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

Andrea Szabó
Economics Department, University of Houston
E-mail: aszabo2@uh.edu

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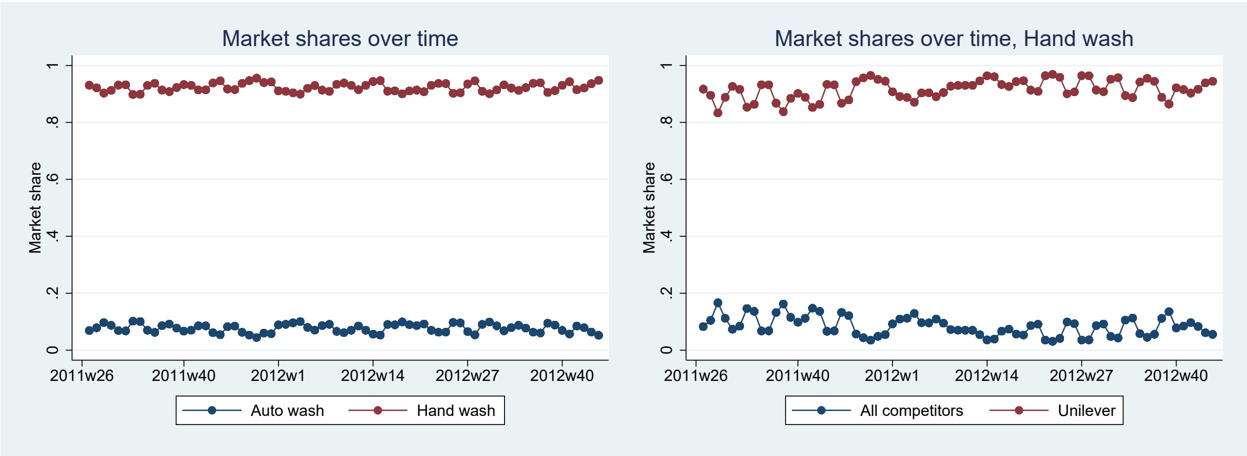
A.1 Additional data characteristics

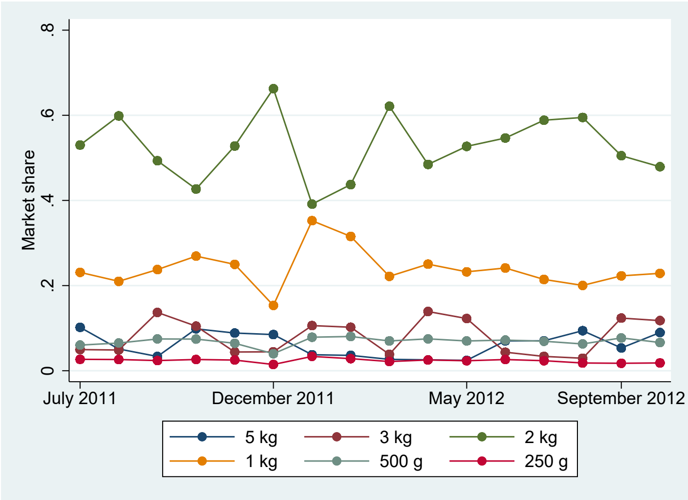
A.1.1 Market characteristics

Figure A.1: Market shares of hand-wash and automatic detergents



Notes: Market shares based on sales value. Left panel: Market share of all hand-wash and automatic detergents. Right panel: Market share of hand-wash detergents only, Unilever and all competitors.

Figure A.2: Market share of Unilever products by package size



Notes: Market share is sales value of the given package size across all stores in a given month divided by the sales value of all 14 Unilever products across all stores in the given month.

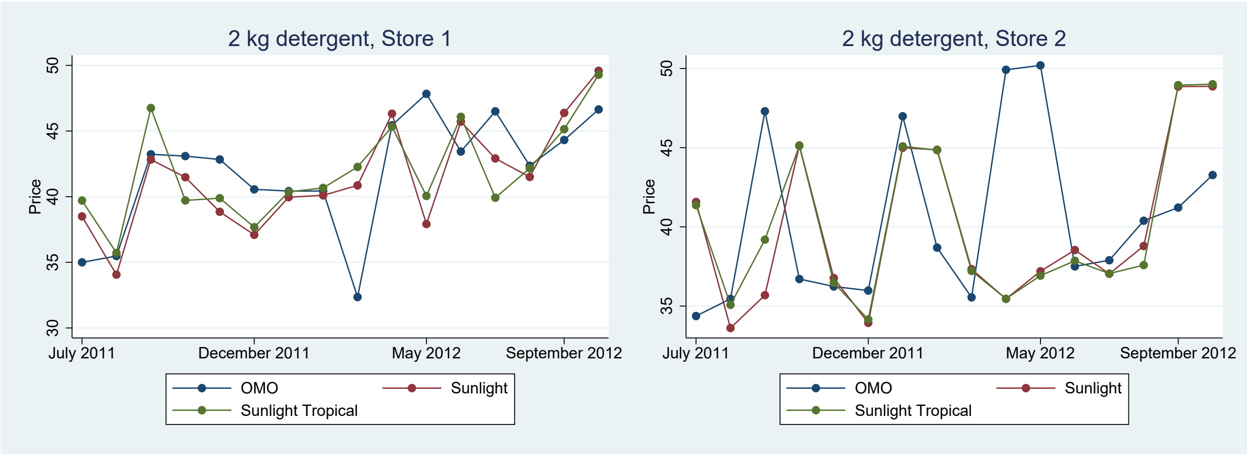
Table A.3: Availability of various brands and sizes

	Sunlight	Sunlight Tropical	OMO
250g	0.94	0.81	0.95
500g	1	0.77	0.99
1kg	1	0.96	1
2kg	1	0.99	1
3kg	0.99		
5kg	0.98		

Notes: Fraction of all markets (months × stores) in the data where the given product is available. N = 5255.

A.1.2 Prices

Figure A.4: Prices of 2 kg packages in selected stores



Notes: Prices of 2 kg packages in Rand in two selected stores.

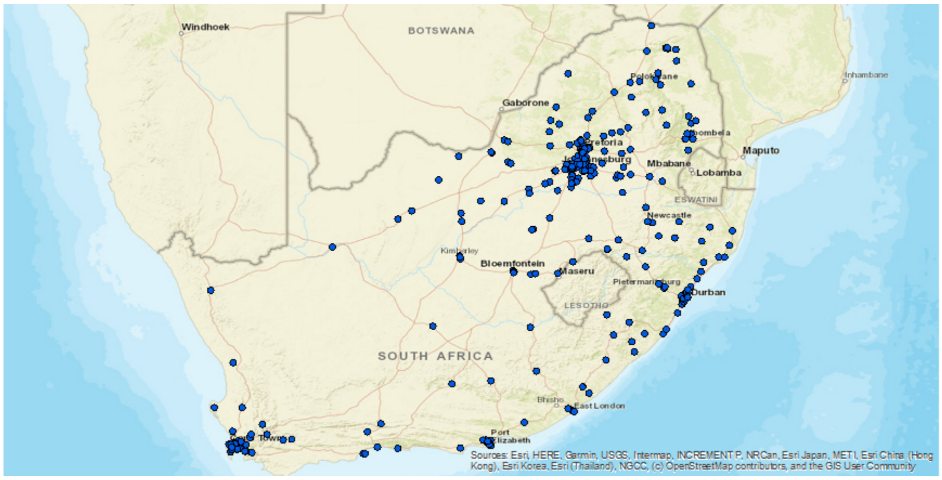
Figure A.5 shows the evolution of prices for two distinct products over time in two selected stores. The first product (Sunlight 250 g, left panel) had only 1 week of promotion during the study period and the second (Sunlight 1 kg, right panel) had the most frequent promotions. In a given store, the price of the product with less promotion stays steady over a longer period. The price 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 A.5: Evolution of prices with and without frequent promotions

Notes: Prices in Rand. Left panel shows Sunlight 250 g. Right panel shows Sunlight 1 kg.

