Econometrica Supplementary Material

SUPPLEMENT TO "ARE POOR CITIES CHEAP FOR EVERYONE? NON-HOMOTHETICITY AND THE COST OF LIVING ACROSS U.S. CITIES"

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APPENDIX A: DATA APPENDIX

A.1. *Data Cleaning*

THE ESTIMATION SAMPLE is cleaned in various ways. Below, I describe each step of the data cleaning process, summarizing the corresponding shares of 2012 RMS store sales and 2012 HMS household purchases dropped in Table A.I.

1. *UPCs missing product ids*: Throughout, I define prices on a per unit basis, limiting my attention to products whose container size is expressed in the modal units for that module. I exclude any module whose modal container size is either not expressed in meaningful units (i.e., counts instead of weights or volume) or in the same units for at least 75% of UPCs. Approximately one quarter of modules do not satisfy these restrictions (reflecting a little over 25% of RMS store sales data and 40% of HMS purchases). Of the modules that are included, products whose container size is not expressed in the modal units for the module represent 1.3% of sales in the RMS data and 1.3% of purchases in the RMS and HMS data.[1]
2. *Sales and purchases in markets without data required for estimation*: The main estimation and price index analysis considers activity with CBSA-level markets. Two point six percent of RMS sales are dropped because they occur outside of CBSAs. Four point five percent of HMS purchases are dropped because they are made by households that do not report income or are residing outside of CBSAs. A further 30% of HMS purchases are excluded from the estimation sample because they are not made in RMS stores (see step (2.1) RMS store-month merge in Table A.I).
3. *Store-month-products with missing price instruments*: Calculating the price instrument requires that I observe a given product sold in an RMS store that is part of the same chain but located in a different DMA. Three point eight percent of RMS sales are dropped because they do not satisfy this requirement, along with 1% of HMS purchases.
4. *Store-month-modules with outlier prices*: To control for data recording errors, I drop any market (store-month-modules) in which I observe a UPC sold at a unit price greater than three times or less than a third of the median unit price paid per unit of any UPC within the same product or module categorization. The typical module loses markets reflecting 2.5% of sales for this reason, though larger markets tend to

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[1]I also exclude random weight items, whose quality can be variable over time. The quality of random weight items, such as fruit, vegetables, and deli meats, varies over time as the produce loses its freshness and it is likely that stores set prices to reflect this. This potential inter-temporal correlation between their unobserved quality of random weight products and their prices would introduce biases in the price elasticities estimated below, so they are excluded from this analysis.

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TABLE A.I

SUMMARY STATISTICS ON THE SHARE OF DATA DROPPED IN EACH STEP OF DATA CLEANING.

Panel A: RMS Store Sales Dropped

Stage	Aggregate Share Dropped	Share Dropped by Module						
		Min	10th	25th	50th	75th	90th	Max
(1) Missing product ids	0.26	0	0	0	6.1e-06	1	1	1
(2) Missing CBSA income	0.026	0	0	0	0.03	0.039	0.053	0.19
(3) Missing price instrument	0.038	0	0	0	0.042	0.062	0.08	1
(4) Store-months with outlier-price items	0.15	0	0	0	0.025	0.076	0.17	0.78
(5) Not enough non-outside good	0.0021	−1.1e-09	0	0	6.4e-05	0.0051	0.19	0.99
(6) Outside good share <1%	0.23	0	0	0	0.087	0.038	0.63	0.92

Panel B: HMS Purchases Dropped

Stage	Aggregate Share Dropped	Share Dropped by Module						
		Min	10th	25th	50th	75th	90th	Max
(1) Missing product ids	0.43	0	0	0	8.9e-05	1	1	1
(2.0) Missing CBSA/household income	0.045	0	0	0	0.067	0.086	0.1	1
(2.1) RMS store-month merge	0.3	0	0	0	0.55	0.62	0.71	1
(3) Missing price instrument	0.0089	0	0	0	0.011	0.021	0.027	0.18
(4) Store-months with outlier-price items	0.045	0	0	0	0.0072	0.023	0.054	0.4
(5) Not enough non-outside good	0.0031	−2.0e-11	0	0	0.0019	0.02	0.1	0.71
(6) Outside good share <3%	0.067	0	0	0	0.015	0.084	0.17	0.59

Note: These tables summarize the share of RMS sales (panel A) and HMS purchases (panel B) that are dropped from the data in each of the data cleaning steps listed in Appendix A.1.

have more outlier prices (potentially due to more frequent/complicated discounting behavior), so the aggregate RMS sales share dropped is 15%.[2]

At this point, the RMS data are aggregated across stores to the CBSA-level markets.

5. *CBSA-months with fewer than 2 non-outside goods sold*: I drop any CBSA-month markets that sell less than two non-outside products.
6. *CBSA-month-modules where the outside good has a market share under 3%*: Finally, for computational reasons, I group any products with small sales shares into a single outside product for each module. This implies that product quality is only identified for products that see nonnegligible sales shares, on average, across markets. In the base specification, I allocate any product to the outside product if its average nonzero sales share across CBSA-month markets falls above the 60th percentile of the products in its respective module. Using this cutoff, products grouped in the outside product account for 6.1% of the store sales observed in the data.[3] I drop any CBSA-month in a module for which the outside good share is less than 3%. These CBSA-months reflect approximately 23% of aggregate RMS store sales, approximately evenly distributed between markets that do not sell any of the outside good

[2] I drop all sales in the store-months where I observe any outlier price because these outlier prices led me to suspect that there could be other errors in the store's data for that month. For example, Nielsen recodes the value of sales in a week to be 1 cent when the store reports a positive quantity sold but zero sales value.

[3] Gandhi, Lu, and Shi (2019) highlighted a selection problem associated with this treatment of low and zero sales shares. To gauge the magnitude of this problem, I test the robustness of my estimates to higher and lower selection criteria for the main model in Section 6.4.1 of the paper.

TABLE A.II

CORRELATION BETWEEN DATA DROPPED AND STORE/HOUSEHOLD INCOME.

