An Empirical Analysis of a Merger of Manufacturers of Complementary (?) Goods[†]

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Abstract: It has become relatively common practice for antitrust analysts to use data from cash register scanners to estimate demand models and simulate the competitive effects of mergers in consumer products merger investigations, but tests of these techniques have been relatively few. A substantial difficulty in examining consummated horizontal mergers to test these models is that mergers likely to cause large price increases are likely to be challenged by antitrust agencies or interested private parties. However, the same theories that predict price increases following mergers of manufacturers of substitute goods would predict price decreases following mergers between manufacturers of complements, which would be unlikely to be seen as grounds for an antitrust challenge. We obtain data on an acquisition of a major brand of peanut butter by a major manufacturer of jellies and jams. Given the popularity of the "peanut butter and jelly sandwich", we would expect these goods to be complements. Econometric estimates of demand systems fail to uncover strong and consistent complementarity between these goods.

[†] The views expressed herein are not purported to reflect those of the Federal Trade Commission, nor any of its Commissioners.

I. Introduction

The use of scanner data in consumer products' merger investigations has expanded rapidly in the last decade, largely because of the increased availability of data. Empirical techniques such as demand estimation and merger simulation have become common elements of consumer products merger investigations (see Hosken et al, 2002). Surprisingly, in light of the policy importance, relatively little work has been done to test the predictions of simulation models. A number of published research papers (see, e.g., Nevo (2000) or Hausman (1994)) have estimated demand systems and calculate estimated price effects of mergers. Very few papers we are aware of, however, have examined how well various models of demand and simulation techniques do in predicting the actual price and quantity effects of specific mergers (exceptions such as Peters, 2003 and Bonfrer and Raju, 2003 will be discussed later).

We test the predictive powers and underlying assumptions of several demand estimation/merger simulation approaches by examining a recently consummated merger. A substantial difficulty in examining consummated horizontal mergers to test these models is that of sample selection: mergers that are likely to generate significant price increases are unlikely to be consummated. Obviously, the antitrust agencies typically block such mergers, or these mergers are never proposed. To avoid this problem, we investigate the impact of a merger of leading manufacturers of two complementary goods; peanut butter and jelly. The same theories that predict price increases following mergers of manufacturers of substitute goods would predict price decreases following mergers between manufacturers of complements. Because basic economic intuition would predict a reduction in prices following this merger, the selection bias resulting from antitrust agencies challenging mergers associated with large expected price increases is avoided. In addition to testing the ability of models to predict the price effects of this merger, the data also enables us to perform several other analyses relevant to the way mergers are sometimes evaluated.

The J.M. Smucker Company (NYSE: SJM) purchased Jif Peanut Butter from Proctor and Gamble (NYSE: PG) in a stock acquisition. The deal was completed on June 1, 2002 (JM Smucker Press Release, June 1, 2002). The merger puts two products, generally assumed to be complements, under single ownership. Both products prior to the merger had large market shares in their respective categories. As mentioned above, most economic theories would predict that the prices of both goods should fall. Because the products are such obvious complements and the product markets are well defined with relatively few important brands (three major brands of peanut butter and two major brands of jelly), this merger appears to be a nearly ideal test ground for the use of flexible demand system estimation and merger simulation.

An analysis of pre- and post-merger prices in several cities reveals that the average price of Smucker's jellies increases relative to the other brands of jellies following the merger, but the price of Jif does not increase as much as the other brands of peanut butter following the merger. In general, our econometric estimates of several functional forms of demand failed to find strong and/or consistent evidence of complementarity between brands of peanut butter and brands of jelly, though they almost always found jellies to be substitutes for other jellies and peanut butters to substitute for other peanut butters. Merger simulations based on these estimated demand systems often produced implied market parameters that seem unreasonable, and rarely predicted merger-induced price changes consistent with observed prices. In this draft, we investigate some of the reasons why much of the analysis appears to be inconsistent with actual outcomes in these markets, but we still have much to do. This is very much a work in progress, and comments or suggestions are very welcome.

We begin this paper with a brief review of the empirical merger simulation literature. We then proceed to a description of the data we have obtained, and then to a discussion of demand estimation techniques we use. Finally, we present some results from merger simulations calibrated using these demand estimates.

II. Literature Review

The idea of using differentiated product oligopoly models of price competition calibrated using market data to predict the impact a merger may have on a market goes back to Baker and Bresnahan (1985). Many papers have addressed various demand specifications, oligopoly models, and estimation techniques that could be used in this type of analysis including Hausman, Leonard, and Zona (1994), and Werden and Froeb (1994). These, and related papers, have established a good foundation for the use of these techniques in antitrust analysis. What remains to be seen is whether the evidence provided by these methods is reliable. Some of the relatively few papers that have tested the predictive ability of these tools are discussed below.

Nevo (2001) evaluated the ready-to-eat cereal market using a random-coefficients discrete-choice model of demand in addition to a differentiated products Bertrand oligopoly model. Though he lacked specific information about how costs may have changed, he generally found that the price changes following two mergers were consistent with the equilibrium predictions if the merger caused marginal costs to decrease by 5%.

Peters (2003) used a generalization of the nested logit model to investigate airline mergers in the US in the 1980s. He compared the predictive ability of this differentiated products oligopoly merger simulation model to that of a reduced form model in which changes in price are estimated as a simple function of market structure. He found that the oligopoly model could account for a significant proportion of the observed price changes, but that the reduced form model performed nearly as well.

Bonfrer and Raju (2003) considered a merger in the facial tissue industry that took place in the mid-1990s. They jointly estimated the demand based on grocery store scanner data using the Almost Ideal Demand Specification (AIDS) and the supply side first-order conditions using prices for pulp and proxies for transportation costs. Their supply side equations were based on a differentiated products price-setting oligopoly model in which firms could have instantaneous responses to changes in other firms' prices (a conjectural variations approach). Two of their findings relate significantly to the current paper. First, they found evidence that there were changes on the demand side following the merger, in other words, demand shifted. Second, their analysis of the conjectural variations parameters indicated that there was a change in the price leader-follower relations among the firms after the merger. Both of these findings are contingent upon the model being correctly specified. For instance, if demand was truly linear in the prices, and did not shift as a result of the merger, it would be possible to conclude that demand had shifted as a result of the merger if it was estimated using an AIDS specification.

III. Data

A. Description of the Data

The data we purchased to use in this research are a subset of the Information Reviews Data collected by Information Resources, Incorporated (IRI). In our analysis we work with city specific chain data from the retail grocery channel. For six IRI "cities", IRI provided us with UPC level data for sixteen retail city-chain combinations. For each city in our sample, we received data for each grocery food chain covered by IRI. In some of our sample cities there was data from three grocery chains. In other cities, there were either two or four chains. The geographic coverage of each city-chain is the same for each city-chain combination in the city. In other words, Chain A in City C covers the same territory as Chain B in City C. The IRI cities in our sample are scattered across the United States. The chains in our sample are not identical across cities. In our sample cities, we have full IRI grocery channel coverage. We do not, however, have data from the mass-merchandiser (e.g., Wal-Mart, KMart, Target) or club store channels (e.g., Costco or Sam's Club).

