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How does price sensitivity change with the macroeconomic environment? The authors explore this question by measuring price elasticity using household-level data across 19 grocery categories over 24 quarters. For each category, they estimate a separate random coefficients logit model with quarter-specific price response parameters and control functions to address endogeneity. This specification yields a novel set of 456 elasticities across categories and time that are generated using the same method and therefore can be directly compared. On average, price sensitivity is countercyclical: It rises when the macroeconomy weakens. However, substantial variation exists, and a handful of categories exhibit procyclical price sensitivity. The authors show that the relationship between price sensitivity and macroeconomic growth correlates strongly with the average level of price sensitivity in a category. They examine several explanations for this result and conclude that a category's share of wallet is the more likely driver versus alternative explanations based on product perishability, substitution across consumption channels, or market power.

Keywords: price elasticity, business cycle, consumer packaged goods, cross-category

Does Price Elasticity Vary with Economic Growth? A Cross-Category Analysis

Price sensitivity is a key determinant of marketing-mix strategies. Therefore, empirical generalizations about variation in price sensitivity—across categories and over time—are immediately useful to marketing managers. For these reasons, price sensitivity is among the most important and widely studied areas of marketing scholarship (e.g., Bijmolt, Van Heerde, and Pieters 2005; Tellis 1988). However, little is known about any systematic relationship between price sensitivity and the macroeconomic environment. Although popular press articles often assert increased price sensitivity and increased price competition during recessions (e.g., Boyle 2009), such claims are typically made without a solid research foundation.

The current study provides an important component of such a research foundation. We explore the relationship between price sensitivity and the macroeconomic environment by estimating quarterly price sensitivity across 19 categories over six years using the new Information Resources Inc. (IRI) data (Bronnenberg, Kruger, and Mela 2008). We use a random coefficients multinomial logit model and account for endogeneity using control functions (Petrin and Train 2010). We find that, on average, price sensitivity rises when the macroeconomy is weak, as measured by gross domestic product (GDP) growth. This result is consistent with prior marketing literature that uses aggregate data to explore the relationship between price sensitivity and the business cycle (e.g., Estalami, Lehmann, and Holden 2001; Gijsenberg et al. 2010; Lamey et al. 2007) and with the large-scale surveys in Kamakura and Du (2012), who find that consumer tastes and budget allocations shift systematically with variation in GDP growth.

Yet this average result masks substantial variation across categories. Price sensitivity is strongly countercyclical—

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rising when the economy weakens—in seven categories, but it is somewhat procyclical in six categories and noncyclical in the remaining six categories. We show that the relationship between price sensitivity and economic growth depends on the average level of price sensitivity for the category. Elastic categories are more likely to exhibit decreased sensitivity when economic growth is weak, whereas inelastic categories are more likely to show decreased sensitivity when economic growth is strong.

To better shed light on these results, we consider four possible explanations: (1) the importance of the category in the overall consumer budget (share of wallet), (2) consumer inventory management challenges for perishable products, (3) consumers substituting from nongrocery categories into grocery categories during weak economic times (e.g., Gicheva, Hastings, and Villas-Boas 2007), and (4) increased price sensitivity in recessions relating to differences in firms' market power across categories (e.g., Domowitz, Hubbard, and Petersen 1986). Our analysis points to a category's share of wallet as the most likely driver of the results, though perishability also has some explanatory power.

In particular, we find that high share-of-wallet categories display higher price sensitivity when the economy is weaker, though they are not particularly price sensitive on average. Furthermore, when we add controls for share of wallet in a sequence of regressions, the relationship between overall price sensitivity and the cyclicality of price sensitivity disappears.

We arrived at these results by proceeding in two stages. First, we used a consistent approach to generate 19 category-level data sets. The combined data sets contain more than 1.87 million purchase observations across 121 brands, including private labels, from 2001 to 2006 (a period during which consumer confidence varied substantially). For each category, we estimated a household-level model of category purchase incidence and brand choice with time-varying price sensitivity, unobserved preference heterogeneity, and accounting for price endogeneity (which has been noted by many, such as Villas-Boas and Winer [1999], as necessary to accurately measure price sensitivity). The choice model is purposely agnostic about the precise mechanism; consumers' responses to prices might change due to perceived shifts in their lifetime budget constraints, risk preferences, or other unobservable factors. We flexibly capture this variation by including price–quarter interaction terms. Our analysis generates directly comparable measures of price sensitivity for 456 category quarters. Second, we relate these category–quarter price sensitivities to GDP growth, using both simple correlation coefficients and regression analysis. Our results on the role of overall elasticity, share of wallet, perishability, and other factors come from this second stage.

Our work is related to meta-analyses of price elasticity by Tellis (1988) and Bijmolt, Van Heerde, and Pieters (2005), as well as work on estimating price elasticity across categories (e.g., Bronnenberg, Mela, and Boulding 2006; Hoch et al. 1995). Our study is distinct from much of the prior literature because it contains an "apples-to-apples" comparison across categories and over time. In the absence of comparable data and methodologies, interpreting variation in price-sensitivity estimates is difficult.

Perhaps most closely related to our work is Gijsenberg et al.'s (2010) analysis, in which they examine cyclical variation in price and advertising elasticities for 163 branded products in 37 categories using national monthly sales data from the United Kingdom. Using a partial-adjustment model (e.g., Hanssens, Parsons, and Schultz 2001) of aggregate sales, Gijsenberg et al. find that (1) price sensitivity is countercyclical, (2) considerable variation exists across categories, and (3) category characteristics provide a useful way to understand the variation. They use survey measures of category involvement as their focal category characteristic. We instead focus on share of wallet (which may be related to involvement), perishability, substitution to other channels, and market concentration. Gijsenberg et al. benefit from observing more economic variation through a longer data set, whereas our disaggregate data set allows us to model household-level heterogeneity and to separate primary and secondary demand effects.[1]

Our findings on the potential drivers of variation in the cyclicality of price sensitivity are important for marketing strategy. During the recent economic crisis, the popular press frequently reported about effective management during economic contractions (e.g., Boyle 2009; Surowiecki 2009). For the most part, little research exists to back up the claims in these reports. Along with a handful of other recent studies, this work begins to provide an empirical research foundation for the effective adaptation of management decisions to the macroeconomic environment. We show that the blanket claims that price sensitivity rises in difficult economic times are incorrect (e.g., Boyle 2009). Therefore, rather than react to the economic climate directly, firms should make decisions to alter pricing strategies based on macroeconomic variables depending on some readily identifiable category characteristics. Our results suggest that one such characteristic is the importance of the category to consumer budgets. In categories that constitute a substantial share of consumer budgets, consumers are indeed more price sensitive in difficult economic times, and managers should react by increasing their focus on pricing tactics. In contrast, in other categories, price sensitivity may decline in such times, and managers should perhaps focus their attention on nonprice tactics.

Overall, our results provide a rich set of measures of price sensitivity across categories and over time. These measures enable us to move beyond average effects and focus on heterogeneity across categories in the cyclicality of price sensitivity. Although our results are descriptive, we hope the analysis points other researchers toward new issues relevant to understanding the relationship between price elasticity and economic growth.

DATA

We used household panel data from the new IRI marketing data set (Bronnenberg, Kruger, and Mela 2008) to study the relationship between changes in price elasticity and economic growth between January 2001 and December 2006. The household sample contains residents of either Eau

[1]Our work also relates to Mela, Gupta, and Lehman's (1997) investigation of how loyal versus nonloyal customers' price sensitivities change over time and during a recession.

Claire, Wis., or Pittsfield, Mass., who are members of IRI's BehaviorScan program.[2]

First, we applied a flexible model of household demand to purchases from 19 categories to estimate time-varying category-level elasticities. Next, we related these category-level elasticities to measures of macroeconomic activity. In particular, we considered quarterly GDP and GDP growth at the national level from the U.S. Census. Our results are similar for other economic indicators. The period of study contains only one relatively mild recession, but substantial quarter-to-quarter variation exists and permits us to analyze how short-term fluctuations in national economic activity correlate with price sensitivity.[3] As Figure 1 depicts, the economy experienced robust growth of 2.2% in the first quarter of 2001, followed by a mild recession in the last half of 2001. Growth remained stagnant for most of 2002–2004 before accelerating in 2005 and 2006.

Data Set Construction

Consumer choice models applied to scanner panel data face a common set of key tasks. We outline our choices next and provide substantial details on these decisions in Appendix A.[4] First, some categories possess unique characteristics that make them less suitable to study or for purposes of cross-category comparison. The IRI data set tracks 30 product categories. We focused on the following 19: carbonated soft drinks, coffee, deodorant, frozen dinners, frozen pizza, hot dogs, ketchup, laundry detergent, margarine/butter, mayonnaise, mustard, paper towels, peanut butter, potato chips, shampoo, spaghetti sauce, toilet tissue, tortilla chips, and yogurt. We excluded the other categories for a variety of reasons (discussed in Appendix A), mainly pertaining to the feasibility of applying the same modeling approach across all categories.

Second, we describe our criteria to select which panelists and purchases to include in the sample. Most studies rely on criteria involving minimum purchase frequency, total number of purchase incidences, or some combination of these criteria. We restricted the panel to those households that made at least one grocery trip in each of the six years, yielding a full sample of 3283 households. For each category, we next calculated the cumulative distribution of purchase occasions across households and excluded those in the bottom 10% that infrequently purchased in a particular category. These two criteria ensured a sufficient number of observations per household and made the selection rule relative to the overall purchase frequency within a category. As a result, different numbers of households are selected across the chosen categories (Table 1, Column 13).

Third, we describe our Universal Product Code (UPC) aggregation strategy to produce brand-level composite products. Each category contains dozens of UPCs. A benefit of the IRI data is that they contain store-level data in both target markets, which we used to construct the brand aggregates and alternative-specific prices. As is common in the brand-choice literature, we aggregated the UPCs in a category into brands to have a more tractable set of choices for estimation and included brands that yielded a cumulative market share of at least 80%. We grouped the remaining smaller brands into a composite "outside" brand with an average market share of 18.3% across categories. Private labels exist in many categories, but because the data set does not have a precise mapping from stores to each large retail chain (Kruger and Pagni 2009, p. 11), we considered all private labels the same "brand" independent of the chain. We removed UPCs with very low sales and with product packaging, form factors, or types that serve a particular market niche or were otherwise irrelevant to our analysis. This filtering procedure left us with the UPCs households purchased most frequently, causing an average 10% reduction in the number of UPCs.

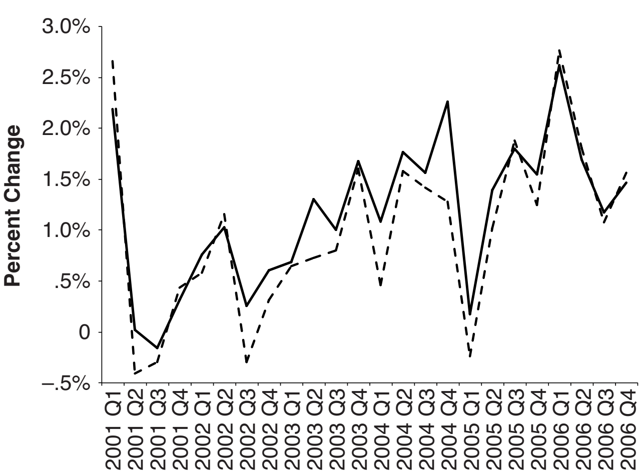
Fourth, we explain how we construct the alternative-specific marketing-mix variables given that we only observe the chosen brand's characteristics. The store data provide price information at the UPC level in all the stores. However, we do not observe the price of a UPC if no sales occurred in that week at a store. We used two methods to fill in missing price information: nonpromoted prices of the same UPC in the same store within the previous four weeks or nonpromoted prices of the same UPC at another store in the same week. If we still could not find a reliable price, we excluded the UPC for that particular store and week. We aggregated the UPC-level prices to create the brand-level prices by converting all prices to comparable units (e.g., price per ounce) and then averaging across UPCs (weighted

[2]IRI chose Eau Claire and Pittsfield to be BehaviorScan markets because they are somewhat representative of the broader U.S. market. Although two markets cannot capture the variation in preferences across the country, the local business cycle in those markets, measured using state-level GDP growth, does mirror the U.S. economy as a whole (ρ = .976 and ρ = .964 for Eau Claire and Pittsfield, respectively). Figure 1 also reports changes in household income, computed as the weighted average from Wisconsin and Massachusetts. Changes in household income are highly correlated (ρ = .932) with changes in national GDP.