Panel A: RMS Sales Dropped vs. CBSA Income

	Dependent Variable: Share of CBSA Sales Dropped at Stage #						
	(1)	(2)	(3)	(4)	(5)	(6)	Cumulative
Ln(Income)	0.034	1.5e-09	0.025	0.045	−0.013	−0.21	−0.12
	(0.02)	(2.2e-10)	(0.0085)	(0.0072)	(0.0017)	(0.012)	(0.016)
Observations	905	905	905	905	905	905	905
R^2	0.0032	0.049	0.0095	0.041	0.066	0.27	0.06

Panel B: HMS Purchases Dropped vs. Household Income

	Dependent Variable: Share of Household Purchases Dropped at Stage #							
	(1)	(2.0)	(2.1)	(3)	(4)	(5)	(6)	Cumulative
Ln(Income)	0.013	−0.026	−0.013	0.0047	0.0049	−5.8e-04	0.0042	−0.013
	(0.0012)	(0.001)	(0.0018)	(3.5e-04)	(4.2e-04)	(8.7e-05)	(5.9e-04)	(9.0e-04)
Observations	57,173	57,173	57,173	57,173	57,173	57,173	57,173	57,173
R^2	0.0022	0.011	9.3e-04	0.003	0.0024	7.8e-04	8.7e-04	0.0036

Note: Standard errors in parentheses. Panel A presents the correlation between the share of RMS store sales dropped in each step of data cleaning against the log income in the store's neighborhood. Panel B presents the correlation between the share of HMS household purchases dropped in each step of data cleaning against the log household income. Each column refers to one of the data cleaning steps listed in Table A.I. Income is adjusted for household size using a square-root equivalence scale.

products and those in which the outside good products sold have positive, but small, collective sales share.[4]

The cleaned data contain approximately 270,000 UPCs categorized into 37,000 products across 708 product modules. Approximately two thirds of these products are purchased by households in the HMS data. The median numbers of products and UPCs per module are 39 and 118, respectively.

One might be concerned that the amount of data dropped varies systematically with local store income or household income. Panel A of Table A.II shows that less RMS sales are dropped from lower-income markets. This negative correlation is driven by the fact that the stores in higher-income neighborhoods sell relatively less of the outside good or do not sell an outside good product at all (step (6) of the cleaning procedures outlined above). Panel B shows that the cumulative share of the HMS purchases dropped is also decreasing in household income. This is mostly driven by the fact that a higher share of purchases is being dropped for lower-income households who are less likely to shop in the chain stores that participate in the Nielsen RMS panel (step (2.1) of the cleaning).

Though the magnitude of the bias in the RMS estimation data towards low-income stores is larger than the bias in the HMS estimation data towards high-income households, the latter is more likely to generate biases in my estimates becuase the variation of HMS purchases, not the RMS sales, with income is used to identify the non-homotheticity parameters. As I noted above, I expect that the tilt in the share of data dropped towards low-income purchases is due to the under-representation of non-chain retailers in the

[4]In Section 6.4.1 of the paper, I test the robustness of the parameter estimates and index results to a more liberal outside good sales share requirement, requiring a 1% minimum outside good sales share and find, if anything, stronger evidence of non-homothetic demand for quality and bias in product offerings of higher-income markets to high-income tastes.

TABLE A.III

SHARE OF EACH INCOME DECILE'S NON-RMS STORE PURCHASES ON PRODUCTS AVAILABLE IN RMS RETAILERS BY CBSA AGAINST CBSA INCOME.

	Dependent Variable: Share of Non-RMS Store Expenditure on Products Sold in Local RMS Stores									
Income Decile:	1	2	3	4	5	6	7	8	9	10
Ln(CBSA PC Income)	0.018	0.019	0.015	0.013	0.0019	0.0073	0.0059	−0.0044	0.0035	−0.0040
(standardized)	(0.0043)	(0.0044)	(0.0045)	(0.0046)	(0.0050)	(0.0044)	(0.0048)	(0.0047)	(0.0064)	(0.0053)
Constant	0.38	0.38	0.37	0.38	0.39	0.39	0.39	0.38	0.41	0.38
	(0.0043)	(0.0044)	(0.0045)	(0.0046)	(0.0050)	(0.0044)	(0.0048)	(0.0047)	(0.0063)	(0.0053)
Observations	733	664	717	674	618	670	610	684	427	535
R^2	0.02	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00

Note: Standard errors in parentheses. This table reports the correlation between how much of the expenditure that Nielsen household panelists spend in non-RMS retailers in their residential CBSA is on products that are also sold in RMS retailers in that CBSA and the CBSA per capita income. Observations are at the income decile-by-CBSA level and weighted by CBSA population. The nth column reports the correlation for nth income decile.

RMS data. For this to bias my results towards finding that low-income households are less well-served than high-income households from the variety offered in high-income stores, it would need to be the case that local independent retailers cater more to the tastes of their local low-income customers in high-income cities than they do in low-income cities. To check for this, I look at whether the products that HMS households report purchasing in non-RMS retailers are less likely to be also sold in RMS retailers in high-income cities than they are in RMS retailers in low-income cities. Table A.III shows that the opposite is the case: RMS stores sell slightly a greater expenditure-weighted share of the products that low-income households purchase in non-RMS retailers and, if anything, a slightly lower expenditure-weighted share of the products that high-income households purchase in non-RMS stores.

A.2. *Estimating the Empirical Distribution of Store Customers*

To study how store offerings vary with local neighborhood income, I estimate the income distribution in the vicinity of the store as a distance-weighted average of the income distributions observed in the Census tracts within 30 km of the centroid of the model residential zip code of Nielsen panelists that report shopping there.

The data include the county and 3-digit zip in which each Nielsen sample store is located. I infer the 5-digit zip of a store as the modal 5-digit zip code reported for HMS shoppers whose 5-digit zip falls within the reported 3-digit zip of the RMS store, ignoring any stores that have fewer than 2 shoppers in any single qualifying 5-digit zip code. I then calculate the income distribution of each sample store $F(Y|s)$ as a generalized beta distribution fitted to the average binned income distribution in tracts nearby the 5-digit zip.[5] The number of households in each income bin for each store is calculated combining tract-level income from the 2010–2014 5-year American Community Survey (ACS) 1% sample and household-store-level trip data from the Nielsen HMS sample for the same period. Let $N_t(k)$ denote the number of households that the ACS reports in each of 16

[5]Income bins are as defined in the ACS data. To fit the binned income distributions for each store to a generalized beta distribution, I assume the income of the first 15 bins is the midpoint of the bracket and the income of the top bracket is the mean income estimated assuming a Pareto distribution.

