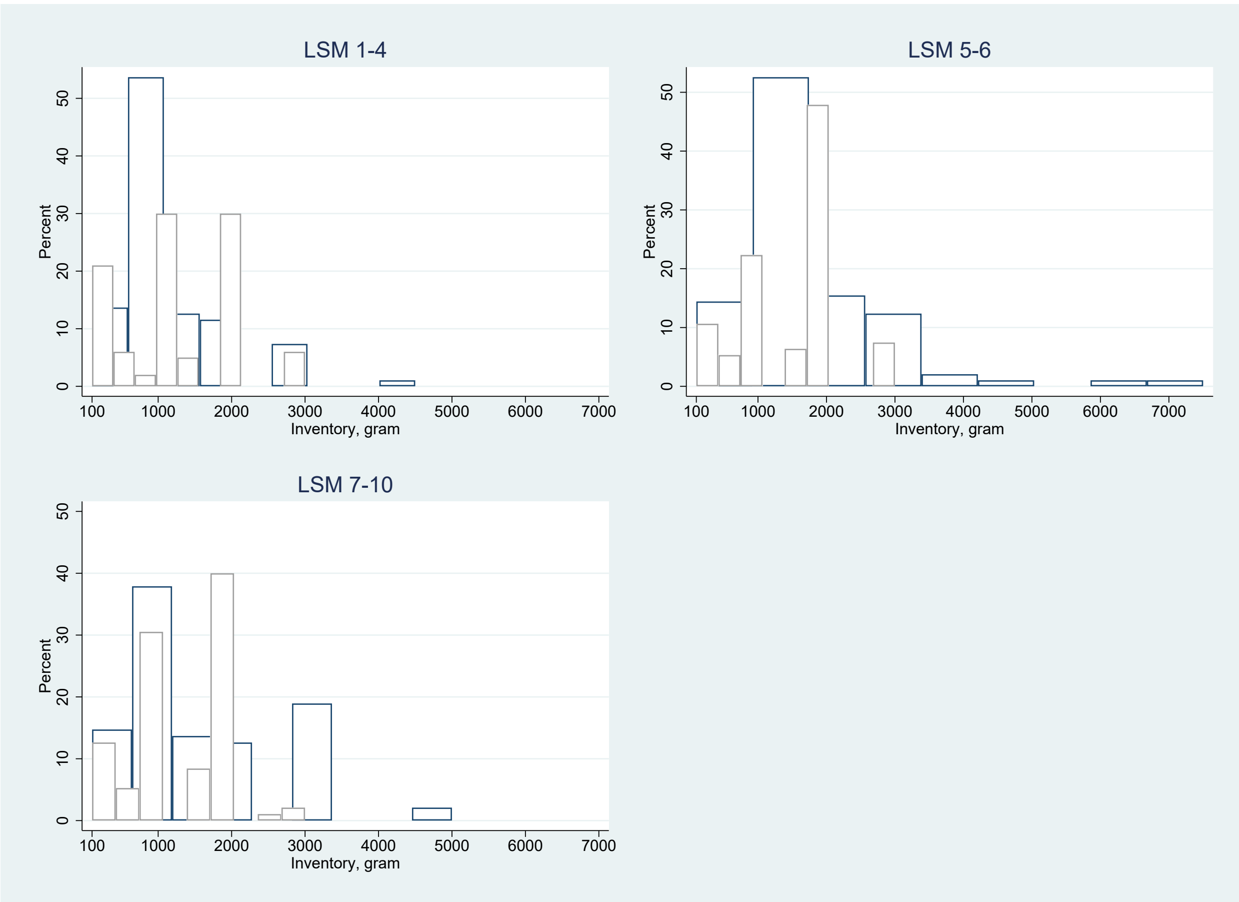
For inventory, the surveyors asked households to show them what kinds of laundry detergent they had at home. The surveyors recorded a description of the item(s) shown to them, including the package size and the amount left in each package - for example, "Sunlight 500 grams in a yellow plastic, dry, half empty" "OMO 2KG in plastic package, dry, ordinary washing powder quarter full" and "OMO washing powder regular 2kg just opened and dry." (No respondents refused to answer this question.) Based on this information, I compute the current inventory of detergents for each household. In some cases, the surveyor recorded that the package was "almost full" or "almost empty." In the first case, I subtract 100 g from the package size, and in the second case, I use 100 g. These numbers correspond to the suggested amount of detergent used for one load. There are 289 recorded inventory levels from the first round of the survey, and 287 from the second round. Respondents without an inventory level showed either liquid detergents or laundry bars (soaps); all households had at least some detergent at home. Figure 7 below shows the distribution of inventories by LSM area. The data reveals some differences in inventory based on income level.

Since I have two visits per household, I see that households do not always buy the same package size, i.e., there is variation between the package sizes recorded during the two visits. Interestingly, the aggregate inventory of the 300 households is very similar at the two time periods.

Further details on how the survey data was combined with the scanner data, and additional details on solving the dynamic programming problem can be found in the Appendix.

Inclusive value process. Once the static demand parameters are estimated, I compute inclusive values using equation 3. I assume a first-order Markov process for the inclusive values of each package sizes. Since the demand parameters contain individual level heterogeneity, the inclusive values vary at the individual level as well. To reduce the number of processes to be estimated, I group individuals. In the simplest specification, I group all individuals, and estimate a single process for each size. In the main specification, I estimate separate processes for each of the three LSM areas. I also show results where the grouping is

Figure 7: Household inventory of detergent in the survey



Notes: Powdered detergent inventory in the survey by income area.

done based on the ownership of washing machines and cars. These are the variables which capture most of the individual level heterogeneity in the demand estimation, therefore I use the same variables to capture the heterogeneity in inclusive values. To relax the first-order Markov process assumption, I also include the second lag of the inclusive value for each size. Alternatively, I take the sum of five lags for each size, as Hendel and Nevo (2006).

Other considerations. The per-period utility also contains a set of dummy variables for each package size. This has two objectives. First, it is possible that there is a one-time utility gain or loss from purchasing a specific size. For example, the largest sizes might be difficult to carry, especially when households walk to the store. This one time transportation cost (which is different from the inventory cost) would be accounted for by the size dummies. Second, the parameters used to compute the inclusive values which enter the dynamic model are obtained from 6 different static BLP estimations. Although the specifications are identical across these estimations, the (average) level of utility may differ across specification. The inclusion of size dummies is useful to account for any possible level effects.

The estimation of the dynamic model uses only markets where all choices are available. Consumption shocks are assumed to follow a log-Normal distribution.

Because the parameters of the inclusive value process enter the dynamic estimation in a complex way, and because the estimation involves multiple simulated objects, it is practical to use subsampling to estimate standard errors. I draw datasets of the same size with replacement, and repeat the estimation 30 times. This includes resampling the dataset on which the inclusive process is estimated.

6.4 Identification

The identification of the static demand parameters follows the identification of the standard BLP procedure, with instruments discussed in Section 6.2. This section provides a description of the identification of the dynamic problem.