[3]The relative stability of the business cycle in our data makes identifying a significant correlation between price elasticities and economic growth more difficult. Although IRI released data from 2007 after we began this project, incorporating the new data is not straightforward because of changes in the mappings from Universal Product Codes to brands.

[4]The SAS code necessary to merge, aggregate, and trim each of the categories and the Stata code to implement the choice model are available at http://www.columbia.edu/~brg2114/IRI/.

Figure 1
GDP GROWTH AND HOUSEHOLD INCOME GROWTH



Notes: Solid line is GDP growth; dashed line is household income growth (weighted average for Wisconsin and Massachusetts).

Table 1
SUMMARY STATISTICS BY CATEGORY

Category	Mean Price (1)	SD Price (2)	Share of Wallet (3)	Perishability (4)	Top Firm's Share (C1) (5)	Share of Top Four Firms (C4) (6)	Mean Promotion (7)	Promotion Mean Feature/ Display (8)	Mean Coupon (9)	Mean Repurchase Frequency (All Brands) (10)	Number of Purchase Observations (11)	Number of Trips (12)	Number of Households (13)	Number of Brands (14)	Units for One Volume Equivalent (15)
Carbonated soft drinks	4.17	.40	.167	Low	.40	.95	.27	.35	.016	.31	462,232	1,241,894	2779	6	192 oz.
Coffee	3.72	.44	.023	Low	.31	.78	.11	.09	.004	.52	74,314	653,102	1521	7	16 oz.
Deodorant	3.03	.28	.008	Low	.27	.77	.09	.03	.010	.40	13,101	261,273	577	8	2.5 oz.
Frozen dinner	3.58	.41	.098	Low	.31	.86	.15	.05	.003	.39	80,334	492,764	1166	7	16 oz.
Frozen pizza	3.21	.51	.029	Low	.36	.76	.16	.08	.005	.41	93,776	634,033	1610	9	16 oz.
Hot dogs	2.59	.37	.015	High	.26	.71	.12	.03	.002	.52	59,652	673,692	1632	8	16 oz.
Ketchup	1.05	.40	.002	Low	.59	.99	.09	.08	.002	.65	45,841	868,562	2090	4	16 oz.
Laundry detergent	.78	.07	.029	Low	.33	.81	.12	.10	.004	.45	63,472	740,525	1697	10	16 oz.
Margarine/butter	1.30	.19	.016	Medium	.51	.91	.11	.03	.002	.55	137,559	854,103	2042	9	1 lb.
Mayonnaise	1.79	.23	.011	Medium	.45	.99	.07	.05	.003	.76	57,301	911,278	2213	5	16 oz.
Mustard	2.81	.38	.005	Low	.29	.70	.08	.05	.0003	.47	25,709	880,239	2075	6	16 oz.
Paper towels	2.04	.21	.018	Low	.30	.94	.11	.11	.006	.47	95,874	798,213	1839	6	1 roll
Peanut butter	1.84	.12	.009	Medium	.35	.93	.09	.05	.001	.59	53,019	664,197	1597	5	16 oz.
Potato chips	3.58	.37	.044	High	.57	.82	.20	.20	.008	.55	156,792	1,154,618	2807	5	16 oz.
Shampoo	3.50	.28	.008	Low	.29	.79	.12	.07	.008	.39	17,881	306,653	689	8	16 oz.
Spaghetti sauce	1.10	.06	.014	Low	.36	.76	.13	.05	.002	.54	81,210	761,202	1832	7	16 oz.
Toilet tissue	.48	.07	.043	Low	.35	.97	.10	.08	.005	.51	100,015	955,147	2268	8	1 roll
Tortilla chips	2.77	.30	.034	High	.76	.92	.22	.19	.005	.49	92,861	1,071,847	2646	5	16 oz.
Yogurt	1.62	.10	.040	High	.46	.84	.13	.04	.002	.48	160,876	735,044	1757	7	16 oz.

by store-level UPC sales). We combined feature and display promotions into a compound variable because their frequency is highly correlated in the data.

Descriptive Statistics

This subsection provides a general description of the variation in the data along several dimensions. Table 1 summarizes the panel observations for the chosen categories. Our complete data set contains 1,871,819 observations across a diverse set of categories: six food categories (frozen dinner, frozen pizza, hot dogs, potato chips, tortilla chips, and yogurt), six condiment/topping categories (ketchup, margarine/butter, mayonnaise, mustard, peanut butter, and spaghetti sauce), two drink categories (carbonated soft drinks and coffee), and five nonfood categories (deodorant, laundry detergent, paper towels, shampoo, and toilet tissue).

First, because our goal was to allow price sensitivity to vary by quarter, we required many purchase observations per quarter to accurately recover the parameters. Across all categories, we observed approximately 4100 purchases per category per quarter. This number ranged from 545 purchases per quarter in deodorant to 19,259 purchases per quarter in carbonated soft drinks. These numbers are large enough to recover quarter-specific price sensitivity with minimal assumptions.

Second, our data contain a great deal of variation in price across categories and over time. Among the categories, ketchup has the highest coefficient of variation of prices over time, whereas spaghetti sauce is the most stable. Table 2 reports several statistics over time, averaged across categories. Consistent with inflation rates, average prices increased approximately 16% over the six-year period. We did not observe any evidence overall or at the category level that prices increase during periods of weak macroeconomic growth, in contrast to Deleersnyder et al.'s (2004) findings for consumer durables.

Third, the mean price-promotion probability is similar across these categories, with the exceptions of carbonated soft drinks, potato chips, and tortilla chips. Price promotions occur roughly 10% of the time across brands and categories, creating an additional source of price variation. Importantly, we do not observe a systematic change in the frequency or depth of promotions during or after the recession.

Fourth, Table 1 contains category characteristics such as share of wallet and perishability, drawn from information in Bronnenberg, Kruger, and Mela (2008, Table 2). We computed a weighted measure for the share of wallet that accounts for households that did not spend anything in the category. Significant variation in the share of wallet exists across categories, with carbonated soft drinks having the highest share (16.7%) and ketchup the lowest share (.2%).

Fifth, the degree of market concentration varies over categories. For example, the mayonnaise market is highly concentrated, with two brands occupying almost the entire market. The deodorant market is relatively unconcentrated, with the top brand holding 27% of the market.

MODEL AND ESTIMATION

Household Utility

We applied a standard nested multinomial logit model with random coefficients to study the variation of price sensitivity over time. The upper nest represents a household's decision to purchase in the category, and the lower nest represents the household's brand choice. We ignored the issue of multiple discreteness (Dubé 2004) and did not model the purchase quantity decision (Chintagunta 1993). Conditional on category incidence ($y_{it} = 1$), the random utility of household i that purchases brand $j = 0, 1, \ldots, J$ during week t is

Table 2

SUMMARY STATISTICS BY QUARTER ACROSS CATEGORIES

Category	*Mean Price (1)*	*SD Price (2)*	*Mean Promotions (3)*	*Mean Feature/ Display (4)*	*Mean Coupon (5)*	*Mean Repeat Purchase (Loyalty) (6)*	*GDP Growth (7)*
2001 Q1	2.54	1.31	.18	.09	.006	.44	2.19%
2001 Q2	2.48	1.24	.19	.09	.007	.46	.02%
2001 Q3	2.48	1.26	.17	.09	.008	.47	–.16%
2001 Q4	2.56	1.31	.17	.09	.008	.47	.31%
2002 Q1	2.56	1.31	.18	.09	.008	.45	.76%
2002 Q2	2.55	1.26	.19	.10	.008	.45	1.02%
2002 Q3	2.55	1.24	.18	.10	.006	.45	.25%
2002 Q4	2.60	1.26	.15	.09	.006	.45	.61%
2003 Q1	2.59	1.27	.15	.09	.005	.45	.68%
2003 Q2	2.70	1.28	.15	.10	.005	.46	1.31%
2003 Q3	2.62	1.24	.19	.09	.006	.45	1.00%
2003 Q4	2.64	1.24	.17	.09	.006	.46	1.68%
2004 Q1	2.66	1.30	.16	.10	.003	.46	1.06%
2004 Q2	2.64	1.27	.14	.11	.003	.47	1.77%
2004 Q3	2.66	1.29	.14	.10	.002	.47	1.56%
2004 Q4	2.77	1.32	.15	.09	.003	.46	2.26%
2005 Q1	2.74	1.34	.15	.10	.004	.46	.18%
2005 Q2	2.79	1.32	.16	.11	.004	.47	1.39%
2005 Q3	2.80	1.33	.15	.11	.003	.47	1.80%
2005 Q4	2.83	1.32	.15	.09	.004	.47	1.55%
2006 Q1	2.77	1.32	.17	.11	.005	.47	2.62%
2006 Q2	2.84	1.29	.19	.12	.005	.46	1.70%
2006 Q3	2.84	1.32	.18	.11	.004	.48	1.17%
2006 Q4	2.94	1.36	.19	.09	.005	.48	1.47%

$$U_{ijt|y_{it}=1} = \beta_{ij} - \alpha_{i1}p_{jt} - \sum_{q=2}^{Q}\alpha_q I\{t \in q\}p_{jt} + \gamma_i I\{s_{jt-1} = j\} + \delta_i x_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where p_{jt} is the price, $s_{jt} = \{0, 1, \ldots, J\}$ indicates the brand purchased on shopping occasion t, and x_{ijt} contains other controls (the feature/display compound measure and coupon). A period represents a week-store visit. The parameter α_{i1} represents the base price coefficient and α_q represents 23 quarter-specific deviations relative to the first quarter (Q = 24).[5] In the next section, we explore several robustness checks that permit other coefficients to vary (over time or brands). The parameter γ_i captures a consumer's "loyalty" or "switching cost" of moving from one brand to another. The parameter vector δ_i captures sensitivities to other controls. The outside option (j = 0) for the brand-choice decision is to purchase a composite outside brand, formed as the collection of smaller brands in the category (as discussed in the "Data" section and Appendix A). It has a normalized utility of ε_{i0t}.

For the category incidence decision, the household receives utility from choosing to purchase in the category of

$$u_{it} = \rho' w_{it} + \psi IV_{it} + \nu_{it1}, \text{ if } y_{it} = 1, \tag{2}$$

where w_{it} includes an intercept and the number of weeks since the household's last purchase, IV_{it} is the inclusive value from the lower decision nest, and ν_{it1} is an i.i.d. logit error. The utility of not purchasing in the category ($y_{it} = 0$) is normalized to ν_{it0}.

We modeled consumer heterogeneity with a multivariate normal distribution across the brand intercepts, base price, feature/display, and state dependence.[6] We used 500 Halton draws per dimension to approximate the integral with Monte Carlo integration. We did not include a random coefficient on the coupon variable (due to insufficient variation) or on the residual from the control functions (see the next section). We used an unrestricted variance–covariance matrix to permit correlation in preferences across attributes. This full variance–covariance matrix enabled us to capture whether more price-sensitive consumers have a stronger preference for lower-priced brands. However, unobserved changes in income might be correlated with household-specific changes in brand intercepts, which would not be captured.