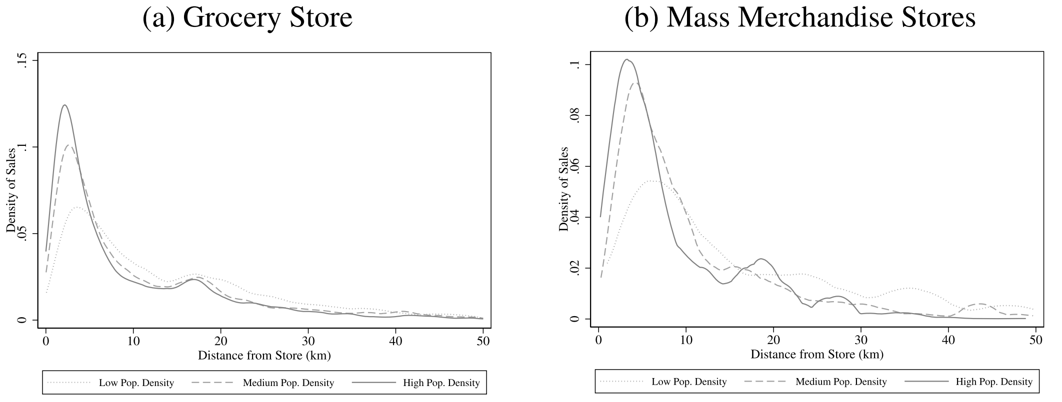

FIGURE A.1.—Sales density by store type. *Notes*: This figure shows the density of sales at different distances from grocery stores (in (a)) and mass merchandise stores (in (b)) separately for stores in high, middle, and low population density zip codes.

income brackets k residing in a Census tract t and N_t denote the total number of households in the ACS sample for tract t. I estimate the share of store s customers in income bracket k as the weighted average of the density of households in each income bracket in each Census tract in the vicinity of store s:

$$d_s(k) = \frac{\sum_{\{t|d_{st}\leq 30 \text{ km}\}} w_s(d_{st}) N_t(k)}{\sum_{\{t|d_{st})\leq 30 \text{ km}\}} w_s(d_{st}) N_t}.$$

Tract weights, $w_s(d_{st})$, are a store type-specific function of distance from the centroid of the tract to the centroid of the store zip (estimated to be the modal residential zip code of the store's customers observed in the Nielsen HMS data). Specifically, the weight for tract t whose centroid is a distance d_{st} from the centroid of the zip code for store s is

$$w_s(d_{st}) = \frac{\text{pop}_t \hat{s}_s(d)}{\sum_{\{t|d_{st}\leq 30\}} \text{pop}_t \hat{s}_s(d)},$$

where pop_t is the total population in each tract t, also from the 2010–2014 5-year ACS and $\hat{s}_s(d)$ is the estimated density of sales for store s as a function of customer distance. The sales density for stores of each type (grocery and mass merchandise in low, medium, and high population density zip codes) is interpolated using the observed densities of the shopping trips observed in the Nielsen HMS data for years 2010 to 2014. These curves are shown for each store type in Figure A.1.

A.3. *Representativeness of Nielsen Samples by Income*

Figure A.2(a) compares the income distribution of the households in the Nielsen HMS sample to the national U.S. population. Figure A.2(b) compares the income distribution of the counties of stores in the Nielsen RMS sample to the counties of stores in the County Business Patterns data set.

(a) Household Income in HMS and ACS Data

(b) Local Store Income in RMS and CBP

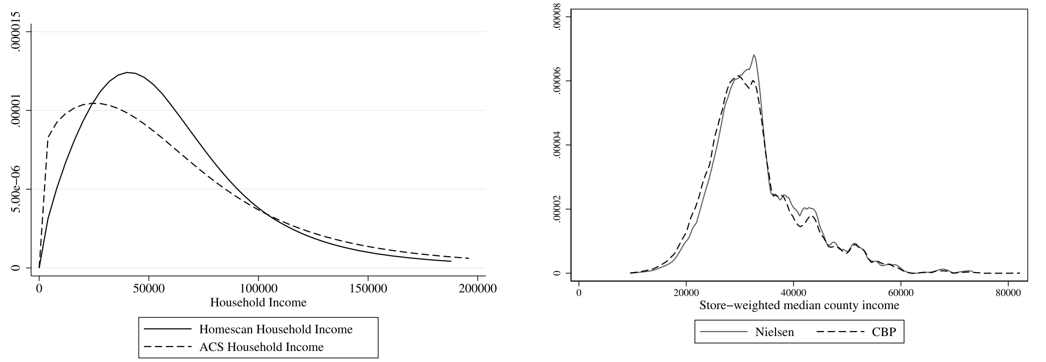

FIGURE A.2.—Distribution of household income in Nielsen HMS and American Community Survey. *Notes*: Figure A.2(a) compares the income distribution among Nielsen household panelists in 2012 with the national household income distribution in that year. The solid line depicts the fitted distribution of household income from the full 2012 Nielsen household (Homescan) sample; the dashed line depicts the fitted distribution of household income from the 2012 ACS single-year estimates. Figure A.2(b) compares the income distribution across the counties where Nielsen participating retailers are located with the income distribution across the counties where all grocery and non-durable stores are located. Each line depicts the distribution of median household income per county from the 2008–2012 ACS, weighted by the number of stores in the county. The solid line weights counties by the number of Nielsen RMS stores in the county, while the dashed line weights counties by the number of stores in the County Business Patterns, limiting attention to the following categories: 445,110: Supermarket; 445,120: Convenience stores; 446,110: Pharmacies and Drug stores; 447,110: Gasoline Stations with Convenience stores; 452,910: Warehouse Clubs and Supercenters; and 452,990: All Other General Merchandise Stores including Dollar stores.

A.4. *CBSA Statistics*

This table shows the number of sample stores, population, and per capita income in each of the 125 CBSAs with 50 or more sample stores. The population and per capita income data are five-year averages from the 2010–2014 ACS.

TABLE A.IV

SAMPLE SIZE, POPULATION, AND INCOME BY CBSA.

CBSA Name	Store Count	Per Capita Income	Population
Akron, OH (AKR)	76	27,823	703,017
Albany-Schenectady-Troy, NY (ALB)	127	32,069	875,567
Albuquerque, NM (ABQ)	102	26,144	899,137
Allentown-Bethlehem-Easton, PA-NJ (ABE)	94	29,397	826,260
Asheville, NC (ASH)	82	26,023	433,204
Atlanta-Sandy Springs-Roswell, GA (ATL)	620	28,880	5,455,053
Augusta-Richmond County, GA-SC (AUG)	97	23,905	575,669
Austin-Round Rock, TX (AUS)	136	32,035	1,835,016
Bakersfield, CA (BAK)	81	20,467	857,730
Baltimore-Columbia-Towson, MD (BAL)	305	35,613	2,753,396
Baton Rouge, LA (BRI)	96	26,639	814,805
Birmingham-Hoover, AL (BIR)	104	26,706	1,135,534

(*Continued*)

TABLE A.IV

Continued.