IRI provided weekly UPC data covering 156 weeks from the week ending October 8, 2000 through the week ending September 28, 2003. Because the parties consummated the merger in June 2002, we split our sample into two 52 week periods on either end of the merger to investigate any pre- and post-merger differences in pricing behavior. The first period covers the first 52 weeks of the sample. The second period covered the final 52 weeks of the sample. The two 52 week periods cover almost exactly the same months and weeks over different years. We were fortunate that the merger occurs fairly close to the middle of the sample period.

For each UPC, we received separately, for each chain and each city, weekly data on distribution (all commodity value -- ACV), revenues and units. IRI provided the revenue and units sold data in aggregate (i.e., total revenue and total units) as well as by promotional activity (e.g., we would receive data on weekly revenues and units in addition to revenue and units sold with a feature only, a display only, both a feature and display, and only a temporary price reduction only).

IRI also provided complete brand and category hierarchies for each UPC. This allowed us to aggregate the UPCs to the brand or even the sub-brand level. The product hierarchy enabled us to identify regular and chunky peanut butter for any given brand and differentiate it from reduced fat or old-fashioned style peanut butter from the same brand. Further, through common descriptors, we were also able to separate jellies and jams by flavor.

For purposes of this analysis, we limited our sample to brand level full fat peanut butter (including both regular and chunky varieties) and grape flavored jams and jellies. Using equivalized units, we aggregated our UPCs over different sizes into a common measure.[1]

In peanut butter, we limited our analysis to only three brands: Jif, the national market share leader, private label peanut butter, and a regional brand. We created a regional brand variable that could either be Skippy or Peter Pan due to extreme heterogeneity in distribution by region. In some areas of the country, either Skippy or Peter Pan would have a significantly larger share and distribution. For example, in one chain, one of the two brands had a mean ACV

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[1] Alternatively, we could have transformed each UPC into measures reflecting total ounces.

of seven while the other brand's mean ACV was one hundred.[2] This unbalanced ACV was not uncommon across city-chain combinations. Jif and private label, however, had mean ACV's very close to one hundred.

In grape jams and jelly, we discovered that three major brands dominated the category in our sample. The market leaders were Welch's, Smucker's, and private label. Other brands accounted for negligible shares of the grape jam and jelly category. We limited our data to the category of grape jam and jelly because this product is likely one of the most commonly used products in making a peanut butter and jelly sandwich. Much of the revenue in the jam category is generated by fruit spreads and marmalades. These other products were priced very differently from grape jams and jellies and we suspect that they are not typical inputs into the peanut butter and jelly sandwich,[3] so we excluded them from our analysis.

B. Summary Statistics

Full fat peanut butter is a much larger category in our sample than grape jelly in both the pre- and post-merger periods. In the earlier period, the PB share of total revenue was 81.9 percent while Grape's share was 18.1 percent. In the later period, the PB share edged up to 82.9 with a corresponding grape share of 17.1 percent. In levels, both categories grew. Dollar sales of PB rose from 9.4 percent from the pre-merger period to the post-merger period. For grape jellies and jams, dollar sales grew 3.6 percent between the two periods. Decomposing

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[2] ACV, or All Commodity Volume, is the percentage of stores carrying the product. Therefore, if Brand A in Chain B in City C had an ACV of seven, this implies that only 7 percent of Chain B's stores in City C carried Brand A.

[3] We took both grape jams and jellies because companies often offered both products at the same price (and generally promoted at the same time). Technically jelly and jams vary by sugar content and consistency. A casual inspection of labels suggests that the differences may be difficult to determine.

the category shares to the brand level, it appears that brand shares remained relatively stable over the period. Table A displays our share estimates by brand.

Table B reveals percentage changes in dollars units in index numbers in our sixteen sample chain-cities. The most significant category growth occurs for Jif and Private Label peanut butters. Both grow statistically significantly in both dollars and units (at the 10 percent level). The regional peanut butter brand grows at a slower rate and the difference is not statistically significantly different from zero. None of the grape brands display a statistically significant change between the pre- and post-merger periods.

In Table C, we display price levels (relative to Private Label Grape Prices in the Pre-Merger Period) and percentage changes in price levels.[4] The most intriguing change is the increase in the price of Smucker's grape jams and jellies. *Ex ante*, in a model of complements we would never predict an increase in price. The Smucker's price increased 8.4 percent over the two periods. This is unlikely to simply reflect increased ingredient costs as the Smucker's price increased more than private label and Welch's.

C. Limitations of the Analysis

Our analysis suffers from a number of limitations. Many of these relate to assumptions made in our estimation or simulation methodology, those will be discussed as they arise. Some, however, stem from the relatively narrow scope of the data we have obtained. We discuss what we see as the primary limitations in this section.

The biggest limitation we face is that we have retail data, in which stores presumably set the prices, but we seek to analyze the impact of a merger of

[4] We use price indices to avoid displaying actual average prices as calculated using Information Resources, Inc. InfoScan Reviews data.

manufacturers. With the advent of scanner data, it is not uncommon for antitrust analysts to be in this exact position when analyzing a pending merger. One possible solution is to try to get wholesale sales data, but this is difficult to get. Even if it is obtained, it is difficult to appropriately account for the inventorying behavior of retailers. Another approach is to make assumptions about how retailers set prices based on the wholesale prices they observe (see Hosken et al, 2002, for a thorough discussion of this approach). For instance, if retailers use a constant percentage markup, then retail and wholesale elasticities are identical. (See Froeb et al, 2002) Another approach would be to consider specific models of retailer interaction as in Villas-Boas (2002). We believe this latest approach is the most interesting, and leave it for future work. Since we have no source of wholesale data, we opt for the second approach mentioned, specifically, we assume retailers use a constant markup rule.

A second problem with our analysis is that we do not observe all of the relevant behavior of the firms competing in these markets. Specifically, we do not obtain data on most forms of advertising (we only have some data on advertising performed by the retailer, as in an advertisement placed in a newspaper insert). Froeb and Tschantz (2001) show that merger price effects can be overestimated or underestimated as a result of ignoring the impact of the merger on advertising. We also lack data on couponing activity. It may be possible to obtain some measures of advertising expenditures, but we know of no source of coupon data.

