ONLINE APPENDIX

The Cyclicality of Sales, Regular and Effective Prices: Business Cycle and Policy Implications

Olivier Coibion	Yuriy Gorodnichenko	Gee Hee Hong
UT Austin and NBER	U.C. Berkeley and NBER	International Monetary Fund

APPENDIX A: ADDITIONAL TABLES AND FIGURES.

Appendix Table 1. Descriptive statistics by category.

Category	Sales: Frequency	Sales: Size	Sales: Share of goods bought on sale	Regular prices: Share of goods bought at cheap reg. prices	Frequency of changes: All	Frequency of changes: Positive	Frequency of changes: Negative	Size of changes: All	Size of changes: Positive	Size of changes: Negative
	(1)	(2)	(3)	(5)	(5)	(6)	(7)	(8)	(9)	(10)
All categories	0.200	-0.252	0.245	0.253	0.054	0.034	0.018	0.027	0.118	-0.126
	(0.083)	(0.081)	(0.105)	(0.048)	(0.038)	(0.031)	(0.014)	(0.054)	(0.055)	(0.093)
Beer	0.154	-0.119	0.171	0.240	0.056	0.036	0.019	0.026	0.075	-0.061
	(0.069)	(0.035)	(0.077)	(0.032)	(0.033)	(0.024)	(0.012)	(0.030)	(0.028)	(0.025)
Blades	0.158	-0.250	0.177	0.243	0.062	0.042	0.019	0.022	0.110	-0.166
	(0.048)	(0.060)	(0.053)	(0.047)	(0.032)	(0.026)	(0.012)	(0.045)	(0.039)	(0.092)
Carbonated beverages	0.261	-0.246	0.317	0.249	0.061	0.038	0.022	0.038	0.132	-0.115
	(0.061)	(0.041)	(0.071)	(0.038)	(0.024)	(0.016)	(0.010)	(0.023)	(0.028)	(0.031)
Cigarettes	0.059	-0.118	0.061	0.241	0.159	0.122	0.036	0.031	0.077	-0.083
	(0.043)	(0.062)	(0.045)	(0.045)	(0.085)	(0.082)	(0.022)	(0.039)	(0.036)	(0.047)
Coffee	0.204	-0.239	0.238	0.252	0.060	0.039	0.019	0.031	0.123	-0.121
	(0.070)	(0.050)	(0.077)	(0.038)	(0.031)	(0.025)	(0.011)	(0.038)	(0.039)	(0.052)
Cold cereals	0.222	-0.324	0.297	0.266	0.042	0.028	0.013	0.040	0.116	-0.106
	(0.068)	(0.060)	(0.083)	(0.045)	(0.019)	(0.015)	(0.007)	(0.030)	(0.044)	(0.055)
Deodorants	0.211	-0.311	0.240	0.242	0.049	0.028	0.020	0.011	0.169	-0.225
	(0.055)	(0.054)	(0.062)	(0.038)	(0.021)	(0.014)	(0.011)	(0.060)	(0.047)	(0.090)
Diapers	0.246	-0.168	0.270	0.232	0.073	0.037	0.033	-0.001	0.096	-0.107
	(0.070)	(0.039)	(0.077)	(0.050)	(0.043)	(0.032)	(0.021)	(0.041)	(0.035)	(0.057)
Facial tissue	0.229	-0.294	0.298	0.264	0.041	0.025	0.015	0.035	0.120	-0.105
	(0.076)	(0.072)	(0.091)	(0.062)	(0.025)	(0.020)	(0.012)	(0.064)	(0.069)	(0.085)
Frozen dinners	0.289	-0.294	0.377	0.262	0.043	0.028	0.014	0.042	0.129	-0.113
	(0.077)	(0.063)	(0.092)	(0.042)	(0.019)	(0.013)	(0.008)	(0.034)	(0.049)	(0.054)
Frozen pizza	0.309	-0.278	0.400	0.264	0.050	0.031	0.017	0.042	0.129	-0.112
	(0.085)	(0.052)	(0.096)	(0.046)	(0.025)	(0.017)	(0.010)	(0.032)	(0.047)	(0.051)
Household cleaning	0.169	-0.245	0.194	0.255	0.039	0.024	0.014	0.023	0.117	-0.138
	(0.060)	(0.058)	(0.068)	(0.048)	(0.019)	(0.014)	(0.010)	(0.053)	(0.048)	(0.086)
Hot dogs	0.241	-0.340	0.333	0.269	0.038	0.027	0.010	0.058	0.128	-0.104