Endogeneity and Estimation

Price endogeneity is particularly important to address in our setting because of our focus on accurately recovering price elasticities and, given the potential macroeconomic variation in our data set, the likelihood that aggregate unobserved demand shocks might be correlated with prices. We used control functions to address price endogeneity because they are easy to incorporate into mixed logit models of demand (Petrin and Train 2010).

To apply control functions, we followed the parametric functional forms in Example 2 of Petrin and Train (2010, pp. 5–6) and modified our existing model in two ways. First, we decomposed the endogenous variable, price p_{jt}, such that it could be expressed as the sum of a linear combination of exogenous instruments Z_{jt} and an unobserved price shock ξ_{jt}:

$$p_{jt} = \theta_j' Z_{jt} + \xi_{jt}. \tag{3}$$

This shock may capture, for example, unobserved time-varying product characteristics or omitted promotional activities. Price endogeneity arises if ξ_{jt} and ε_{ijt} are correlated. Second, we decomposed the error term into ε^1_{jt} such that $\varepsilon_{ijt} = \varepsilon^1_{jt} + \varepsilon^2_{ijt}$ and ξ_{jt} are distributed jointly normal and independent over j. Here, ε^1_{jt} characterizes demand shocks that are common across all consumers, representing the average utility a consumer obtains from the unobserved attribute of product j on shopping occasion t. Such unobserved product attributes could include the shelf space and shelf location in the store, or any time-varying brand preference that creates a deviation from the mean preference β_{jt}. The second component of the error term, ε^2_{ijt}, is distributed i.i.d. extreme value. These assumptions yielded a brand-choice utility with the control function in the following form:

$$U_{ijt|y_{it}=1} = \beta_{ij} - \alpha_{i1}p_{jt} - \sum_{q=2}^{Q}\alpha_q I\{t \in q\}p_{jt} + \gamma_i I\{s_{jt-1} = j\} + \delta_i x_{ijt} + \lambda\xi_{jt} + \sigma\eta_{jt} + \varepsilon^2_{ijt}, \tag{4}$$

where η_{jt} is an i.i.d. standard normal error that is integrated out through simulation in the maximum likelihood estimation. These distributional assumptions provide a realistic and easy-to-compute process for capturing price endogeneity and are necessary to produce a mixed logit model with the same scale normalization as the original model without control functions.

To select instruments, we exploited the multimarket nature of the data set and used prices of the brand in other markets (Hausman 1996; Nevo 2001). The intuition is that the contemporaneous prices of a brand in two markets should be correlated through a common marginal cost, but unobserved demand shocks should be independent across locations conditional on observables. We chose a set of markets located far from the two panelist markets to minimize the chance that regional correlations in demand shocks might violate this independence assumption.

We estimated the model using a sequential strategy because simultaneous estimation is infeasible given the size of our data sets. First, we estimated the reduced-form pricing regression in Equation 3 with ordinary least squares (OLS) to recover the residual ξ_{jt}. Second, we included these residuals as an additional regressor (control function) in the brand-choice utility as in Equation 4, which we estimated as a mixed logit using simulated maximum likelihood. Third, given the parameter estimates from this brand-choice stage, we estimated the category purchase incidence model in Equation 2. Although sequential estimation of the nested logit

[5]By "base price coefficient," we do not mean the price coefficient on the regular price; rather, we mean that the coefficient provides a base level on which the other price coefficients are added.

[6]For several categories, the standard deviation on the price coefficient implies that some consumers exhibit purchase behavior consistent with a positive price coefficient. Gedenk and Neslin (1999), among others, note similar findings in other categories. We experimented with log-normal and triangular distributions on a subset of categories but found that a normal distribution still fit the data better.

model (steps 2 and 3) resulted in an efficiency loss, the size of our data set should reduce the importance of this concern. However, we risk overstating the precision of our incidence results because we cannot correct for biases in the standard errors in the first stage without simultaneous estimation.

Discussion

All empirical research entails making certain decisions that trade off a more realistic and/or flexible model for parsimony and computational ease. To conduct a consistent analysis across many categories, we made several modeling choices to keep the model flexible and tractable, necessarily ignoring several complicating factors.

Given the nature of our research question, estimating price sensitivity accurately and robustly is critical, and we made several choices regarding our specific method. As described previously, we captured changes in price sensitivity over time by estimating different price coefficients for every quarter. This approach is similar to one Mela, Gupta, and Lehmann (1997) use, though they use discrete heterogeneity and employ a three-quarter moving window to generate a sufficient number of observations in each target quarter. The fundamental challenge is that we must simultaneously address both cross-sectional heterogeneity and temporal variation in preferences. The quarterly price terms impose little a priori structure on changes in price sensitivity.[7] Furthermore, they facilitate an easy and flexible comparison with quarterly values of GDP growth. The cost of this assumption is that we cannot estimate random coefficients for the quarter-specific price terms, because estimation using simulated maximum likelihood estimation becomes computationally burdensome with so many random coefficients. Therefore, we assume the quarterly price terms are homogeneous across consumers, such that each price–quarter coefficient effectively shifts the mean of the preference distribution across consumers.

A related assumption is that whereas the price coefficients change over time, other coefficients do not. We made this decision for three reasons. First, the unobserved shocks ξ_{jt} from the control function will absorb any time-varying unobserved brand-specific factors, such that these omitted factors should not contaminate our estimate of the price-sensitivity parameters. Second, the 19 categories we consider are all mature. We assume that the characteristics of each brand's composite product are relatively stable during our focal time period and that macroeconomic cycles should not directly alter consumers' perceptions of brand value. Third, including time-varying intercepts would dramatically increase the number of parameters to estimate.

We also used a hierarchical estimation strategy that estimates category-specific elasticities and then correlates these elasticities with GDP growth, rather than a specification that explicitly conditions on GDP growth in the model. We chose not to include GDP growth directly in the model because (1) it involves making functional form assumptions to link GDP growth to price coefficients, (2) standard errors in the estimates would be inflated because GDP only varies by quarter, and (3) excluding GDP growth from the model leaves more flexibility to examine the mediators of the relationship between GDP growth and price elasticities (as we do in the section "Assessing Potential Explanations").

In the Web Appendix (www.marketingpower.com/jmr_webappendix), we provide analysis that helps explain particular modeling choices regarding price variation over time, control functions, promotion flexibility over time, state dependence, and purchase size. Ideally, the results would be insensitive to any such modeling choices. Although we could not explore all possible modeling choices, the results in the Web Appendix help explain our choices and suggest that our core qualitative results are likely to be robust to several alternative specifications.

However, assessing the robustness of other assumptions is more difficult. For example, although we addressed price endogeneity using control functions, we assumed that feature/display activities are exogenous.[8] We assumed that household observations are independent across categories and do not model cross-category joint decisions or shopping baskets (Manchanda, Ansari, and Gupta 1999). Furthermore, for computational reasons, we do not structurally account for forward-looking behavior. Consumers may make forward-looking decisions given their beliefs about the timing of temporary price discounts and inventory management issues (e.g., Erdem, Imai, and Keane 2003). To account for inventory dynamics descriptively, our nested logit model includes the number of weeks since the last purchase as an explanatory variable in the category-incidence utility. Finally, for computational reasons and to facilitate estimation with many categories, we did not model the budget constraint explicitly.

In summary, given the particular goals of this study, we placed a high value on conducting a consistent analysis across many categories to estimate price sensitivity as flexibly as possible. With this aim, we made choices that we believe are reasonable, and we explore the robustness of our results to these choices in Appendix B.

ESTIMATION RESULTS

Price Sensitivity by Category and Over Time

Table 3, Panels A, B, and C, present the total, primary, and secondary elasticities, respectively, for each category and quarter.[9] We focus on price elasticity because it is a common measure in the literature and facilitates comparison between our results and prior work. We emphasize the total elasticity results because they summarize the main points. Our results are qualitatively unchanged using the secondary demand elasticity estimates as the unit of analysis.

Before discussing the results, we note that we report elasticities as $-(dq/dp \times p/q)$, such that most appear as positive numbers. This convention facilitates the discussion of pro- and countercyclical price sensitivity in the next section. Because price elasticities are negative, using "procyclical

[7]For example, an alternative formulation might let the price coefficient flexibly vary as a function of time and parameters, perhaps using a high-order polynomial. However, this alternative entails a parametric form assumption that we would prefer to avoid.

[8]Kuksov and Villas-Boas (2008) find some evidence in support of this assumption in the ketchup category. Specifically, they test for endogeneity in price, promotions, and features and only find evidence of price endogeneity.

[9]The elasticity results are available for download at http://www.columbia.edu/~brg2114/IRI/, in addition to the SAS and Stata scripts necessary to aggregate the data and to estimate the models.

Table 3
ELASTICITIES

Category	Carbonated Soft Drinks (1)	Coffee (2)	Deodorant (3)	Frozen Dinner (4)	Frozen Pizza (5)	Hot Dogs (6)	Ketchup (7)	Laundry Detergent (8)	Marga-rine/ Butter (9)	Mayon-naise (10)	Mustard (11)	Paper Towel (12)	Peanut Butter (13)	Potato Chips (14)	Shampoo (15)	Spaghetti Sauce (16)	Toilet Tissue (17)	Tortilla Chips (18)	Yogurt (19)	Average (20)
A: Total Elasticities																				
2001 Q1	3.36	2.91	3.52	1.85	.71	1.89	2.42	1.63	1.92	3.31	2.28	.49	4.30	1.31	1.65	2.50	1.21	1.50	1.93	2.14
2001 Q2	2.95	2.84	2.31	1.75	.99	1.68	2.21	1.69	1.73	3.44	2.10	.41	4.39	1.22	1.55	2.47	1.15	1.20	1.89	2.00
2001 Q3	3.28	2.75	1.57	1.84	1.02	2.04	3.08	1.66	1.79	3.72	2.13	.78	4.38	1.05	1.70	2.83	.93	1.33	1.93	2.10
2001 Q4	2.87	2.51	1.95	1.65	1.08	1.73	3.83	1.43	1.96	3.66	2.43	.81	5.22	.93	1.57	2.74	1.41	1.07	2.00	2.15
2002 Q1	2.84	2.41	2.47	1.17	1.28	2.06	1.87	1.71	1.85	3.07	2.24	.81	4.45	1.20	1.58	2.49	1.43	1.08	1.80	1.99
2002 Q2	2.72	2.41	2.60	1.70	1.23	2.01	1.84	1.55	1.85	2.99	2.12	.62	4.52	1.08	1.48	2.54	1.17	1.03	1.79	1.96
2002 Q3	2.76	2.42	3.05	1.95	1.13	1.83	2.10	1.52	1.82	3.37	1.98	.80	3.99	1.06	1.48	2.63	1.02	1.07	2.03	2.00
2002 Q4	2.61	2.51	3.47	1.78	1.07	1.85	2.35	1.51	1.75	3.58	2.14	.34	4.14	1.04	1.51	2.56	1.76	1.07	2.13	2.06
2003 Q1	2.80	2.54	3.57	1.55	.69	1.82	2.38	1.80	1.82	3.53	2.22	.43	4.22	1.19	1.31	2.23	1.12	.96	2.07	2.01
2003 Q2	2.64	2.65	4.00	1.67	.89	1.71	2.14	1.59	1.54	3.09	2.18	.10	3.93	1.43	1.27	2.59	1.36	.85	2.25	1.99
2003 Q3	2.74	2.71	3.21	1.78	.82	1.94	2.93	1.54	1.71	3.60	2.30	.12	3.80	1.22	1.26	2.43	1.81	.78	2.39	2.06
2003 Q4	2.77	2.56	3.44	1.67	.91	1.90	3.19	2.05	1.58	3.73	2.36	.03	4.09	1.18	1.47	2.89	.87	.89	2.01	2.08
2004 Q1	2.75	2.78	2.99	1.47	.96	1.86	3.07	1.98	1.56	3.34	2.36	.02	3.88	1.20	1.56	2.49	1.83	1.07	1.98	2.06
2004 Q2	2.65	2.71	3.88	1.55	.81	1.84	2.34	1.81	1.65	3.75	2.25	–.08	3.62	1.01	1.78	2.43	.96	1.16	2.08	2.01
2004 Q3	2.59	2.66	3.32	1.82	.77	1.60	2.73	1.61	1.69	3.46	2.38	.40	4.07	1.03	1.54	2.77	.56	1.17	1.38	1.98
2004 Q4	2.63	2.63	1.44	1.65	.82	1.86	3.09	1.80	1.64	3.55	2.25	.76	3.86	.96	1.39	2.76	.69	.97	1.73	1.92
2005 Q1	2.77	2.56	2.44	1.66	.66	1.91	2.64	1.95	1.82	4.31	2.30	.39	3.62	.88	1.43	2.98	.39	1.11	1.60	1.97
2005 Q2	2.72	2.90	2.68	1.63	.72	1.91	2.12	1.94	1.47	4.23	2.29	.50	3.97	1.31	1.67	2.37	.19	1.26	1.15	1.95
2005 Q3	2.87	2.82	2.82	1.56	1.02	1.99	3.21	1.86	1.65	3.88	2.32	.95	4.15	1.24	1.59	2.41	.50	1.24	1.25	2.07
2005 Q4	2.75	2.48	3.10	1.66	.78	2.06	3.65	1.64	1.81	4.46	2.16	.76	4.24	1.02	1.46	2.16	.20	1.16	1.25	2.04
2006 Q1	2.94	2.86	2.98	1.25	.42	2.15	2.22	1.89	1.73	4.67	2.10	.27	3.45	.61	1.43	2.56	.24	1.17	1.20	1.90
2006 Q2	2.62	2.72	3.16	1.53	.63	1.82	2.28	1.99	1.63	5.06	2.15	–.24	3.35	1.04	1.46	2.53	.24	1.32	1.31	1.93
2006 Q3	3.06	2.58	3.52	1.56	.48	1.81	2.42	1.85	1.72	4.89	2.23	–.14	3.14	.90	1.34	2.69	.67	1.23	1.19	1.95
2006 Q4	2.73	2.42	2.52	1.01	.23	2.00	3.66	1.59	1.89	5.48	2.37	–.47	3.36	.73	1.16	2.74	.37	1.26	1.18	1.91

