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Abstract

This paper evaluates the e cacy of a structural model of oligopoly commonly used for merger review. Using only pre-merger data, AIDS, linear, and logit demand systems are estimated using standard techniques. A static Bertrand oligopoly model is used to simulate the price e-1.55896(e)4.458(e)4.4411TJ 284.640Td [.)-613.223(T)-3.78125(h)-5.44629(e

mergers and challenge mergers that are predicted to increase price[1]. Static oligopoly

in an increase in consumer prices. Thus, the merger simulations underestimate the price
impact of a marginally anticompetitive merger and substantially overestimate the price

antitrust agencies must make *ex ante* predictions about how a change in market structure will a ect market prices and hence impact consumer welfare.

proxy for the "but-for" state of the world and then estimate the price effect of the merger using a difference-in-difference estimator. The largest limitation on *ex post* studies of the price effects of mergers is data availability. Most existing studies are in three historically regulated industries where pricing data are publicly available: airlines, banking, and hospitals.[3]

On net, this literature suggests that the government may not be aggressive enough in challenging mergers. Unfortunately, the retrospective literature does not offer specific guidance as how to improve government enforcement. The mergers analyzed in this literature span a great deal of time and many disparate industries (hospitals, consumer products, banking, gasoline, airlines, academic publishing) where specific institutional characteristics play an important role in understanding the competitive effects of mergers. Other than demonstrating that mergers in concentrated markets can increase prices, this literature does not identify which "key" factors cause some mergers to result in increased consumer prices.

Given the limitations of retrospective evidence, economists have attempted to build economic models to simulate the price effects of mergers. Baker and Bresnahan (1985) was the first paper that proposed a general framework in which to explicitly predict the price effects of mergers. Rather than estimating a full demand system, Baker and Bresnahan estimate the merging firms' joint and individual residual demand curves to determine which hypothetical mergers were likely to be anticompetitive in the brewing industry. Subsequent work developed techniques that allowed researchers to explicitly estimate the entire demand system and then use these demand estimates to simulate moving from one static Bertrand equilibrium to another with one fewer firm. Several papers, including work by Hausman, L,.

program with AIDS demand at the bottom level to simulate several hypothetical mergers. Nevo uses the Berry, Levinsohn and Pakes (1995) model of demand to simulate both hypothetical mergers and actual mergers in the ready-to-eat cereal industry. Bass, Huang and Rojas (2008) examine the impact of misspecification of the demand system on merger simulations using a series of Monte Carlo experiments. They find that the logit demand model generates the best predictions of merger e ects acros

study of mergers in airline industry are the most similar evaluation studies to ours. While the focus Nevo's paper is in applying the BLP model to a consumer goods market rather than the formal evaluation of structural modeling, Nevo finds that his merger simulations are close to actual price changes for the two mergers in the ready-to-eat cereal industry

government decides which of the two antitrust agencies (the Federal Trade Commission or Department of Justice) will investigate the merger and whether to require the parties to submit additional information about the merger.[7] If the merger appears to be problematic, the government issues a "second request" to the parties. This second request is essentially a detailed subpoena asking for all documentary information the parties have that may be relevant to determining the effects of the merger on the marketplace.[8] The second request typically asks for all documents describing the following: competition between market participants, the cost and requirements to enter the market, information about the products the merging parties view as substitutes, and any claims that a merged company would operate more efficiently. The government's investigat

merging parties' products), define a geographic market (the narrowest area in which anti-competitive effects could occur, for the nationally distributed branded consumer products mergers like those studied here this is typically the entire U.S.), analyze likely competitive effects, analyze claims that the merged firms will operate more efficiently leading to lower prices, and determine if entry into the market would be likely and sufficient to maintain competition.

The Guidelines discuss two types of anticompetitive effects: coordinated effects and unilateral effects.[11] The investigation of possible coordinated anticompetitive effects focuses on how a specific transaction will increase the likelihood of collusion, either tacit or explicit, following the merger. Stigler's (1964) early article describing market characteristics that facilitate collusion still highlights the key issues.[12]

The investigation of possible unilateral anticompetitive effects focuses on how a merger changes the merged firm's incentives to price its products. If the merging firms' products are close substitutes, then the merged firm will have an incentive to increase the price of its products above pre-merger levels because it internalizes some of the substitution following the price increase. The workhorse model used in antitrust analysis assumes that the firms sell differentiated products and engage in Bertrand price competition.[13] Assuming the economist knows the parameters of the demand system, information sufficient to calculate own- and cross-price elasticities, it is straightforward to simulate the price effects of a merger, or to determine what level of efficiencies (decreases in marginal cost due to the increased efficiency of the merged firms) are required to maintain pre-merger prices.[14] Since the simulation approach focuses entirely on price competition and ignores

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[11]These phrases are used to describe concepts that are similar to cooperative and non-cooperative games.