IV. Demand Estimation

A. Model Choice, Variable Creation and Limiting Assumptions

In mergers of branded product manufacturers sold through retail outlets, antitrust analysts often implement a limited number of specifications to estimate the matrix of own- and cross-price elasticities for several applications. First demand estimation is often used as a corroborative mechanism to assess documents and anecdotal information collected during an investigation. For example, if direct interviews with retailers suggest that the merging firms' brands are the two "closest" substitutes, demand analysis using scanner data should provide similar results. Conversely, if demand estimation yields very different results from the preponderance of anecdotal or documentary evidence, this calls into question whether the demand models are properly specified (or whether sufficient data exists to perform the analysis). When the documentary and anecdotal evidence are inconsistent, demand analysis may help the analyst better understand how to weigh the evidence. In many cases, provided that demand analysis yields reasonable results, the matrix of own- and cross-price elasticities may be used as an input into demand simulation. Some of the most commonly employed models are constant elasticity of demand (CE), the multi-stage Almost Ideal Demand System (AIDS), linear demand, and logit based demand models. In this paper we are analyzing a merger of goods that are commonly thought to be complements. Discrete-choice based models are not appropriate for these types of goods because these models look at consumers' decisions to buy one of a set of goods, whereas the interaction between complements relates to decisions to buy both. In the following analysis we study four demand specifications: CE, linear, and two- and three-level AIDS. We do not know of any paper that has tried to compare the ability of a demand simulation/merger simulation approach to predict the impact of a merger across a wide range of demand specifications.

We estimate both pre- and post-merger demand elasticities for all four demand specifications. As described earlier, the pre- and post- merger periods are divided into 52-week periods covering the same months on either side of the merger date. We estimate own- and cross- price elasticities for six brands – three brands in full fat regular peanut butter (both creamy and chunky aggregated) and three brands in grape jelly. The brands are Jif, Private Label Peanut Butter, a Regional Peanut butter brand, Smucker's, Welch's, and Private Label grape jams and jellies (aggregated). As mentioned earlier, we re-label either Skippy or Peter Pan as "Regional" since it is rare to have both brands distributed extensively in our chain-city combinations in our sample data. It is our opinion that it is not meaningful to estimate demand for a brand when many chain-city combinations have very small ACV for one of the two regional peanut butter brands. Please note that this does not mean that the quantities, prices, and shares used in our sample are nationally representative. The results in this paper are only applicable to our sixteen city-chain combinations.

The left hand side (LHS) variables are fairly straightforward to calculate. For the linear and CE demand models, the left hand side is simply the actual (or log of) reported equivalized units for Brand X in City-Chain Y in Week Z. In the AIDS models, the left hand side variables at the bottom level are share of revenues. IRI reports the dollar sales by UPC by chain-city by week.

For the right hand side (RHS) price variables, we calculate an average price per equivalized unit by dividing total revenues by total equivalized units per week.[5] This automatically introduces bias into our estimates because the RHS price variables are calculated using the LHS variables effectively putting the LHS variable on both sides of every equation. Further there are potential measurement error issues in addition to simultaneity issues. The "average price" that we calculate may contain some sale and some regular prices. Stores may run temporary sales that occur in the middle of our sample week. Or alternatively, some stores in a City-Chain combination may run a sale while other stores in that same City-Chain combination do not in a given week. In this paper, we are not proposing any new solutions to these difficulties.

We control for the same demand shifters on the right hand side in all specifications. Let Z denote a vector of demand shifters. Z is comprised of dummy variables for each week and a city-chain dummy variable for each chain-city combination. That is, in each specification, we create 52 dummy variables that take on the value one in a given week, zero otherwise (e.g., there is a week 2 dummy variable, a week 3 dummy, etc.). For each city-chain pair, there is also a dummy variable. For example, there would be a dummy variable that takes the value of one if the data are from Chain A in City B, zero otherwise. Similarly there would be a dummy variable with value one for Chain B in City B, chain C in City B, etc. We experimented with various promotional controls as well. For instance, we tried to put in controls for percentage of units of each brand sold with any promotion. Unfortunately in all specifications, this led to unbelievable elasticity estimates. Clear substitutes often became complements and many

[5] Equivalized units are provided by IRI. In PB, the equivalized unit is a 16 oz jar. By using equivalized units, we are quickly able to aggregate UPCs over size.

own-price elasticities became unbelievable (either the magnitude became unreasonable or the coefficients took the wrong sign).[6]

We do not control for potential endogeneity issues. We assume that we estimating well identified demand curves (as opposed to a series of simultaneously shifting demand and supply curves). There are several practical reasons for this. First, even if we assume that we have a simultaneous equations problem, it is unlikely that we would be able to find appropriate instruments (see Rubinfeld 2000). Instruments must be brand-specific and must be available in the same time dimension as the retail sales data (in this case weekly). Moreoever, even if we had access to firm specific cost accounting data, we would also need to know how the supply chain operated. We would need to know the lag time between production and distribution to the retail outlets (in other words we would like to know how fast cost shocks pass through to retailers, or if there is any pass-through for transitory shocks at all). For purposes of this analysis, we assume that weekly prices are generated as random exogenous shocks, and consumers respond to these shocks via their consumption decisions.

B. Demand Specifications

1. Constant Elasticity (CE) or Log-Linear

A common specification in antitrust analysis would be the basic CE specification.

$$(1)\ \ln Q_{imt} = \alpha_i + \sum_j \gamma_{ijm} \ln p_{jm} + Z_{imt}\Omega + e_{imt}$$

[6] The use of promotional variables in calculating elasticities is a major topic in the marketing literature. There are some marketing specialists adamantly opposed to using controls such as percentage of units sold on promotion. Note, however, that the marketing literature often focuses on very different questions from antitrust practitioners. Marketing approaches are not necessarily appropriate for our purposes.

The subscripts *i* and *j* denote brands *i* and *j*, *m* denotes city-chain combination *m*, and the vector Z are the previously-mentioned RHS demand shifters (dummy variables for weeks 2 through 52 and dummy variables for 15 of the 16 chains). The constant, α_i, takes into account a general constant term in addition to the excluded week 1 and the excluded chain-city combination. The γ's are elasticity estimates.

2. Linear Demand

Another specification that we analyzed, and is frequently employed in merger investigations, is a simple linear demand model. This model is identical to equation (1) above except prices and quantities are used directly, instead of their logarithms.

$$(2)\; Q_{imt} = \alpha_i + \sum_j \psi_{ijm} p_{jm} + Z_{imt}\Omega + e_{imt}$$

We estimate elasticities at the sample mean quantity and price of brand *i* and price *j*.

3. Two-Level AIDS Model

Hausman (2002) implements a two-level AIDS-based demand system. The system employs a multi-stage budgeting format based on Gorman (1959). The model is a multi-stage budgeting system in that the representative consumer first chooses how much she will spend on peanut butter and grape jelly (top level). She then chooses which brand to purchase based on price and other observable characteristics of the brand (bottom level). This model is "AIDS-based" because the lower level is based on Deaton and Muellbauer's (1984) AIDS model. The bottom level equation specification is as follows:

$$(3) \qquad w_{imt} = \alpha_{im} + \sum_j \gamma_{ijm} \ln p_{jm} + \beta_i \ln\left(Y_{mt} / \overline{P}_{mt}\right) + Z_{imt}\Omega + e_{imt} = \frac{p_{imt} q_{imt}}{Y_{mt}}$$

where

(4) $\ln \overline{P}_{mt} = \sum_j w_{jm} \ln p_{jmt}$ (the Stone price index).