Table 3
CONTINUED

B: Primary Demand Elasticities

Category	*Carbonated Soft Drinks (1)*	*Coffee (2)*	*Deodorant (3)*	*Frozen Dinner (4)*	*Frozen Pizza (5)*	*Hot Dogs (6)*	*Ketchup (7)*	*Laundry Detergent (8)*	*Marga-rine/ Butter (9)*	*Mayon-naise (10)*	*Mustard (11)*	*Paper Towel (12)*	*Peanut Butter (13)*	*Potato Chips (14)*	*Shampoo (15)*	*Spaghetti Sauce (16)*	*Toilet Tissue (17)*	*Tortilla Chips (18)*	*Yogurt (19)*	*Average (20)*
2001 Q1	.20	.22	.05	.12	.06	.14	.33	.16	.14	.54	.08	.01	.50	.09	.12	.25	.04	.22	.04	.17
2001 Q2	.17	.21	.03	.12	.09	.14	.34	.15	.13	.55	.08	.01	.50	.09	.12	.23	.03	.18	.04	.17
2001 Q3	.19	.21	.02	.12	.10	.18	.47	.16	.15	.60	.09	.01	.53	.07	.13	.26	.03	.21	.04	.19
2001 Q4	.15	.18	.03	.11	.10	.14	.46	.13	.16	.61	.09	.02	.63	.07	.11	.26	.04	.16	.04	.18
2002 Q1	.15	.19	.03	.07	.12	.19	.24	.16	.16	.48	.09	.02	.55	.09	.11	.25	.05	.16	.04	.17
2002 Q2	.14	.19	.03	.11	.12	.19	.27	.15	.15	.50	.09	.01	.50	.08	.11	.24	.04	.16	.04	.16
2002 Q3	.14	.18	.04	.13	.10	.17	.28	.14	.15	.57	.08	.02	.54	.08	.12	.25	.03	.16	.04	.17
2002 Q4	.13	.18	.05	.12	.10	.16	.25	.15	.13	.62	.08	.01	.52	.08	.11	.25	.05	.16	.04	.17
2003 Q1	.14	.18	.05	.10	.06	.16	.29	.19	.15	.56	.09	.01	.50	.09	.09	.21	.03	.15	.04	.16
2003 Q2	.13	.19	.05	.11	.09	.16	.24	.16	.12	.55	.09	.00	.50	.11	.10	.24	.04	.13	.05	.16
2003 Q3	.14	.19	.04	.12	.07	.17	.34	.17	.13	.55	.09	.00	.49	.09	.10	.23	.06	.11	.05	.17
2003 Q4	.14	.18	.05	.11	.08	.17	.42	.20	.11	.63	.09	.00	.49	.09	.11	.29	.03	.13	.04	.18
2004 Q1	.14	.18	.04	.10	.09	.16	.42	.22	.13	.53	.09	.00	.46	.09	.12	.22	.05	.16	.04	.17
2004 Q2	.13	.17	.05	.10	.08	.16	.28	.17	.13	.63	.09	.00	.41	.07	.13	.23	.03	.18	.04	.16
2004 Q3	.13	.17	.04	.12	.07	.13	.31	.16	.13	.57	.09	.01	.50	.08	.12	.26	.02	.18	.03	.16
2004 Q4	.13	.18	.02	.11	.08	.16	.38	.17	.12	.62	.09	.02	.43	.07	.10	.26	.02	.14	.03	.17
2005 Q1	.14	.19	.03	.11	.06	.16	.33	.21	.13	.76	.09	.01	.49	.07	.11	.31	.01	.17	.03	.18
2005 Q2	.14	.18	.03	.11	.07	.16	.30	.21	.11	.74	.09	.01	.48	.10	.12	.24	.01	.20	.02	.18
2005 Q3	.15	.21	.04	.11	.10	.17	.42	.20	.12	.70	.09	.02	.49	.09	.11	.24	.01	.20	.02	.18
2005 Q4	.14	.16	.04	.11	.08	.17	.48	.17	.13	.67	.09	.02	.46	.07	.11	.22	.01	.18	.02	.18
2006 Q1	.16	.19	.04	.08	.04	.18	.30	.21	.13	.80	.09	.01	.41	.04	.11	.25	.01	.17	.02	.17
2006 Q2	.13	.17	.05	.11	.06	.17	.32	.21	.12	.91	.09	.01	.42	.07	.11	.26	.01	.21	.02	.18
2006 Q3	.17	.16	.05	.10	.05	.13	.32	.19	.14	.83	.09	.00	.36	.06	.09	.27	.02	.19	.02	.17
2006 Q4	.14	.16	.03	.06	.03	.16	.51	.15	.14	.96	.09	.01	.38	.05	.08	.24	.01	.20	.02	.18

Table 3
CONTINUED

Category	Carbonated Soft Drinks (1)	Coffee (2)	Deodorant (3)	Frozen Dinner (4)	Frozen Pizza (5)	Hot Dogs (6)	Ketchup (7)	Laundry Detergent (8)	Margarine/Butter (9)	Mayonnaise (10)	Mustard (11)	Paper Towel (12)	Peanut Butter (13)	Potato Chips (14)	Shampoo (15)	Spaghetti Sauce (16)	Toilet Tissue (17)	Tortilla Chips (18)	Yogurt (19)	Average (20)
C: Secondary Demand Elasticities																				
2001 Q1	3.17	2.69	3.48	1.73	.65	1.75	2.09	1.47	1.79	2.77	2.20	.48	3.80	1.21	1.53	2.25	1.17	1.27	1.90	1.97
2001 Q2	2.78	2.62	2.28	1.63	.90	1.55	1.87	1.53	1.60	2.89	2.02	.40	3.89	1.13	1.42	2.24	1.12	1.02	1.85	1.83
2001 Q3	3.09	2.54	1.55	1.72	.93	1.86	2.60	1.50	1.65	3.12	2.05	.77	3.85	.98	1.57	2.56	.90	1.12	1.89	1.91
2001 Q4	2.71	2.33	1.92	1.54	.97	1.60	3.36	1.30	1.80	3.05	2.34	.80	4.59	.86	1.46	2.49	1.37	.91	1.95	1.97
2002 Q1	2.69	2.22	2.43	1.09	1.15	1.87	1.63	1.55	1.69	2.59	2.15	.80	3.90	1.11	1.46	2.24	1.39	.91	1.76	1.82
2002 Q2	2.59	2.22	2.56	1.59	1.11	1.83	1.57	1.40	1.70	2.49	2.03	.61	4.02	1.00	1.37	2.31	1.13	.88	1.76	1.80
2002 Q3	2.62	2.24	3.01	1.82	1.02	1.66	1.82	1.38	1.67	2.80	1.90	.78	3.46	.98	1.37	2.38	.99	.91	1.99	1.83
2002 Q4	2.49	2.33	3.42	1.66	.97	1.69	2.09	1.36	1.62	2.96	2.06	.33	3.63	.96	1.40	2.31	1.71	.91	2.09	1.89
2003 Q1	2.65	2.36	3.52	1.45	.63	1.66	2.09	1.61	1.67	2.96	2.13	.42	3.72	1.09	1.22	2.02	1.09	.82	2.03	1.85
2003 Q2	2.51	2.46	3.94	1.56	.80	1.56	1.90	1.42	1.43	2.55	2.09	.10	3.43	1.33	1.17	2.35	1.32	.73	2.20	1.83
2003 Q3	2.60	2.53	3.17	1.66	.75	1.78	2.59	1.36	1.58	3.04	2.21	.12	3.31	1.13	1.16	2.19	1.76	.67	2.34	1.89
2003 Q4	2.63	2.38	3.39	1.56	.82	1.73	2.77	1.85	1.47	3.10	2.27	.03	3.60	1.10	1.35	2.60	.84	.76	1.98	1.91
2004 Q1	2.61	2.60	2.95	1.37	.87	1.70	2.65	1.76	1.44	2.80	2.27	.02	3.42	1.11	1.44	2.27	1.78	.91	1.94	1.89
2004 Q2	2.52	2.54	3.82	1.45	.73	1.68	2.06	1.64	1.52	3.12	2.16	.08	3.21	.94	1.65	2.20	.93	.98	2.04	1.85
2004 Q3	2.46	2.49	3.28	1.71	.70	1.47	2.42	1.45	1.56	2.88	2.29	.39	3.57	.96	1.43	2.51	.55	.98	1.35	1.81
2004 Q4	2.50	2.46	1.42	1.54	.74	1.71	2.71	1.62	1.51	2.93	2.17	.75	3.43	.89	1.29	2.50	.67	.82	1.70	1.76
2005 Q1	2.63	2.37	2.40	1.55	.59	1.75	2.31	1.74	1.69	3.55	2.21	.38	3.13	.82	1.32	2.67	.37	.94	1.57	1.79
2005 Q2	2.59	2.72	2.65	1.51	.65	1.75	1.81	1.73	1.36	3.49	2.20	.49	3.49	1.21	1.54	2.14	.19	1.06	1.13	1.77
2005 Q3	2.72	2.61	2.78	1.46	.92	1.82	2.79	1.67	1.53	3.19	2.23	.93	3.66	1.15	1.48	2.18	.49	1.04	1.23	1.89
2005 Q4	2.61	2.32	3.06	1.55	.70	1.90	3.17	1.47	1.68	3.79	2.08	.74	3.77	.95	1.35	1.94	.19	.98	1.23	1.87
2006 Q1	2.78	2.67	2.94	1.16	.38	1.97	1.93	1.67	1.60	3.88	2.01	.26	3.04	.57	1.32	2.31	.23	1.00	1.18	1.73
2006 Q2	2.49	2.55	3.11	1.42	.57	1.65	1.95	1.78	1.51	4.14	2.06	–.23	2.93	.97	1.35	2.28	.23	1.11	1.29	1.75
2006 Q3	2.89	2.41	3.47	1.46	.43	1.67	2.11	1.66	1.58	4.06	2.13	–.14	2.78	.84	1.25	2.42	.65	1.05	1.17	1.78
2006 Q4	2.59	2.25	2.49	.95	.20	1.84	3.15	1.44	1.76	4.52	2.28	–.46	2.99	.68	1.08	2.50	.36	1.07	1.16	1.73

Notes: Derived from the coefficients shown in Table C.1 in the Web Appendix (www.marketingpower.com/jmr_webappendix): control functions and price coefficients vary by quarter. To facilitate interpretation, for this and all subsequent tables, we report elasticities as $-(dq/dp \times p/q)$; therefore, they generally appear as positive numbers.

price sensitivity" to mean higher in absolute value can be confusing, and the literature has not been consistent in the term's usage. The benefit of our reporting format is that procyclical price sensitivity means a positive correlation between price elasticity and GDP growth. Countercyclical price sensitivity means a negative correlation, such that positive GDP growth is correlated with decreasing price sensitivity.