Estimating the dynamic parameters, i.e. the parameters of the utility from consumption and the parameters of the storage cost functions requires solving the dynamic programming problem for each parameter trial. This results in two sets of parameters. The first are the parameters of the polynomials used to approximate the value function. In the main estimation, I use 26 terms for approximating the value function, which includes the state variables of the consumer. Besides the constant, I include a cubic function of log inventory, the inclusive values, and quadratic functions of both choice specific extreme value shocks and consumption shocks. The second set of parameters which can be identified from the dynamic programming problem is a set of size fixed effects. These fixed effects can be interpreted as a one time cost of purchasing a specific size compared to the outside option. More formally, approximate the value function in (4) as

$$V(i_t, v_t, \boldsymbol{\omega}_t, \boldsymbol{\varepsilon}_t) = \boldsymbol{\varphi}\mathbf{r}_t,$$

where $\mathbf{r}_t$ is a vector of polynomial terms, and $\boldsymbol{\varphi}$ are the parameters to be estimated. Specifically,

$$\boldsymbol{\varphi}\mathbf{r}_t = m_t + \eta F(x_t) + \delta\boldsymbol{\varphi}\mathbf{r}_{t+1}, \tag{5}$$

where

$$m_t = \gamma \ln(c_t + v_t) - (\theta_1^C(\log i_t) + \theta_2^C(\log i_t)^2 + \theta_3^C(\log i_t)^3) + \omega_{xt} + \varepsilon_{xt}.$$

Identification relies on data from the household survey, which provides data on current inventory, consumption, purchase, and household characteristics. In typical scanner data studies, only purchase is observed, and there is no information on either inventory at home or consumption. This makes it difficult to identify the dependence between purchase size, inventory, and consumption. The information contained in my survey alleviates this difficulty. In this case, it is not necessary to simulate initial household inventory, or compute the optimal consumption for each potential size purchased. Similarly, I can directly compute future inventory as current inventory plus size purchased, minus consumption.

In addition, the survey has the same demographic information about the households (for example, area income, ownership of washing machine and cars) as the elements which enter in the static demand estimation. This makes it possible to match the inclusive values obtained from the static demand estimation to surveyed households, and thus to their inventory, consumption and purchase choices.

Using these survey data and inclusive values, for a given realization of shocks and a given draw of dynamic parameters, (5) can be written as

$$m_t = \boldsymbol{\varphi}(\mathbf{r}_t - \delta\mathbf{r}_{t+1}) - \eta F(x_t)$$

where m_t, $\mathbf{r}_t$, $\mathbf{r}_{t+1}$ and $F(x_t)$ are all known. Thus, the parameters $(\eta, \boldsymbol{\varphi})$ can be estimated using OLS.[13]

With both inventory and consumption observed, identification of the remaining dynamic parameters γ and $(\theta_1^C, \theta_2^C, \theta_3^C)$ follows the standard arguments in Rust (1996), Magnac and Thesmar (2002), and Aguirregabiria (2005) (see Hendel and Nevo (2006, p.1653)).

[13] Hendel and Nevo (2006) also include size specific dummies $F(x_t)$ in the per period utility, but they cannot identify these through the dynamic programming problem. The difference is that they do not know optimal consumption of the households. Because of this, they estimate these fixed effects as part of their full optimization procedure.

6.5 Computing inclusive values for the dynamic problem

In the dynamic problem the interpretation of inclusive values is relative to the outside option of not buying any detergent, the value of which is normalized to zero. Since the static demand estimation is a series of BLP demand estimations, one for each package size, the interpretation of the inclusive values are different. For a given size, the computed inclusive value is the value of buying the specific size compared to everything else (including the outside option), rather than the value of compared to only the outside option. To directly apply the inclusive values computed from the static demand estimation in the dynamic problem, these two different definitions need to be reconciled. More specfically, the relation between inclusive values across the two probems is given by:

$$\omega_x - \sum_{j \neq x} \omega_j = \widetilde{\omega}_x$$

for package sizes $x = 1, ..., 6$. Solving yields

$$\omega_1 = \left(3\omega_1 - \sum_{j \neq x}^{6} \widetilde{\omega}_j \right) /8$$

7 Estimation results

7.1 Static demand estimates

I begin by documenting parameter estimates of the static choice between brands, conditional on size. In Table 7, each column shows the results from a separate BLP estimation for the choice of brands given a specific package size. As described above, these estimates use data from markets where there are no bundling opportunities. As can be seen, the number of unique months as well as the number of unique stores is almost always the same, reflecting the fact that bundling opportunities do not arise only is specific months or in specific stores. Each of these specifications passes the J-test for the validity of the moment conditions, and the Newey and West (1987) D-test always rejects the null that the nonlinear parameters are jointly 0.

In general, the parameter estimates are sensible. The price coefficient has the expected negative sign and is statistically significant in each specification. Consumers are less likely to buy small packages in stores that are open on Sunday: the corresponding coefficient is negative for smaller packages and positive for larger packages. Households headed by a male have less elastic demand. This could reflect the fact that these households are wealthier, or it could reflect differences in preferences (e.g., men could pay less attention to laundry detergents when shopping).[14]

Coefficients on the (constant $\times$ car only) interaction terms are positive and significant for the larger packages (1kg and above) and switch signs for smaller packages. This indicates that large packages are valued particularly by consumers who own a car but do not own a washing machine.[15] This makes sense, as these are the consumers who use hand-wash detergents more and can more easily transport the larger packages. Coefficients on the (constant $\times$ no car or washm) are positive and significant for the smaller packages and switch signs for larger packages (2kg and above). This too makes sense, as these are again the consumers who use hand-wash detergents, but face higher costs of transporting larger packages.

[14] More generally, the lower price elasticity of male shoppers is consistent with the findings of Fitzpatrick (2017) in Uganda.

[15] The excluded category is composed of consumers who own both a car and a washing machine.

Table 7: Parameter estimates: static demand

	250g	500g	1kg	2kg	3kg	5kg
Linear parameters						
Price / 100	-95.843***	-53.630***	-36.165***	-15.818***	-10.121***	-15.525***
	(13.868)	(18.117)	(4.366)	(1.412)	(1.173)	(5.507)
Omo	0.492***	0.383	0.613***	1.110***	-	-
	(0.183)	(0.247)	(0.249)	(0.173)		
Sun	0.334***	0.551***	0.357	0.383***	-3.786	2.630
	(0.154)	(0.222)	(0.219)	(0.138)	(5.223)	(2.335)
Constant	-3.782	-0.835	-2.203	1.006	-	-
	(4.115)	(2.060)	(2.848)	(1.194)		
LSM 14	-0.153	0.177	-0.106	-0.099	-0.268***	0.246***
	(0.114)	(0.140)	(0.142)	(0.114)	(0.109)	(0.105)
LSM 56	0.028	0.103	-0.061	-0.058	-0.116*	0.163***
	(0.086)	(0.102)	(0.100)	(0.070)	(0.070)	(0.081)
Mall	-0.232***	-0.108	-0.047	-0.188*	0.088	-0.297***
	(0.094)	(0.108)	(0.106)	(0.096)	(0.117)	(0.115)
City center	-0.224***	-0.146***	-0.140***	0.075	-0.088	-0.113
	(0.051)	(0.051)	(0.052)	(0.072)	(0.087)	(0.074)
Sunday	-0.053	-0.228***	-0.012	0.121***	0.059	0.096
	(0.058)	(0.048)	(0.054)	(0.056)	(0.066)	(0.080)
Neighboring stores	-4.797***	-1.053	0.377	1.996	2.471***	1.867*
	(1.138)	(0.799)	(1.159)	(1.233)	(0.963)	(1.026)
Dist. to nearest store	-0.743***	0.024	0.472*	0.996***	0.672***	0.819***
	(0.227)	(0.203)	(0.263)	(0.286)	(0.238)	(0.260)
HH share flat	-0.188	0.104	-0.751**	-1.696***	-2.164***	-0.919
	(0.403)	(0.39)	(0.369)	(0.522)	(0.502)	(1.196)
HH share house	-0.310	0.118	0.004	-1.164***	-1.192***	-1.806***
	(0.299)	(0.346)	(0.360)	(0.460)	(0.344)	(0.601)
HH share White	1.601***	1.420***	2.570***	0.888***	0.648**	0.970***
	(0.473)	(0.374)	(0.542)	(0.317)	(0.331)	(0.416)
HH share Black	-0.761***	-0.426**	-0.472**	-0.218	-0.011	0.229
	(0.186)	(0.209)	(0.220)	(0.205)	(0.214)	(0.228)
HH share urban	0.340*	0.272	0.112	-0.437	-0.689***	-0.423***
	(0.199)	(0.195)	(0.194)	(0.284)	(0.197)	(0.193)
Omo × HH share Black	0.116	0.682***	0.205	0.194***	-	-
	(0.118)	(0.176)	(0.144)	(0.088)		
Sunlight × HH share Black	0.647***	1.112***	1.016***	1.014***	-	-
	(0.107)	(0.176)	(0.142)	(0.075)		
Omo × HH share urban	-0.313**	-0.236	-0.207	-0.745***	-	-
	(0.152)	(0.212)	(0.228)	(0.163)		
Sun × HH share urban	-0.346***	-0.075	0.022	-0.265**	-	-
	(0.136)	(0.189)	(0.196)	(0.127)		
Omo × LSM 14	-0.035	-0.365***	-0.084	-0.296***	-	-
	(0.119)	(0.149)	(0.149)	(0.115)		
Sun × LSM 14	0.106	-0.321***	0.071	-0.119	-	-
	(0.098)	(0.139)	(0.134)	(0.086)		
Omo × LSM 56	-0.075	-0.142	-0.113	0.011	-	-
	(0.081)	(0.101)	(0.095)	(0.066)		
Sun × LSM 56	-0.040	-0.132	-0.096	0.016	-	-
	(0.073)	(0.095)	(0.092)	(0.054)		