CBSA Name	Store Count	Per Capita Income	Population
Boise City, ID (BC)	78	24,715	639,616
Boston-Cambridge-Newton, MA-NH (BOS)	562	39,572	4,650,876
Bridgeport-Stamford-Norwalk, CT (BRI)	87	49,688	934,215
Buffalo-Cheektowaga-Niagara Falls, NY (BUF)	163	28,171	1,135,667
Canton-Massillon, OH (CAN)	67	24,646	403,629
Cape Coral-Fort Myers, FL (CC)	70	27,578	647,554
Charleston, WV (CHA)	56	26,851	225,248
Charleston-North Charleston, SC (CH)	104	28,033	697,281
Charlotte-Concord-Gastonia, NC-SC (CHA)	449	28,403	2,298,915
Chattanooga, TN-GA (CHA)	99	25,315	537,397
Chicago-Naperville-Elgin, IL-IN-WI (CHI)	1082	31,488	9,516,448
Cincinnati, OH-KY-IN (CIN)	259	29,008	2,131,793
Claremont-Lebanon, NH-VT (CLA)	50	30,451	217,906
Cleveland-Elyria, OH (CLE)	245	28,499	2,067,490
Colorado Springs, CO (CS)	76	29,398	669,070
Columbia, SC (COL)	127	25,615	784,698
Columbus, OH (CMH)	218	29,145	1,948,188
Dallas-Fort Worth-Arlington, TX (DAL)	705	29,766	6,703,020
Dayton, OH (DAY)	102	26,345	801,259
Deltona-Daytona Beach-Ormond Beach, FL (DAB)	89	23,935	597,824
Denver-Aurora-Lakewood, CO (DEN)	310	34,173	2,651,392
Des Moines-West Des Moines, IA (DM)	123	31,342	590,741
Detroit-Warren-Dearborn, MI (DET)	507	28,182	4,292,647
Durham-Chapel Hill, NC (DUR)	77	30,945	525,050
El Paso, TX (ELP)	94	18,684	827,206
Fayetteville, NC (PAY)	62	22,647	374,036
Fayetteville-Springdale-Rogers, AR-MO (FAY)	62	25,291	483,396
Flint, MI (FLI)	82	22,536	418,654
Fresno, CA (FRE)	86	20,231	948,844
Grand Rapids-Wyoming, MI (GRW)	91	25,786	1,007,329
Greensboro-High Point, NC (GHP)	117	24,619	735,777
Greenville-Anderson-Mauldin, SC (GRE)	157	24,583	842,817
Gulfport-Biloxi-Pascagoula, MS (GBP)	52	23,006	378,972
Harrisburg-Carlisle, PA (HAR)	66	30,404	555,154
Hartford-West Hartford-East Hartford, CT (HRT)	116	35,991	1,215,159
Hickory-Lenoir-Morganton, NC (HIC)	62	21,385	363,936
Houston-The Woodlands-Sugar Land, TX (HOU)	690	29,594	6,204,141
Huntington-Ashland, WV-KY-OH (HUN)	51	23,326	364,514
Indianapolis-Carmel-Anderson, IN (IND)	195	27,778	1,931,182
Jackson, MS (JAK)	68	24,311	574,998
Jacksonville, FL (JAC)	228	27,950	1,380,995
Kansas City, MO-KS (KC)	152	30,101	2,040,869
Kingsport-Bristol-Bristol, TN-VA (BRI)	56	23,471	308,800
Knoxville, TN (KNX)	136	25,833	847,765
Lafayette, LA (LAF)	67	25,781	475,457
Lakeland-Winter Haven, FL (LWH)	66	21,157	617,323
Lansing-East Lansing, MI (LAN)	53	26,126	467,122
Las Vegas-Henderson-Paradise, NV (LV)	205	26,040	2,003,613
Lexington-Fayette, KY (LEX)	72	28,216	483,997
Little Rock-North Little Rock-Conway, AR (LR)	85	26,222	716,849
Los Angeles-Long Beach-Anaheim, CA (LA)	906	29,506	13,060,534
Louisville/Jefferson County, KY-IN (LOU)	182	27,488	1,253,305

(*Continued*)

TABLE A.IV

Continued.

CBSA Name	Store Count	Per Capita Income	Population
Madison, WI (MAD)	82	32,778	620,368
Manchester-Nashua, NH (MAN)	77	34,767	402,776
Memphis, TN-MS-AR (MEM)	228	25,191	1,337,014
Miami-Fort Lauderdale-West Palm Beach, FL (MIA)	314	27,240	5,775,204
Milwaukee-Waukesha-West Allis, WI (MIL)	222	29,733	1,565,368
Minneapolis-St. Paul-Bloomington, MN-WI (MIN)	299	34,593	3,424,786
Mobile, AL (MOB)	69	23,009	414,045
Myrtle Beach-Conway-North Myrtle Beach, SC-NC (MYR)	86	24,709	396,187
Nashville-Davidson–Murfreesboro–Franklin, TN (NAS)	235	28,521	1,730,515
New Haven-Milford, CT (NH)	113	32,794	863,148
New Orleans-Metairie, LA (NO)	170	27,458	1,226,440
New York-Newark-Jersey City, NY-NJ-PA (NYC)	1697	36,078	19,865,045
North Port-Sarasota-Bradenton, FL (NP)	84	30,813	722,784
Ogden-Clearfield, UT (OGD)	56	24,890	614,521
Oklahoma City, OK (OKC)	94	26,994	1,297,998
Omaha-Council Bluffs, NE-IA (OM)	141	29,147	886,157
Orlando-Kissimmee-Sanford, FL (ORL)	271	24,876	2,226,835
Oxnard-Thousand Oaks-Ventura, CA (OX)	75	33,308	835,790
Palm Bay-Melbourne-Titusville, FL (MEL)	71	27,360	548,891
Pensacola-Ferry Pass-Brent, FL (PEN)	52	25,199	462,339
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD (PHL)	802	32,850	6,015,336
Phoenix-Mesa-Scottsdale, AZ (PHX)	505	26,893	4,337,542
Pittsburgh, PA (PIT)	361	30,272	2,358,793
Portland-South Portland, ME (POR)	112	32,001	518,387
Portland-Vancouver-Hillsboro, OR-WA (PVH)	232	30,560	2,288,796
Port St. Lucie, FL (PSL)	54	27,481	433,646
Providence-Warwick, RI-MA (PROV)	257	30,218	1,604,317
Raleigh, NC (RAL)	210	31,468	1,189,579
Richmond, VA (RIC)	202	30,944	1,234,058
Riverside-San Bernardino-Ontario, CA (RSB)	338	22,571	4,345,485
Roanoke, VA (ROA)	52	27,505	310,934
Rochester, NY (ROC)	115	28,320	1,082,578
Sacramento–Roseville–Arden-Arcade, CA (SAC)	189	29,252	2,197,422
St. Louis, MO-IL (STL)	272	30,024	2,797,737
Salisbury, MD-DE (SAL)	90	27,353	381,868
Salt Lake City, UT (SLC)	93	26,516	1,123,643
San Antonio-New Braunfels, TX (SA)	233	25,298	2,239,222
San Diego-Carlsbad, CA (SD)	238	31,043	3,183,143
San Francisco-Oakland-Hayward, CA (SF)	365	42,540	4,466,251
San Jose-Sunnyvale-Santa Clara, CA (SJ)	139	42,176	1,898,457
Savannah, GA (SAV)	55	25,818	361,161
Scranton–Wilkes-Barre–Hazleton, PA (SCR)	70	25,304	562,644
Seattle-Tacoma-Bellevue, WA (SEA)	390	36,061	3,557,037
Shreveport-Bossier City, LA (SHR)	78	24,833	445,305
Spartanburg, SC (SPA)	59	22,055	317,057
Spokane-Spokane Valley, WA (SPO)	54	25,685	533,456
Springfield, MA (SPR)	81	27,179	626,775
Springfield, MO (SGF)	78	23,233	444,728
Stockton-Lodi, CA (STL)	52	22,642	701,050
Syracuse, NY (SYR)	98	27,741	662,236
Tampa-St. Petersburg-Clearwater, FL (TAM)	375	27,252	2,851,235
Toledo, OH (TOL)	97	25,312	608,847