	(0.082)	(0.067)	(0.098)	(0.056)	(0.023)	(0.018)	(0.008)	(0.048)	(0.054)	(0.065)
Laundry and detergents	0.247	-0.282	0.323	0.258	0.049	0.030	0.018	0.032	0.125	-0.116
	(0.065)	(0.049)	(0.077)	(0.042)	(0.021)	(0.016)	(0.009)	(0.035)	(0.047)	(0.059)
Margarine and butter	0.183	-0.253	0.237	0.261	0.047	0.034	0.012	0.041	0.088	-0.062
	(0.071)	(0.074)	(0.085)	(0.049)	(0.032)	(0.028)	(0.009)	(0.037)	(0.041)	(0.046)
Mayonnaise	0.145	-0.267	0.183	0.257	0.047	0.035	0.012	0.038	0.095	-0.089
	(0.063)	(0.083)	(0.074)	(0.052)	(0.032)	(0.028)	(0.010)	(0.047)	(0.046)	(0.069)
Milk	0.137	-0.172	0.158	0.243	0.057	0.038	0.018	0.028	0.072	-0.056
	(0.058)	(0.042)	(0.065)	(0.038)	(0.031)	(0.026)	(0.013)	(0.022)	(0.026)	(0.028)
Mustard and ketchup	0.153	-0.206	0.171	0.261	0.051	0.035	0.014	0.036	0.112	-0.116
	(0.067)	(0.066)	(0.071)	(0.044)	(0.027)	(0.022)	(0.011)	(0.051)	(0.039)	(0.073)
Paper towels	0.214	-0.254	0.291	0.259	0.049	0.031	0.017	0.034	0.103	-0.086
	(0.065)	(0.054)	(0.075)	(0.047)	(0.028)	(0.023)	(0.012)	(0.044)	(0.046)	(0.059)
Peanut butter	0.154	-0.217	0.195	0.261	0.050	0.033	0.016	0.028	0.084	-0.071
	(0.065)	(0.077)	(0.076)	(0.056)	(0.033)	(0.028)	(0.013)	(0.043)	(0.044)	(0.057)
Photo	0.186	-0.302	0.206	0.232	0.062	0.034	0.027	-0.027	0.161	-0.266
	(0.065)	(0.100)	(0.069)	(0.061)	(0.047)	(0.033)	(0.027)	(0.139)	(0.093)	(0.181)
Razors	0.243	-0.227	0.260	0.224	0.069	0.039	0.028	-0.003	0.131	-0.202
	(0.078)	(0.074)	(0.083)	(0.052)	(0.038)	(0.027)	(0.023)	(0.089)	(0.067)	(0.135)
Salty snacks	0.223	-0.251	0.264	0.265	0.035	0.023	0.011	0.048	0.128	-0.106
	(0.057)	(0.038)	(0.065)	(0.031)	(0.015)	(0.010)	(0.006)	(0.025)	(0.031)	(0.036)
Shampoo	0.214	-0.275	0.236	0.239	0.064	0.037	0.025	0.004	0.158	-0.218
	(0.048)	(0.043)	(0.052)	(0.033)	(0.026)	(0.016)	(0.013)	(0.049)	(0.036)	(0.075)
Soup	0.178	-0.300	0.226	0.256	0.049	0.034	0.014	0.041	0.126	-0.131
	(0.079)	(0.077)	(0.101)	(0.043)	(0.023)	(0.018)	(0.009)	(0.040)	(0.041)	(0.068)
Spaghetti sauce	0.214	-0.265	0.268	0.268	0.056	0.037	0.018	0.035	0.119	-0.113
	(0.073)	(0.067)	(0.084)	(0.048)	(0.027)	(0.020)	(0.012)	(0.043)	(0.042)	(0.062)
Sugar and substitutes	0.117	-0.197	0.133	0.249	0.041	0.027	0.013	0.019	0.095	-0.110
	(0.066)	(0.078)	(0.074)	(0.057)	(0.026)	(0.020)	(0.013)	(0.066)	(0.059)	(0.103)
Toilet tissue	0.218	-0.250	0.313	0.273	0.052	0.033	0.018	0.029	0.090	-0.071
	(0.063)	(0.052)	(0.075)	(0.048)	(0.030)	(0.024)	(0.011)	(0.035)	(0.039)	(0.043)
Toothbrushes	0.194	-0.323	0.219	0.239	0.047	0.026	0.020	0.000	0.192	-0.276
	(0.056)	(0.062)	(0.065)	(0.039)	(0.021)	(0.013)	(0.012)	(0.075)	(0.062)	(0.106)
Toothpaste	0.215	-0.288	0.255	0.252	0.044	0.026	0.017	0.024	0.153	-0.187
	(0.058)	(0.046)	(0.069)	(0.040)	(0.020)	(0.015)	(0.009)	(0.046)	(0.043)	(0.077)
Yogurt	0.224	-0.249	0.290	0.260	0.039	0.025	0.013	0.034	0.095	-0.073
	(0.074)	(0.062)	(0.089)	(0.054)	(0.023)	(0.017)	(0.009)	(0.036)	(0.041)	(0.042)

Notes: UPCs have equal weights when aggregated to the category level.

Appendix Table 2. Moments for all (sales and regular) price changes.

Category	All price changes					
	Frequency			Size		
	All	Positive	Negative	All	Positive	Negative
	(1)	(2)	(3)	(4)	(5)	(6)
Total	0.238	0.124	0.114	0.001	0.206	-0.224
	(0.093)	(0.051)	(0.051)	(0.044)	(0.071)	(0.079)
Beer	0.168	0.091	0.077	0.008	0.097	-0.102
	(0.082)	(0.046)	(0.040)	(0.026)	(0.028)	(0.031)
Blades	0.205	0.112	0.093	0.001	0.197	-0.238
	(0.066)	(0.040)	(0.035)	(0.042)	(0.043)	(0.059)
Carbonated beverages	0.315	0.163	0.152	0.006	0.201	-0.206
	(0.083)	(0.045)	(0.042)	(0.021)	(0.035)	(0.037)
Cigarettes	0.199	0.141	0.058	0.022	0.083	-0.098
	(0.091)	(0.084)	(0.034)	(0.040)	(0.036)	(0.050)
Coffee	0.231	0.122	0.109	0.005	0.198	-0.211
	(0.076)	(0.046)	(0.040)	(0.036)	(0.043)	(0.047)
Cold cereals	0.241	0.125	0.116	0.002	0.254	-0.275
	(0.077)	(0.042)	(0.040)	(0.031)	(0.057)	(0.060)
Deodorants	0.260	0.130	0.130	-0.002	0.278	-0.297
	(0.069)	(0.036)	(0.039)	(0.042)	(0.046)	(0.053)
Diapers	0.313	0.152	0.161	-0.011	0.144	-0.159
	(0.087)	(0.053)	(0.050)	(0.032)	(0.032)	(0.040)
Facial tissue	0.253	0.125	0.128	-0.009	0.247	-0.260
	(0.082)	(0.044)	(0.048)	(0.054)	(0.064)	(0.068)
Frozen dinners	0.319	0.162	0.158	0.002	0.246	-0.254
	(0.078)	(0.042)	(0.042)	(0.032)	(0.059)	(0.061)
Frozen pizza	0.354	0.181	0.173	0.004	0.232	-0.239
	(0.092)	(0.050)	(0.048)	(0.028)	(0.049)	(0.052)
Household cleaning	0.179	0.091	0.088	-0.006	0.203	-0.227
	(0.060)	(0.033)	(0.035)	(0.045)	(0.045)	(0.056)
Hot dogs	0.300	0.157	0.143	0.009	0.279	-0.293
	(0.089)	(0.051)	(0.047)	(0.048)	(0.063)	(0.067)
Laundry and detergents	0.289	0.147	0.142	0.002	0.236	-0.246
	(0.078)	(0.043)	(0.041)	(0.028)	(0.044)	(0.047)
Margarine and butter	0.220	0.116	0.104	0.007	0.200	-0.213
	(0.076)	(0.046)	(0.040)	(0.044)	(0.066)	(0.069)
Mayonnaise	0.179	0.099	0.080	0.008	0.197	-0.226
	(0.074)	(0.047)	(0.039)	(0.057)	(0.065)	(0.076)
Milk	0.179	0.096	0.084	0.005	0.131	-0.141
	(0.069)	(0.040)	(0.037)	(0.025)	(0.035)	(0.039)
Mustard and ketchup	0.153	0.085	0.068	0.008	0.161	-0.186
	(0.061)	(0.038)	(0.037)	(0.050)	(0.043)	(0.061)
Paper towels	0.253	0.130	0.123	-0.001	0.203	-0.216
	(0.078)	(0.045)	(0.042)	(0.034)	(0.047)	(0.050)
Peanut butter	0.182	0.098	0.085	0.007	0.164	-0.178
	(0.069)	(0.043)	(0.038)	(0.048)	(0.058)	(0.069)
Photo	0.232	0.116	0.116	-0.021	0.254	-0.297
	(0.079)	(0.049)	(0.052)	(0.084)	(0.075)	(0.100)