Cont'd on next page

Table 7 cont'd

	250g	500g	1kg	2kg	3kg	5kg
Non-linear parameters						
Price × male	19.500***	23.054	8.586***	0.292	-0.417	6.251
	(8.722)	(16.274)	(2.759)	(1.281)	(0.975)	(5.303)
Constant × income	5.969	1.725	1.646*	1.506	5.787	1.558
	(3.928)	(1.685)	(0.963)	(1.158)	(4.623)	(2.502)
Constant × no car or washm	4.200***	2.119***	4.982*	-1.918*	-5.301	-1.570
	(1.599)	(0.849)	(2.728)	(1.132)	(250.704)	(4.780)
Constant × washm only	3.990***	2.612***	6.962***	1.838***	2.649	1.538
	(1.337)	(0.779)	(2.705)	(0.676)	(1.671)	(1.202)
Constant × car only	-4.433	-6.881	5.550**	2.299***	2.910***	1.396*
	(613.361)	(1579.413)	(2.665)	(0.780)	(1.188)	(0.817)
J	1.355	1.651	0.097	1.230	4.137	0.501
p-value	0.508	0.438	0.755	0.541	0.530	0.778
Newey-West D	93.163	73.915	98.520	46.067	29.945	33.820
p-value	0.000	0.000	0.000	0.000	0.000	0.000
N	2798	2888	3193	3230	1049	1029
Markets	1064	1088	1088	1088	1049	1029
Months	16	16	16	16	16	15
Stores	326	326	326	326	324	325

Notes: Parameter estimates from the BLP model. Standard errors robust to heteroskedasticity and intra-market correlation in parentheses. All specifications contain province and quarter fixed effects. J is the overidentification test statistic with corresponding p-value. Newey-West D is a likelihood ratio test for the null hypothesis that the nonlinear parameters are jointly 0 with the corresponding p-value.

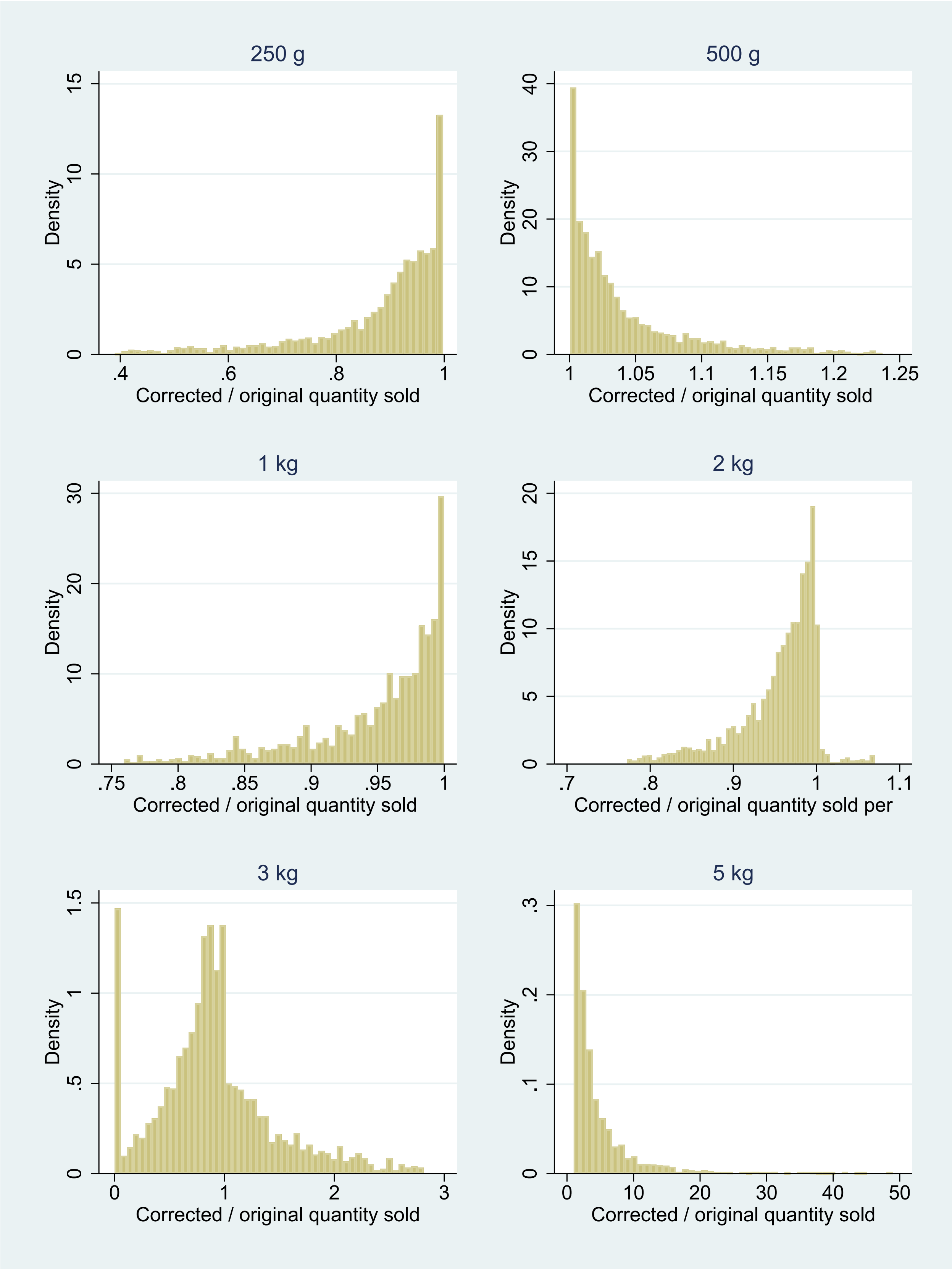
7.2 The effect of bundling opportunities

Table 8 shows the effect of accounting for possible bundling. The upper panel describes markets with bundling opportunities. Each column corresponds to a total quantity purchased by a consumer (at a given time). The "Sold" row shows the average number of packages sold of a given size in the data. The "Corrected sold" row shows the estimated number of consumers purchasing that quantity, either by buying one package of the corresponding size, or through bundling. For example, while on average 51.84 units are sold of the 5 kg packages, I estimate that on average 173.98 consumers buy a total of 5 kg - that is, I estimate that, on average, 122.14 (= 173.98 − 51.84) consumers find it profitable to buy 5 kg of detergent by creating a bundle of smaller packages. Similarly, although the average number of 250 g packages sold is 164.73, some of these are purchased as part of a bundle - accordingly, I estimate that the average number of consumers buying a total of 250 g is only 137.68.

I also calculate the ratio of Corrected sold and Sold separately for each market; the table shows the average and the median of this measures. On the median market, there are over 3 times as many households who purchase 5 kg of detergent as households who purchase a 5 kg package. This suggests that looking purely at the sales data can be very misleading regarding the share of households who are willing and able to purchase larger quantities.