(*Continued*)

TABLE A.IV
Continued.

CBSA Name	Store Count	Per Capita Income	Population
Tucson, AZ (TUC)	150	25,524	993,144
Tulsa, OK (TUL)	109	26,635	954,055
Virginia Beach-Norfolk-Newport News, VA-NC (VB)	344	29,098	1,697,898
Washington-Arlington-Alexandria, DC-VA-MD-WV (WAS)	568	43,884	5,863,608
Wichita, KS (WIC)	66	25,848	636,095
Wilmington, NC (WIL)	54	28,435	263,804
Winston-Salem, NC (WS)	114	24,978	648,045
Worcester, MA-CT (WOR)	138	31,558	924,722
Youngstown-Warren-Boardman, OH-PA (YOU)	98	23,357	559,144

Note: This table shows the number of Nielsen participating retailers, population, and per capita income in each of the 125 CBSAs with 50 or more participating retailers. The population and per capita income data are five-year averages from the 2010–2014 ACS.

APPENDIX B: STYLIZED FACTS APPENDIX

The main results in the paper measure the relative product variety available across CBSAs using the products sold by a random sample of 50 stores in each CBSA. Alternatively, one could sample stores in proportion to the number or density of stores operating in each CBSA. Figure A.3 replicates Panel (a) of Figure 2 measuring product variety using two types of proportional samples of stores. The first samples stores in proportion to the number of stores of a given channel (food, mass merchandiser, drug, and convenience) reported to be open in that CBSA in the County Business Patterns (CBP) data for 2012. Specifically, I drew a number N_c stores in a CBSA c, where N_c equals one-fifth of the

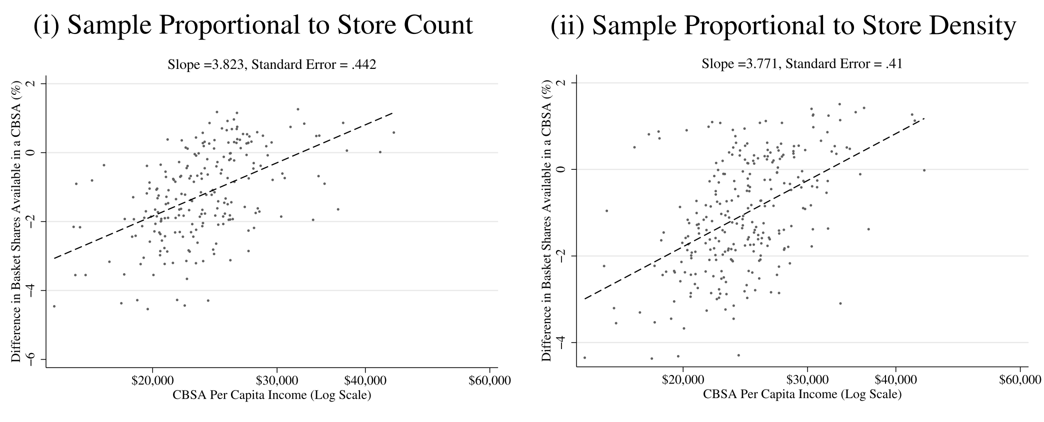

FIGURE A.3.—Availability differences for alternative sampling methods. *Notes*: These figures replicate Panel (a) of Figure 2 from the main text measuring product availability using two alternative samples of stores from each CBSA. The products available in each CBSA are defined as the set of products sold and average unit prices charged in a random sample of 100 bootstrap samples of N_c stores in each CBSA c in 2012. In Panel (i), N_c is equal to 20 percent of the total number of stores from each channel reported in the County Business Patterns (CBP) data for CBSA c, conditional on the RMS data having that number of stores in the sample. In Panel (ii), N_c is proportional to the density of stores from each channel reported in the County Business Patterns (CBP) data for CBSA c, set equal to the number of stores one would expect within a 10km radius, conditional on the RMS data having that number of stores in the sample.

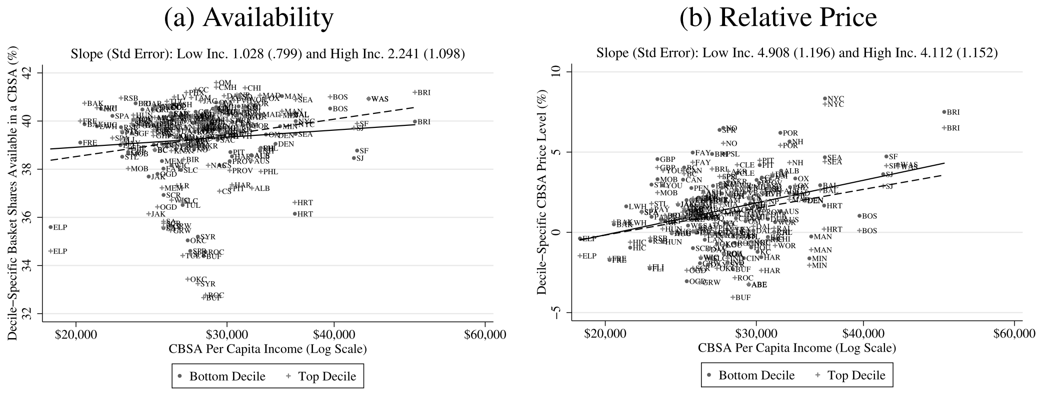

FIGURE A.4.—Availability and relative price of high- and low-income baskets across CBSAs. Figure A.4(a) plots CBSA-level data for the expenditure share of high-income Nielsen HMS panelists that is represented in the CBSA product set (in red) and the corresponding expenditure share of low-income panelists represented in that product set (in blue) against CBSA per capita income. The panelist expenditure shares are calculated for 2012 and are CBSA-specific, in that they exclude the expenditures of any panelists residing in the CBSA whose availability is being measured. FigureA.4(b) plots CBSA-level data for the average price level faced by consumers in the top income decile (in red) and the average price level faced by households in the bottom income decile (in blue) against CBSA per capita income. The price level in each CBSA for a given income decile is calculated as the weighted average log of the ratio between the price a product is sold for in a CBSA relative to the price that product is sold at in the national sample where weights are defined as the value of the purchases of that product made by households in the respective income decile in the Nielsen household-level panel. Panelists are defined as high- (or low-) income if their size-adjusted income falls in the top (bottom) decile of panelist incomes. The products available and prices charged in each CBSA are defined as the set of products sold and average unit prices charged in a random sample of 50 Nielsen stores in a given CBSA in 2012. The plots show the mean availability share and price indexes calculated in 100 bootstrap iterations of this sampling procedure. CBSA income is household income adjusted for size using a square-root equivalence scale.