Broadly, the values in Table 3, Panel A, show substantial variation across and within categories over time. Most quarter-specific elasticity values are elastic rather than inelastic. Consistent with previous findings (e.g., Bell, Chiang, and Padmanabhan 1999), comparing Panels B and C of Table 3 reveals that secondary demand effects are larger than primary demand effects in all the categories. Table 4 provides descriptive statistics of these elasticities by category. The most elastic categories are peanut butter, mayonnaise, deodorant, and carbonated soft drinks, and the least elastic categories are paper towels, frozen pizza, toilet tissue, and potato chips. Some categories have significant timewise variation in elasticity (e.g., deodorant ranges from 1.44 to 4.00 with a standard deviation of .67), whereas others have little such variation (e.g., hot dogs, margarine/butter).[10]

Our elasticity numbers are broadly consistent with those of prior studies. As we report in the Web Appendix (www.marketingpower.com/jmr_webappendix), comparing our results with the studies cited in Bijmolt, Van Heerde, and Pieters's (2005) meta-analysis of price-elasticity studies yields a correlation coefficient between our estimates and the average of prior studies of .32. Given the wide range of methods used in the prior studies, this correlation suggests a degree of consistency between our results and prior work.

Making sense of the array of numbers in Table 3 and the cross-category differences in Table 4 is not straightforward. It demonstrates a challenge of deriving empirical generalizations about elasticity over time and across categories: This variation occurs despite the use of ample data and of a consistent methodology across categories. As Hanssens (2009) notes, results in one category may not transfer to other categories, even within consumer packaged goods sold in grocery stores. We dedicate much of the next two subsections to understanding the patterns across categories and time periods.

Price Sensitivity and GDP Growth

In this section, we examine how price sensitivity changes over time. We use the terms "procyclical," "noncyclical," and "countercyclical" to describe the direction of correlation with quarterly GDP growth fluctuations from 2001 to 2006. To begin, we present simple correlations between the category elasticities and GDP growth. Figure 2 plots the quarterly GDP growth and the quarterly average total price elasticity (from Table 3, Panel A, Column 20). The correlation between the two series is –.29 (p-value = .165). Lagged GDP growth is even more closely correlated with the estimated average elasticity across categories, with a correlation coefficient of –.46 (p-value = .010). These correlations yield our first broad empirical pattern: In general, price sensitivity is countercyclical, consistent with the intuition that consumers become more price sensitive during weaker economic periods. This result is consistent with Gijsenberg et al. (2010), who find price sensitivity tends to increase during economic downturns.

Averaging over categories masks substantial heterogeneity in the relationship between price sensitivity and GDP growth. Table 5 lists the correlation between GDP growth

[10]We also determined whether the individual posterior price parameters were consistent with a panelist's household income. The correlation between a household's posterior price coefficient and reported income was generally negative, consistent with the intuition that higher-income households are less price sensitive. We obtained this result without using demographic information to estimate the choice models, making this exercise an "out-of-sample" check of our results.

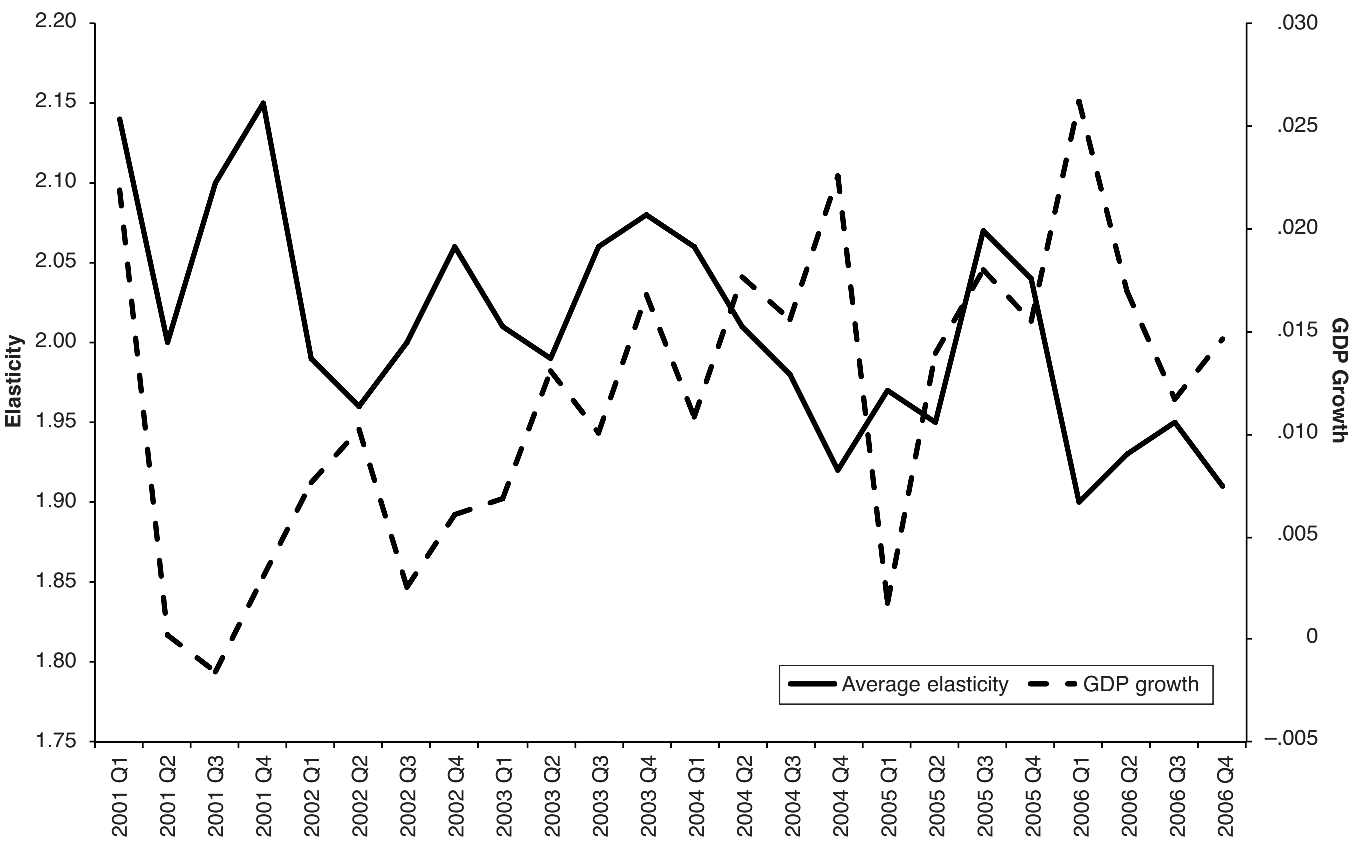
Table 4

SUMMARY OF CORE RESULTS BY CATEGORY

	Total Elasticity				*Primary Demand Elasticity*				*Secondary Demand Elasticity*			
	Mean Elasticity (1)	*SD (Across 24 Quarters) (2)*	*Max (Most Inelastic) (3)*	*Min (Most Elastic) (4)*	*Mean Elasticity (5)*	*SD (Across 24 Quarters) (6)*	*Max (Most Inelastic) (7)*	*Min (Most Elastic) (8)*	*Mean Elasticity (9)*	*SD (Across 24 Quarters) (10)*	*Max (Most Inelastic) (11)*	*Min (Most Elastic) (12)*
Carbonated soft drinks	2.81	.20	3.36	2.59	.15	.02	.20	.13	2.66	.18	3.17	2.46
Coffee	2.64	.16	2.91	2.41	.18	.02	.22	.16	2.45	.15	2.72	2.22
Deodorant	2.92	.67	4.00	1.44	.04	.01	.05	.02	2.88	.66	3.94	1.42
Frozen dinner	1.61	.22	1.95	1.01	.11	.02	.13	.06	1.51	.20	1.82	.95
Frozen pizza	.84	.25	1.28	.23	.08	.02	.12	.03	.76	.23	1.15	.20
Hot dogs	1.89	.13	1.60	2.15	.16	.02	.13	.19	1.73	.12	1.47	1.97
Ketchup	2.66	.58	3.83	1.84	.35	.08	.51	.24	2.31	.50	3.36	1.57
Laundry detergent	1.73	.18	2.05	1.43	.18	.03	.22	.13	1.56	.15	1.85	1.30
Margarine/ butter	1.73	.13	1.96	1.47	.13	.01	.16	.11	1.60	.11	1.80	1.36
Mayonnaise	3.84	.66	5.48	2.99	.65	.13	.96	.48	3.20	.54	4.52	2.49
Mustard	2.23	.11	2.43	1.98	.09	.00	.09	.08	2.15	.11	2.34	1.90
Paper towel	.37	.39	.95	–.47	.01	.01	.02	-.01	.36	.38	.93	–.46
Peanut butter	4.01	.45	5.22	3.14	.48	.06	.63	.36	3.53	.40	4.59	2.78
Potato chips	1.08	.19	1.43	.61	.08	.01	.11	.04	1.00	.17	1.33	.57
Shampoo	1.48	.15	1.78	1.16	.11	.01	.13	.08	1.37	.14	1.65	1.08
Spaghetti sauce	2.57	.20	2.98	2.16	.25	.02	.31	.21	2.33	.18	2.67	1.94
Toilet tissue	.92	.52	1.83	.19	.03	.02	.06	.01	.89	.51	1.78	.19
Tortilla chips	1.12	.16	1.50	.78	.17	.03	.22	.11	.95	.14	1.27	.67
Yogurt	1.73	.39	2.39	1.15	.03	.01	.05	.02	1.70	.38	2.34	1.13

Notes: To facilitate interpretation, elasticities are reported as –(dq/dp × p/q); therefore, they generally appear as positive numbers rather than negative numbers.

Figure 2
AVERAGE ELASTICITY BY QUARTER



and quarterly elasticities for each category. Frozen dinner, frozen pizza, margarine/butter, paper towel, peanut butter, toilet tissue, and yogurt have countercyclical price sensitivity: people are more price sensitive when the economy is weaker. In contrast, coffee, deodorant, hot dogs, laundry detergent, mayonnaise, and mustard all display procyclical price sensitivity.[11]

The categories in Table 5 are sorted in descending elasticity. The table reveals that with the notable exception of peanut butter, less elastic categories are more likely to be countercyclical: as GDP growth declines, less elastic categories become more elastic. After a median split of the categories by average elasticity, the correlation across quarters between elasticity and GDP growth for the less elastic categories is –.49 (p-value = .016). In contrast, the correlation across quarters between elasticity and GDP growth for more elastic categories is .34 (p-value = .099), implying elastic categories are more often procyclical. Figure 3 depicts the temporal variation in price elasticity split across categories at the median price elasticity. The highly elastic categories move with GDP growth, whereas the less elastic categories display the opposite pattern.