[12]There has been considerable subsequent theoretical work, such as Green and Porter (1984), as well as empirical work that is formal, Porter and Zona (1993), and descriptive, Ashenfelter and Grady (2005). Block and Feinstein (1986), Newmark (1988), and Sproul (1993) each have examined a number of collusion cases to more generally evaluate the effectiveness of U.S. prosecution of cartels.

[13]See, for example, Deneckere and Davidson (1985).

[14]Many useful analyses of these models are the subject of confidentiality orders because they were produced as a part of on-going litigation. Published examples that show how these models work include

issues of product repositioning and advertising, which can be very important in branded consumer products markets, it is our impression that many antitrust practitioners take the predictions from merger simulations as upper bounds on the likely price effects of a merger. A key advantage of the merger simulation approach is it obviates the need to define markets. The merger simulation provides an estimate of the key question of concern to the government: will the merger increase price and, if so,

versus $1.00-$1.75 a quart). Because synthetics and semi-synthetics represented a small niche in the motor oil market and because neither Pennzoil nor Quaker State was very successful in this niche at the time of the merger, we focus on conventional motor oils in this study.

Within the conventional motor oil market there were substantial differences (30%-50%) in the prices and perceived quality of the five "premium" motor oils (Castrol, Havoline, Pennzoil, Quaker State, and Valvoline) sold in the U.S. relative to the price and quality of the large number of regular brands (typically private label or branded with a gasoline company name, e.g., Exxon or Chevron). This is consistent with a model of price competition amongst firms selling differentiated products.

The oil merger represented the combination of the largest brand, Pennzoil, with one of its five competitors, Quaker State. However, competition from different types of motor oil (semi-synthetics and synthetics), a large number of generic or gasoline brand motor oils, and a general trend away from do-it-yourself oil changes to quick-lube facilities would likely mitigate the potential anticompetitive effects of the merger. Possibly for these reasons, the merger was approved without any modification required by the antitrust agencies.

Aurora Foods was a holding company that owned a number of popular brands of food products, including Duncan Hines cake mix, Mrs. Pauls fish products, Lenders bagels, and Celeste pizzas. In July 1997, Aurora, which owned the Mrs. Butterworth brand of maple flavored breakfast syrup, purchased the Log Cabin syrup brand from Kraft for 222 million dollars. At the time of the acquisition, there were three major brands of breakfast syrup (Aunt Jemima, Log Cabin, and Mrs. Butterworth), a brand with strong regional distribution (Hungry Jack), and a number of small regional brands and private label brands. On the surface, this merger would appear to be problematic as it combined two of the three major branded products in one company. However, there were many

substitutes for these products at lower price levels (private label syrups), at higher price levels (real maple syrups), and among other types of flavorings for breakfast foods, e.g., jams and jellies. According to the trade press, part of the justification for the transaction was that Log Cabin did not fit well into Kraft's food portfolio, and that Aurora (which purchased and marketed established brands of food products) could more e ectively sell the product. We have not been able to locate any public discussion of either of the antitrust agencies investigating the merger.

2.2 Data

The data used in this study are scanner data, and were obtained from Information Resources Incorporated. These data include weekly total revenue and unit sales for each Universal Product Code (UPC) in each industry. For example, in examining the motor oil market, we received data on each package size of Pennzoil Motor oil sold (i.e., data broken out separately for single quarts and five quart packages) and each "weight" of motor oil (10W30, 10W40 and 5W30). IRI collects this data from each of the major retail channels of distribution for a sample of stores in a region, and then obtains a measure of sales in the metropolitan area by aggregating the store level data to the region level using

)32.06S.1643(o)-2.4.86191)0.971648(g)-2.26309(h2.26309(0Td[(M)3.87434(o)-2.2646948(e)0.646948(i)0.970422(.)0.970422

5W30) and aggregated over weight to create a single measure of units sold and revenue for each observation defined by brand, region, and week. We did this for each of the brands shown in Table 1. We undertook a similar aggregation for the pancake syrup where the aggregation was over package size. As is standard in estimating consumer demand using retail scanner data (see, e.g., Nevo (2001) and Rojas (2008), we calculate price as average revenue; i.e., sales revenue divided by volume.