For comparison, the lower panel of Table 8 shows the average number of units sold on markets with no bundling opportunities in the data. For some package sizes, average quantity sold differs substantially from the top panel - which is likely explained at least in part by the presence vs. absence of bundling opportunities. Remarkably, the necessary adjustment implied by the estimates in the top panel are in the "right" direction for all but the smallest package size (i.e., it is precisely when the number of units sold on the top panel is lower (higher) compared to markets without bundling opportunities that the estimates indicate a necessary adjustment upward (downward)). Figure 8 displays the ratio of corrected and original quantities sold by package size.

Figure 8: Ratio of corrected and original quantities sold



Notes: 330 markets.

Table 8: Effect of buying in bundles

	5 kg	3kg	2kg	1kg	500g	250g
Markets with bundling opportunities						
Sold	51.84	85.95	1087.95	733.96	199.20	164.73
Corrected sold	173.98	119.66	964.93	639.98	212.73	137.68
Average ratio	5.75	2.81	0.83	0.82	1.28	0.72
Median ratio	3.357	1.49	0.90	0.93	1.07	0.82
N of markets	1577	566	1998	566	1589	1589
Markets without bundling opportunities						
Sold	119.73	164.28	536.30	514.02	282.55	195.57
N of markets	1029	1049	1088	1088	1088	1064

Notes: Average number of units sold per market.

7.3 Inclusive values

I compute the inclusive values based on the parameter estimates in Table 7. Table 9 shows the estimated processes when a single process is estimated for all simulated individuals.

Table 9: Inclusive values

	250 g	500 g	1 kg	2 kg	3 kg	5 kg
ω_{t-1}^{250}	0.976***	0.015***	0.004	-0.123***	0.102***	0.128***
	(0.003)	(0.002)	(0.003)	(0.008)	(0.011)	(0.009)
ω_{t-1}^{500}	0.018***	0.987***	0.004**	0.033***	-0.054***	-0.076***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.007)	(0.005)
ω_{t-1}^{1}	0.005***	-0.001	0.983***	0.108***	-0.059***	-0.036***
	(0.001)	(0.001)	(0.002)	(0.005)	(0.006)	(0.005)
ω_{t-1}^{2}	0.002	0.007*	0.045***	0.524***	0.269***	0.105***
	(0.004)	(0.004)	(0.005)	(0.020)	(0.024)	(0.017)
ω_{t-1}^{3}	-0.001	0.002*	-0.016***	0.141***	0.890***	0.115***
	(0.002)	(0.001)	(0.002)	(0.007)	(0.009)	(0.006)
ω_{t-1}^{5}	0.004	-0.012***	0.002	0.067***	-0.045***	0.689***
	(0.003)	(0.003)	(0.004)	(0.011)	(0.015)	(0.015)
Constant	-0.025***	-0.023***	-0.079***	0.172***	-0.290***	-0.550***
	(0.008)	(0.007)	(0.009)	(0.032)	(0.033)	(0.034)
Adj. R^2	0.99	0.99	0.98	0.78	0.94	0.85
N	1,154,800	1,162,800	1,162,800	1,163,200	1,115,200	1,148,000

Notes: Estimates of the inclusive value process. The explanatory variables are lagged values of the inclusive value of every package size.

Table 10 shows the adjusted R^2 from other specifications. First, I estimate separate processes by income area or car/washing machine ownership. Dividing households into these groups does not improve the fit of the regressions. In each case, for every size x, the largest coefficient estimate is on ω_{t-1}^{x}, i.e., the own lagged inclusive value, similarly to the the detailed specification shown in Table 9 .

To relax the first order Markov process assumption, I also estimate the inclusive value process in two alternative ways: adding the second lag of each size, and adding the total of five lags of each size, as in Hendel and Nevo (2006). As shown in the bottom section of Table 10, neither of these improves the fit meaningfully compared to the baseline specification.

Table 10: Fit of different inclusive value specifications

	250 g	500 g	1 kg	2 kg	3 kg	5 kg
LSM						
LSM 14	0.99	0.99	0.98	0.75	0.93	0.86
LSM 56	0.99	0.99	0.98	0.79	0.94	0.86
LSM 78	0.99	0.99	0.98	0.79	0.94	0.84
Ownership status						
No car or washm	0.98	0.98	0.94	0.54	0.79	0.76
Washm only	0.98	0.98	0.94	0.59	0.78	0.76
Car only	0.98	0.98	0.94	0.51	0.76	0.75
Car and washm	0.98	0.98	0.92	0.55	0.77	0.77
Alternative specifications						
Sum of five additional lags	0.99	0.99	0.98	0.83	0.97	0.92
Second lag added	0.99	0.99	0.98	0.80	0.95	0.86

Notes: Adjusted R^2 values from different specifications of the inclusive value process. The top panel estimates separate processes by income area. The middle panel estimates separate processes by car/washing machine ownership. On the bottom panel, the first row includes the sum of five additional lags (t-2 to t-6) and the last row includes one additional lag (t-2).

7.4 Results of the dynamic model

This section summarizes the results from the estimation of the above dynamic model. I begin by discussing the estimated inventory cost and fixed cost of purchase and then turn to evaluating the model performance.

Table 11 reports the dynamic parameters from various specifications. Columns (1) - (4) assume a flexible three-degree polynomial structure for the storage cost as a function of inventory. These specifications also contain six fixed costs parameters from purchasing each of the available sizes. Column (1) is estimated using all stores and assumes a single inclusive value process for all (simulated) individuals. This specification uses survey data from all income areas. In columns (2) to (4), I present results separately for stores in different income areas, where column (2) results are for low income, (3) for middle and (4) for high income areas. In these cases, I estimate separate inclusive value processes for each income area and use only survey data from households who live in the given income area.

To interpret the inventory cost parameters, consider the following example: If the inventory at the beginning of the period is 1 kg (tne median in the data), then according to column (1), buying a 500 g package increases the storage cost from 10.78 to 13.65, compared to 15.08 if buying a 1 kg package. The average savings due to non-linear pricing is 6.19 from buying a 1 kg package instead of two 500g packages.

There are variations in the one-time purchase costs for different sizes and across income areas. These costs can be interpreted, for example, as transportation costs. Buying a larger package may require hiring a cab rather than walking home from a store. The estimated fixed cost increases in package size, with the cost of buying a 5 kg package about 10 times higher than the smallest package. These costs are similar in low- and middle-income areas, while they are between 20-40% lower in high-income areas. In high-income areas more households own a car, and it is reasonable to assume that they face lower transportation costs.

Continuing the example above, based on column (1), transportation costs are estimated to add an additional 4.63 Rand (=13.37 - 8.74) to the cost of purchasing a 1 kg package compared to buying a 500 g package. In this case, the sum of the fixed cost of purchase and storage costs (4.63 + 1.43) is similar in magnitude to the total quantity discount.

In summary, the estimates indicate that these fixed costs are larger in magnitude than any cost associated with keeping a larger package at home. This has implications in my policy experiments. It is expected that decreasing these fixed costs, such as through the introduction of mobile stores, can have important welfare effects (see Section 8).

After presenting the dynamic parameters, I proceed to describe the shape of the inventory cost function predicted by these specifications. In the model, inventory costs and the package size dummies explain why a household does not purchase the product that has the lowest unit price. Thus, the identification of the storage cost parameters is connected to differences in unit prices across package sizes. In a typical application, the unit price is linearly decreasing in size, so the larger sizes usually have a larger price discount. In these typical cases a consumer would incur a substantial loss if they decided not to purchase the less expensive, larger product. When, in the data, some consumers do not buy the larger size, the model explains this by estimating a positive storage cost. With decreasing unit prices, we expect to find increasing storage costs as a function of inventory.[16]

In my case, there is no or very little price discount in the data for packages larger than 2 kg (i.e., 3 and 5 kg) - even though these larger sizes account for about 14 percent of the total market. In some cases, the unit price of 5 kg is higher.[17] Figure A.16 in the Appendix presents the distribution of the unit prices across markets and sizes and shows that there is little to no price discount beyond 2 kg. This feature of the data implies that the storage cost is potentially flat or even declining after the 2 kg package.