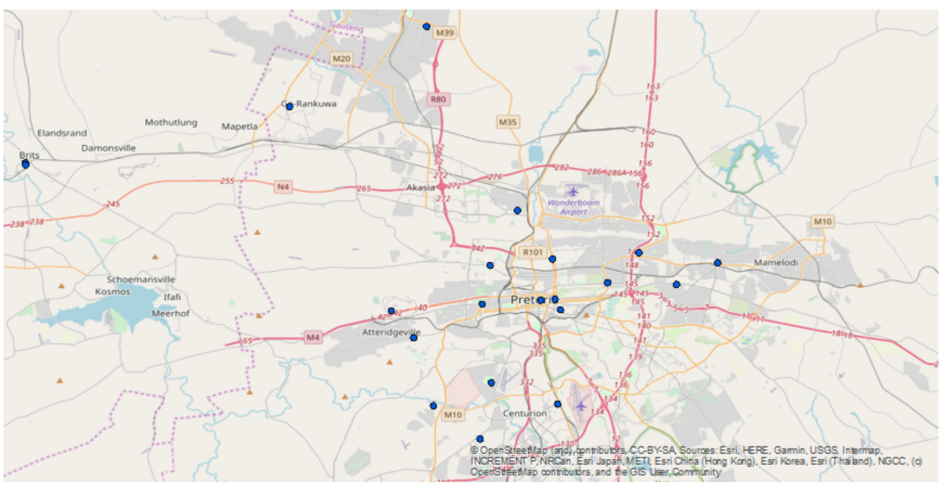
A.1.3 Store characteristics

Figure A.6: Location of stores in the sample



Notes: Locations based on GPS coordinates of the stores, collected from www.shoprite.co.za

Figure A.7: Location of the stores in the sample around Pretoria



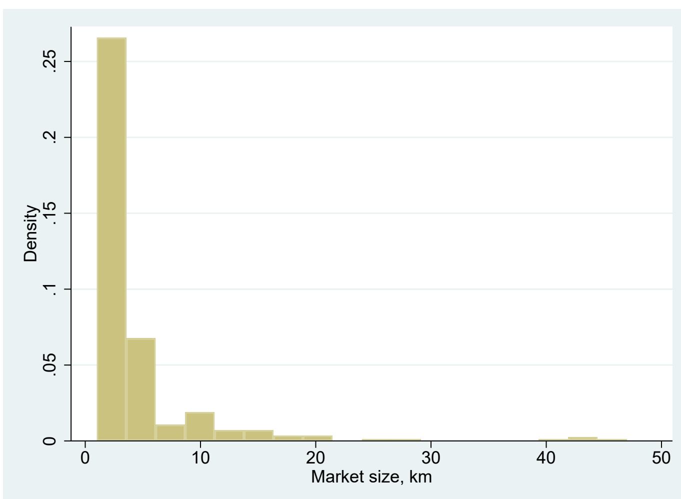
Notes: Locations based on GPS coordinates of the stores, collected from www.shoprite.co.za

Table A.8: Other store characteristics

	Percent
Low-income area	17.27
Middle-income area	43.64
High-income area	39.09
In a shopping mall	8.79
In city centre	24.85
Sunday closing time	
13:00	18.18
14:00	26.67
15:00	13.33
15:30	1.82
16:00	3.33
17:00	16.06
18:00	2.42
19:00	3.33
20:00	12.42
21:00	0.30
Closed on Sunday	2.12

Notes: Income area categories are from Unilever. Other characteristics based on store locator information at www.shoprite.co.za

Figure A.9: Distribution of the market radius



Notes: Distribution of market radius corresponding to each store. See the main text for the market size definition.

A.1.4 Census Data

The paper uses dataset "4.6. Household goods" from the "Census 2011: Community Profiles" CD. The data is accessed using SuperCross, a software provided by the South African Census.