The LHS, w_{imt}, represents revenue share of brand *i* in city-chain combination *m* at time *t*. Y_{mt} is segment expenditures (the sum of all expeditures on PB and grape jelly at City-Chain combination m in week t). The Z_{imt} represents other demand shifters. To calculate the weights in the Stone price index, we "fix" the weights. That is, we take the revenue shares of each brand over the entire 52 week period and use these same weights to calculate the Stone price index in every period. This method has been implemented in various papers.[7] In this paper, we only impose adding up ($\sum_i \alpha_i = 1$) and homogeneity ($\sum_j \gamma_{ij} = 0$). In the current application, we do not impose symmetry ($\gamma_{ij} = \gamma_{ji}$), which may be a reasonable restriction for an individual's demand curve, but need not hold for an aggregate demand curve.

The top level in Hausman's model is given by

(5) $\ln q = \mu_0 + \rho \ln Y^D + \eta \ln \overline{P} = \ln\left(Y/\overline{P}\right)$

where *q* denotes segment quantity (so in this example the segment is all peanut butter and grape jelly). The variable Y^D is disposable income and $\ln \overline{P}$ is the Stone price index for the combination of PB and grape jelly. In this paper, we estimate the model excluding disposable income. We also add the demand shifting RHS variables, Z. The uncompensated elasticity formula is as follows:

(6) $\varepsilon_{ij} = (1+\eta)w_j + \frac{1}{w_i}\left[\beta_i \eta w_j + \gamma_{ij}\right] - 1[i = j]$.

[7] Some practitioners use different price indices such as the Tornqvist price index. In this paper, we primarily follow Hausman (1994 and 2002).

4. Three-Level, Two-Segment Nested AIDS Model

Hausman's (1994) first AIDS-based system applied to antitrust had three levels. At the top level, a consumer chooses how much of an industry's product she will purchase (this is the same as in the Two-Level AIDS based model). The representative consumer chooses how much to spend on both PB and grape jelly. At the middle level, the consumer chooses how much to spend at the segment (nest) level where the two segments are PB and grape jelly. For example, first the consumer allocates her budget for PB and grape jelly. Then she determines how much of each to buy (the middle level). Finally, at the bottom level she chooses her brands. For example, the consumer decides how much Jif to buy relative to Private Label PB within her PB segment budget. She also chooses between Smucker's, Welch's, and any other suitable brand for her grape jelly budget. The model is set up as follows:

(7) $$w_i = \alpha_i + \sum_j \gamma_i \ln p_j + \beta_i (\ln Y^G - \ln \overline{P}^G) \text{ where } i, j \in G$$

(8) $$\ln q^G = \alpha^G + \sum_{H \in \Gamma} \delta^{GH} \ln \overline{P}^H + \theta^G \ln Y^I = \ln\left(Y^G / \overline{P}^G\right)$$

(9) $$\ln q^I = \mu_0 + \rho \ln Y^D + \eta \ln \overline{\overline{P}}^I = \ln\left(Y^I / \overline{\overline{P}}^I\right)$$

where (8) – (10) represent the bottom, middle, and top equations respectively. Equation (10) is unchanged from previous specifications. The *g*- and *h*-superscripts now denote segments (i.e., g = PB, h = grape jelly). Thus q^G could be total quantity of PB purchased. The superscript I denotes industry (i.e., all PB and grape jelly). Thus q^I would be total quantity of PB and grape jelly purchased. All prices with overbars are Stone prices. For example,

$$\ln \overline{P}^G = \sum_{j \in G} w_j \cdot \ln p_j$$

$$\ln \overline{\overline{P}}^{I} = \sum_{H \in \Gamma} W^{H} \ln \overline{P}^{H}$$

where W^H is the share of segment H in total industry expenditures I. In our example, $\ln \overline{P}^{G}$ may be the log of the Stone price index for PB (the weighted average of the log price of Jif, Private Label PB, and the Regional Brand). Similarly, $\ln \overline{\overline{P}}^{I}$ is the log of the weighted average of the PB and grape jelly Stone price indexes. Y^D, as in the two level model, is disposable income.

In the bottom level, equation (8), we impose adding up ($\sum_i \alpha_i = 1$) and homogeneity ($\sum_j \gamma_{ij} = 0$). In the middle level, we also impose homogeneity (by setting $\sum_{H \in \Gamma} \delta^{GH} + \theta^{G} = 0$). In other words, doubling all prices and segment expenditures leads to no change in quantity demanded. As in the two-level AIDS model, we do not impose symmetry ($\gamma_{ij} = \gamma_{ji}$). After estimating all three equations, the uncompensated elasticity formula is:[8]

$$(10) \qquad \varepsilon_{ik} = w_k \left\{ 1[k \in G] + \delta^{GH} + \theta^{G}(1+\eta) W^{H} \right\} + \frac{1}{w_i} \left\{ \beta_i \delta^{GH} w_k + \beta_i (1+\eta) \theta^{G} W^{H} w_k + \gamma_{ik} [k \in G] \right\} - 1[i = k].$$

C. Results

1. Pre-Merger Elasticities

We present the elasticity matrices from the pre-merger period in Table D. Casual observation of the four matrices reveals some evidence that PB and grape jelly brands are complements. As a general rule, the two non-AIDS based models, the CE and linear model, yield elasticities closer to our ex ante view of the world that PB and grape jelly are complements, though neither of these even

[8] A detailed derivation is available upon request.

shows a strong consistent complementarity between PB and jelly.[9] In the CE estimates, only one of the 18 cross-elasticities between a PB and a jelly shows a statistically significant level of complementarity (the elasticity of demand for Private Label PB with respect to a change in the price of Private Label Grape Jelly). The linear model shows the most complementarity where expected with four significantly negative cross-elasticities between PBs and jellies, out of 18 such cross-elasticities. The three-level AIDS specifications yield the most implausible results.

In Tables D-1 and D-2 (the CE and linear demand models), we notice that the Jif equations display complementarity with some grape jelly brands. There are similar effects for Private Label PB as well as Welch's grape jelly. The two-level non-nested AIDS model (D-3) also performs adequately whereas most of the three-level nested AIDS model generates results at odds with the other three specifications. Further, in D-1 and D-2, the estimated cross-elasticity for each PB brand with respect to Welch's is always negative suggesting that Welch's is a complement in demand for all three PB brands.

Another interesting pattern that emerges from D-1 through D-3 is that the cross-elasticity of demand for Private Label PB with respect to the Private Label Grape Jelly price reveals clear complementary. This is likely to occur because retailers have control over both their Private Label PB and Grape Jelly promotional schedule. Retailers can bundle the two products together to maximize their sales via advertisements in circulars, end of aisle displays, or

[9] In any merger analysis, demand estimation is usually approached as a complement to the overall analysis. Thus, if two products are well-understood to be substitutes or complements based on all available evidence, we would likely reject any model either generated in-house or presented to staff that showed otherwise. We would either question the specification, the data, or the manipulations of the data that led to the counterintuitive outcome. At the same time, econometric analysis may help us weigh conflicting information gathered from other sources (i.e., documents, interviews, etc…)

other promotional activities. The retailer captures the full benefit of the bundled sales activity rather than splitting benefits between a PB manufacturer and a grape jelly manufacturer.