Implied storage costs are plotted in Figure 9 for the specifications in columns (1)-(4). I also add a quadratic and a fourth-degree polynomial cost function specification (corresponding to column (2)) to show that the inverse U-shaped feature of the implied cost function is not due to the functional form assumptions. I consistently find declining storage costs for larger sizes. As expected, the turning point is around the 2 kg size. Estimation using the quadratic specification yields a minimized objective function value that is 3 times as high as the corresponding cubic specification, indicating an inferior fit for the data. Nevertheless, the quadratic specification also shows a declining part consistent with the lack of quantity discounts at larger sizes.

Columns (5) - (8) show alternative specifications of the dynamic model for the lowest income area to illustrate specific features of the model and to check robustness in various ways. In column (5) I double the potential consumption shock (setting the mean to 100 g), in column (6) I restrict the maximum inventory level to 6.2 kg, the maximum I observe in the survey data (the median is 1 kg). I do not find any noteworthy changes in implied costs.

In column (7) I remove the consumption parameter, that is, I assume that there is a fixed utility of consumption for the households. In the model, the identification of this parameter comes from two sources of variation in the data, both of which produce variation between planned and realized consumption levels. First, there is a consumption shock to planned consumption. Second, some purchases do not allow for the full planned consumption, because consumption cannot be higher than the current inventory of the households. Column

[16] This is indeed what Hendel and Nevo (2006) finds.

[17] Recall that I corrected for this feature of the data in situations where "bundling" is possible. However, in some cases the 5 kg package has a higher unit price than a 3 kg package but there is no bundling opportunity (because the smaller packages a consumer might use to create a 5 kg bundle have even higher unit prices).

(7) shows that the fixed costs of purchase are substantially lower if there is no utility from consumption. This makes sense: since there is no consumption utility gain from buying a larger package, smaller fixed costs for these packages are sufficient to explain the data.

In column (8), I do not include any fixed costs of purchase. This results in negative consumption utility, which, based on the model, helps explain why households are not opting for the lowest unit-priced options.

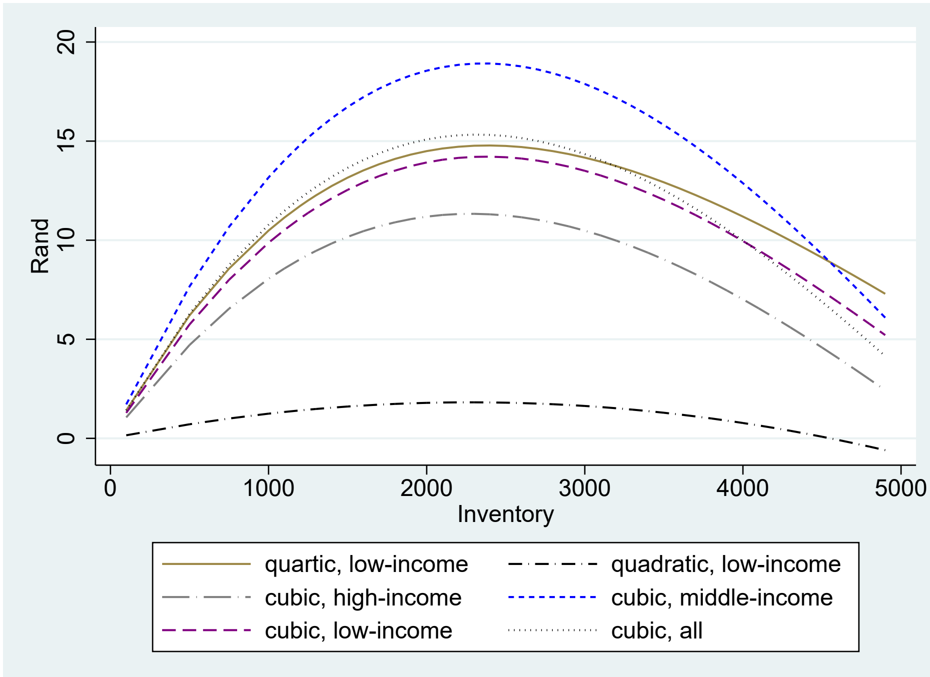
In column (9), I show the results when I ignore bundling in the static estimation and I do not correct the market shares which enter in the dynamic estimation.

Table 11: Dynamic parameter estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cost of inventory									
Linear	144.937	132.286	176.286	108.749	117.952	91.495	50.779	-185.427	215.049
	(11.872)	(6.583)	(14.404)	(13.998)	(7.034)	(2.304)	(3.284)	(41.727)	(15.429)
Quadratic	-395.200	-358.286	-474.966	-300.049	-318.921	-228.780	-131.419	504.853	-600.107
	(35.212)	(20.582)	(40.565)	(41.627)	(22.463)	(6.842)	(7.223)	(417.007)	(44.718)
Cubic	238.165	224.523	286.850	180.072	201.062	140.130	76.241	-241.141	361.203
	(22.297)	(14.344)	(25.191)	(25.887)	(15.784)	(5.19)	(4.191)	(395.441)	(27.959)
Utility from consumption									
	1293.931	1202.743	1579.109	843.810	925.319	707.786	x	-6551.698	1870.295
	(110.669)	(64.667)	(142.439)	(113.519)	(60.892)	(28.084)		(2792.634)	(151.835)
Size dummies									
250 g	-5.398	-5.869	-5.770	-4.049	-5.258	-4.776	-3.164	x	-8.089
	(0.296)	(0.162)	(0.377)	(0.284)	(0.17)	(0.08)	(0.118)		(0.401)
500 g	-8.736	-9.717	-10.283	-6.267	-8.472	-6.661	-2.282	x	-11.562
	(0.559)	(0.388)	(0.69)	(0.587)	(0.391)	(0.154)	(0.062)		(0.747)
1 kg	-13.371	-15.091	-16.933	-10.198	-12.888	-9.393	-1.473	x	-21.455
	(1.11)	(0.731)	(1.355)	(1.133)	(0.758)	(0.319)	(0.116)		(1.514)
2 kg	-23.630	-27.005	-31.744	-18.535	-22.682	-15.584	-2.104	x	-40.287
	(2.245)	(1.48)	(2.7)	(2.363)	(1.541)	(0.627)	(0.196)		(3.09)
3 kg	-34.352	-39.876	-51.365	-30.547	-33.057	-21.280	-2.454	x	-67.485
	(4.026)	(2.539)	(4.691)	(4.491)	(2.677)	(0.97)	(0.241)		(5.379)
5 kg	-54.057	-62.350	-75.956	-44.358	-51.741	-34.748	-6.052	x	-97.135
	(5.596)	(3.695)	(6.667)	(6.049)	(3.851)	(1.522)	(0.51)		(7.685)

Notes: Column (1) is for all stores, columns (2)-(4) are for stores in low, middle and high income areas, respectively. Column (5) shows results with increased consumption shocks. Column (6) caps inventory at 6.2 kg. Column (7) and (8) are variations of column (2) with no consumption or no fixed cost of purchase parameters, respectively. Standard errors are bootstrapped as described in the text with $N = 30$.