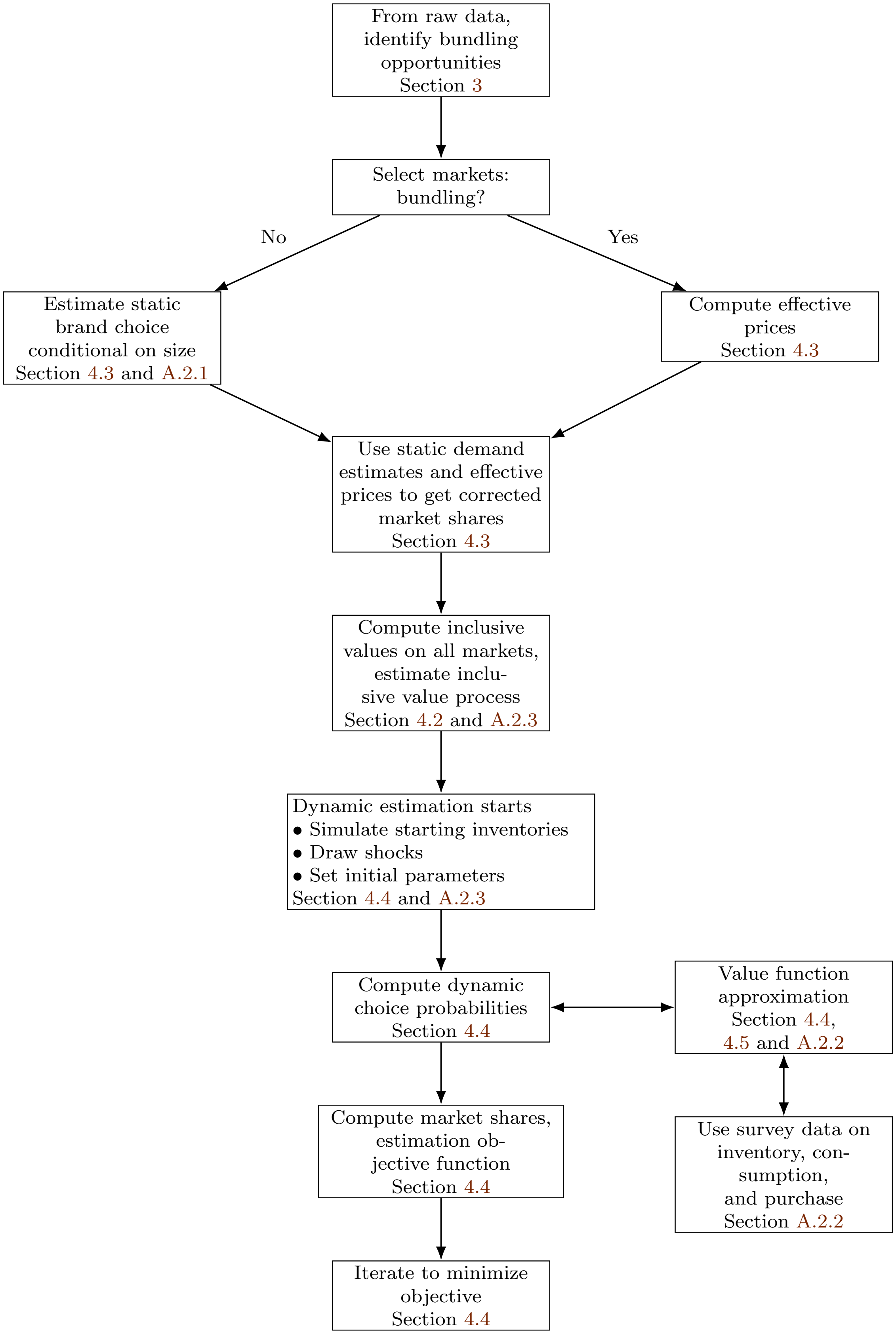
Table A.10: Household demographics

	South Africa	Markets in the sample
Monthly household income	9092.11	10410.27
Urban area	68.03	84.48
Male household head	57.61	59.89
Owns car and washm	22.40	28.73
Owns no car or washm	55.81	46.44
Owns washm only	12.02	14.79
Owns car only	9.77	10.04
Population group of household head		
Black African	77.71	69.7
White	10.96	13.49
Other	11.33	16.8
Type of dwelling		
House	66.97	67.41
Flat/apartment	12.45	18.3
Other (Informal dwelling, shack in backyard)	20.58	14.28
N	10,261,921	3,012,142

Notes: Based on 2011 South African Census. Households in sample markets are identified based on their distance from a store. See Section 2.2.4 for details. Income is monthly household income in Rand. Other variables are percentages of total.

A.2 Estimation details

Figure A.11: Estimation flow chart



A.2.1 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 $S_{jt}^{(x)}$. Berry et al. (1995) show that, for given $\mu_h(.)$, it is possible to numerically solve for $\boldsymbol{\xi}_{xt}$ from the equations $s_{jxt}(\mathbf{a}_{jxt}, \boldsymbol{\beta}_x, \boldsymbol{\xi}_{xt}, \mu_h(\mathbf{a}_{jxt})) = S_{jt}^{(x)}$, i.e., equating the model-predicted market shares to those observed in the data. 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, $\boldsymbol{\beta}_x\mathbf{a}_{jxt}$, includes price, brand dummies, store characteristics and average demographics. Store characteristics are included as they are likely to be correlated with consumer choices as well as prices and/or the availability 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. In this application, perhaps uniquely among similar discrete choice demand applications, I see very segregated markets. This arises from the segregation of South African neighborhoods, and it implies that there is little to no variation in, e.g., ethnicity within markets. In addition, as described in the paper, 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 is shown in Table A.18 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 A.10 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 modeled here), or a different size. For example, the fact that a household has a car is likely to be an important determinant of which size they purchase.[1] For the full set of nonlinear variables included, see Table A.18 under "Nonlinear parameters."

Instruments. To identify the model, instruments are needed for two reasons: to control for price endogeneity, and to identify the nonlinear parameters. Instruments based on product characteristics, such as the differentiation IVs of Gandhi and Houde (2019), are not feasible in the current context. There are no product characteristics in $\mathbf{a}_{jxt}$ other than prices and 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.

To instrument for price, similar to Nevo (2001), I construct instruments using the prices of the same product in different markets. Specifically, I rank a store's neighbors based on the magnitude of the correlation between the prices in the two stores. To determine the number of neighboring prices used as instrument, I successively 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 for 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.

[1] 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 in 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.

A.2.2 Laundry detergent survey and value function approximation details

The survey data is used for estimating the value function of the households, which in turn is an input for computing the dynamic choice probabilities in estimating the dynamic parameters of the model. Estimation of the value function is via value function approximation (see Section 4.5 in the paper), which requires describing the relationship between consumption, inventory, and purchase. Previous studies do not have data on consumption and inventory as these are not available in scanner data, which poses a challenge for identification. Even though my survey was conducted in a different time period than the scanner data, it helps alleviate these identification challenges as long as households with a given inventory and consumption choose similar sizes. The level or distribution of households' inventory, consumption, or purchase patterns (market shares) do not need to be the same at the time of the survey and the scanner data.

Out of the 300 respondents in my survey, 91.3% typically buy powdered detergents only.[2] This is very close to the market share from 2012 (see Figure A.1).

A.2.2.1 Sampling

The survey was entirely funded by the University of Houston. It was approved by the Human Subject Committee of the University of Houston, and was conducted in accordance with the standards of that institution regarding the ethical treatment of human subjects (Protocol number: 2626). Participation in the survey was voluntary and respondents could stop participating in the survey at any time. Only adults between the ages of 18 and 65 were asked to participate.

Surveys were collected from 300 households in December 2020 and again in March 2022. For logistical reasons, sampling had to be restricted to a single metropolitan area. I chose the area around Pretoria because of the diverse socio-economic characteristics of its population.

I first took all the stores in my dataset located within 20 miles from Pretoria (25 stores). I then extended this area 5 miles to the north to include more rural areas, resulting in a total of 27 stores. Of these 27 stores, 4 are located in low-income areas, 15 stores in middle-income areas and 8 stores in high-income areas. One of these stores was closed at the time of the survey due to damage from a tornado. Of the remaining 26 stores, I randomly selected a store from each of the three income areas. I selected the sample of households to be surveyed around each of these 3 stores as follows.

[2] Only 4 respondents stated that they typically buy liquid detergents and only 1 said that they typically use bar soap instead of detergent. 21 additional respondents buy a combination of powdered detergent and either liquid or bar soap.

For each store, I randomly selected 5 of the 10 closest small area layers of the 2011 South African Census. Surveyors were provided maps of each of these 5×3 areas. From each map, they selected a street intersection, and starting from there interviewed 5 households in each direction. Specifically, surveyors visited every 5th house in each direction, subject to the constraint that the final sample had to be stratified based on dwelling type recorded in the Census ("house," "flat," and "informal/other"). Surveyors recorded the GPS coordinate and a detailed description of the selected houses. Based on this information, surveyors visited the same houses during the second round of the survey.

A.2.2.2 Purchase, consumption, and inventory data

Recall that inventory levels at the start and end of a period, consumption and purchase during the period satisfy $i_{t+1} = i_t - c_t + x_t$. For each household, I define the period $[t, t+1]$ as consisting of the one month just before the survey visit. To infer the household's purchase x_t and inventory i_t from the survey, I proceed as follows. I compute the sum of the observed stock and consumption, call this SC. If SC is smaller than the size of the package kept by the household, X, then I assume that the package was purchased more than a month ago. In this case, I assign $x_t = 0$ and $i_t = SC$. If $SC \geq X$, then I assign $x_t = X$ and $i_t = SC - X$. I drop 2 observations where $i_t = 0$, 26 observations where the package was unopened, as well as 5 outliers whose inventory i_t is above 4 kg (over 3 standard deviations above the average of 1173 g). This results in 542 survey observations used in the value function approximation.