Razors	0.269	0.137	0.132	-0.014	0.189	-0.230
	(0.093)	(0.052)	(0.059)	(0.063)	(0.057)	(0.076)
Salty snacks	0.227	0.116	0.111	0.002	0.207	-0.217
	(0.068)	(0.036)	(0.034)	(0.021)	(0.036)	(0.038)
Shampoo	0.264	0.133	0.130	-0.009	0.241	-0.268
	(0.071)	(0.037)	(0.039)	(0.034)	(0.035)	(0.043)
Soup	0.207	0.111	0.096	0.009	0.237	-0.260
	(0.080)	(0.043)	(0.045)	(0.054)	(0.066)	(0.071)
Spaghetti sauce	0.245	0.129	0.117	0.006	0.218	-0.231
	(0.074)	(0.041)	(0.042)	(0.042)	(0.056)	(0.063)
Sugar and substitutes	0.136	0.071	0.065	-0.003	0.153	-0.180
	(0.068)	(0.038)	(0.039)	(0.056)	(0.057)	(0.072)
Toilet tissue	0.270	0.139	0.131	0.000	0.198	-0.211
	(0.081)	(0.047)	(0.041)	(0.028)	(0.047)	(0.048)
Toothbrushes	0.227	0.112	0.116	-0.011	0.287	-0.316
	(0.065)	(0.034)	(0.037)	(0.050)	(0.054)	(0.061)
Toothpaste	0.246	0.124	0.122	-0.002	0.254	-0.271
	(0.071)	(0.038)	(0.038)	(0.033)	(0.039)	(0.045)
Yogurt	0.271	0.137	0.134	0.001	0.204	-0.210
	(0.082)	(0.045)	(0.044)	(0.034)	(0.060)	(0.062)

Notes: UPCs have equal weights when aggregated to the category level.

Appendix Table 3. Alternative standard errors.

Dependent variable	Equal weights to all UPCs	Standard errors			
	Point estimate	Driscoll-Kraay	Cluster by category/market	Cluster by month	Cluster by market
	(1)	(2)	(3)	(4)	(5)
Sales					
Frequency	0.224	(0.092)***	(0.060)***	(0.047)***	(0.174)
Size	0.303	(0.066)***	(0.065)***	(0.037)***	(0.141)**
Share of goods bought on sale	0.161	(0.104)	(0.070)**	(0.053)***	(0.220)
Regular price					
Share of goods bought at cheap regular prices	0.126	(0.042)***	(0.046)***	(0.023)***	(0.159)
Frequency of changes					
All	-0.018	(0.032)	(0.022)	(0.018)	(0.045)
Positive	-0.041	(0.024)*	(0.017)***	(0.014)***	(0.027)
Negative	0.026	(0.011)**	(0.010)***	(0.007)***	(0.020)
Size of changes					
All	-0.109	(0.044)***	(0.028) ***	(0.030)***	(0.048)**
Positive	0.070	(0.050)	(0.043)	(0.028)***	(0.106)
Negative	-0.036	(0.060)	(0.065)	(0.037)	(0.118)
Inflation					
posted prices	-0.061	(0.017)***	(0.014)***	(0.008)***	(0.027)*
effective prices	-0.219	(0.024)***	(0.026)***	(0.013)***	(0.037)***

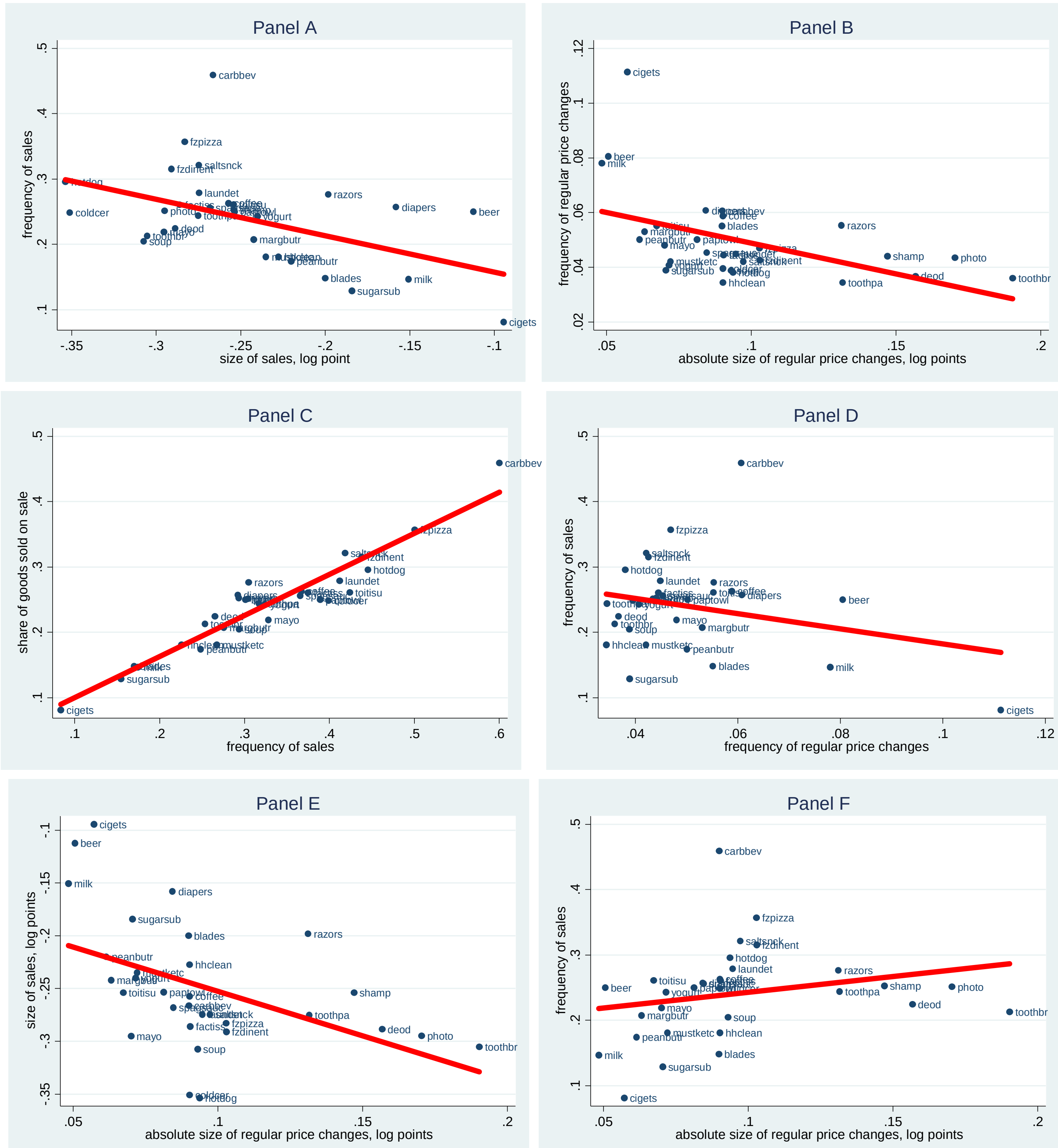
Notes: The table shows the baseline point estimates (column 1) and standard errors (column 2) which correspond to results presented in column 3 of Tables 1 and 2. Columns 3 and 4 show alternative estimates of standard errors associated with column (1). Column (3) clusters standard errors by market and category (1550 clusters) which allows for arbitrary collation of errors across time. Column (4) clusters standard errors by month (132 clusters) which allow for arbitrary cross-sectional correlation. Column (5) clusters standard errors by market (50 clusters). *,**,*** indicates statistical significance at 1, 5 and 10 percent.