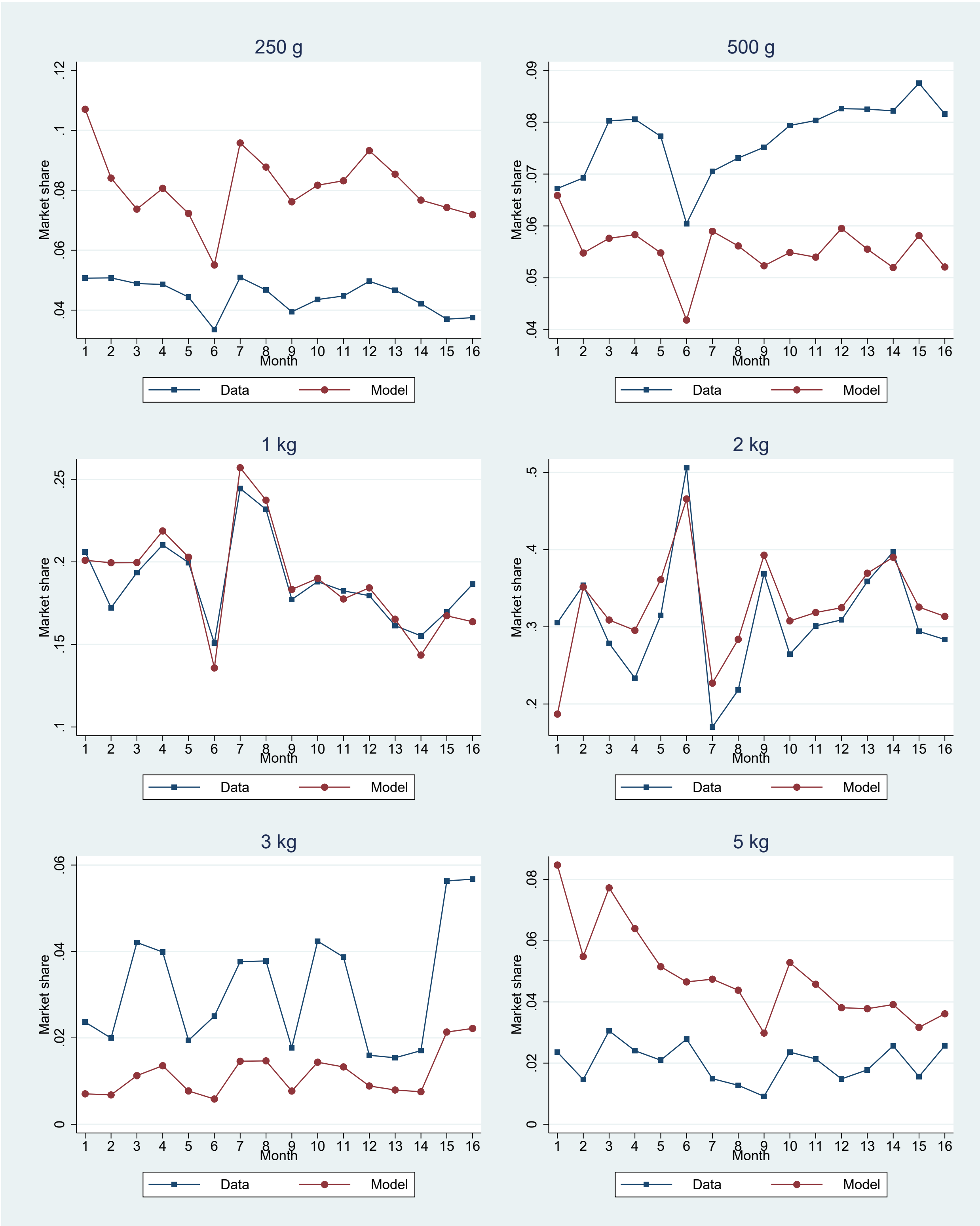
Figure 9: Estimated inventory cost



Notes: Inventory costs predicted by the dynamic model. Cubic specifications correspond to columns (1) - (4) in Table 11. Quartic and quadratic specifications are for low-income areas. See the text for details.

To investigate the performance of the model, I use the estimated parameters to plot the model-implied purchase patterns over time. I simulate 100 consumers for each market over 16 months. Figure 10 shows the fit of the model separately for each of the package sizes for stores in low income areas. As expected, purchases of package sizes with larger market shares are explained better by the model compared to less popular sizes. Nevertheless, the model appears to capture well the over-time fluctuations in market shares due to the temporary price promotions. Similar graphs for the other income areas areas are presented in the Appendix.

Figure 10: Model fit, low-income areas



Notes: Market shares of different sizes observed in the data and predicted by the dynamic model. 100 simulated consumers for each store. Stores are in low-income areas.

8 Analyzing package size choices in South African grocery stores

In Africa as well as many other parts of the world, large grocery store chains are opening small-scale stores, sometimes mobile stores, in low-income areas. Since these stores have limited space, they typically do not carry a full selection of products, and often restrict the package sizes offered as well.

What is the impact of increased consumer access, and what would be the welfare-maximizing package sizes for these stores to carry? To study the impact of increased access and associated reduction in transportation costs, I use the estimated model to analyze a counterfactual scenario where consumers' fixed cost of purchase decreases. To simulate the impact of a grocery store that only has space to carry one package size, I study the problem of a social planner choosing the welfare maximizing package size.

8.1 Counterfactual: reducing the fixed cost of purchase

In this section, I ask what would happen to purchase probability if the estimated fixed cost of purchase (such as the transportation cost) was reduced or removed. Specifically, I take the estimated model, and predict purchase probability for 16 months with fixed costs set to 0. I then repeat this, but replace the 0 fixed costs with several reduced fixed costs, such as a 25 percent or 50 percent reduction in fixed costs relative to the baseline estimate. I compare these results with my baseline estimates from Figure 10.

Table 12: Market shares when reducing the fixed cost of purchase

		Low-income area					High-income area				
		Baseline	Base*0.75	Base*0.50	Base*0.25	Zero	Baseline	Base*0.75	Base*0.50	Base*0.25	Zero
No purchsae	Average	0.29	0.17	0.10	0.08	0.02	0.24	0.13	0.09	0.08	0.02
	Median	0.28	0.18	0.12	0.09	0.02	0.24	0.15	0.11	0.08	0.03
250 g	Average	0.08	0.09	0.10	0.11	0.07	0.12	0.11	0.12	0.13	0.09
	Median	0.08	0.10	0.11	0.13	0.08	0.11	0.12	0.14	0.15	0.10
500 g	Average	0.06	0.08	0.11	0.14	0.11	0.13	0.17	0.18	0.20	0.14
	Median	0.06	0.09	0.13	0.16	0.13	0.13	0.19	0.22	0.23	0.17
1 kg	Average	0.19	0.28	0.31	0.31	0.22	0.20	0.25	0.26	0.26	0.20
	Median	0.19	0.29	0.34	0.36	0.24	0.19	0.27	0.29	0.29	0.22
2 kg	Average	0.33	0.32	0.30	0.25	0.37	0.28	0.28	0.27	0.22	0.31
	Median	0.32	0.31	0.29	0.26	0.40	0.29	0.25	0.24	0.23	0.31
3 kg	Average	0.01	0.00	0.01	0.02	0.04	0.00	0.00	0.01	0.01	0.06
	Median	0.01	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.06
5 kg	Average	0.05	0.06	0.07	0.09	0.17	0.03	0.06	0.07	0.09	0.17
	Median	0.05	0.00	0.00	0.00	0.06	0.03	0.00	0.00	0.00	0.07

Notes: Each column corresponds to a different scenario where the consumer's choice set is restricted to the given size (or the outside option). The simulations span a period of 16 months, with 50 individuals per store.

Table 12 displays the results of these counterfactual experiments. Each column corresponds to a separate simulation with reduced fixed costs. The column labeled ”Zero” represents the extreme case where there are no fixed purchase costs for any size.

The findings indicate that both small and large package sizes can gain market share. The market share of the 2 kg package will decrease and that of the 1 kg package will increase. The latter makes sense as mean consumption is also around 1 kg. Once we eliminate the fixed cost of purchase, households make more frequent purchases in order to avoid the storage cost.