These correlations are robust to alternative measures of economic activity—such as lagged GDP growth, household income growth, and the Consumer Confidence Index—and to using Spearman's rank correlation. Instead of using the price elasticities themselves, we also correlated economic growth measures with the implied quarter-specific price coefficients (i.e., the sum of the base price coefficient and the quarter-specific price coefficient). The quarter-specific price coefficients have the benefit of being independent of changes in market shares and prices, and the correlations produce nearly identical results.

Given the small sample of 24 periods, the finding that some of the correlations do not achieve high levels of statistical significance is not surprising. To help address the low power of the test, though at the expense of imposing a particular functional form, we pooled the quarterly elasticities across categories and investigated their relationship with GDP growth in a series of linear regressions. The unit of observation was the category–quarter. Each regression includes category fixed effects, and we clustered standard errors by quarter to account for the fact that GDP growth does not change by category.

Table 6 presents the coefficients from these regressions.[12] Column 1 shows a negative but insignificant main effect for the relationship between elasticity and GDP growth. Column

[11]We took a correlation coefficient of .20 or lower in absolute value as the threshold to assign the categories to "noncyclical," and the general patterns discussed are robust to alternative thresholds near the chosen cut-off.

[12]Greene (1995, p. 436) notes that even though the dependent variable is measured with error (because the elasticities are estimates themselves), the regression coefficient estimates are consistent and unbiased because the measurement error is absorbed into the error term of the regression.

Table 5
CORRELATION OF ELASTICITY WITH GDP GROWTH BY CATEGORY

Category	*Correlation of Total Elasticity with GDP Growth*	*Procyclical (P), Countercyclical (C), or Noncyclical (N)*	*Average of Total Elasticity Over 24 Quarters*	*Correlation of Primary Demand Elasticity with GDP Growth*	*P, C, or N*	*Correlation of Secondary Demand Elasticity with GDP Growth*	*P, C, or N*
Peanut butter	–.41	C	–4.01	–.56	C	–.38	C
Mayonnaise	.27	P	–3.84	.30	P	.26	P
Deodorant	.30	P	–2.92	.26	P	.30	P
Carbonated soft drinks	–.12	N	–2.81	–.15	N	–.12	N
Ketchup	.05	N	–2.66	–.02	N	.06	N
Coffee	.34	P	–2.64	–.15	N	.37	P
Spaghetti sauce	–.17	N	–2.57	–.10	N	–.18	N
Mustard	.20	P	–2.23	.28	P	.19	N
Hot dogs	.22	P	–1.89	.01	N	.24	P
Margarine/butter	–.33	C	–1.73	–.52	C	–.30	C
Laundry detergent	.34	P	–1.73	.37	P	.33	P
Yogurt	–.40	C	–1.73	–.43	C	–.40	C
Frozen dinner	–.31	C	–1.61	–.29	C	–.31	C
Shampoo	–.07	N	–1.48	–.14	N	–.06	N
Tortilla chips	.13	N	–1.12	.12	N	.13	N
Potato chips	–.13	N	–1.08	–.14	N	–.13	N
Toilet tissue	–.40	C	–.92	–.41	C	–.40	C
Frozen pizza	–.47	C	–.84	–.42	C	–.47	C
Paper towel	–.25	C	–.37	–.25	C	–.25	C

Notes: To facilitate interpretation, correlations are based on elasticities calculated by –(dq/dp × p/q); therefore, a positive correlation between GDP growth and elasticity means that elasticity rises with GDP growth.

Figure 3
ELASTICITY OVER TIME, SPLIT BY OVERALL ELASTICITY

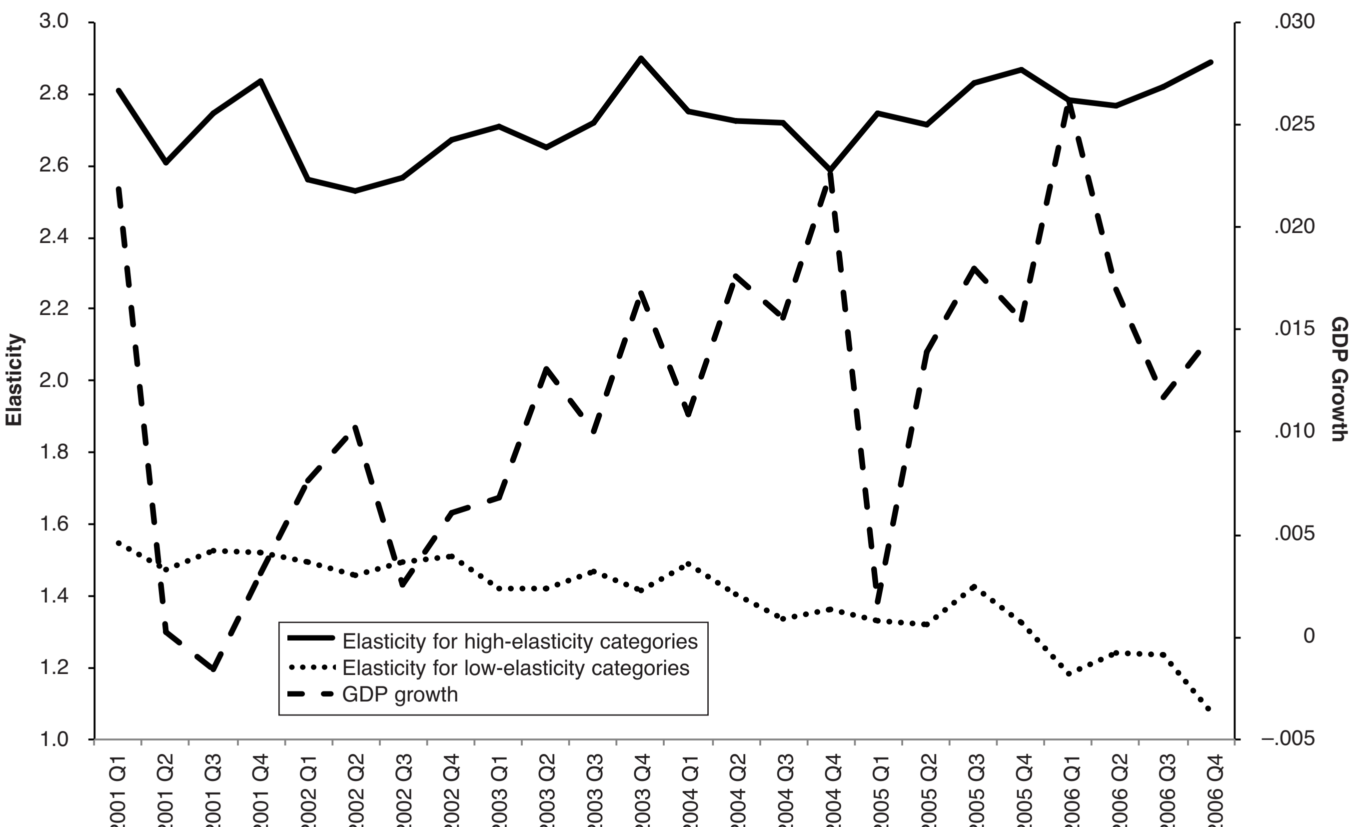


Table 6
ELASTICITY AND GDP GROWTH

Dependent Variable →	*Total Elasticity (1)*	*Total Elasticity (2)*	*Primary Elasticity (3)*	*Primary Elasticity (4)*	*Secondary Elasticity (5)*	*Secondary Elasticity (6)*
GDP growth	–2.670	–14.341	–.176	–.581	–2.497	–13.764
	(2.219)	(5.877)*	(.219)	(.530)	(2.129)	(5.419)*
GDP growth × average elasticity		5.807		.202		5.606
		(2.590)*		(.322)		(2.333)*
Observations	456	456	456	456	456	456
R-square	.89	.89	.94	.94	.88	.88

*$p < .05$.
Notes: We used OLS regression with category fixed effects; unit of observation is the category quarter; GDP growth is measured as decimal; and robust standard errors clustered by time (quarter) in parentheses.

2, however, shows that this nonresult goes away when we include the interaction between GDP growth and average elasticity. The coefficient on this interaction implies that less elastic categories drive the negative and significant association between GDP growth and time-varying elasticity. Elastic categories are relatively procyclical. Thus, Columns 1 and 2 in Table 6 provide further evidence that the relationship between GDP growth and elasticity is related to the average elasticity of the category. The next section explores several possible explanations for these results.

Assessing Potential Explanations

This pattern presents a puzzle: Why do the categories that are more price sensitive exhibit procyclical price sensitivity? Next, we explore four possible explanations: share of wallet, perishability, primary demand effects, and market concentration. We find support for share of wallet as a likely driver of the results, though perishability also has explanatory power. Specifically, high share-of-wallet categories display countercyclical price sensitivity even though they are not particularly price sensitive on average. We find that controlling for share of wallet eliminates any significant relationship between overall price sensitivity and the cyclicality price elasticity.

Before we delve into our analysis, we must add an important caveat—namely, that we cannot reject the possibility that the differences in share of wallet and perishability across categories proxy for some other factors that we did not measure. In this way, our analysis is descriptive and cannot lead to definitive causal statements. Still, we believe our explanations and results are suggestive and highlight the importance of conducting further research.

Share of wallet. A category's share of wallet may play a role in explaining our results for two reasons. First, Estelami, Lehmann, and Holden (2001) provide evidence that consumers are more aware of prices when the macroeconomy is weak. Consumers may therefore become particularly aware of prices for high share-of-wallet products due to their relative weight in the budget constraint and thus become increasingly price sensitive in those categories. Second, the impact of increasing price sensitivity in the face of a tightening budget constraint in categories with a higher share of wallet is relatively large because reducing spending by a certain percentage has a larger impact on the overall budget constraint in high share-of-wallet categories.

To examine this hypothesis, in Columns 1 and 2 of Table 7, we contrast above- and below-median share-of-wallet categories, as reported in Column 3 of Table 1 (and derived from Bronnenberg, Kruger, and Mela 2008). These figures show that the relationship between GDP growth, elasticity, and overall price sensitivity (documented in Table 6) is strongest in high share-of-wallet categories. More importantly, Column 3 shows that controlling for share of wallet makes the observed relationship between average elasticity and the cyclicality of elasticity small and insignificant. Column 7 indicates that additional controls for perishability do not alter this pattern.

Thus, share of wallet provides a likely explanation of the puzzle in the previous section on the relationship between cyclicality and overall price sensitivity. It is not a result on elasticity per se but rather on the importance of the category to the consumer's overall budget. Next, we examine three other possible explanations and show that share of wallet is a more likely driver of the main result than these other explanations.

Perishability. If consumers become more price sensitive in difficult economic times, they may exercise more patience in searching for low prices before purchasing. Consumers have the most flexibility in bulk buying and in postponing their purchases in nonperishable categories because they are easily stored, which might induce a relationship between price sensitivity and economic growth in these categories. In contrast, in perishable categories, this behavior is less likely to be feasible (e.g., Lim, Currim, and Andrews 2005).

Using the figures in Column 4 of Table 1, we split the categories between highly perishable and non–highly perishable categories. Columns 4–6 of Table 7 indicate the role of perishability using this median split. Column 4 includes only the non–highly perishable categories, and Column 5 includes only the highly perishable categories. The results show no significant relationship between cyclicality and category elasticity in the highly perishable categories but show that a strong effect exists in the non–highly perishable categories, confirming the hypothesis that perishability influences the relationship between price sensitivity and the business cycle. Column 6 shows that including controls for perishability as interactions (rather than as separate regressions) has substantial explanatory power. The estimates also imply that the relationship between cyclicality and overall levels of elasticity holds when controlling for perishability. Thus, although perishability has some explanatory power overall, it does not appear to provide an answer to the puzzle of the correlation between overall price sensitivity and the cyclicality of price sensitivity.