3   Demand Systems and Merger Simulation

Merger simulation requires a functional form assumption for demand, demand parameter estimates, an assumption on cost functions, and the assumption that firms play a static pricing game. After demand is estimated, the Bertrand pricing equations are calibrated trge6alib,e

regions, X_{nt} is total sales in region n at time t and is deflated by a fixed weight price index P_{nt} where the weights are $w_{jn} = \frac{1}{T} \sum_{t=1}^{T} s_{jnt}$ as in Hausman and Leonard (2005), and ϵ_{int} is an error term. The M_t are month dummies that capture monthly seasonal effects.

The restrictions of consumer theory are often imposed in order to reduce the number of parameters in the AID system. "Adding up" is automatically imposed because revenue shares must sum to 1 within a market. Because of this, brand J's share equation is dropped during the estimation and recovered through the adding-up restrictions $\gamma_{Ji} = -\sum_{j=1}^{J-1} \gamma_{ji}$ and $\beta_J = -\sum_{j=1}^{J-1} \beta_j$. The consumer does not display money illusion if and only if and for all j, $\sum_{k=1}^{J} \gamma_{jk} = 0$. This restriction reduces the number of parameters by $J - 1$. The cross-price derivatives of the implicit underlying Hicksian demands are symmetric if and only if $\gamma_{ij} = \gamma_{ji}$. This further reduces the number of parameters by $\frac{(J-1)*(J-2)}{2}$. Both of these restrictions are rejected at $p < .05$ in both of our datasets and they are left unimposed throughout. Rejecting these restrictions is typical when estimating demand on aggregate data (see Deaton .1643(o)-2.266.28-22.08Td7.637(d)1.942837(d)1.942214726309(u)1h and

where $s_i(p_1, ..., p_J)$ is the market share of sales belonging to product i, and $\epsilon_{j,i}(p_1, ..., p_J)$ is the elasticity of brand j with respect to the price of brand i. These first order conditions for all J brands in the market and the Nash-Bertrand equilibrium is the set of prices that solve the complete set of J first order conditions.

The J first-order conditions are linear in the marginal costs $\{mc_j\}_{j=1}^{J}$. Using pre-merger prices and shares and demand estimated on pre-merger data, these equations are solved for marginal costs. This procedure requires knowledge of exactly which values of price and revenue share are representative of the pre-merger equilibrium. Average pre-merger prices and shares are used in this paper. Because the share equations vary across

has the advantage of yielding an analytical solution to the post-merger equilibrium. The system is specified as:

$$q_{int} = \alpha_{in} + \beta Y_{nt} + \sum_{k=1}^{J} \gamma_k p_{knt} + \sum_{m=1}^{11} \delta_m D_m M_t + \varepsilon_{int} \tag{5}$$

where q_{int} is the volume per capita of brand i in region n at time t and Y_{nt} is per capita expenditures in region n at time t. Following Werden (1997), we stack the J demand equations in matrix notation as $q = a - Bp$ where B is a J by J vector of slope coefficients and a contains intercepts and demand shifters. Define D with elements $d_{ij} = bm$

As it is not clear what observable characteristics of motor oils and breakfast syrups capture the determinants of utility, we decompose ξ_{int} into a brand specific component and a market specific deviation from that mean $\xi_i + \Delta\xi_{int}$. The mean utility of the outside good, indexed by 0, is normalized to 0. The brand fixed-effects ξ_i capture all product characteristics that do not vary across markets defined by region and time. Motor oils and syrups do not display product characteristics that vary acr

be one serving per person per month. We demonstrate the sensitivity to assumptions on total market size by later using four different measures of potential market size in both datasets.

3.1 Identification of Demand

In most market models price is jointly determined by supply and demand. In models of demand for differentiated products like the unconstrained AID or linear demand systems each of the J demand equations has $J + 1$ endogenous regressors: J prices and an expenditure term. It is extremely difficult to find J instrumental variables reported at a useful frequency. For example, while crude oil is one input into the production of motor oil it is not clear what 7 other cost shifters available at the weekly frequency might be used as instruments. In light of this difficulty Hausman, Leonard and Zona (1994) and others have used two different approaches that use the structure of typical retail scanner datasets to create instruments. These approaches are described here.