number of stores the CBP report as open in CBSA c in 2012, limiting my attention to CBSAs where the Nielsen RMS data have at least N_c sample stores.

The second method samples in proportion to the density of stores of each channel type. Specifically, I drew samples equal to the number of stores that would be predicted to be within a 10 km radius of a person residing in a given CBSA ($10^2\pi N_c/A_c$, where A_c is the area of the CBSA in square km).

The variety differences across CBSA are much larger when using the proportional samples of stores than they are when using the fixed-sized samples of stores ($N_c = 50$). This is not surprising: high-income cities tend to be larger and more dense and, accordingly, have more stores and more scope for non-overlapping product variety that serves local tastes. The welfare benefits from the variety in markets with more stores in aggregate (or higher store density) are likely muted by the fact that many households do their grocery shopping at a single store.

APPENDIX C: DERIVATIONS

C.1. *Within-Module Consumption Decision*

Consumer i, spending Z on the non-grocery items, chooses how to allocate expenditures between products within a module m conditional on their expenditure in that module, w_m, to maximize

$$u_{im}(w_m, Z) = \sum_{g \in G_m} q_{mg} \exp\bigl(\gamma_m(Z)\beta_{mg} + \mu_m(Z)\varepsilon_{img}\bigr)$$

subject to the module-level budget constraint, $\sum_{m \in \mathbf{M}} \sum_{g \in \mathbf{G_m}} p_{mg} q_{mg} \leq w_m$, and non-negativity constraints, $q_{mg} \geq 0 \; \forall mg \in \mathbf{G}$.

Recall that the additive log-logit functional form implies that consumers optimally purchase a positive quantity of only one product in a module. This product maximizes their marginal utility of expenditure in a module conditional on their non-grocery expenditure:[6]

$$g^*_{im}(Z) = \arg\max_{g \in \mathbf{G_m}} \frac{\exp\bigl(\gamma_m(Z)\beta_{mg} + \mu_m(Z)\varepsilon_{img}\bigr)}{p_{mg}}.$$

Since all of a consumer's module expenditure, w_m, is allocated to this optimal product, g^*_{im}, the consumer's optimal module bundle, $\mathbb{Q}^*_{im}(w_m, Z)$, can be written as

$$\mathbb{Q}^*_{im}(w_m, Z) = \bigl(q^*_{im1}(w_m, Z), \dots, q^*_{imG_m}(w_m, Z)\bigr)$$
$$\text{where } q^*_{img}(w_m) = \begin{cases} w_m / p_{mg} \\ \quad \text{if } g = \arg\max\limits_{g \in \mathbf{G_m}} \dfrac{\exp\bigl(\gamma_m(Z)\beta_{mg} + \mu_m(Z)\varepsilon_{img}\bigr)}{p_{mg}}, \\ 0 \quad \text{otherwise.} \end{cases} \tag{A.1}$$

That is, a consumer i optimally consumes as much of their optimal product, $g^*_{im}(Z)$, as their module expenditure, w_m, will afford them and zero of any other product in the module.

C.2. *Derivations of Expenditure Share for Moment Equations*

Equation (A.1) states that

$$\mathbb{Q}^*_{im}(w_m, Z) = \bigl(q^*_{im1}(w_m, Z), \dots, q^*_{imG_m}(w_m, Z)\bigr)$$
$$\text{where } q^*_{img}(w_m, Z) = \begin{cases} w_m / p_{mg} & \text{if } g = \arg\max\limits_{g \in \mathbf{G_m}} \tilde{p}_{img}, \\ 0 & \text{otherwise,} \end{cases}$$

where $\tilde{p}_{img} = \frac{\exp(\gamma_m(Z)\beta_{mg} + \mu_m(Z)\varepsilon_{ig})}{p_{mg}}$. If we rewrite consumer i's optimal consumption quantity using an indicator function to identify which product is selected by the consumer, the optimal grocery share for consumer i on product g in module m, conditional on their non-grocery expenditure Z and the vector of module prices they face, $\mathbb{P}_m$, is

$$s_{img|m}(Z, \mathbb{P}_m) = \mathbb{I}\Bigl[g = \arg\max_{g \in \mathbf{G_m}} \tilde{p}_{img}\Bigr].$$

[6]Note that the marginal utility of expenditure in a module and, therefore, the optimal product choice, g^*_{im}, depends on a consumer's non-grocery expenditure, Z, but is independent of their module expenditure, w_m.

The expected value of this expenditure share is derived by integrating over the idiosyncratic utilities in module m, $\boldsymbol{\varepsilon}_{im}$:

$$\begin{aligned}
&\mathbb{E}_{\varepsilon}\big[s_{img|m}(Z, \mathbb{P}_m)\big] \\
&\quad = \mathbb{E}_{\varepsilon}\Big[\mathbb{I}\Big[g = \arg\max_{g \in \mathbf{G_m}} \tilde{p}_{img}\Big]\Big] \\
&\quad = \Pr\big[\tilde{p}_{img} \geq \tilde{p}_{img'}, \forall g' \in \mathbf{G_m}\big] \\
&\quad = \Pr\bigg[\varepsilon_{img} - \varepsilon_{img'} \geq \frac{\gamma_m(Z)(\beta_{mg} - \beta_{mg'}) - (\ln p_{mg} - \ln p_{mg'})}{\mu_m(Z)}, \forall g' \in \mathbf{G_m}\bigg] \\
&\quad = \frac{\tilde{p}_{img}}{\sum_{g' \in \mathbf{G_m}} \tilde{p}_{img'}}.
\end{aligned}$$