Substitution. Building on recent work by Gicheva, Hastings, and Villas-Boas (2007), we examine the possibility that

Table 7

EXPLAINING THE ELASTICITY RESULT

Category	*Above Median Share of Wallet (1)*	*Below Median Share of Wallet (2)*	*Use Interaction for Share of Wallet (3)*	*Not Highly Perishable Only (4)*	*Highly Perishable Only (5)*	*Use Interaction for Highly Perishable (6)*	*Use Both Interactions (7)*
GDP growth	–20.480 (8.561)**	–7.199 (6.343)	–3.213 (5.701)	–16.258 (6.253)**	6.445 (11.795)	–16.258 (6.265)**	–3.027 (5.711)
GDP growth × average elasticity	8.391 (4.353)*	3.546 (2.899)	2.489 (2.735)	6.515 (2.741)**	–7.478 (7.121)	6.515 (2.746)**	2.506 (2.720)
GDP growth × share of wallet			–373.740 (195.744)*				–477.475 (202.194)**
GDP growth × share of wallet × average elasticity			121.763 (78.776)				160.087 (81.519)*
GDP growth × highly perishable						22.703 (12.371)*	32.320 (12.703)**
GDP growth highly perishable × average elasticity						–13.992 (7.836)*	–19.815 (8.019)**
Observations	216	240	456	360	96	456	456
R-square	.87	.87	.89	.89	.71	.89	.89

*$p < .10$.
**$p < .05$.
Notes: We estimated regression using OLS regression with category fixed effects; unit of observation is the category quarter; the dependent variable is category-quarter total elasticity; GDP growth measured as decimal; robust standard errors are clustered by time (quarter) in parentheses; definitions of perishability and share of wallet from Bronnenberg, Kruger, and Mela (2008); share of wallet is the weighted version; and the median split for Columns 1 and 2 does not change regardless of whether we use the weighted or unweighted share-of-wallet values.

procyclicality results from high levels of substitution into the elastic categories from other expenditures, such as eating out at restaurants. Our results reject this hypothesis in that secondary—not primary—demand drives the observed effects. Specifically, Gicheva, Hastings, and Villas-Boas (2007) show that grocery purchases rise (and restaurant purchases fall) in response to increases in gasoline prices: consumers substitute away from food-away-from-home and toward groceries to offset the reduced disposable income. If people substitute into grocery categories from other categories, they are likely to substitute into the more discretionary grocery categories. Furthermore, these purchases are likely to be the least price-sensitive purchases because they replace purchases for relatively expensive items outside the grocery store.

Columns 3 and 4 of Table 6 explore this hypothesis. The results show no significant relationship between primary demand elasticity, overall category elasticity, and GDP growth. The coefficient on the interaction between GDP growth and category elasticity is small and insignificant. In contrast, the coefficient on the interaction in the secondary demand regression (Column 6) is large and significant. Although the elasticity variation across quarters appears only in the secondary demand component of estimation, the model allows for an effect on primary demand through the inclusive value. Given that the results suggest no such impact, we argue that substitution into the inelastic categories is unlikely to explain the patterns of cyclicality.[13] Substitution instead might exist across brands within the category.

Concentration. A large literature stream in economics examines the links between business cycles, market concentration, and price–cost margins (e.g., Domowitz, Hubbard, and Petersen 1986). These studies argue that less concentrated industries are more competitive, leading to lower markups and less flexibility to adjust prices in response to a demand shock. Motivated by this work, we examine the possibility that the puzzle we identify is related to the market concentration of the different categories.

In particular, among other requirements, this argument implies that concentrated markets are less elastic, which is related to the basic economic intuition that firms with more market power tend to price toward the less elastic portion of demand. We find no clear correlation between market concentration and price sensitivity: the correlation between estimated elasticity (Table 4, Column 1) and the share of the top firm (Table 1, Column 5) is –.10, whereas the correlation between elasticity and the four-firm concentration ratio (Table 1, Column 6) is .13. The inconsistency across the share of the top firm and the top four firms and the relatively weak correlations suggest little systematic relationship between elasticity and the concentration ratio. Therefore, cross-sectional variance in market concentration is unlikely to explain the observed correlation between cyclicality of price sensitivity and overall levels of price sensitivity in our data.[14]

In summary, of the four explanations we explore, our results are most consistent with share of wallet driving the observed relationship between levels of price sensitivity and its cyclicality. However, we cannot rule out other possible

[13]Substitution may still occur through changes in purchase quantities, even if consumers' purchase incidence decisions are unchanged. To check this hypothesis, for each category, we examined the average purchase quantity across quarters within a consumer. We found no systematic variation over time in purchase quantity across categories, suggesting that substitution across categories through changes in purchase quantity is unlikely to explain the patterns of cyclicality we observe in price elasticities.

[14]Market concentration is the outcome of many interacting factors in an industry. For example, product differentiation across brands, and not concentration explicitly, could potentially create less elastic demand for these products. However, given that we do not find evidence that concentration plays a role in explaining the elasticity and GDP growth relationship, teasing out the effects of the underlying drivers of concentration would be difficult.

explanations. Instead, we view our results as suggestive of a broader pattern and a motivation for further research projects on specific categories to explicitly model and tease out the various factors, such as share of wallet, changes in budget constraints, firm price and promotion decisions, and inventories.

CONCLUSION

In this article, we use a consistent methodology to estimate price elasticity for a panel of households over 24 quarters in 19 categories. The approach uses a nested logit structure to account for brand choice and category incidence, random coefficients to model household-level preference heterogeneity, and control functions to address price endogeneity. The combination of a large data set, many categories, and a flexible estimation approach means our analysis provides a consistent and deep picture of the variation in price sensitivity over time and across categories.

The results demonstrate that price sensitivity is, on average, highest when the macroeconomy is weak. However, this average effect masks important variation: price sensitivity moves positively with GDP growth in a handful of categories that have relatively high levels of elasticity. In addition, we find a strong correlation between average price sensitivity and the way price sensitivity changes with GDP growth. Price sensitivity is relatively countercyclical in categories with a low average level of sensitivity.

We suggest four explanations for this result: (1) the importance of the category in the overall consumer budget (share of wallet); (2) inventory management challenges for perishable products; (3) consumers substituting from non-grocery purchases into grocery purchases during the recessions, particularly in (perhaps discretionary) elastic categories; and (4) more concentrated categories creating market power that leads to increased price sensitivity in a recession. We conclude that our results are most consistent with the share-of-wallet explanation.

Our analysis suffers from several limitations that might represent fruitful avenues for further research. First, given that our data encompass 24 quarters, less than a full business cycle, we must be cautious about generalizing our results too broadly. Although we observe variation in GDP growth over this period and these fluctuations correlate well with our price-sensitivity estimates, our results should be viewed as most informative about how short-term fluctuations in economic output correlate with price sensitivity and perhaps only suggestive about the broader business cycle. Given this caveat, our results could be considered a conservative estimate of the potential effect because the relative stability of the business cycle (as measured by quarterly GDP growth) in our sample reduces the statistical power of our analysis. Second, in trying to achieve a broad scope of 19 categories over six years, we made several simplifying assumptions. For example, we did not explicitly model the purchase-quantity decision. Although we believe our choices achieve the appropriate balance between computational feasibility, consistency across categories, and econometric sophistication, our assumptions may affect the estimated price sensitivity across categories and over time. Third, a broad analysis necessarily requires some restrictions in scope. One question beyond our scope, and which may be worthwhile to pursue as further research, is to explore the specific consumer model that drives the temporal variation in price elasticity that we document. Although our data set is a consumer panel, the demographic information was recorded at a single point in time, making estimating any link between changes in price elasticity and demographic variables difficult. Fourth, we do not analyze consumer choices at mass retailers such as Wal-Mart. Therefore, substitution to such retailers would be subsumed in the overall incidence estimates, potentially broadening our interpretation of the incidence results to include mass retailers as one of the channels of substitution. Finally, without exogenous variation in share of wallet, perishability, propensity for substitution across channels, and concentration, our analysis of the drivers of the differences in cyclicality across categories is necessarily descriptive. We cannot definitively conclude that share of wallet is the true underlying reason for the correlations we observe.

Despite these limitations, our article documents variation in price sensitivity across categories and over time using a richer and more consistent empirical framework than prior studies. We show that, in general, price sensitivity is countercyclical and that variation across categories is related to the average price sensitivity of the category. Our results suggest that the countercyclicality of share-of-wallet categories is a likely explanation for the source of this relationship.

These results are important for effectively adapting marketing strategies to the economic climate. The recent economic crisis brought a flood of commentary in the popular press on how management tactics should change in difficult economic times (e.g., Boyle 2009; Surowiecki 2009; highlighted for the academic marketing community by Bradlow 2009). Much of this commentary was made without a research foundation. Our research is one of a small set of recent studies that has begun to provide that foundation. In particular, we document that (1) asserting that price sensitivity rises or falls across all categories as the macroeconomy weakens is not correct; (2) this finding relates to the importance of the category to consumer budgets; (3) prices should fall primarily in those categories that are an important component of consumer budgets; and (4) in contrast, in other categories, raising prices may even be optimal.

Overall, we believe that our results provide a more nuanced understanding of how price sensitivity varies with the business cycle. Whereas prior studies (e.g., Estalami, Lehmann, and Holden 2001; Gijsenberg et al. 2010; Lamey et al. 2007) have documented that price sensitivity rises on average when the economy is weak, we show that the variation around this average is substantial. Furthermore, the variation is related to readily identifiable features of the category: average price sensitivity driven by category share of wallet. Managers and researchers who take the average as a directly transferable empirical generalization are likely to make mistakes in determining and understanding optimal pricing strategies over time.

APPENDIX A: DATA SET CONSTRUCTION

Category Choice

The IRI data set tracks 30 product categories. We focused on the following 19: carbonated soft drinks, coffee, deodorant, frozen dinners, frozen pizza, hot dogs, ketchup, laundry detergent, margarine/butter, mayonnaise, mustard, paper towels, peanut butter, potato chips, shampoo, spaghetti sauce, toilet tissue, tortilla chips, and yogurt.[15]

We dropped the other categories for several reasons. Specifically, we excluded the separate categories of razors and blades because of the complications that the tied-goods nature of demand poses for modeling (see Hartmann and Nair 2010). We excluded diapers because most households did not make purchases over the full length of the sample. We did not consider milk or beer because both industries are heavily regulated, and the milk category lacks strong national brands. We excluded soup because of missing values in the raw data files. We excluded cereals because consumer preferences are tightly linked to particular cereal brands (e.g., Cheerios), and each manufacturer (e.g., General Mills) produces so many distinct brands as to render estimation of a household-level random coefficients logit model with six years of data practically infeasible. We dropped the remaining categories of facial tissue, photography supplies, sugar substitutes, toothbrushes, and toothpaste because of a lack of observations in each quarter for each brand.

Sample-Selection Criteria

First, we restricted the panel to those households that made at least one grocery trip in each of the six years, yielding a full sample of 3283 households. For each category, we next calculated the cumulative distribution of purchase occasions across panelists and excluded those in the bottom 10% who infrequently purchased a particular category. These two criteria ensured a sufficient number of observations per household and made the selection rule relative to the overall purchase frequency within a category. As a result, we selected different numbers of households across the chosen categories (Table 1, Column 13).

The IRI data contain household demographic information measured at the beginning of the panel. To ensure that our selection criteria minimally biased category-specific samples, we compared the means of select household variables (number of trips, income, household size, and education level) in each category with the means of the full sample. Although some minor differences exist, we do not view the differences as systematic or qualitatively meaningful (see the Web Appendix, Table D.5, at www.marketingpower.com/jmr_webappendix).