Based on the data, 32.87% of the households did not purchase detergent during the current month.

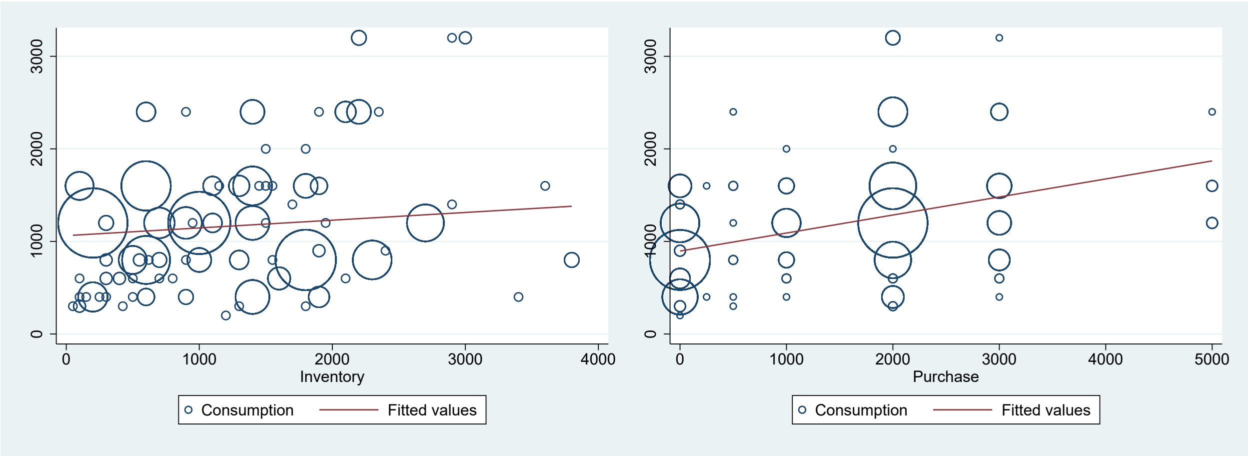
A.2.2.3 Patterns in the survey data

Three patterns are visible in the survey data. First, reported consumption is not correlated with inventory at home (correlation = 0.12, left panel of Figure A.12). This makes sense since the households are unlikely to use more detergent just because they have a new package at home.

Second, there is a stronger relationship between consumption and purchase size (correlation = 0.42, right panel of Figure A.12). Households who tend to buy larger packages consume more on average.

Third, average inventory during the first and the second round of the survey, conducted 16 months apart, is not statistically different. This is true both for all households and for households within income groups (Figure A.13). If average inventory is the same at the start and at the end of the period, this implies that average consumption equals average quantity

Figure A.12: Consumption as a function of inventory and purchase in the survey



Notes: Scatterplots and linear fits of consumption as a function of inventory and purchase, all in grams. N = 542.

purchased over this period period. (Note that 16 months is also the difference between the first and last period observed in the scanner data.)

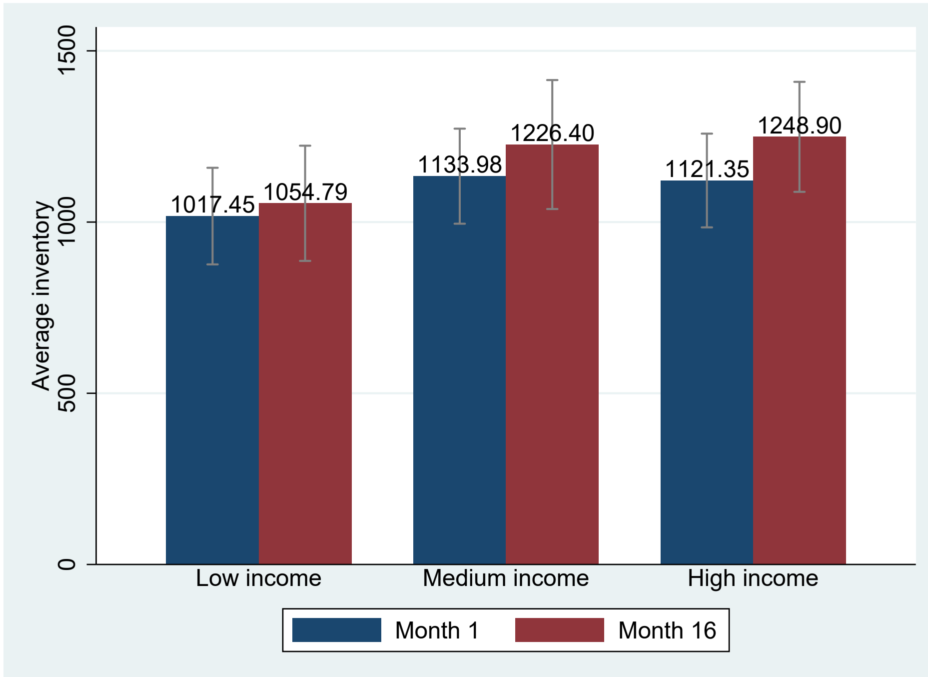
A.2.2.4 Value function approximation

For the value function approximation (equations (5) and (6) in the paper), I draw 400 markets from the relevant income groups (low only, medium only, high only, or all), and draw 50 individuals on each market, with corresponding inclusive values, from the BLP exercise. For each simulated individual, I draw a purchase x_t based on the market shares. The survey data provides information on the joint distribution of inventory i_t and consumption c_t conditional on purchase, and I draw inventory and consumption pairs for each simulated individual from this distribution.

Future inventory i_{t+1} is computed as $i_t + x_t - c_t$. Future values for inclusive values are predicted from the Markov process described in Section A.2.3 below. Based on the patterns described in the previous section, households' consumption needs are assumed to be a time-invariant constant, plus an idiosyncratic shock drawn from a log-normal distribution parametrized as in Hendel and Nevo (2006).

With these ingredients, for a given set of dynamic parameters, the value function can be approximated as described in Section 4.5 of the paper.

Figure A.13: Average inventory of households in the survey



Notes: Inventory in grams. Month 1 and 16 refer to the two surveys. p-values of Month 1 vs. Month 16 differences: 0.7520, 0.5018, 0.1353, respectively.

A.2.3 Details of the dynamic estimation

Markets and simulations. The dynamic estimation uses both markets with and without bundling opportunities. I drop only markets that do not have all brands and sizes, to keep the consumer's choice set constant (430 out of 5255 markets). I also drop markets where I do not observe at least 16 consecutive time periods (this can happen because some stores opened during the period and/or the store did not carry all sizes during the 16 month period). This results in 528, 1248 and 992 markets, respectively, for each income area.

From the static part of the estimation, I have 400 simulated consumers on each of these markets. To reduce the computational complexity of the dynamic estimation, I draw 50 of these consumers on each market. For each individual, the model predicts individual choice probabilities $Pr(x_{ht} = x)$ for each possible package size. I compute each of these choice probabilities for 10 draws of the consumption shock ν_{ht} and take the average.