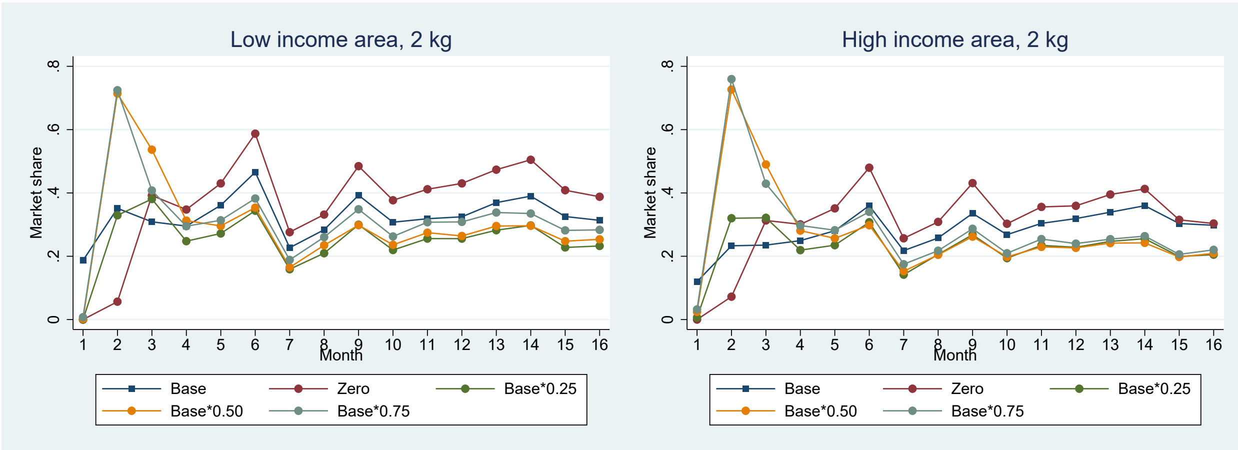
In the extreme scenario where all fixed costs are eliminated, there is a large increase in the largest package size. The purchase probability of the 5 kg package size increases from 5 (3) percent for low (high) income areas to 17 percent when fixed costs are eliminated. There is a decline in the market share of the 2 kg package but there appears to be no decline in the smallest sizes. This substitution effect is due to consumers who were already buying one of the largest packages shifting their purchase towards the largest size.

Figures A.22 and A.23 in the Appendix show the simulated market shares over time for each package size separately for low and high income areas. These graphs show some important dynamics of the substitution between sizes when fixed costs are reduced. There is a decline of the smallest sizes in the fist 4 months with a large increase in the largest sizes during the same period. This raises the average inventory of the households, and since purchase depends on inventory, demand for the 2 kg and higher package sizes eventually declines. There is a clear and sustained increase in demand for the 1 kg package. As shown on Figure 11, this occurs with a sustained decline of the most popular 2 kg package size. These patterns seem to be more pronounced in low income areas, where the estimated fixed cost was higher. These results underline the importance of the fixed purchase cost in shaping demand. Table 13 shows the associated consumption and inventory changes under these counterfactuals.

Clearly, care should be taken in interpreting the purchase probabilities presented above. This exercise does not take into account potential longer term consumption effects, such as households using more detergent as a result of increased access.

Similarly, I did not impose any constraint on inventory accumulation. In the no cost scenario, inventory held by the households will increase by up to a factor of 5 compared to the baseline. This overlooks factors like limited storage space, a preference for fresh products to avoid spoilage, etc. Inventory decisions by the households may thus involve additional considerations than those in the model - particularly for inventory levels not observed in the data,

Figure 11: The effect of reducing the fixed cost of purchase



Notes: 50 simulated consumers for each store.

8.2 A planner's problem: Only one size in the stores

In this section, I use the above estimates to answer the following question: Assuming that a store can carry only one size of laundry detergent, what size would a social planner choose?[18]

This question has current relevance in the South African context, where grocery store chains are expanding in low-income informal neighborhoods. Traditionally, these areas were served only by a collection of small informal stores, and high travel costs meant that consumers had limited access to formal supermarkets - not unlike the situation of "food deserts" in the US (see Marshall and Pires (2018)). For rapid expansion, supermarket chains have recently started setting up small square-footage stores by turning shipping containers or trailers into retail space. These small stores are supplied by the supermarket chain, use formal payment methods, but only have very limited space - and thus sell a limited number of items. For example, they may only sell one size of laundry detergent. Given a store that can sell only one size of laundry detergent, what size should it sell?

In many cases, stores tend to carry one of the smallest package sizes available, such as the 250 g detergent. One common view is that consumers buy these packages as a temporary solution until they make the next trip to a large grocery store. Similarly, because these small stores are located in low-income areas, it is assumed that households will seek the cheapest product even if its unit price is relatively high. These considerations ignore the trade-offs highlighted by the model above, namely, the trade-off between quantity discounts, fixed costs of purchase, and inventory costs. I now use the estimated model to quantify these trade-offs.

[18]The social planner perspective on the choice of package size could be different from the question of which package size maximizes profits. On the latter, see Björnerstedt and Verboven (2016) in the context of merger analysis.

Table 13: Household inventory and consumption when reducing the fixed cost of purchase

		Low-income area		High-income area	
		Consumption	Inventory	Consumption	Inventory
Base	Average	94.95	274.67	86.26	280.56
	Median	96.13	259.92	82.83	252.81
Base*0.75	Average	97.72	699.51	88.64	739.87
	Median	97.85	703.12	84.48	746.48
Base*0.50	Average	97.72	782.88	88.64	811.11
	Median	97.85	791.40	84.48	821.13
Base*0.25	Average	97.72	858.74	88.64	895.25
	Median	97.85	866.56	84.48	894.01
Zero	Average	97.72	1348.26	88.64	1400.86
	Median	97.85	1201.38	84.48	1244.70

Notes: Each row corresponds to a different scenario where the consumer faces reduced fixed cost of purchasing each size compared to the baseline case. "Zero" refers to the case with no fixed costs. Simulations span a period of 16 months, with 50 individuals per store. Consumption and inventory are measured in 10 g.

Specifically, I estimate a social planner problem where the planner chooses one package size to maximize the sum of households' utility based on Equation (2).

Specifically, let $V_h(\sigma_1, X) = V_h(\sigma_1)|_{x \in X}$ denote the solution of problem (2) for consumer h given a set X of available package sizes (as well as the outside option of not buying the product). The planner solves

$$\max_X \sum_h V_h(\sigma_1, X)$$

where X can be the set of 250 g products, the set of 500 g products, ..., the set of 5 kg products.

Since the choice of which size to buy is the result of a dynamic problem of individual consumers, the planner's problem described above (which size to sell) is conceptually difficult. I consider consumers faced with the choice of either buying a single available package size or not buying anything. I vary the single available size between six possible sizes (the six sizes observed in the data), and solve the consumer's dynamic problem in each case. I calculate consumers' utility streams over a period of 16 months and I compare these across the six scenarios. I do this separately by income areas in order to model the possibility that a store could decide to tailor the package size to local demand. The potential value of such customization has recently been highlighted by Klopack (2022) in the context of US fast-food chains.

The results are in Table 14. Each column corresponds to a different scenario with the consumer's choice set restricted to the specific size (or the outside option). The simulations span a period of 16 months, with 50 individuals per store. The starting inventory values are drawn randomly from the distribution observed in the survey and kept the same as in the main estimation. The results show the average monthly values of consumption, inventory, purchase probability and utility level. (The results for the middle-income area are very similar to those for the low-income area, and are displayed in the Appendix.)