In general, we do not see consistent evidence that PB and jelly are complements from this analysis. There are several potential explanations for this. One explanation is that all of our demand models are mis-specified. Given the flexibility of these demand systems, it seems unlikely that they would not be able to pick up on a level of complementarity if it was present in the data. A second explanation is that we are looking at weekly sales, and it is possible that there is a lag in the complementarity. For instance, if peanut butter is on sale this week, a shopper may stock up on it, but not on jelly. However, having stocked up on peanut butter in a previous week may make that shopper more likely to stock up on jelly when it goes on sale. Since we do not have individual level data, these inventorying stories will be difficult to address. One possible way to deal with this possibility is to aggregate the data over several weeks, but this comes at the cost of smoothing much of the price variation. This issue needs to be addressed in future work.

2. Post-Merger Elasticities

In the post-merger world, elasticity calculations appear qualitatively similar to the pre-merger results. Table E displays the elasticity matrices. As in the pre-merger world, a degree of complementarity between PB and grape jelly brands might exist. For instance, in the post-merger world, the Jif-Smucker's cross-elasticity estimates suggest that in all four specifications, a reduction in Smucker's' price results in a corresponding increase in Jif's quantity demanded. Further the magnitude of the Jif-Smucker's cross-elasticity estimates increased (in absolute value) in all four specifications.[10] Similarly to the pre-merger period, Welch's also appears to be a complement to all three PB brands in the CE and linear specifications (see Tables E-1 and E-2 and compare them to D-1 and D-2).

V. Merger Simulations

The models used in this paper to predict the effect of the merger on prices all fall into the general category of differentiated products Bertrand oligopoly models. The basic idea is that prices for each brand are selected to maximize the profits of the brand's owner, and that brand owners use Nash conjectures about the prices set for other brands. Before the acquisition, Smucker's takes into account only the effect a change in the price of Smucker's jelly would have on the demand for Smucker's jelly. After the acquisition, Smucker's would also consider the impact on demand for Jif. In general, if the two brands were substitutes (complements), one would expect the merger to cause prices to increase (decrease). Since the pre-merger elasticities reported in Table D show no clear pattern of substitution or complementarity between the brands, we can expect mixed results, which is what we get.

A. General Theory

If we write the demand[11] for brand i as $q_i(p)$, where p is a vector of prices for all brands, then the profit associated with brand i can be written as $q_i(p)p_i$-$C_i(q_i(p))$-F_i where $C_i()$ and F_i represent the variable and fixed costs of brand i. It is reasonable to think that the cost of producing the marginal jar of peanut butter or jelly does not vary substantially over the range of quantities that will be

[10] For every specification and every brand equation, we performed F-tests to determine whether the point estimates were equal between the pre- and post-merger periods. We rejected equality of coefficients in every instance.
[11] For now, we will use general notation for the demand function. In practice, when solving these models, we will use each of the four demand specifications estimated in the previous section.

considered in our analysis, so we assume $C_i(q_i(p))=c_i\, q_i(p_i)$. Let O(i) be the set of all brands owned by the company which owns brand i. The profits of the owner of brand i can be written as:

(11) Profit of owner of brand i = $\sum_{j \in O(i)} q_j(p)(p_j - c_j) - F_j.$

For well-behaved demand functions, maximizing this profit requires the following first order condition to be satisfied:

(12) $$\sum_{j \in O(i)} \tfrac{\partial q_j(p)}{\partial p_i}(p_j - c_j) + q_i(p) = 0 \quad \forall i.$$

A merger simulation is simply a study of how the equilibrium prices implied by the set of first order conditions given by (12) change when the ownership structure (the O(i)'s) change due to the merger. The functional forms used in these first order conditions vary depending on the demand specification, but the analysis is otherwise identical.

The marginal costs of the merging firms are often very difficult to estimate, especially if one were to try to include opportunity costs. Antitrust analysts often have limited data on the costs of the merging companies, and little or no reliable cost data for competitors not involved in the merger. An approach often used is to calculate the marginal costs implied by equilibrium prior to the merger. Essentially, a demand curve is estimated as detailed above, then the marginal costs implied by the first order conditions given in (12) are calculated using some measure of pre-merger prices. In this paper, we will use average price over each 52-week period as our measures of pre-merger and post-merger prices.[12] Keeping in mind that opportunity costs are not easily accounted for, these implied marginal costs can provide a good reality check on the myriad of

[12] To be precise, in the linear model, we simply use the mean price across all weeks, cities, and chains. In the other three specifications, which depend on log prices, we take the average of log prices across all weeks, cities and chains.

assumptions that have been made up to this point. For instance, if a company owned two brands for which the input costs seemed likely to be nearly equal (grape soda and orange soda, for instance), finding very different implied marginal costs for these two brands may raise some red flags at this stage.

B. Pre-Merger Equilibrium Analysis

Before looking at the predicted impact of Smucker's acquisition of Jif, we will present some analysis of the implications of the demand estimation and assumed equilibrium pricing in the pre-merger period. We will start by looking at the implied marginal costs, then address the sensitivity of the models' predictions to the assumption that firms are able to perfectly determine their profit-maximizing price.

1. Pre-Merger Implied Marginal Costs

Table F shows the implied pre-merger marginal costs, where costs and prices have been normalized so that the average price of private-label grape jelly in the 52 week pre-merger period is 100.

We can see that the implied marginal costs of several of these products vary substantially across the four demand specifications. For instance, the implied marginal cost of a jar of Jif is as low as 76.9 and as high as 147.7. We do not possess any information about actual marginal costs, so it is difficult to use these estimates as any type of screen. However, for instance, a reasonable question to ask would be why the marginal cost of Jif is so much higher than the implied marginal costs of the other brands of peanut butter in the linear model.

2. Profit Function Sensitivity Analysis

A number of factors could potentially prevent firms from reaching their optimal price exactly. For instance, inaccurate estimates of demand or costs, or unrealistic expectations of competitors' prices could prevent a firm from pricing optimally. Of course, the more costly it is to deviate from the optimal price, in terms of lost profits, the more expense and effort we would expect firms to expend to find the optimal price. We analyze in this section the sensitivity of a brand's profits[13] to small deviations from the optimal price in each of the four models.[14]

To this end, we propose a thought experiment. For a particular demand specification, suppose that the oligopoly model of price competition is the correct model, and that the observed pre-merger prices are truly the equilibrium prices (meaning the calculated implied marginal costs are the true marginal costs). Then imagine that one firm, for whatever reason, decided to set a price not equal to the equilibrium price. Arbitrarily, we will alter the price of Jif in this analysis.