Starting inventory. To obtain households' starting inventory, I follow Erdem, Imai and Keane (2003) and Hendel and Nevo (2006), who take as the starting inventory the inventory levels obtained from simulating the model for a number of periods from an inventory of 0 for all households. Specifically, for each set of dynamic parameters, I use the inclusive values and market shares to simulate the model from a starting inventory of zero for all households for

16 periods. I then take the resulting inventory levels as the starting inventory, and simulate another 16 periods which are used for estimation. The maximum potential inventory is set to twice the largest package size in the data.

Consumption. To compute consumption c_{ht} for the dynamic estimation, I first draw a sequence of 16 monthly purchased quantities based the observed market shares and take consumption to be the average of each sequence, c_h. This is based on the patterns described above, which suggest that consumption is correlated with purchase (but not inventory) and that, over a 16-month period, consumption is roughly equal to average purchase.

When simulating the model, I impose the constraint that current consumption (including the consumption shock) cannot be larger than current inventory, i.e., $c_{ht} + \nu_{ht} = min\{c_h + \nu_{ht}, i_t\}$.

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 size. 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, and estimate either a single process for each size (Table A.19), or separate processes for each of the three income areas (top panel of Table A.20). I also show results where the grouping is done based on the ownership of washing machines and cars (middle panel of Table A.20). These are the variables which capture most of the individual level heterogeneity in the demand estimation, therefore I use the same variables to capture heterogeneity in the evolution of inclusive values. I assess the first-order Markov process assumption by including additional lags of the inclusive values of different sizes, as in Hendel and Nevo (2006) (bottom panel of Table A.20).

A.3 Additional results

Table A.14: Markets with no bundling opportunities

	Unique stores	Unique month	Markets (store × 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.

Table A.15: Correlation between bundling opportunities and market characteristics

	Low income	Middle income	Mall	City center	Sunday	% Black	% Flat
250 g	0.048	-0.005	-0.036	0.035	0.014	0.153	-0.022
	(0.024)	(0.015)	(0.018)	(0.018)	(0.015)	(0.032)	(0.036)
	0.25	0.25	0.25	0.25	0.25	0.26	0.25
500 g	0.053	-0.006	-0.035	0.029	0.012	0.147	-0.040
	(0.024)	(0.015)	(0.018)	(0.019)	(0.016)	(0.031)	(0.037)
	0.23	0.23	0.23	0.23	0.23	0.24	0.23
1 kg	0.004	-0.002	0.015	-0.008	0.000	-0.043	0.077
	(0.012)	(0.009)	(0.010)	(0.010)	(0.012)	(0.019)	(0.020)
	0.38	0.38	0.38	0.38	0.38	0.38	0.38
2 kg	0.020	-0.012	-0.012	-0.010	0.001	0.014	0.065
	(0.014)	(0.011)	(0.013)	(0.013)	(0.019)	(0.021)	(0.027)
	0.32	0.32	0.32	0.32	0.32	0.32	0.32
3 kg	0.018	-0.011	-0.018	-0.002	-0.006	0.033	0.044
	(0.014)	(0.010)	(0.013)	(0.012)	(0.013)	(0.018)	(0.026)
	0.40	0.40	0.40	0.40	0.40	0.40	0.40
5 kg	0.022	-0.012	-0.019	-0.002	0.002	0.057	-0.004
	(0.013)	(0.009)	(0.010)	(0.010)	(0.012)	(0.018)	(0.024)
	0.49	0.49	0.49	0.49	0.49	0.49	0.49
	% House	**% Male HH head**	**% Urban**	**% White**	**No car or washm**	**Washm only**	**Car only**
250 g	0.009	0.113	-0.081	-0.038	0.139	-0.412	0.889
	(0.039)	(0.103)	(0.037)	(0.033)	(0.042)	(0.096)	(0.250)
	0.25	0.25	0.25	0.25	0.25	0.25	0.25
500 g	0.011	0.143	-0.079	-0.033	0.135	-0.433	0.911
	(0.039)	(0.107)	(0.035)	(0.035)	(0.041)	(0.094)	(0.254)
	0.23	0.23	0.23	0.23	0.23	0.24	0.23
1 kg	-0.086	-0.085	-0.012	0.006	-0.040	-0.017	0.041
	(0.026)	(0.067)	(0.022)	(0.021)	(0.029)	(0.058)	(0.150)
	0.38	0.38	0.38	0.38	0.38	0.38	0.38
2 kg	-0.084	0.023	-0.050	-0.004	0.029	-0.149	0.291
	(0.032)	(0.080)	(0.022)	(0.024)	(0.033)	(0.065)	(0.165)
	0.32	0.32	0.32	0.32	0.32	0.32	0.32
3 kg	-0.072	0.059	-0.056	0.000	0.048	-0.158	0.309
	(0.030)	(0.076)	(0.021)	(0.024)	(0.028)	(0.063)	(0.158)
	0.40	0.40	0.40	0.40	0.40	0.40	0.40
5 kg	-0.019	0.063	-0.061	-0.020	0.081	-0.159	0.333
	(0.026)	(0.071)	(0.019)	(0.024)	(0.026)	(0.053)	(0.147)
	0.49	0.49	0.49	0.49	0.49	0.49	0.49