Table 14: Counterfactual simulations

	Low-income						High-income					
	250 g	500 g	1 kg	2 kg	3 kg	5 kg	250 g	500 g	1 kg	2 kg	3 kg	5 kg
Consumption												
Average	34.06	54.08	81.86	89.49	89.25	92.51	36.38	54.46	73.03	75.53	69.42	74.50
Median	25	50	96.89	87.52	88.33	92.01	25	50	72.70	70.72	66.80	70.04
Inventory												
Average	10.59	13.86	47.64	168.36	120.69	251.91	21.00	35.50	103.12	146.93	113.83	213.55
Median	0	0	0.75	92.78	131.74	268.50	0	0	104.97	113.64	107.99	207.73
Purchase probability												
Average	0.48	0.46	0.45	0.34	0.22	0.17	0.50	0.51	0.51	0.30	0.17	0.13
Median	0.49	0.45	0.43	0.32	0.18	0.15	0.50	0.52	0.51	0.28	0.15	0.08
Utility level (expected)												
Average	156.47	161.51	165.85	176.38	169.80	183.92	116.75	119.35	122.70	125.82	119.88	131.62
Median	154.89	160.07	163.93	168.83	166.58	181.08	113.14	115.84	117.43	119.99	117.53	129.23

Notes: Each column corresponds to a different scenario where the consumer's choice set is restricted to the given size (or the outside option). The simulations span a period of 16 months, with 50 individuals per store. Consumption and inventory are measured in 10 g.

In the data, the market share of the smallest, 250 g package is 4.22% in low-income areas. According to the corresponding simulation, this market share would increase to 48% if this size was the only one available to the consumer (i.e., on average 52% of consumers would choose the outside option in a given month). The counterfactual increase for the largest, 5 kg package is much smaller: from 2.10% observed in the data to 17%. The counterfactual market share is smaller in high-income areas, 13%, reflecting lower observed consumption and preferences towards smaller sizes.

Counterfactual purchase probabilities are generally higher in the high-income area for 1 kg and smaller sizes. At the same time, the purchase probabilities are lower for 2 kg and larger sizes. The increase in utility from the smallest to the largest package size is more pronounced in low-income areas.

If the only consideration is expected utility, the 5 kg package would be the welfare-maximizing option in both areas. This would be the optimal size for a planner limited to offering only one size to consumers.

However, with the 5 kg package as the only option, consumer inventory would be much larger than what is currently observed in the data. Package sizes of 2 and 3 kg would result in average inventory (and consumption) closer to what is observed in the data. In both low and high-income areas the 2 kg package yields the second highest consumer welfare. In low-income areas, the difference between the 2 and the 3 kg package is less pronounced.

According to this model, offering only the smallest package size is not the optimal choice in either income area (in fact, offering only the 250 g package delivers the lowest average utility in both income areas). This observation is in line with the results of Section 7.2 which indicated that many households only purchased small packages as part of a bundle that allowed them to save money when buying a larger total quantity.

It is worth pointing out that, if only the 250 g or the 500 g product is offered, both median and mean consumption is lower than what is observed in the data. The reason is that these are smaller quantities than the mean monthly consumption. Since this exercise maintains the discrete choice assumption that consumers purchase only one product (once a month), consumption must necessarily decrease. Would it be reasonable to assume that, in this case, the consumer would prefer to purchase these smaller package sizes multiple times rather than opting for a larger size? The estimated fixed cost results help to answer this: based on Table 11, the fixed cost of purchasing N packages of size Q is always higher than the fixed cost of purchasing a single package of size NQ. This suggests that a consumer would not want to make multiple small purchases.

Table 15: Counterfactual simulations with reduced fixed cost of purchase

	Low income						High income					
	250 g	500 g	1 kg	2 kg	3 kg	5 kg	250 g	500 g	1 kg	2 kg	3 kg	5 kg
Consumption												
Average	34.80	55.37	86.17	97.67	97.63	97.72	37.39	56.26	76.80	81.34	78.37	81.38
Median	25.00	50.00	97.60	97.85	97.79	97.85	25.00	50.00	75.83	75.97	72.98	76.09
Inventory												
Average	12.79	26.87	198.18	634.05	626.00	646.51	24.52	55.17	270.47	621.70	291.61	590.22
Median	0.00	0.00	150.64	672.20	632.66	638.15	0.00	0.00	236.72	660.67	246.96	579.22
Purchase probability												
Average	0.53	0.53	0.73	0.65	0.41	0.25	0.56	0.62	0.84	0.62	0.27	0.23
Median	0.53	0.54	0.73	0.63	0.35	0.20	0.56	0.62	0.86	0.57	0.24	0.16
Utility level (expected)												
Average	157.41	163.80	182.69	227.46	225.54	227.56	117.64	122.06	141.37	176.86	140.84	172.95
Median	156.02	162.76	179.81	225.41	223.91	225.65	114.10	118.19	136.83	175.26	135.03	170.64

Notes: Simulations for the base*0.75 case. Each column corresponds to a different scenario where the consumer's choice set is restricted to the given size (or the outside option). The simulations span a period of 16 months, with 50 individuals per store. Consumption and inventory are measured in 10 g.

What would be the welfare maximizing package size if the fixed cost of purchase went down? This corresponds to a situation where opening small stores makes access to the product easier, but at the same time, they can carry only one package size. To answer this question, I repeat the above exercise, but decrease the fixed cost of purchase by 25 percent for each package size. Table 15 shows the results. (In Table A.25 in the Appendix, I show corresponding results when the fixed costs are set to zero.)

In this case, there are important changes. First, there are very little differences in expected utility between the 2 kg, 3 kg and 5 kg sizes for low-income areas. Second, there is also little difference in the associated inventory holding. The main difference is how frequently households wish to purchase the product. The average household would purchase the 2 kg package 10 times over the simulated 16-month period, the 3 kg package 6 times, and the 5 kg package 4 times. With lower fixed costs, there is an 8 percentage point increase in purchase probability compared to Table 14 if the largest package is offered, and purchase probability doubles if the 3 kg package is offered. When access improves, consumers are even more likely to buy the largest packages.

For high-income areas, the 2 kg package size provides the highest expected utility, in contrast to the 5 kg package in Table 14.

In summary, the welfare maximizing package size offered in a small store may be different from the most popular package size purchased in a regular store. Considerations such as ease of access, frequency of purchase, or storage costs all enter households' decision about which package size to buy. In addition, these results appear to show that offering one of the larger package sizes, rather than one of the smaller sizes, would yield higher consumer welfare.

9 Conclusion

This paper analyzes consumer choices between different package sizes of a storable product in South Africa. It provides a comprehensive dynamic demand estimation under nonlinear prices and, in addition, temporary promotions that often target only specific sizes. These two facts combined can result in situations where consumers are better off buying two smaller packages instead of a larger one, which can lead to misleading conclusions regarding consumers' preferences for small package sizes in developing countries.

The results are based on high-frequency scanner data for an entire product category, and geo-coded store locations linked to consumer demographics. The dataset includes both rural and low-income populations, and it is complemented with a survey that directly collects information on consumption and inventory to improve the identification of several dynamic parameters of the model.

My first finding is that accounting for bundling opportunities has important effects for the interpretation of observed market shares. I estimate that, on the median market, there are over 3 times as many households who purchase 5kg of the product as households who purchase a single 5 kg package (the largest available package size). These findings run against the common belief that in similar environments households often purchase products with the lowest package price rather than the lowest unit price.

Currently grocery chains are expanding in low-income neighborhoods throughout Africa by opening small-scale stores with limited space that sell a limited number of items. To study which package size is efficient, I solve the planner's dynamic problem when consumers are faced with the choice of either buying a single available package size or not buying anything. I find that if a store is restricted to offering a single package size, offering the 3 kg package would provide the highest consumer utility. This is the second largest package size sold in the data – by contrast, offering the smallest (250 g) package size would deliver one of the lowest values of consumer utility.

This paper also contributes to the development economics literature, where there is long-standing interest in interventions designed to motivate households to save. In my data, over a year, a household that consumes the average amount of detergent and always buys the largest package will spend 11.08 USD less than if it always bought the smallest package. These are remarkably large savings on a single product category that typical households regularly purchase in a grocery store. From a policy perspective, this suggests that making these saving opportunities salient, as is often done in other contexts, can be an effective tool to increase welfare.

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