The final equality holds because the idiosyncratic utilities, ε_{im}, are i.i.d. draws from a type I extreme value distribution. Imposing the parametric forms for $\gamma_m(Z) = (1 + \gamma_m \ln Z)$ and $\mu_m(Z) = (\alpha_m^0 + \alpha_m^1 \ln Z)^{-1}$ from equations (4) and (5), respectively, ensures that the consumer's expected expenditure share is common with other consumers with the same income that face the same product prices:

$$\mathbb{E}_{\varepsilon}\big[s_{img|m}(Z, \mathbb{P}_m)\big] = \frac{\exp\big[(\alpha_m^0 + \alpha_m^1 \ln Z)\big((1 + \gamma_m \ln Z)\beta_{mg} - \ln p_{mg}\big)\big]}{\sum_{g' \in \mathbf{G_m}} \big(\exp\big[(\alpha_m^0 + \alpha_m^1 \ln Z)\big((1 + \gamma_m \ln Z)\beta_{mg'} - \ln p_{mg'}\big)\big]\big)}.$$

I interpret the expected expenditure share function derived above as the expected share of expenditure that a group of households with the same non-grocery expenditure, Z, facing identical prices for products in module m spend on product g. If the group of households is in the same market, then this expected expenditure share will be the income-specific market share of product g in module m, which I denote by $s_{mg|m}(Z, \mathbb{P}_m)$. $s_{mg|m}(Z, \mathbb{P}_m)$ is the within-module share of expenditure that a group of households with the non-grocery expenditure, Z, and facing a common vector of module prices, $\mathbb{P}_m$, allocates to product g:

$$\begin{aligned}
s_{mg|m}(Z, \mathbb{P}_m) &= \mathbb{E}_{\varepsilon}\big[s_{img|m}(Z, \mathbb{P}_m)\big] \\
&= \frac{\exp\big[(\alpha_m^0 + \alpha_m^1 \ln Z)\big(\beta_{mg}(1 + \gamma_m \ln Z) - \ln p_{mg}\big)\big]}{\sum_{g' \in \mathbf{G_m}} \big(\exp\big[(\alpha_m^0 + \alpha_m^1 \ln Z)\big(\beta_{mg'}(1 + \gamma_m \ln Z) - \ln p_{mg'}\big)\big]\big)}.
\end{aligned}$$

Dividing this market share for product g in module m by the market share for a fixed product $\bar{g}_m$ in the same module m results in a relative market share that depends only on model parameters, consumer income, and the prices of product g and $\bar{g}_m$:[7]

$$\frac{s_{mg|m}(Z, \mathbb{P}_m)}{s_{m\bar{g}|m}(Z, \mathbb{P}_m)} = \frac{\exp\left[\left(\alpha_m^0 + \alpha_m^1 \ln Z\right)\left(\beta_{mg}(1 + \gamma_m \ln Z) - \ln p_{mg}\right)\right]}{\exp\left[\left(\alpha_m^0 + \alpha_m^1 \ln Z\right)\left(\beta_{m\bar{g}}(1 + \gamma_m \ln Z) - \ln p_{m\bar{g}}\right)\right]}.$$

I linearize the relative expenditure share equation by taking the log of both sides:

$$\begin{aligned} &\ln\left(s_{mg|m}(Z, \mathbb{P}_m)\right) - \ln\left(s_{m\bar{g}|m}(Z, \mathbb{P}_m)\right) \\ &\quad = \left(\alpha_m^0 + \alpha_m^1 \ln Z\right)\left[(\beta_{mg} - \beta_{m\bar{g}})(1 + \gamma_m \ln Z) - (\ln p_{mg} - \ln p_{m\bar{g}})\right]. \end{aligned}$$

APPENDIX D: RESULTS APPENDIX

D.1. *Identification*

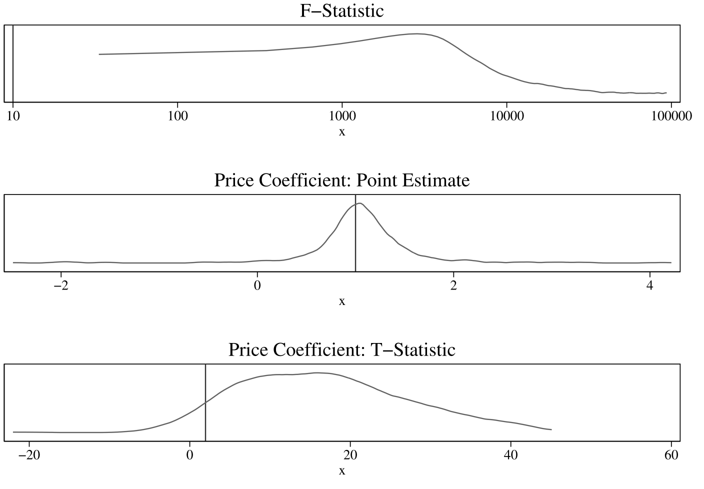

FIGURE A.5.—Summary statistics for first-stage results. *Notes*: The above plots depict the distribution of the price instrument coefficients and F-statistics in the module-level first-stage regression of log relative price paid against price instruments, brand dummies, and all of the above interacted with the log median income of the county in which a store is located.

[7]The utility function assumes weak separability between modules and the independence of irrelevant alternatives (IIA) property both across modules and across products with the same quality parameter. Although neither of these are realistic characteristics of consumer behavior, they are useful for the purposes of estimation as they imply that relative market expenditure shares can be derived as functions of observed variables, such as household income, expenditures, and transaction prices.

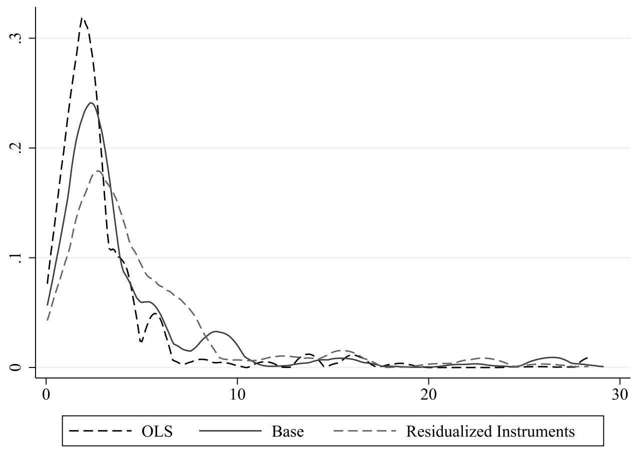

FIGURE A.6.—Distribution price coefficients across modules with different price instruments. *Notes*: The above plot depicts the distribution of estimates of the module-level α_m^0 parameters in the baseline model that allows for non-homotheticity in the demand for quality but not in price sensitivity (i.e., restricting that $\alpha_m^1=0$). The three kernel densities show the distribution of estimates obtained in OLS specification as well as instead using the two different price instruments described under Identification in Section 5.3.1 of the paper.