Appendix Table 4. Share of Regular-Priced Goods Bought at Low Prices

Universe of UPCs	Cheap regular price			
	Bottom 10 percent	Bottom 20 percent	Bottom 25 percent	Bottom 33 percent
	(1)	(2)	(3)	(4)
Panel A: equal weights to aggregate UPCs to category level				
Ω_{all}	0.145***	0.126***	0.199***	0.324***
	(0.041)	(0.042)	(0.055)	(0.072)
Ω_{max}	0.320***	0.140	0.213**	0.346**
	(0.072)	(0.089)	(0.105)	(0.141)
Ω_{90}	0.283***	0.280***	0.376***	0.427***
	(0.060)	(0.066)	(0.078)	(0.104)
Ω_{75}	0.195***	0.180***	0.279***	0.380***
	(0.050)	(0.060)	(0.076)	(0.095)
Panel B: expenditure shares (market specific) as weights to aggregate UPCs to category level				
Ω_{all}	0.170***	0.191***	0.285***	0.369***
	(0.046)	(0.055)	(0.070)	(0.090)
Ω_{max}	0.297***	0.097	0.179	0.312**
	(0.077)	(0.099)	(0.115)	(0.147)
Ω_{90}	0.306***	0.319***	0.428***	0.434***
	(0.063)	(0.076)	(0.089)	(0.112)
Ω_{75}	0.198***	0.194***	0.288***	0.331***
	(0.054)	(0.068)	(0.082)	(0.105)

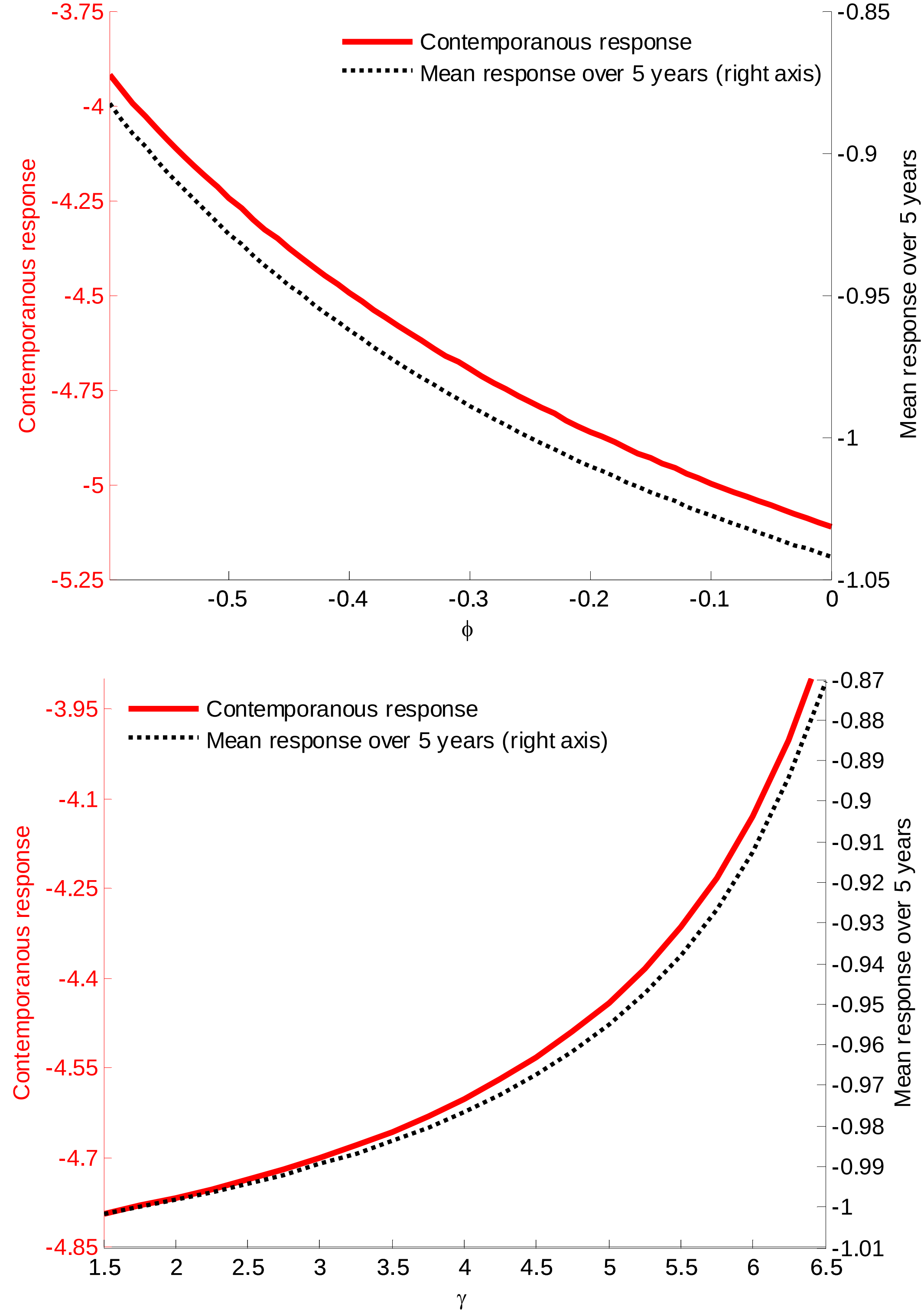
Notes: The table presents estimated coefficients for the cyclicality of the share of goods bought at "cheap" regular prices, using alternative thresholds for identifying "cheap" prices (indicated in column headers), alternative groupings of UPCs used to calculate relative prices (indicated by rows) and different aggregation procedures to go from UPC level to category-market level (Panel headings). In all regressions, month and category/market fixed effects are included, which corresponds to column (3) in Table 2. *,**,*** indicates statistical significance at 1, 5 and 10 percent.