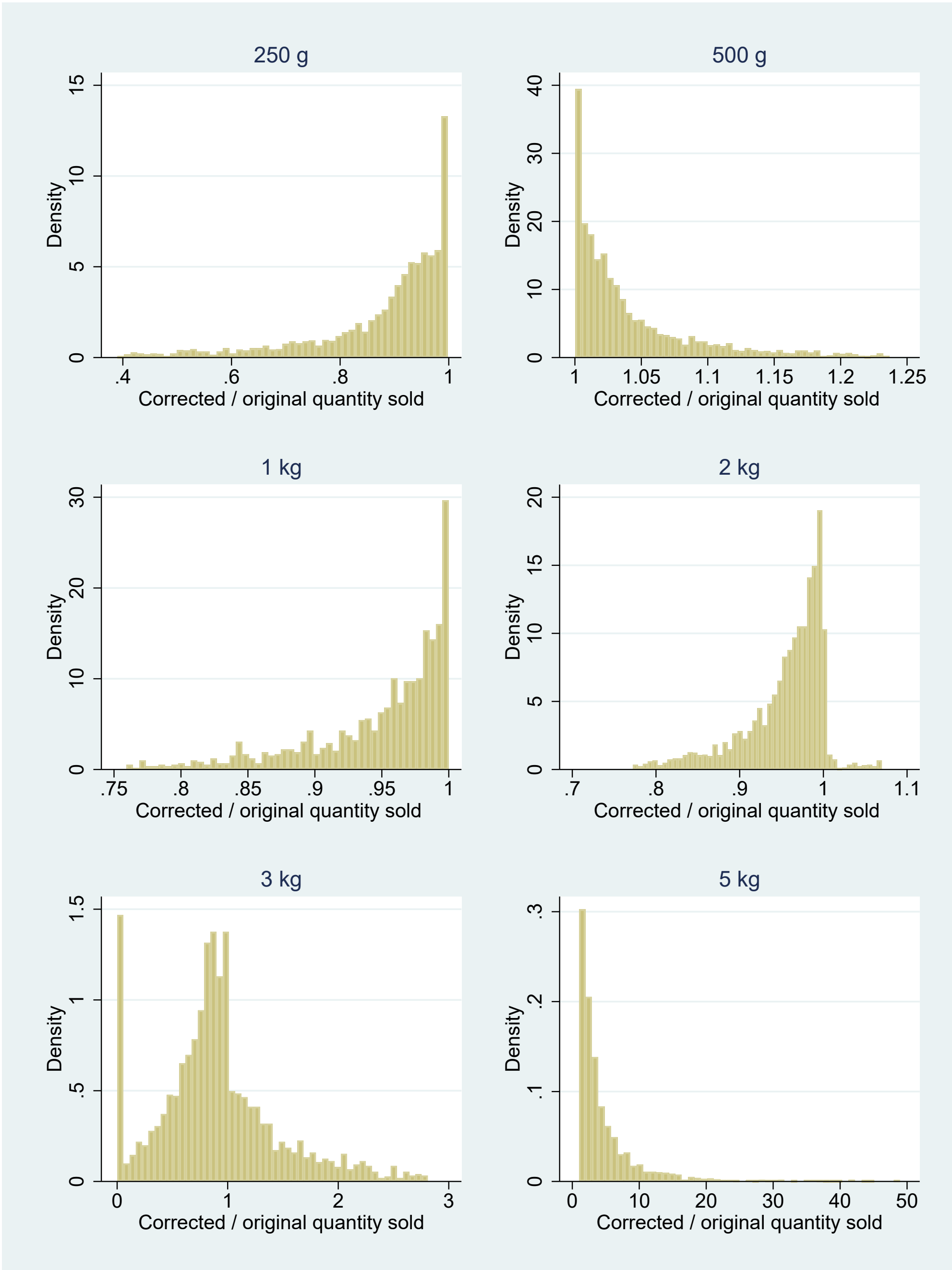
Notes: Regressions of an indicator for the presence of bundling opportunities on market characteristics. Observations are brands of the size listed in the row heading across all markets. Each cell is from a different regression. All regressions control for month and province fixed effects, market size, distance to closest store and number of other stores in the market. Number of observations for each size are shown in Table A.16.

Table A.16: Correlation between bundling opportunities and market characteristics

	250 g	500 g	1 kg	2 kg	3 kg	5 kg
Low income area	0.037	0.045	0.008	0.016	0.009	0.008
	(0.028)	(0.028)	(0.016)	(0.017)	(0.017)	(0.015)
Middle income area	0.018	0.021	0.003	-0.002	-0.002	-0.006
	(0.016)	(0.016)	(0.011)	(0.012)	(0.011)	(0.009)
Mall	-0.017	-0.016	0.006	-0.015	-0.013	-0.015
	(0.021)	(0.022)	(0.012)	(0.015)	(0.015)	(0.012)
City center	0.025	0.019	-0.006	-0.012	-0.002	-0.005
	(0.016)	(0.017)	(0.010)	(0.013)	(0.013)	(0.010)
Sunday hours	0.010	0.009	-0.001	0.001	-0.006	-0.000
	(0.016)	(0.017)	(0.012)	(0.020)	(0.014)	(0.013)
HH share Black	0.297	0.271	-0.081	0.007	0.051	0.059
	(0.071)	(0.070)	(0.036)	(0.037)	(0.039)	(0.035)
HH share White	-0.069	-0.068	-0.117	-0.074	0.004	0.015
	(0.086)	(0.081)	(0.040)	(0.056)	(0.055)	(0.054)
HH share flat	0.263	0.177	-0.059	0.067	0.035	0.083
	(0.088)	(0.082)	(0.076)	(0.099)	(0.072)	(0.061)
HH share house	0.163	0.101	-0.123	-0.030	-0.058	0.040
	(0.086)	(0.080)	(0.079)	(0.099)	(0.073)	(0.057)
HH share male HH head	0.512	0.506	-0.169	0.152	0.233	0.286
	(0.120)	(0.125)	(0.074)	(0.094)	(0.091)	(0.081)
HH share urban	-0.049	-0.044	-0.014	-0.053	-0.070	-0.059
	(0.040)	(0.039)	(0.026)	(0.027)	(0.029)	(0.025)
HH share no car or washm	-0.193	-0.205	-0.105	-0.043	-0.018	0.050
	(0.133)	(0.127)	(0.067)	(0.080)	(0.074)	(0.062)
HH share washm only	-0.391	-0.382	-0.198	-0.168	-0.020	-0.008
	(0.175)	(0.169)	(0.100)	(0.129)	(0.123)	(0.111)
HH share car only	-0.428	-0.294	0.017	-0.103	-0.024	-0.042
	(0.337)	(0.338)	(0.182)	(0.238)	(0.224)	(0.209)
Adj. R^2	0.26	0.24	0.38	0.33	0.40	0.49
Adj. R^2 controls only	0.25	0.23	0.38	0.32	0.40	0.49
N	14,189	14,483	15,548	15,696	5,199	5,167

Notes: Regressions of an indicator for the presence of bundling opportunities on market characteristics. Observations are brands of the size listed in the column heading across all markets. All regressions control for month and province fixed effects, market size, distance to closest store and number of other stores in the market.

Figure A.17: Ratio of corrected and original quantities sold



Notes: Distribution of the ratio of corrected and observed quantity sold across markets. Ratios above 1 indicate that some consumers purchased the given quantity by creating bundles of smaller packages; ratios below 1 indicate that some consumers used the given package size to create bundles of larger total quantities. 5-95 percentile range shown by package size. N = 2709, 2752, 1352, 3057, 2816, 2040, respectively.