D.2. *Measurement Error in Product Quality Estimates*

In practice, the quality of each product, relative to the outside good, $\tilde{\beta}_{mg} = \beta_{mg} - \beta_{m\bar{g}_m}$, is calculated as the mean of CBSA-month-specific quality shocks, $\tilde{\beta}_{mgt}(\hat{\theta}_{1m}^{NL}) = \beta_{mgt}(\hat{\theta}_{1m}^{NL}) - \beta_{m\bar{g}_m t}(\hat{\theta}_{1m}^{NL})$, that rationalize the relative sales shares on that product relative to the outside product given the nonlinear parameter estimates, across the CBSA-months in which the product is sold; that is, $\hat{\tilde{\beta}}_{mg} = \frac{1}{N_g}\sum_t \tilde{\beta}_{mgt}(\hat{\theta}_{1m}^{NL})$. Variation in the quality of the outside product across CBSA-months will generate measurement error in the quality estimates. $\tilde{\beta}_{mg}$, for example, may understate the relative quality of products that tend to be sold in CBSA where higher-quality outside products are sold. If this measurement error is correlated with the relative purchase probability of high- versus low-income households, it might yield biases in the income-quality elasticity gradient (γ_m).

To gauge the degree of this error and associated bias, I calculate the relative qualities of "inside" products in two ways. First, I difference the base quality estimate for each product g from the quality estimate for a common product in each module, $\bar{g}_m^1$, that is, $\tilde{\beta}_{mg} - \tilde{\beta}_{m\bar{g}_m^1}$. This relative quality estimate will be subject to the measurement error noted above (i.e., if g is sold in CBSAs with higher-quality outside products than the CBSAs in which $\bar{g}_m^1$ is sold, $\tilde{\beta}_{mg} - \tilde{\beta}_{m\bar{g}_m^1}$ will be a downward biased estimate of the true relative quality of product g relative to product $\bar{g}_m^1$).

I then calculate an alternative measure of the quality of g relative to $\bar{g}_m^1$ that is not subject to this measurement error. Specifically, I difference the market-level quality estimates for product g relative to that for product $\bar{g}_m^1$ within each market and then take the average of this mean across the $N_{g\bar{g}_m^1}$ CBSAs that sell both g and and the common product $\bar{g}_m^1$, that is, $\frac{1}{N_{g\bar{g}_m^1}}\sum_t(\tilde{\beta}_{mgt}(\hat{\theta}_{1m}^{NL}) - \tilde{\beta}_{m\bar{g}_m^1 t}(\hat{\theta}_{1m}^{NL}))$. This procedure purges the relative quality estimate

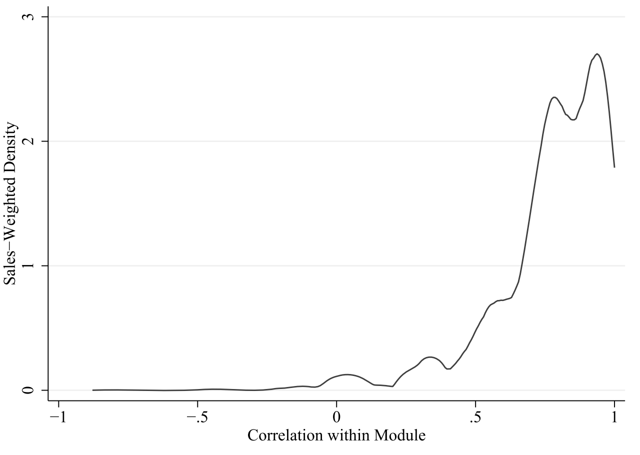

FIGURE A.7.—Correlation between base and alternative relative product quality estimates. *Notes*: The above plots depict the distribution of the module-level correlations between two relative quality measures. The first is equal to the mean quality for each product across the CBSAs in which it is sold differenced from the mean quality for a common product across the CBSAs in which it is sold. The second is the difference of the quality of each product in the module in a store from the quality of the common product in that CBSA, averaged over all of the CBSAs in which both products are sold. Module-level correlations are weighted by sales.

from any variation in the outside product quality level across markets, which appears in both the $\tilde{\beta}_{mgt}(\theta^{NL}_{1m})$ and $\tilde{\beta}_{m\bar{g}^1_m t}(\theta^{NL}_{1m})$ so is differenced out before averaging.[8]

Comparing these two quality measures assuages concerns that measurement error induced by the variable quality of the outside good across markets generates biases in the estimates. Figure A.7 shows that the two quality measures are highly correlated: the median correlation coefficient across products within modules is 0.83 and over 0.5 in over 85 percent of modules. More importantly, Figure A.8 shows that there is no systematic variation in the implicit errors in the base quality estimates (i.e., the difference between the base and alternative relative quality measures) across the consumption baskets of high- and low-income households that might generate a bias in the γ_m estimates.

[8]I do not obtain my base quality estimates via this procedure because it limits the sample of markets I can use for estimation to those that have a common product. To maximize the number of store-month markets included in the calculations described above and, in turn, the number of products for which this alternate quality measure is feasible, I select as the common product, $\bar{g}^1_m$, the product in each module that appears in the highest number of sample markets. Still, over twenty percent of products are dropped from the analysis entirely because they are not sold in any of the subset of the 5000 randomly-sampled markets that sell the most commonly-sold product for that module. In over a quarter of modules, the most commonly-sold product is sold in fewer than half of the 5000 randomly-sampled markets. Limiting the sample in this respect might result in the sample becoming biased towards one or two chains that carry similar products.

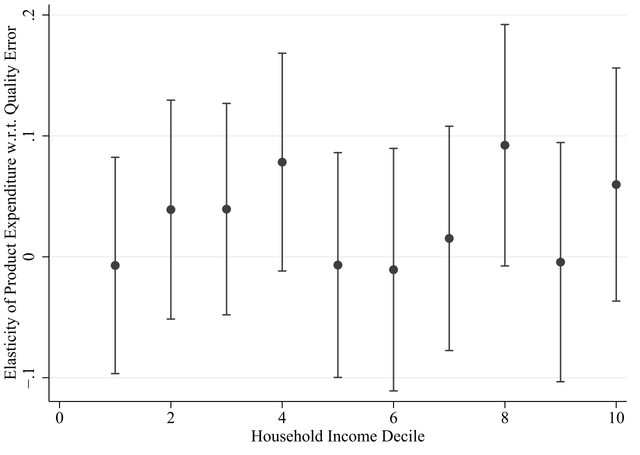

FIGURE A.8.—Correlation between HMS panelist expenditures and errors in relative quality by income decile. *Notes*: The above plot shows the elasticity of the expenditure of HMS panelists in different deciles of size-adjusted income with respect to the errors in relative product quality estimated using the method outlined in Appendix Section D.2.

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