Appendix Figure 1. Correlations between key moments



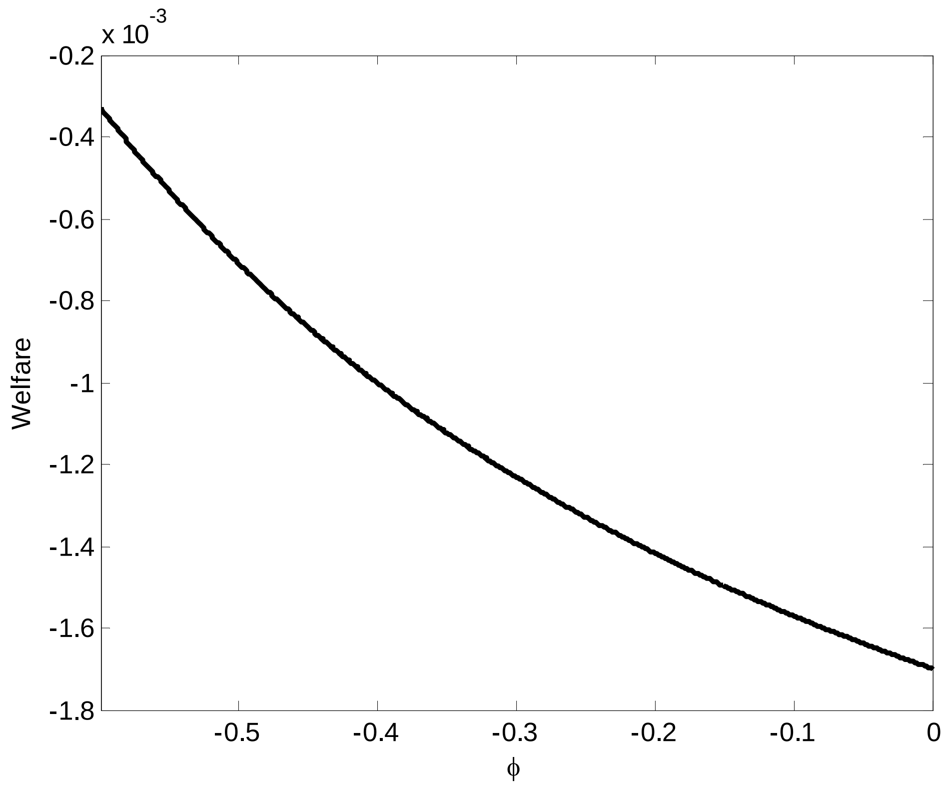
Notes: Figures report average (across time and goods) moments at the category level. Expenditure shares are used as weights to aggregate goods. Red line shows the best fit linear projection.

Appendix Figure 2. Sensitivity of Output Gap Response to Contractionary Monetary Policy Shock



Notes: This figure shows the sensitivity of the output gap response to a monetary policy shock as a function of two parameters ϕ (elasticity of iceberg cost with respect to shopping effort) and γ (elasticity of substitution across stores). The bottom panel is for the case with $\phi = -0.35$. The mean response is the average response of output gap over 20 periods.

Appendix Figure 3. Welfare as a function of ϕ (elasticity of iceberg cost with respect to shopping effort).



Notes: This figure shows how welfare varies with ϕ holding the size of the shocks constant. Since the household's utility is log in consumption, changes in welfare can be interpreted as percent losses in consumption equivalents. $\phi = 0$ corresponds to fixed shopping effort.

APPENDIX B: WITHIN-CATEGORY SUBSTITUTION

While we focus on expenditure-switching across stores by households for a given UPC product, the literature on price measurement has long emphasized another margin of substitution, namely across goods. Our primary motivation for focusing on switching across stores for a given good is that, as in the construction of the CPI, it is helpful to consider the cost of a fixed basket of goods for welfare purposes. The substitution bias long emphasized in the literature, in which CPI inflation will be overstated because it ignores the possibility of consumers switching goods when relative prices change, instead involves a change in the composition of the basket which will have implications for welfare. Nonetheless, we also consider this additional margin here for two reasons. First, the substitution bias has primarily been considered as a source of long-run bias in inflation measurements, while the cyclical properties of this margin have not been considered. Second, comparing the degree of store-switching to the amount of cross-good substitution provides one metric to assess the relative importance of store-switching for the measurement of inflation.

To quantify the degree of substitution across goods, we first construct the quantity-weighted average "effective" price *across all goods j within category c* in store *s* and geographic area *m* as

$$\bar{P}^{eq}_{mcts} = \frac{\sum_{j\in c} TR_{msctj}}{\sum_{j\in c} TQ_{msctj}\times EQ_j}. \tag{B.1}$$

where EQ_j is the quantity equivalent of good *j*. Hence, in calculating $\bar{P}^{eq}_{mcts}$, all prices are converted into quantity-equivalent measures so that e.g. the price of a 6-pack of beer is comparable to a 12-pack and $\bar{P}^{eq}_{mcts}$ measures the price of beer per liter. $\bar{P}^{eq}_{mcts}$ can change because individual prices change or because consumers reallocate their consumption of goods within a given category. For category *c,* store *s* and market *m*, we compute the monthly inflation rate $\log\left(\bar{P}^{eq}_{mcst}/\bar{P}^{eq}_{mcs,t-1}\right)$. Then, we aggregate across all stores in market *m* to get the average category-level inflation rate, using either equal or expenditure weights.[1] Finally, we cumulate monthly inflation rates into annual inflation rate $\bar{\pi}^{eq}_{mct}$ which we refer to as the "within-category effective inflation rate". While for $\bar{\pi}^{eff}_{mct}$ we fix the composition of the consumption basket but allow consumers to switch stores, for $\bar{\pi}^{eq}_{mct}$ we fix the store weights but allow consumers to substitute goods in the basket.

Because some categories include much more heterogeneity in goods than others, we consider two classification schemes for measuring the substitution of goods within categories. The first (and broadest) includes all UPCs within a category. The second allows substitution only within subcategories which approximately corresponds to adding another digit to the level of disaggregation. For example, we use all

[1] Because quantity equivalents are not available or are not comparable for some categories, we exclude the following categories from this analysis: deodorants, frozen dinners, photos, and soups.

types of milk when we calculate $\bar{P}^{eq}_{mcts}$ for the first classification. In contrast, the second classification considers separately such subcategories as whole milk, skimmed milk, 2% milk, etc.

The sensitivity of these inflation rates to economic conditions is then assessed using

$$\bar{\pi}^{eq}_{mct} = \beta UR_{mt} + \lambda_t + \theta_{m,c} + error \quad \text{(B.2)}$$

which is equivalent to the specification used to measure the sensitivity of effective across-store inflation rates to economic conditions. The results, presented in Appendix Table B.1 below, point to a statistically significantly negative relationship between unemployment rates and within-category effective inflation rates. Thus, as in our baseline results, this indicates significant substitution by households in response to changing local economic conditions but along a different margin, namely substituting across different goods within a category. Importantly, the quantitative magnitudes are of the same order as those identified for across-store substitution.

Appendix Table B.1. Within category substitution.

	Equal weights for all stores	Sales shares to aggregate stores
	(1)	(2)
Substitution within broad categories	-0.338***	-0.332***
	(0.098)	(0.107)
Substitution within narrower categories	-0.347***	-0.341***
	(0.090)	(0.099)

Notes: The table reports estimates of specification (B.2). The dependent variable is the within-category effective inflation rate. The table reports estimated coefficients on the local seasonally-adjusted unemployment rate. Number of observations is 94,851. Driscoll and Kraay (1998) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

APPENDIX C: STORE-SWITCHING AND MONETARY NON-NEUTRALITY

Our model can be reduced to

Phillips curve: $\pi_t = \beta E_t \pi_{t+1} + \kappa x_t$

IS curve: $x_t = E_t x_{t+1} - \psi(i_t - E_t \pi_{t+1} - r_t^n)$

where ψ is the elasticity of the output gap to real interest rates and depends on structural parameters, including store-switching parameters. Assume a simple Taylor rule

$$i_t = \chi \pi_t + \varepsilon_t$$

where ε is monetary policy shock which follows AR(1) $\varepsilon_t = \rho \varepsilon_{t-1} + v_t$, $\chi > 1$, and $0 \leq \rho < 1$.