Suppose that instead of setting the price of Jif optimally, Jif is priced 5% below the equilibrium price (and all other brands remain at their equilibrium prices). How much would Jif profits fall due to this sub-optimal pricing? It turns out that for the linear demand specification with the estimates presented in the previous section, Jif profits would fall by almost 5% as a result of this out-of-equilibrium pricing. For each of the three other models (CE, 2-level AIDS, and 3-level AIDS), profits fall by less than half a percent. Graphically, this means the profit functions of Jif are relatively flatter with respect to changes in the price of Jif for these other demand models than they are for the linear model. These profit functions are graphed in Figure 1. On the horizontal axis is the Jif price divided by the equilibrium Jif price. On the vertical axis is Jif profits at the

[13] Since we have no way to estimate fixed costs, any mention of profits in this section refers to operating profits.

[14] This discussion closely parallels Glenn Harrison's (1989) critique of the experimental auction literature, which rested on payoff functions being relatively unresponsive to deviations away from the equilibrium. Much of the discussion that followed Harrison's critique focused on the point that the disutility of suboptimal actions in those environments would depend on individual utility functions. In models of the firm, it is standard to take the objective function of the firm to be the profit function, so Harrison's critique seems to fit.

hypothetical price divided by equilibrium Jif profits. The curves represent the normalized profit functions for each of the four demand specifications. Notice that each curve reaches its peak at a relative price of one, which is when the hypothetical price equals the optimal price. The profit curve associated with the linear demand specification falls off precipitously relative to the profit curves for the other demand models as the price deviates from the equilibrium price. The differing curvatures of the demand specifications produce variation in the shapes of the profit curves, but here, the main cause of the distinct differences between the profit functions is that the own price elasticities of Jif vary substantially across the demand specifications, as seen in Table D.

There are many ways to interpret this information. One interpretation is that accurately estimating the optimal price would be relatively more important if demand was linear instead of any of the three other specifications. Another way to look at this is that if we relax the assumption that firms are inherently capable of determining optimal prices, perhaps because they rationally limit their marketing research or face some type of menu cost, then we may well expect to see prices deviate from the optimal prices by considerably more if demand takes either a constant elasticity, 2-level AIDS, or 3-level AIDS form than if demand takes a linear form. For instance, Figure 1 indicates that in the three models excluding the linear model, prices can vary by roughly 10% above or 10% below the equilibrium price without causing profits to drop below 99% of the equilibrium level.

Obviously, firms would like to be at 100% of optimal profits, in fact they would like to increase the nominal level of their optimal profits. So, perhaps the shape of the profit function is of little importance. However, it does seem reasonable to conjecture that firms would be less likely to miss the optimal price by 5% when it costs them 5% of their profits than when it costs them less than

1%. Another way to interpret this would relate to the information content of an observed price change. If there was good reason to believe that a firm's demand looked like the linear demand estimated for Jif above, a price change of 5% to 10% would seem relatively likely to have been caused by some sort of structural change (changes in costs, ownership, or demand conditions). However, this same price change may be more likely to indicate that the firm is searching for the optimal price under the other estimated demand curves, and may less likely to signal any structural change.

C. Predicted Merger Effects

The implied pre-merger marginal costs given in Table F can be used as an estimate of post-merger marginal costs. If there is reason to believe the costs would change in some particular way between the pre- and post-merger periods, appropriate adjustments could be made. Although it is entirely possible that Smucker's' acquisition of Jif may have influenced the marginal costs of these brands, we have no information regarding those effects, so for now, we simply use the calculated pre-merger implied marginal costs. Following this section will be a detailed discussion of the relationship between pre-merger and post-merger implied marginal costs.

Using the implied pre-merger costs and the new ownership structure in which Smucker's also owns Jif in the first order conditions given by equation 12, the post-merger equilibrium prices can be calculated. Table G indicates the predicted percentage increase in the price of each brand as a result of the merger. Notice that the predicted effects are generally very small. For Jif, the largest predicted price change is a 3.9% increase under the 3-level AIDS specification. For Smucker's, the Constant Elasticity model predicts a rather large price decrease of 11.6%, and the 3-level AIDS model predicts a 5.2% price increase. Few of the models predicted sizable price changes for the non-merging brands, which is not terribly surprising given that these are second-order effects and that the first order effects were often quite small.

Since the price of Smucker's actually increased relative to the other jelly brands after the merger, we do not see strong support for the Constant Elasticity model. The 3-level AIDS model predicts price increases for Jif and Smucker's. The Smucker's prediction is consistent with how prices actually changed, but Jif's price actually fell relative to the other PBs. So, the performance of the 3-level AIDS model is also mixed. The other models suggest that the merger would have very little impact on any prices. This is not to say that these models predict there will be no change in prices, just that the merger is not likely to have much impact. This is a comparative statics prediction of the impact of the merger, unfortunately, we cannot say with any confidence that every other relevant characteristic of the markets for these products was held fixed.

All kinds of factors these models are not intended to predict could have changed between our pre-merger and post-merger eras. For instance, demand for the products could have shifted due to changes in consumer preferences. In fact, statistical tests of the demand curves indicated that the estimated parameters of all four demand specifications changed significantly between pre- and post-merger periods. Maybe a new fad diet made people shy away from jelly or consume more peanut butter. Such a change in tastes would impact prices, but would clearly not be predicted by a differentiated product oligopoly model. Economists are not likely to ever have much chance of predicting changes in preferences such as this. However, peanut butter and jelly seem very likely to represent relatively mature markets given that they have been staples of the American diet for so long. Another possibility is that advertising for the brands caused their demand curves to shift. The types of models currently employed for merger analysis generally do not account for this type of market activity, but it is clearly something that would lend itself to economic analysis. However, we do not have data on advertising, so we must leave that for another study.

D. Comparison of Calculated Implied Pre-Merger and Post-Merger Marginal Costs

Just as we used pre-merger market data to calculate implied marginal costs in the pre-merger era, we can use demand estimates based on post-merger market data to calculate post-merger implied marginal costs. Comparing pre-merger and post-merger implied costs may indicate whether certain demand models (in combination with the equilibrium model of pricing) yield consistent estimates of underlying parameters. For instance, if the implied marginal costs of one non-merging brand of peanut butter decreased significantly after the merger, and the marginal cost of the other non-merging peanut butter brand increased significantly, one may look at the demand specification that yielded those cost estimates with a degree of skepticism. On the other hand, if there seems to be a reasonable correlation between pre- and post-merger implied costs for a particular demand specification, that would lend the model some credence. If we had a model that correctly predicted how demand would shift and costs did not change, this procedure would yield consistent estimates of the underlying cost functions of the firms in the pre- and post-merger eras. In this retrospective view of a merger, estimating the demand systems based on pre- and post- merger data allows us to use the data to explain the demand shift rather than using a model of firm behavior to do so. Table H lists the percentage increase in the implied marginal costs from the pre-merger estimates to the post-merger estimates.