Table A.18: Parameter estimates: static demand

	250g	500g	1kg	2kg	3kg	5kg
Linear parameters						
Price / 100	-97.290	-53.601	-36.182	-15.916	-10.113	-15.526
	(13.923)	(17.745)	(6.917)	(1.402)	(1.171)	(5.507)
Omo	0.492	0.371	0.614	1.109		
	(0.183)	(0.247)	(0.349)	(0.172)		
Sun	0.313	0.543	0.358	0.377	-3.877	2.630
	(0.151)	(0.222)	(0.256)	(0.138)	(5.294)	(2.335)
Constant	-3.798	-0.917	-2.136	0.917		
	(4.222)	(2.119)	(4.850)	(1.189)		
Low-income area	-0.148	0.164	-0.106	-0.108	-0.269	0.246
	(0.114)	(0.140)	(0.188)	(0.112)	(0.110)	(0.105)
Middle-income area	0.029	0.105	-0.062	-0.053	-0.116	0.163
	(0.086)	(0.102)	(0.135)	(0.069)	(0.070)	(0.081)
Mall	-0.235	-0.107	-0.044	-0.196	0.089	-0.297
	(0.094)	(0.108)	(0.179)	(0.094)	(0.117)	(0.115)
Center	-0.222	-0.147	-0.140	0.073	-0.088	-0.113
	(0.051)	(0.052)	(0.085)	(0.070)	(0.088)	(0.074)
Open Sunday	-0.052	-0.229	-0.012	0.122	0.059	0.096
	(0.058)	(0.048)	(0.089)	(0.056)	(0.066)	(0.080)
Neighboring stores	-4.808	-1.073	0.398	2.041	2.480	1.867
	(1.159)	(0.805)	(1.742)	(1.216)	(0.965)	(1.026)
Dist. to nearest store	-0.749	0.001	0.478	0.988	0.674	0.819
	(0.229)	(0.203)	(0.381)	(0.282)	(0.239)	(0.260)
HH share flat	-0.193	0.061	-0.745	-1.648	-2.172	-0.919
	(0.407)	(0.390)	(0.556)	(0.519)	(0.504)	(1.196)
HH share house	-0.306	0.094	0.004	-1.117	-1.195	-1.806
	(0.299)	(0.347)	(0.605)	(0.455)	(0.344)	(0.601)
HH share White	1.601	1.467	2.555	0.877	0.656	0.970
	(0.475)	(0.379)	(0.970)	(0.315)	(0.332)	(0.416)
HH share Black	-0.758	-0.419	-0.472	-0.213	-0.008	0.229
	(0.188)	(0.208)	(0.372)	(0.204)	(0.214)	(0.228)
HH share urban	0.320	0.263	0.113	-0.415	-0.693	-0.423
	(0.199)	(0.195)	(0.222)	(0.278)	(0.198)	(0.193)
Omo × HH share Black	0.110	0.679	0.204	0.201		
	(0.118)	(0.175)	(0.171)	(0.087)		
Sunlight x HH share Black	0.647	1.113	1.014	1.012		
	(0.107)	(0.176)	(0.155)	(0.074)		
Omo × HH share urban	-0.302	-0.222	-0.208	-0.746		
	(0.151)	(0.212)	(0.325)	(0.163)		
Sun × HH share urban	-0.320	-0.066	0.022	-0.258		
	(0.132)	(0.189)	(0.234)	(0.127)		
Omo × Low-inc area	-0.042	-0.350	-0.083	-0.273		
	(0.118)	(0.148)	(0.196)	(0.113)		
Sun × Low-inc area	0.098	-0.313	0.071	-0.112		
	(0.098)	(0.139)	(0.139)	(0.086)		
Omo × Mid-inc area	-0.077	-0.140	-0.113	0.009		
	(0.081)	(0.101)	(0.118)	(0.066)		
Sun × Mid-inc area	-0.043	-0.132	-0.096	0.014		
	(0.073)	(0.095)	(0.102)	(0.054)		

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Table A.18 cont'd

	250g	500g	1kg	2kg	3kg	5kg
Non-linear parameters						
Price × male	19.839	22.998	8.600	0.388	-0.446	6.251
	(8.907)	(15.893)	(2.759)	(1.261)	(0.973)	(5.303)
Constant × income	6.094	1.818	1.636	1.575	5.871	1.558
	(4.059)	(1.736)	(0.962)	(1.165)	(4.681)	(2.502)
Constant × no car or washm	4.237	2.175	4.919	-1.799	-5.297	-1.570
	(1.619)	(0.870)	(2.673)	(1.093)	(256.806)	(4.780)
Constant × washm only	4.027	2.701	6.896	1.831	2.682	1.538
	(1.346)	(0.793)	(2.651)	(0.675)	(1.688)	(1.202)
Constant × car only	-2.050	-6.024	5.490	2.276	2.925	1.396
	(61.514)	(693.013)	(2.613)	(0.778)	(1.198)	(0.817)
J	1.305	1.613	0.095	1.156	4.137	0.501
p-value	0.521	0.446	0.758	0.561	0.530	0.779
Newey-West D	48.441	51.073	52.501	20.960	29.922	33.820
p-value	0.000	0.000	0.000	0.001	0.000	0.000
N (market × products)	2798	2888	3193	3230	1049	1029
Unique markets	1064	1088	1088	1088	1049	1029
Unique months	16	16	16	16	16	15
Unique 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.

Table A.19: Inclusive values

	250 g	500 g	1 kg	2 kg	3 kg	5 kg
ω_{t-1}^{250}	0.964	0.020	0.012	-0.144	0.103	0.143
	(0.005)	(0.002)	(0.002)	(0.007)	(0.008)	(0.007)
ω_{t-1}^{500}	0.020	0.985	0.006	0.021	-0.044	-0.060
	(0.003)	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)
ω_{t-1}^{1}	0.017	-0.006	0.976	0.134	-0.072	-0.058
	(0.002)	(0.001)	(0.002)	(0.005)	(0.005)	(0.004)
ω_{t-1}^{2}	-0.031	0.013	0.049	0.524	0.254	0.130
	(0.004)	(0.003)	(0.004)	(0.019)	(0.019)	(0.011)
ω_{t-1}^{3}	0.009	-0.002	-0.007	0.127	0.883	0.095
	(0.002)	(0.001)	(0.002)	(0.007)	(0.007)	(0.005)
ω_{t-1}^{5}	0.009	-0.011	-0.014	0.087	-0.022	0.705
	(0.004)	(0.002)	(0.003)	(0.009)	(0.012)	(0.011)
Constant	-0.030	-0.033	-0.029	0.236	-0.322	-0.524
	(0.007)	(0.005)	(0.007)	(0.027)	(0.026)	(0.027)
Adj. R^2	0.98	0.99	0.98	0.78	0.94	0.86
N	1,794,000	1,814,800	1,814,800	1,815,200	1,750,000	1,795,200

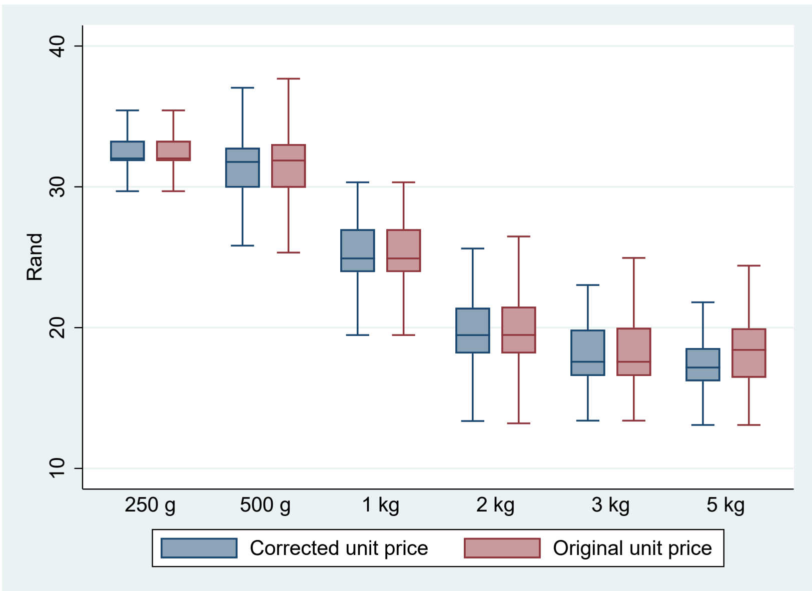
Notes: Estimates of the inclusive value process. The explanatory variables are lagged values of the inclusive value of every package size.