We guess that the solution of the model to MP shocks (s.t. natural interest rate does not vary) is

$$\pi_t = a\varepsilon_t$$
$$x_t = b\varepsilon_t$$

Then the Phillips curve becomes

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t \Leftrightarrow a\varepsilon_t = \beta E_t a\varepsilon_{t+1} + \kappa b\varepsilon_t \Leftrightarrow b = a(1-\beta\rho)/\kappa$$

The IS curve becomes

$$x_t = E_t x_{t+1} - \psi(i_t - E_t \pi_{t+1} - r_t^n) \Leftrightarrow b\varepsilon_t = \rho b\varepsilon_t - s(\chi a\varepsilon_t + \varepsilon_t - a\rho\varepsilon_t)$$
$$\Leftrightarrow (1-\rho)b = -\psi a(\chi - \rho) - \psi$$

Plugging in expression for b from above implies

$$(1-\rho)b = -\psi a(\chi-\rho) - \psi \Leftrightarrow \frac{(1-\rho)a(1-\beta\rho)}{\kappa} = -\psi a(\chi-\rho) - \psi$$
$$\Leftrightarrow a\left[\frac{(1-\rho)(1-\beta\rho)}{\kappa} + \psi(\chi-\rho)\right] = -\psi$$
$$\Leftrightarrow a = -\frac{\psi}{\left[\frac{(1-\rho)(1-\beta\rho)}{\kappa} + \psi(\chi-\rho)\right]}$$

And therefore

$$b = \frac{a(1-\beta\rho)}{\kappa} = -\frac{\psi(1-\beta\rho)}{\kappa\left[\frac{(1-\rho)(1-\beta\rho)}{\kappa} + \psi(\chi-\rho)\right]} = \frac{-\psi(1-\beta\rho)}{[(1-\rho)(1-\beta\rho) + \psi\kappa(\chi-\rho)]} < 0$$

Thus, $\frac{\partial b}{\partial \psi} < 0$, the degree of monetary non-neutrality (absolute value of b) is increasing in the elasticity of the output gap to the real interest rate.

In our model, this elasticity is given by (see equation 3.21):

$$\psi = \left[1 + \frac{1}{2}\left(\frac{\sigma - 1}{\sigma\mu}\right)\left(\frac{1}{1 - \frac{1}{\phi} - \frac{\gamma}{2}}\right)\right]^{-1}$$

such that a more negative value of ϕ (i.e. more elastic shopping effort) or a greater value of γ reduces ψ. Hence, increasing the degree of store-switching in the model reduces the elasticity of the output gap to the real interest rate and therefore lowers the degree of monetary non-neutrality in the model.

APPENDIX D: SECOND ORDER APPROXIMATION TO UTILITY WITH ENDOGENOUS SHOPPING EFFORT AND STORE-SWITCHING

The second-order approximation to utility is:

$$U_t = \log C_t + \log(1 - L_t - S_t)$$

$$\approx \log \bar{C} + \frac{1}{\bar{C}}(C_t - \bar{C}) - \frac{1}{2}\left(\frac{1}{\bar{C}}\right)^2 (C_t - \bar{C})^2 + \log(1 - \bar{L} - \bar{S}) + \frac{-1}{1-\bar{L}-\bar{S}}(L_t - \bar{L}) + \frac{-1}{1-\bar{L}-\bar{S}}(S_t - \bar{S}) - \frac{1}{2}\left(\frac{1}{1-\bar{L}-\bar{S}}\right)^2 (L_t - \bar{L})^2 - \frac{1}{2}\left(\frac{1}{1-\bar{L}-\bar{S}}\right)^2 (S_t - \bar{S})^2 - \left(\frac{1}{1-\bar{L}-\bar{S}}\right)^2 (L_t - \bar{L})(S_t - \bar{S}) + h.o.t.$$

$$= t.i.p. + \left(\check{C}_t + \tfrac{1}{2}\check{C}_t^2\right) - \tfrac{1}{2}\check{C}_t^2 - \eta_L\left(\check{L}_t + \tfrac{1}{2}\check{L}_t^2\right) - \eta_S\left(\check{S}_t + \tfrac{1}{2}\check{S}_t^2\right) - \tfrac{1}{2}\eta_L^2\check{L}_t^2 - \tfrac{1}{2}\eta_S^2\check{S}_t^2 - \eta_L\eta_S\left(\check{L}_t + \tfrac{1}{2}\check{L}_t^2\right)\left(\check{S}_t + \tfrac{1}{2}\check{S}_t^2\right) + h.o.t.$$

$$= t.i.p. + \check{C}_t - \eta_L\check{L}_t - \tfrac{1}{2}\eta_L(1 + \eta_L)\check{L}_t^2 - \eta_S\check{S}_t - \tfrac{1}{2}\eta_S(1 + \eta_S)\check{S}_t^2 - \bar{L}\eta_S\check{L}_t\check{S}_t + h.o.t.$$

where $\eta_L \equiv \frac{\bar{L}}{1-\bar{L}-\bar{S}} = \left(\frac{\sigma-1}{\sigma}\right)\left(\frac{\alpha}{\mu}\right)$, $\eta_S \equiv \frac{\bar{S}}{1-\bar{L}-\bar{S}} = -\frac{\phi}{2}$ when $\bar{\tau} = \mu$, and following Woodford (2003), $X_t - \bar{X} = \bar{X}\left(\check{X}_t + \frac{1}{2}\check{X}_t^2\right)$.

From the derivation of the model in the text with $\bar{\tau} = \mu$, we have $\check{Y}_t = \check{X}_t + \check{Z}_t$ and $\check{S}_t = \frac{\alpha}{\mu}\left(\frac{\sigma-1}{\sigma}\right)\frac{1}{\phi-1-\frac{1}{2}\gamma\phi}\check{L}_t$. Given the production function $Y_t(i) = Z_t N_t(i)^\alpha$, it follows that

$$\Rightarrow N_t = \int_0^1 N_t(i)\,di = \int_0^1 \left(\frac{Y_t(i)}{Z_t}\right)^{1/\alpha} di = \left(\frac{Y_t}{Z_t}\right)^{1/\alpha}\int_0^1 \left(\frac{Y_t(i)}{Y_t}\right)^{1/\alpha} di = \left(\frac{Y_t}{Z_t}\right)^{1/\alpha}\int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\sigma/\alpha} di$$

$$\Rightarrow Y_t = Z_t N_t^\alpha \left\{\int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\frac{\sigma}{\alpha}} di\right\}^{-\alpha}$$

$$\Rightarrow \check{Y}_t = \check{Z}_t + \alpha\check{N}_t - d_t$$

where $d_t \equiv \alpha \log\left\{\int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\frac{\sigma}{\alpha}} di\right\}$. From the labor market clearing conditions, we have $N_t = L_t \Rightarrow \check{N}_t = \check{L}_t$. It follows that

$$\check{L}_t = \check{N}_t = \frac{1}{\alpha}\left(\check{Y}_t - \check{Z}_t + d_t\right) = \frac{1}{\alpha}\check{X}_t + \frac{1}{\alpha}d_t$$