Some of these changes are quite large, and there is often little correlation within a category. For instance, in the linear model, the marginal cost of

Regional PB increases 80% while the marginal cost of Private Label PB falls by 54%. If there were brand-idiosyncratic cost shocks that could account for this pattern, they would normally become apparent in a merger investigation. However, it also possible that this indicates that the model did not fit the data particularly well. Similar, though somewhat less extreme examples can be found in the other three demand specifications. The model under which the cost changes seem the least troublesome is the 3-stage AIDS model. In that model, the implied marginal costs of the jellies all fall by from 6% to 9%. The changes in peanut butter marginal costs are not nearly as uniform in that model, however, with changes ranging from a 13% increase to a 12% decrease. This variation across brands of peanut butter is still considerable, but it seems more plausible than the implications about changes in marginal costs produced by the three other models.

VI. Conclusion

Peanut butter and jelly strike us as being nearly prototypical complementary goods. The fact that they do not turn out to be strong and consistent complements must make us question a number of items: (1) our models of demand; (2) our estimation techniques, especially with respect to consumer inventorying behavior; and (3) possibly the data, especially the extent to which unobserved (to us) coupon activity and advertising drive sales in this category.

Given that the merger simulation models are calibrated with our demand estimates, we do not feel we can offer any sort of verdict with regard to merger simulation based on these results. However, it appears that the price of one of the merging brands (Smucker's) actually increased significantly following the merger, even relative to similar products. It is possible that extended models of competition in which instruments other than price are used by competitors may help to explain this seemingly anomalous result, though this is purely speculative.

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Figures and Tables

Figure 1: Profit consequences of hypothetical unilateral price deviations

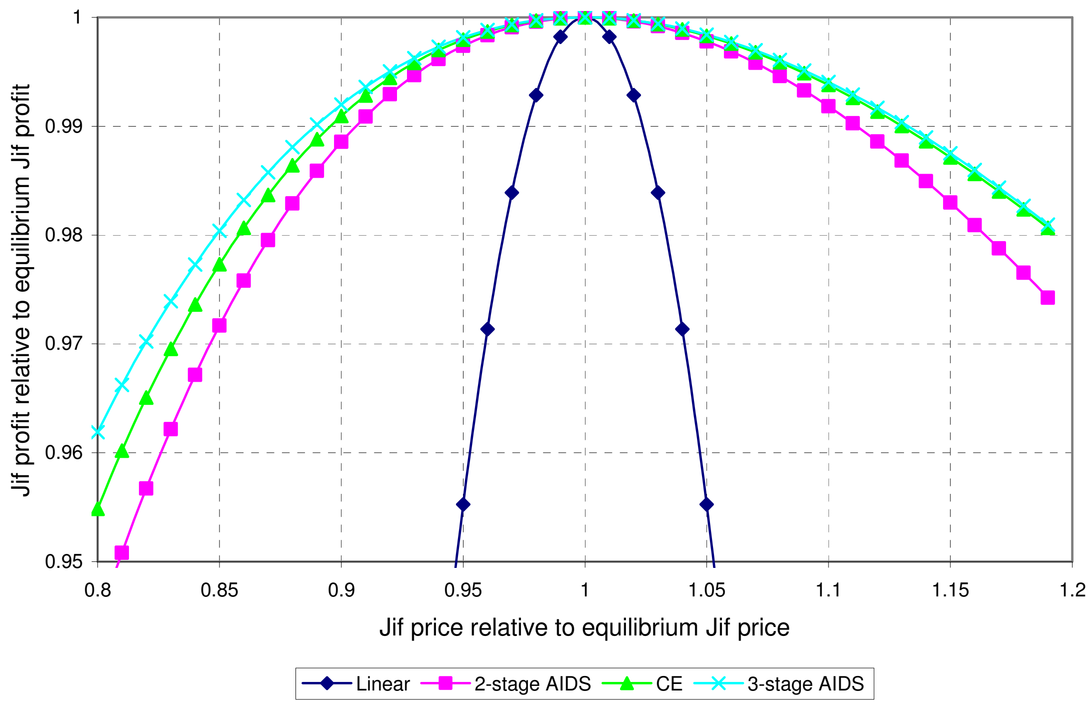

Table A: Brand Shares by Category (PB and Grape)

	Pre-Merger	Post-Merger
Jif	36.4%	36.5%
Private Label PB	28.6%	30.1%
Regional PB	35.1%	33.4%
Smucker's	28.6%	29.9%
Welch's	42.8%	41.3%
Private Label Grape	28.7%	28.8%

Authors' estimate based in part on Information Resources, Inc. InfoScan Reviews data.

Table B: Changes in Index Dollars and Units

	Dollars			Units		
	Pre-	Post-	Sig.	Pre-	Post-	Sig.
Jif	100	110.1	*	100	109.9	*
Private Label PB	100	114.3	*	100	112.6	*
Regional PB	100	104.2		100	107.4	
Smucker's	100	108.6		100	99.1	
Welch's	100	99.5		100	96.8	
Private Label Grape	100	103.8		100	105.2	

Authors' estimate based in part on Information Resources, Inc. InfoScan Reviews data.

Table C: Price Levels (Private Label Grape Pre-Merger Level = 100)

	Index Prices			Change
	Pre-	Post-	Sig.	(Actual)
Jif	193.44	194.26		0.4%
Private Label PB	160.65	164.91	*	2.7%
Regional PB	185.53	187.34		1.0%
Smucker's	133.25	144.42	*	8.4%
Welch's	122.46	124.80	*	1.9%
Private Label Grape	100.00	100.90		0.9%

Authors' estimate based in part on Information Resources, Inc. InfoScan Reviews data.

Table D: Pre-Merger Elasticity Matrices, (% Δ q-row/ % Δ p-column)

D-1: Constant Elasticity

	Jif	Private Label PB	Regional PB	Smucker's	Welch's	PL Grape
Jif	**-1.82**	**0.27**	**0.27**	-0.07	-0.04	0.10
Private Label PB	**0.36**	**-1.52**	**0.33**	0.04	-0.07	**-0.31**
Regional PB	**0.58**	**0.67**	**-1.58**	-0.01	-0.09	**0.21**
Smucker's	0.15	0.36	**0.37**	**-2.89**	0.18	**0.46**
Welch's	-0.03	-0.14	0.07	**0.32**	**-2.11**	**0.36**
Private Label Grape	-0.25	0.15	-0.06	**0.46**	**0.56**	**-2.00**

D-2: Linear

	Jif	Private Label PB	Regional PB	Smucker's	Welch's	PL Grape
Jif	**-4.23**	**0.76**	0.12	-0.01	**-0.62**	0.08
Private Label PB	0.53	**-2.48**	0.10	**-0.26**	-0.26	**-0.70**
Regional PB	0.29	**1.78**	**-1.81**	0.03	-0.24	0.29
Smucker's	-0.66	0.14	0.59	**-5.61**	0.15	0.17
Welch's	**-3.42**	0.19	-0.13	**0.39**	**-5.65**	**0.95**
Private Label Grape	0.11	-0.20	-0.33	**0.25**	**0.39**	**-2.52**