Table A.20: Fit of different inclusive value specifications

	250 g	500 g	1 kg	2 kg	3 kg	5 kg
Income area						
Low-income area	0.97	0.99	0.98	0.76	0.94	0.88
Middle-income area	0.98	0.99	0.98	0.79	0.95	0.87
High-income area	0.98	0.99	0.98	0.78	0.93	0.85
Ownership status						
No car or washm	0.97	0.98	0.94	0.54	0.80	0.78
Washm only	0.97	0.98	0.94	0.63	0.78	0.77
Car only	0.97	0.98	0.94	0.51	0.77	0.77
Car and washm	0.97	0.98	0.93	0.58	0.78	0.78
Alternative specifications						
Sum of five additional lags	0.98	0.99	0.98	0.84	0.96	0.90
Second lag	0.98	0.99	0.98	0.80	0.95	0.87

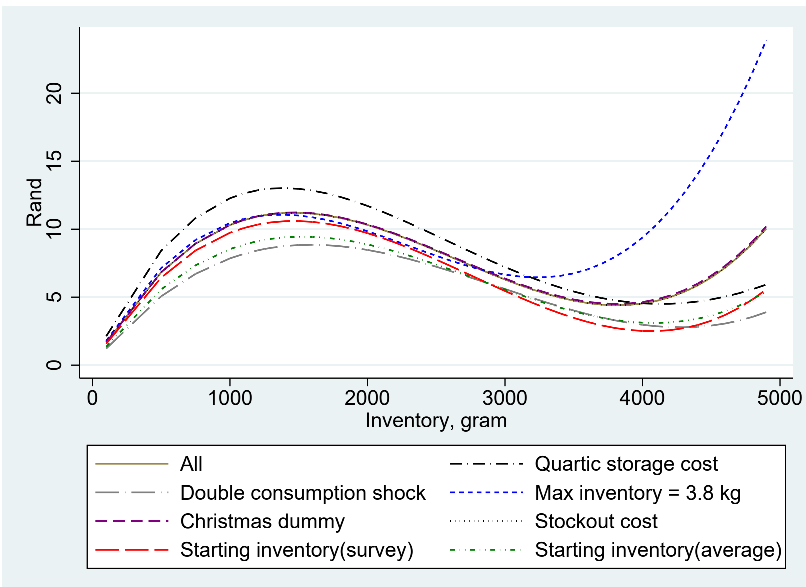
Notes: Adjusted R^2 values from different specifications of the inclusive value process. The top panel estimates separate processes by income area. The middle panel estimates separate processes by car/washing machine ownership. Both of these include the first lag of all sizes. On the bottom panel, the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

Figure A.21: Average unit price by package size



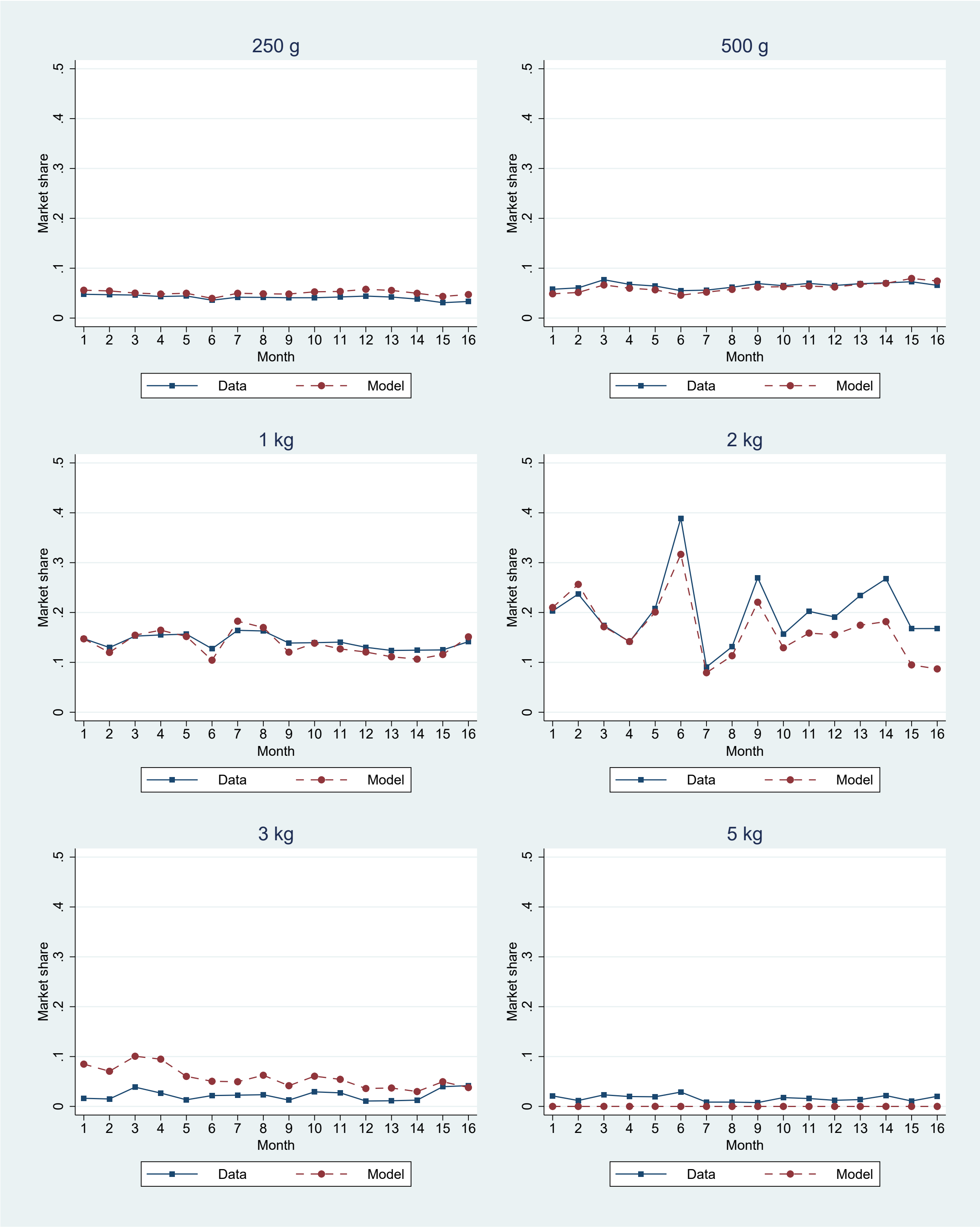
Notes: The plots show the interquartile range, median, min and max values of price per 1kg of detergent. Original unit prices refer to prices observed in the data. Corrected refers to prices corrected for bundling opportunities as described in the paper.

Figure A.22: Inventory cost estimates from alternative specifications



Notes: Inventory cost estimates under the different specification discussed in Section 5.3 in the paper. Estimates are for all income areas. "All" shows the main specification (from column 1 of Table 6).

Figure A.23: Model fit



Notes: Market shares of different sizes observed in the data and predicted by the model, based on column 1 in Table 6.

Table A.24: Household inventory and consumption when reducing transportation cost

	Low-income area		High-income area	
	Consumption	Inventory	Consumption	Inventory
Baseline	63.25	157.90	62.75	216.82
Access to car	69.75	302.77	63.18	290.91

Notes: Average consumption and inventory at baseline and a counterfactual where all households have access to a car. Consumption and inventory are measured in 10 g.

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