Also, one can show (see Gali 2008) that $d_t = \alpha\log\left\{\int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\frac{\sigma}{\alpha}} di\right\} \approx \frac{1}{2}\frac{\sigma}{\Theta}\mathrm{var}_i\left(\log\left(P_t(i)\right)\right)$. Define $\Delta_t \equiv \mathrm{var}_i\left(\log\left(P_t(i)\right)\right)$. Woodford (2003) shows that

$$\Delta_t = \theta\Delta_{t-1} + \frac{\theta}{1-\theta}\pi_t^2 + hot$$

Hence, $E(\Delta_t) = \frac{\theta}{(1-\theta)^2}E(\pi_t^2)$. Thus, $E(d_t) \approx \frac{1}{2}\frac{\sigma}{\Theta}\frac{\theta}{(1-\theta)^2}E(\pi_t^2)$.

Finally, for the link between consumption and output, given $C_t = \left(C_{A,t}^{\frac{\gamma-1}{\gamma}} + C_{B,t}^{\frac{\gamma-1}{\gamma}}\right)^{\gamma/(\gamma-1)}$, $\left(C_{A,t} + C_{B,t}\right) = Y_t$, and $\frac{C_{A,t}}{C_{B,t}} = \left\{\frac{\tau_t}{\mu}\right\}^{\gamma}$, we have $C_t = Y_t \Phi_t$ where $\Phi_t \equiv \left(\left(\frac{\tau_t}{\mu}\right)^{\gamma-1} + 1\right)^{\frac{\gamma}{\gamma-1}} \Big/ \left\{\left(\frac{\tau_t}{\mu}\right)^{\gamma} + 1\right\}$. So

$$C_t - \bar{C} = \bar{\Phi}(Y_t - \bar{Y}) + \bar{Y}\frac{\partial \Phi_t}{\partial \tau_t}\bigg|_{\tau_t=\bar{\tau}}(\tau_t - \bar{\tau}) + 0(Y_t - \bar{Y})^2 + \frac{1}{2}\bar{Y}\frac{\partial^2 \Phi_t}{\partial \tau_t^2}\bigg|_{\tau_t=\bar{\tau}}(\tau_t - \bar{\tau})^2 + \frac{\partial \Phi_t}{\partial \tau_t}\bigg|_{\tau_t=\bar{\tau}}(\tau_t - \bar{\tau})(Y_t - \bar{Y})$$

Note that steady-state levels with $\bar{\tau} = \mu$ are given by $\bar{\Phi} = 2^{\frac{1}{\gamma-1}}$, $\frac{\partial \Phi_t}{\partial \tau_t}\Big|_{\tau_t=\bar{\tau}} = 0$, and $\frac{\partial^2 \Phi_t}{\partial \tau_t^2}\Big|_{\tau_t=\bar{\tau}} = -\frac{\gamma}{\mu^2}\frac{\bar{\Phi}}{4}$, so

$$C_t - \bar{C} = \bar{\Phi}\bar{Y}\check{Y}_t + 0 + 0 - \tfrac{1}{8}\gamma\bar{\Phi}\bar{Y}\check{\tau}_t^2$$

$$\Rightarrow \check{C}_t = \check{Y}_t - \tfrac{1}{8}\gamma\check{\tau}_t^2 = \check{Y}_t - \tfrac{1}{8}\gamma\phi^2\check{S}_t^2 = \check{X}_t + \check{Z}_t - \tfrac{1}{8}\gamma\phi^2\zeta^2\check{X}_t^2$$

Now substituting into our approximation to utility yields

$$\begin{aligned}
U_t &= \log C_t + \log(1 - L_t - S_t) \\
&\approx t.i.p. + \check{C}_t - \eta_L\check{L}_t - \tfrac{1}{2}\eta_L(1+\eta_L)\check{L}_t^2 - \eta_S\check{S}_t - \tfrac{1}{2}\eta_S(1+\eta_S)\check{S}_t^2 - \eta_L\eta_S\check{L}_t\check{S}_t + h.o.t. \\
&= t.i.p. + \left(\check{X}_t - \check{Z}_t + -\tfrac{1}{8}\gamma\phi^2\zeta^2{\check{X}_t}^2\right) - \left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{\alpha}{\mu}\right)\left(\tfrac{\check{X}_t}{\alpha} + \tfrac{d_t}{\alpha} + \tfrac{1}{2}\left\{\tfrac{\check{X}_t}{\alpha} + \tfrac{d_t}{\alpha}\right\}^2\right) + \\
&\qquad \tfrac{\phi}{2}\left(\zeta\check{X}_t + \zeta d_t + \tfrac{1}{2}\left\{\zeta\check{X}_t + \zeta d_t\right\}^2\right) - \tfrac{1}{2}\left(\left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{\alpha}{\mu}\right)\right)^2\left\{\tfrac{\check{X}_t}{\alpha} + \tfrac{d_t}{\alpha}\right\}^2 - \tfrac{1}{2}\left(\tfrac{\phi}{2}\right)^2\left\{\zeta\check{X}_t + \zeta d_t\right\}^2 - \\
&\qquad \left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{\alpha}{\mu}\right)\tfrac{-\phi}{2}\left\{\tfrac{\check{X}_t}{\alpha} + \tfrac{d_t}{\alpha}\right\}\left\{\zeta\check{X}_t + \zeta d_t\right\} + h.o.t. \\
&= t.i.p. + \left[1 - \left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{1}{\mu}\right)\tfrac{\frac{1}{2}\phi(1-\gamma)-1}{\phi-\frac{1}{2}\phi\gamma-1}\right]\check{X}_t + \left[-\left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{1}{\mu}\right)\tfrac{\frac{1}{2}\phi(1-\gamma)-1}{\phi-\frac{1}{2}\phi\gamma-1}\right]d_t \\
&\quad -\tfrac{1}{2}\left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{1}{\mu}\right)\left[\tfrac{1}{\alpha} + \tfrac{1}{4}\gamma\phi^2\left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{1}{\mu}\right)\tfrac{1}{\left(\phi-\frac{1}{2}\phi\gamma-1\right)^2} - \tfrac{\phi}{2}\left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{1}{\mu}\right)\tfrac{1}{\left(\phi-\frac{1}{2}\phi\gamma-1\right)^2}\right]\check{X}_t^2 \\
&\quad -\tfrac{1}{2}\left\{\left(\tfrac{\sigma-1}{\sigma}\right)\left(\tfrac{1}{\mu}\right)\tfrac{\frac{1}{2}\phi(1-\gamma)-1}{\phi-\frac{1}{2}\phi\gamma-1}\right\}^2\check{X}_t^2 + h.o.t.
\end{aligned}$$