The raw panel data contain purchases at grocery stores, drug stores, and mass-market stores (panelists scanned all purchased items when they got home from their shopping trips). We focus on grocery purchases for three reasons. First, the store-level data do not include sales in mass-market stores, making accurately constructing choice sets for purchases in mass-market stores difficult. Second, for the categories we study, grocery is overwhelmingly the dominant channel for the sample households, accounting for 96% of sales on average (see the Web Appendix, Table D.6 at www.marketingpower.com/jmr_webappendix). Third, consistent with prior literature, our analysis of price sensitivity focuses on within-store price variation. Although price sensitivity may vary across channels, given the small portion of sales outside grocery stores, we expect little impact from including the other channels. Given this sample selection, any interpretation of our results should be conditioned on grocery store shopping trips.

Brand Aggregation

Each category contains dozens of UPCs. As is common in the brand-choice literature, we aggregated the UPCs in a category into a set of brands to have a more tractable set of choices for estimation. In conducting our UPC aggregation, we used heuristics from the literature (e.g., Andrews and Currim 2005; Hoch et al. 1995). Categories differ in the set of associated product attributes, but most have information on product packaging (e.g., plastic wrapped vs. boxed), form factor (e.g., ground vs. whole coffee), product type (e.g., margarine vs. butter), and size. Including the appropriate set of UPCs in each brand is important to ensure that the brands are comparable in intended usage and thus most likely to correspond to consumers' perceptions of the relevant product substitutes. We attempted to strike a balance between an overly restrictive and an overly inclusive definition of a brand. With this goal in mind, we describe our aggregation strategy.

First, in each category, we removed any UPCs with product packaging, form factors, or types that serve a particular market niche or are otherwise irrelevant for our analysis. For example, we removed specialty health products (e.g., peanut butter substitutes made with soy nuts) and industrial-sized products (e.g., 7.5-pound blocks of margarine). Second, some categories contain a large number of UPCs with types or forms with very low sales. To aid this analysis, we examined the switching matrix defined by product type, form, packaging, and size. When a small number of purchasers switch from one attribute level to another, we argue that consumers are less likely to view them as substitutes. For example, we removed all coffee-pod products because consumers who purchased regular ground coffee were unlikely to ever purchase coffee pods, and vice versa. We examined these switching probabilities across all attributes and categories and removed UPCs with low overall sales and low switching probabilities. Third, given the remaining UPCs, we focused on the most popular package types and sizes. For example, in yogurt, we included six- and eight-ounce cups, adjusting unit prices accordingly. In laundry detergent, we focused on liquid detergents, which make up more than 95% of category sales, and packages of 80, 100, 120, and 200 ounces, which constitute more than 95% of liquid detergent sales. We applied similar logic to each category.

This filtering procedure left us with the UPCs that households purchased most frequently, causing an average 10% reduction in the number of UPCs. The exact nature of the aggregation scheme varied depending on the characteristics of the category; we found applying the same rules to all the categories difficult and thus used our best judgment on several occasions.

The second nontrivial question is how to define a brand in our analysis. Some categories contain many manufacturers (e.g., shampoo), and each firm produces extensive product lines with different items targeted at different customer segments. In assigning particular UPCs to a brand, we followed two basic rules. First, the decision should reflect a common perception of brand differentiation (e.g., Neutro-

[15]We split two categories. We divided "mustard & ketchup" into two separate categories and "salty snacks" into potato chips and tortilla chips, dropping popcorn and cheese snacks because of insufficient observations.

gena is not Pantene). Second, the resulting set of brands should be comparable in the composition and purpose of their products.

In estimating the model, we sorted brands from largest to smallest market share and included those that yielded a cumulative market share of at least 80% or until we had included all brands with a market share greater than 4%. These criteria ensured a broad degree of market coverage. We grouped the remaining brands into a single "outside" brand whose average market share was 18.3%, ranging from 1.5% for mayonnaise to 33.4% for hot dogs.

Private labels exist in each category, but their market shares vary. The data set does not have a precise mapping from stores to each (large) retail chain (Kruger and Pagni 2009, p. 11), so we cannot clearly identify the chain for each private label. Therefore, we considered all private labels the same "brand" regardless of chain. This composite private label's market share is large enough to be an "inside" brand in 15 categories ranging from 4.4% (carbonated soft drinks) to 23.1% (ketchup).

Marketing-Mix Covariates

The store data provide price information at the UPC level in all the stores. However, we did not observe the price of a UPC if no sales occurred in that week at a store, and yet we still required a method of specifying the price for all brands available in a given week. An inventory stockout and zero sales are observationally equivalent given the nature of our data. To fill in missing prices, we searched for nonpromoted prices of the same UPC in the same store within the previous four weeks or nonpromoted prices of the same UPC at another store in the same week. If we still could not find a reliable price, we excluded the UPC for the particular store and week.

We aggregated the UPC-level prices to create the brand-level prices by converting all prices to comparable units (e.g., price per ounce). Next, we calculated the brand price as the share-weighted average of UPC prices in a given store-week. The weight of a UPC is equal to its share of volume in that brand at a store in a given year. We calculated the denominator of the share-weights in each year to allow them to change over time as market shares evolved. We experimented with alternative price aggregation schemes without finding a meaningful impact on our parameter estimates. As a robustness check on whether price inflation is important, we deflated prices in the deodorant category and reestimated the full model. The resulting price-elasticity series by quarter had a correlation of .987 with the elasticities using the nominal data.

APPENDIX B: UNDERSTANDING THE MODELING CHOICES

Given the numerous modeling choices we faced, we provide analysis that helps explain our particular modeling choices regarding price variation over time, control functions, the outside option, promotion flexibility over time, state dependence, and purchase size. Although the results would ideally be insensitive to certain modeling choices, fully exploring all possible robustness checks would be difficult.

Comparison to Alternative Specifications

We compared our main specification with two alternative specifications. First, we examined the use of quarter-specific price coefficients and then the control functions. Our objective here is to understand the benefits and costs of our main estimation strategy relative to approaches that assume a constant price coefficient or ignore price endogeneity.

Table D.1 in the Web Appendix (www.marketingpower.com/jmr_webappendix) compares the fit of our main specification with a model that assumes constant price sensitivity over time. Specifically, the estimated utility function becomes

$$u_{ijt} = \beta_{ij} - \alpha_{i1}p_{jt} + \gamma_i I\{s_{jt-1} = j\} + \delta_i x_{ijt} + \varepsilon_{ijt}. \quad \text{(B1)}$$

The results in the Web Appendix, Table D.1 (www.marketingpower.com/jmr_webappendix) show that allowing the extra 23 price–quarter covariates improves the fit for 15 of 19 categories as measured by the Bayesian information criterion (BIC) and for 18 of 19 categories as measured by the Akaike information criterion. The improvement in fit is especially large for potato chips, yogurt, peanut butter, carbonated soft drinks, and margarine/butter, suggesting that time-varying covariates are particularly important when studying these categories over the 2001–2006 period. We observed relatively little benefit from including the extra price covariates for deodorant, frozen pizza, ketchup, and shampoo.

Table D.2 in the Web Appendix (www.marketingpower.com/jmr_webappendix) compares our estimates with a specification without control functions (that is otherwise identical). As expected, ignoring price endogeneity substantially changes the estimated elasticity. Column 12 shows the ratio of the elasticity estimate with control functions to the elasticity estimate without control functions at the brand-choice stage. On average, this ratio is 1.42, implying that controlling for endogeneity through control functions raises estimated secondary demand elasticity by 42%.

The impact of the control functions varies substantially across categories. The price elasticity estimates in a handful of categories are unaffected. Specifically, we observe less than a 10% difference in elasticity estimates for margarine/butter, frozen pizza, and potato chips. In contrast, the estimated elasticities are different for coffee, deodorant, mayonnaise, and carbonated soft drinks. Some of this variation might relate to differences in the efficacy of the control functions. Table D.2, Column 5, in the Web Appendix (www.marketingpower.com/jmr_webappendix) lists the adjusted R-square values from the first-stage control function regressions and Column 6 provides the adjusted R-square values when the first stage excludes the price instruments. Overall, the first-stage regressions achieve reasonable predictive power, and the instruments contribute significantly to the explanatory power of the model beyond the other exogenous controls.

Time-Varying and Brand-Specific State Dependence

Our baseline model allows the impact of price to vary over time but assumes state dependence (γ_1) is constant over time and across categories. We experimented separately with time-varying state dependence and brand-specific state dependence to gauge the degree to which this extra flexibility improves model performance. We tested time-varying state dependence in several categories (deodorant, hot dogs, mayonnaise, peanut butter, paper towels, and toilet paper) but found that it did not improve model fit in terms of BIC for five of the six categories. Although some of the quarter-specific state dependence terms were significant, they were often small, suggesting that time-varying state dependence is unlikely to be substantively relevant.

Similarly, we tested whether allowing for brand-specific state dependence might improve the model fit. Consumers might display more or less "stickiness" toward some brands in a category, and forcing the state-dependence coefficient to be constant across brands might obscure such underlying variation. The results, however, suggest little to no meaningful variation across brands in this set of categories, consistent with Dubé, Hitsch, and Rossi's (2009) findings for margarine and orange juice. Thus, we decided to fix state dependence across brands for the sake of model parsimony and tractability.

Time-Varying Promotion Effects and Brand Intercepts

Consumers could possibly respond differently to promotional activities as the strength of the economy varies. Consumers' response to feature and display promotions could follow a countercyclical pattern in high-elasticity categories, implying that consumers substitute between responsiveness to prices and responsiveness to promotions. Ignoring this dimension of variation in price sensitivity could bias our results.

We examined this issue by including in our baseline model a set of quarterly dummies interacted with our composite feature-display variable (as we did for price). We tested this specification using coffee, mayonnaise, and peanut butter, which vary in their mean elasticities and degree of market concentration. In each category, a handful of quarter-specific feature-display variables were significant, but the quarter-specific price variables were largely unchanged. The BIC increased for this specification in each category, suggesting that the inclusion of the additional variable did not significantly improve the model fit.

Furthermore, omitted brand factors, such as changes in packaging or attributes, might vary over time, and our results might reflect changes in these unobservables rather than price sensitivity. To alleviate this concern, we reestimated the ketchup and deodorant categories using a quartic polynomial for time for each brand at the level of the brand-week. The elasticity estimates change very little, with the correlation between the coefficients for ketchup at .996 and for deodorant at .953. The correlation of elasticity with GDP growth for ketchup remained at .05, and the correlation with GDP growth for deodorant changed from .30 to .29. Although this does not eliminate the possibility of changes in other categories, it suggests that further controls for brand changes over time are likely to change little while adding inefficiency and computational burden.

Purchase Size

Another potential concern is that households purchase larger product sizes during a recession to take advantage of lower per-unit costs. We chose to focus on brand choice and collapsed the most popular sizes into the single-brand-choice option. Our model does not separate differences in brand intercepts across sizes and might ascribe any differences to price variation.

To determine whether there are grounds for concern, we chose a category, laundry detergent, that our intuition suggested might be particularly prone to size switching among consumers. Using the store-level data, we examined unit market shares by package size for the four most popular sizes, accounting for 95.3% of all category sales. Table D.8 in the Web Appendix (www.marketingpower.com/jmr_webappendix) reports the average unit shares for these sizes in 2001, from 2002 to 2003, and from 2004 to 2006. A cursory inspection of the patterns in the table suggests some support for the hypothesis that consumers switched from smaller to larger sizes during the recession. The share of the largest size increased from 7.2% to 10.6% from 2001 to 2006, whereas the share of the smallest size decreased from 11.5% to 3.8%. However, the share of the most popular size was steady during the first half of the sample and later increased by approximately 6%, whereas the share for the second largest decreased by approximately 1.5%. These changes in unit shares are consistent with some consumers switching from smaller to larger sizes during the recession, but the differences are not large, and therefore we do not expect this issue to substantively affect our results.

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