D-3: Two-Level Non-Nested AIDS (Fixed Weights), Aggregate Elasticity = -1.83

	Jif	Private Label PB	Regional PB	Smucker's	Welch's	PL Grape
Jif	**-1.84**	**0.26**	**0.23**	-0.03	0.05	0.06
Private Label PB	**0.27**	**-1.76**	**0.11**	**0.10**	0.01	**-0.37**
Regional PB	-0.37	-0.23	**-2.23**	**0.07**	-0.04	**0.08**
Smucker's	**0.16**	-0.25	**0.08**	**-3.55**	**0.39**	**0.37**
Welch's	**0.43**	-0.18	**0.26**	**0.38**	**-2.45**	**0.54**
Private Label Grape	0.11	-0.03	-0.09	**0.47**	**0.45**	**-2.09**

D-4: Three-Level Nested AIDS (Fixed Weights), Aggregate Elasticity = -1.83

	Jif	Private Label PB	Regional PB	Smucker's	Welch's	PL Grape
Jif	**-1.98**	**0.40**	**0.37**	0.01	0.01	0.01
Private Label PB	**0.19**	**-2.01**	**0.05**	0.01	0.01	0.01
Regional PB	**-0.22**	**-0.19**	**-2.18**	0.01	0.02	0.01
Smucker's	0.31	-0.91	-1.12	**-1.65**	**1.94**	**1.08**
Welch's	0.18	0.14	0.17	**0.37**	**-2.15**	**0.24**
Private Label Grape	0.16	0.13	0.16	**0.43**	**0.28**	**-2.10**

Bold type indicates statistically significant at least at the 10% level.
In AIDS models, **bold** type only indicates significant coefficient at the bottom level regressions. It does reflect whether the elasticity itself is different from zero.
Authors' estimate based in part on Information Resources, Inc. InfoScan Reviews data.

Table E: Post-Merger Elasticity Matrices, (% Δ q-row/ % Δ p-column)

E-1: Constant Elasticity

	Jif	Private Label PB	Regional PB	Smucker's	Welch's	PL Grape
Jif	**-1.87**	0.04	**0.26**	**-0.26**	-0.13	-0.00
Private Label PB	**0.51**	**-1.80**	**0.41**	-0.08	**-0.20**	0.03
Regional PB	**0.58**	**0.37**	**-1.86**	0.09	-0.13	**-0.38**
Smucker's	**0.39**	**0.62**	**0.41**	**-2.641**	0.00	0.05
Welch's	-0.10	0.09	-0.12	**0.28**	**-2.09**	0.06
Private Label Grape	**0.46**	**-0.27**	**-0.29**	**0.46**	**0.54**	**-1.49**

E-2: Linear

	Jif	Private Label PB	Regional PB	Smucker's	Welch's	PL Grape
Jif	**-5.61**	-0.16	**0.98**	-0.15	**-1.22**	0.13
Private Label PB	0.28	**-1.37**	0.15	0.02	-0.14	-0.06
Regional PB	**1.66**	0.16	**-5.08**	0.10	**-0.81**	-0.37
Smucker's	0.40	0.71	**1.09**	**-3.37**	-0.16	0.64
Welch's	**-3.11**	0.32	-0.03	**0.35**	**-4.64**	-0.24
Private Label Grape	**1.22**	-0.17	-0.11	**0.46**	-0.06	**-1.53**

E-3: Two-Level AIDS (Fixed Weights), Aggregate Elasticity = -2.09

	Jif	Private Label PB	Regional PB	Smucker's	Welch's	PL Grape
Jif	**-2.10**	-0.03	**0.30**	-0.11	**0.08**	**0.13**
Private Label PB	**0.11**	**-1.84**	**0.08**	0.02	-0.03	0.06
Regional PB	**0.14**	**0.08**	**-2.15**	0.12	0.01	**-0.34**
Smucker's	-0.41	**0.05**	**0.21**	**-3.02**	0.01	0.07
Welch's	**0.16**	**0.18**	-0.02	**0.38**	**-2.16**	**0.31**
Private Label Grape	**0.44**	**-0.49**	**-0.59**	**0.56**	0.02	**-1.52**

E-4: Three-Level Nested AIDS (Fixed Weights), Aggregate Elasticity = -2.09

	Jif	Private Label PB	Regional PB	Smucker's	Welch's	PL Grape
Jif	**-2.17**	**-0.10**	**0.23**	-0.12	0.06	0.12
Private Label PB	**0.05**	**-1.90**	**0.01**	0.01	-0.04	0.05
Regional PB	**0.05**	**0.01**	**-2.24**	0.11	-0.01	-0.36
Smucker's	-0.54	-0.06	0.09	**-3.04**	**-0.03**	**0.04**
Welch's	0.11	0.14	-0.06	**0.37**	**-2.17**	**0.30**
Private Label Grape	0.37	-0.55	-0.65	**0.55**	**0.00**	**-1.54**

Bold type indicates statistically significant at least at the 10% level.
In AIDS models, **bold** type only indicates signicant coefficient at the bottom level regressions. It does reflect whether the elasticity itself is different from zero.
Authors' estimate based in part on Information Resources, Inc. InfoScan Reviews data.

Table F: Pre-Merger Implied Marginal Costs

Brand	Linear	CE	2-level AIDS	3-level AIDS
Jif	147.7	89.0	90.4	76.9
Private Label PB	96.3	56.2	70.7	72.0
Regional PB	82.9	69.8	104.2	87.7
Smucker's	109.5	87.1	95.6	87.7
Welch's	100.8	65.0	72.9	63.1
Private Label Grape	89.7	96.8	94.5	43.4

Authors' estimate based in part on Information Resources, Inc. InfoScan Reviews data.

Table G: Actual and Predicted Price Increases

Brand	Actual	Linear	CE	2-level AIDS	3-level AIDS
Jif	0.4%	-0.4%	0.8%	0.6%	3.9%
Private Label PB	2.7%	-0.1%	-0.1%	0.0%	0.9%
Regional PB	1.0%	-0.1%	0.0%	-0.1%	0.3%
Smucker's	8.4%	0.0%	-11.6%	-2.6%	5.2%
Welch's	1.9%	0.1%	0.0%	-0.2%	0.8%
Private Label Grape	0.9%	0.0%	-2.1%	-0.4%	1.1%

Authors' estimate based in part on Information Resources, Inc. InfoScan Reviews data.

Table H: Percentage Increase in Implied Marginal Costs Post-Merger

Brand	Linear	CE	2-level AIDS	3-level AIDS
Jif	7%	4%	16%	13%
Private Label PB	-50%	38%	19%	-14%
Regional PB	81%	26%	-2%	6%
Smucker's	-3%	67%	17%	-9%
Welch's	-3%	1%	-7%	-9%
Private Label Grape	-52%	-71%	-73%	-9%

Authors' estimate based in part on Information Resources, Inc. InfoScan Reviews data.