Therefore expected utility is

$$\begin{aligned}
EU_t &\approx -\tfrac{1}{2}\left\{\left(\tfrac{\sigma-1}{\sigma\mu}\right)\tfrac{\frac{1}{2}\phi(1-\gamma)-1}{\phi-\frac{1}{2}\phi\gamma-1}\tfrac{\sigma}{\Theta}\tfrac{\theta}{(1-\theta)^2}\right\}E(\pi_t^2) \\
&\quad -\tfrac{1}{2}\left\{\left(\tfrac{\sigma-1}{\sigma\mu}\right)\left[\tfrac{1}{\alpha} + \tfrac{1}{4}\gamma\phi^2\left(\tfrac{\sigma-1}{\sigma\mu}\right)\tfrac{1}{\left(\phi-\frac{1}{2}\phi\gamma-1\right)^2} - \tfrac{\phi}{2}\left(\tfrac{\sigma-1}{\sigma\mu}\right)\tfrac{1}{\left(\phi-\frac{1}{2}\phi\gamma-1\right)^2}\right] + \left\{\left(\tfrac{\sigma-1}{\sigma\mu}\right)\tfrac{\frac{1}{2}\phi(1-\gamma)-1}{\phi-\frac{1}{2}\phi\gamma-1}\right\}^2\right\}E\left(\check{X}_t^2\right) \\
&\quad + t.i.p. + h.o.t.
\end{aligned}$$

which after rearranging yields the expression in the text.

APPENDIX E: CONSTRUCTION OF DATA MOMENTS

This appendix describes how we constructed moments for the empirical analysis in sections I and II.

Frequency of sales. The IRI dataset provides a flag to indicate whether a given good was on sale in a given store in a given week. In addition to this flag, we use filters as in Nakamura and Steinsson (2008). Specifically, if a price is reduced temporarily (up to three weeks) and then returns to the level observed before the price cut, we identify this episode as a sale. When we apply this filter, we use two approaches to identify a price spell. In the first approach (approach "A"), we treat missing values as interrupting price spells. In other words, if a price was $4 for two weeks, then the price was missing for a week, and then was again observed at $4 for another three weeks, we treat the data as reporting two price spells with durations of two and three weeks. In the second approach (approach "B"), missing values do not interrupt price spells if the price is the same before and after periods of missing values. For example, in the previous example, approach "B" yields one price spell with a duration of five weeks. To identify the incidence of sales, we use the union of sales flags that we obtain from the IRI dataset directly and from applying approaches "A" and "B". In the end, using approaches "A" and "B" does not materially change the incidence of sales identified by the sales flag provided in the IRI dataset.

The frequency of sales is computed at the monthly frequency as the fraction of weeks in a month when a good is identified by the sales flag as being on sale. For example, suppose that the time series for a price is observed for eight weeks {4,2,4,4,4,2,2,4} with sales flag series {0,1,0,0,0,1,1,0}, that is, sales occur in weeks #2, #6, and #7 when the price is cut from $4 to $2. Then, the frequencies of sales in the first and second months are ¼ and ½ respectively.

Size of sales. The size of the sale is computed as the (log) difference between the sales price (the incidence of a sale is identified by the sales flag) and the price preceding the sale. Since one may have more than one sale in a month, we take the average size of sales in a month. For example, suppose that the time series for a price is observed for eight weeks {4,2,4,4,3,4,2,4} with sales flag series {0,1,0,0,1,0,1,0}, that is, sales occur in weeks #2 (the price is cut from $4 to $2), #5 (the price is cut from $4 to $3), and #7 (the price is cut from $4 to $2). Then, the size of the sale in the first instance of a sale is log($2/$4), which is a negative magnitude. Since this is the only sale in the first month, the average size of sales in this month is log($2/$4). In the second month, there are two sales with sizes log($3/$4) and log($2/$4). The average size of sales in the second month is taken as the arithmetic average 0.5*{ log($3/$4)+ log($2/$4)}. In some cases, we can observe no price preceding a sale but we observe a price immediately after the sale. In this situation, we calculate the size of a sale as the log price during a sale minus the log price immediately after the sale.

Share of goods sold on sale. The share of goods sold on sale for a given good in a given market (or store) in a given month is calculated as the following ratio. The numerator is the number of units sold during episodes identified as sales by the sales flag. The denominator is the total number of sold units.

Frequency of regular price changes. A price change in a given week is identified as regular if the following criteria are satisfied: i) the sales flag does not identify this week as a period when a good is on sale; ii) the sales flag does not identify the preceding week as a period when a good is on sale; iii) the price change is larger than one cent or one percent in absolute value (or more than 0.5 percent for prices larger than $5). The last criterion removes small price changes which could arise from rounding errors and the like. Again, we use approaches "A" and "B" to identify the price in the preceding period. The incidence of regular price changes is the union of incidents identified by "A" and "B". The frequency of regular price changes is computed at the monthly frequency as the fraction of weeks in a month when a good is identified as having a regular price change.

Size of regular price changes. The size of a regular price change is computed as the (log) difference between the price in the period identified as having a regular price change and the price in the preceding period (using approach "A" and "B" to identify the preceding period). Since one may have more than one regular price change in a month, we take the average size of regular price changes in a month.

Share of goods bought at cheap regular prices. For each month, market and UPC, we construct the cross-sectional distribution of regular prices. We define a regular price as cheap if the price falls in the bottom X% of the cross-sectional distribution (e.g., bottom 20%). The share of goods bought at cheap regular prices is the share of units sold at cheap regular prices in the total number of units sold at regular prices.

Weighting. To aggregate across goods to the category level, we employ three weighting schemes: *i*) equal weights; *ii*) expenditure shares for a given market and year ("market specific"); *iii*) cross-market expenditure shares for a given year ("common"). The market-specific expenditure share weights are calculated as

$$\omega_{mctj} = \frac{\sum_s TR_{msctj}}{\sum_k \sum_s TR_{msctk}}$$

and the common expenditure share weights are calculated as

$$\omega_{ctj} = \frac{\sum_m \sum_s TR_{msctj}}{\sum_m \sum_k \sum_s TR_{msctk}}$$

where *m*, *s*, *c*, *t*, and *j* index markets, stores, product categories, time, and UPC, and TR_{msctj} is the revenue from selling good *j* in the year covering month *t*.

To aggregate across goods and categories to the store level, we employ two weighting schemes: *i*) equal weights; *ii*) expenditure shares for a given store, good and year. The expenditure share weights are calculated as

$$\omega_{msctj} = \frac{TR_{msctj}}{\sum_k \sum_c TR_{msctk}}$$

where TR_{msctj} is the revenue from selling good *j* in the year covering month *t*.