As is typical of scanner data, we have observations of many products over different regions and time periods in both of our datasets. While somewhat controversial, the first approach uses prices in other regions as instruments.[16] Prices in other regions are valid instruments under two conditions. The first assumption is that prices are partially driven by a common marginal cost component. The second assumption is that demand shocks are independent across regions.[17] The first stage for each of the endogenous prices in the AID system is given by:

$$\ln p_{int} = \alpha_{in} + \log\left(\frac{\bar{X}_{\neg nt}}{P_{\neg nt}}\right) + \sum_{j=1}^{J} \beta_{ij} \log(\bar{p}_{j\neg nt}) + \sum_{m=1}^{11} \gamma_m^{dd} M_t + \epsilon_{int} \tag{9}$$

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[1] These instruments have been used by Hausman, Leonard and Zona (1994), Hausman and Leonard (2002), and Hausman and Leonard (2005) amongst others. While the problem is easier in discrete choice models because there are fewer endogenous regressors (only one price in flat logit), a similar approach is taken by Nevo (2000) who estimates logit and BLP demand.

[1] This assumption has been criticized by Bresnahan (1997) who provides several reasons why demand shocks might be correlated across regions.

where $\log(\bar{\mathbf{p}}_{j\neg}$

techniques. The first uses a difference-in-difference estimator where the price effect of the merger is identified as the change in the price of a branded product relative to private label products. We also estimate the price effect using a difference estimator; i.e., the absolute difference in price pre and post-merger. This approach has also been taken by Vita and Sacher (2001) and Peters (2006). We then summarize the results from our merger simulations. The remainder of the section examines the most likely explanations for the differences in the simulated and actual price effects.

We use both pre and post-merger data to estimate the actual price effects in two different ways. First, we estimate a difference in difference model using private label products as a control group. The following equation is fitted to the data with OLS separately for each brand i:

$$
\log(p_{int}) = \gamma_{in}^{dd} + \delta^{dd} PostMerger_t + \beta^{dd} Branded_i * PostMerger_t + \sum_{m=1}^{11} \zeta_m^{dd}
$$

"di erence" estimator. The specification is given by:

$$\log(\mathsf{p}_{\mathrm{int}}) = \quad^{\mathsf{d}}_{\mathrm{in}} + \quad^{\mathsf{d}}\mathsf{PostMerger}_t + \sum_{m=1}^{11} \quad^{\mathsf{d}}_{\mathsf{m}}\mathsf{M}_t + \quad^{\mathsf{d}}_{\mathrm{int}} \qquad (11)$$

Columns 1 and 2 of Table 2 present the actual price e ects of the motor oil and syrup mergers calculated with two di erent methods. The merging firms' brands are in bold font. Standard errors clustered on time are in parentheses. Column 1 presents di erence-in-di erence estimates of the price e ects where the control group includes private label products. Column 2 drops the control group and presents before and after di erence estimates.

The motor oil merger had moderate but statistically significant price e ects. Prices increased after the merger by 8 percent for Quaker State motor oil after the merger relative to private label prices and this result is significant at the .01 level. The before and after comparison gave a 6 percent increase, implying that private label prices increased by roughly 2 percent after the merger. Pennzoil had a smaller price increase of 4 percent relative to the change in private label products and 2 percent relative to Pennzoil's own pre-merger price. The syrup merger, despite reducing the number of nationally branded products from three to two, had no significant price e ect.

Columns 3 through 8 of Table 2 present the simulated price e ects calculated on pre-merger data with AIDS, linear, and logit demand each estimated by OLS and the instrumental variable technique described in the previous section. We present 90 percent confidence intervals instead of standard errors because the sampling distribution of the simulated price e ects is not normal. Figure 1 presents QQ plots for the simulated price changes from the motor oil merger using AIDS estimated by 2SLS with average prices in other regions as instruments.[18] These figures plot the quantiles of the simulated price

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[1] Wolpin (2007) points out that structural modeling inevitably requires some specification search because the model parameters need to be of certain values. In the merger simulation literature, the model is predicated on estimated demand parameters implying own-price elasticities that are less than -1 and

Figure 1: QQ Plots of Sampling Distribution of Simulated Percentage Price Changes: Oil Merger with AIDS demand Estimated by 2SLS
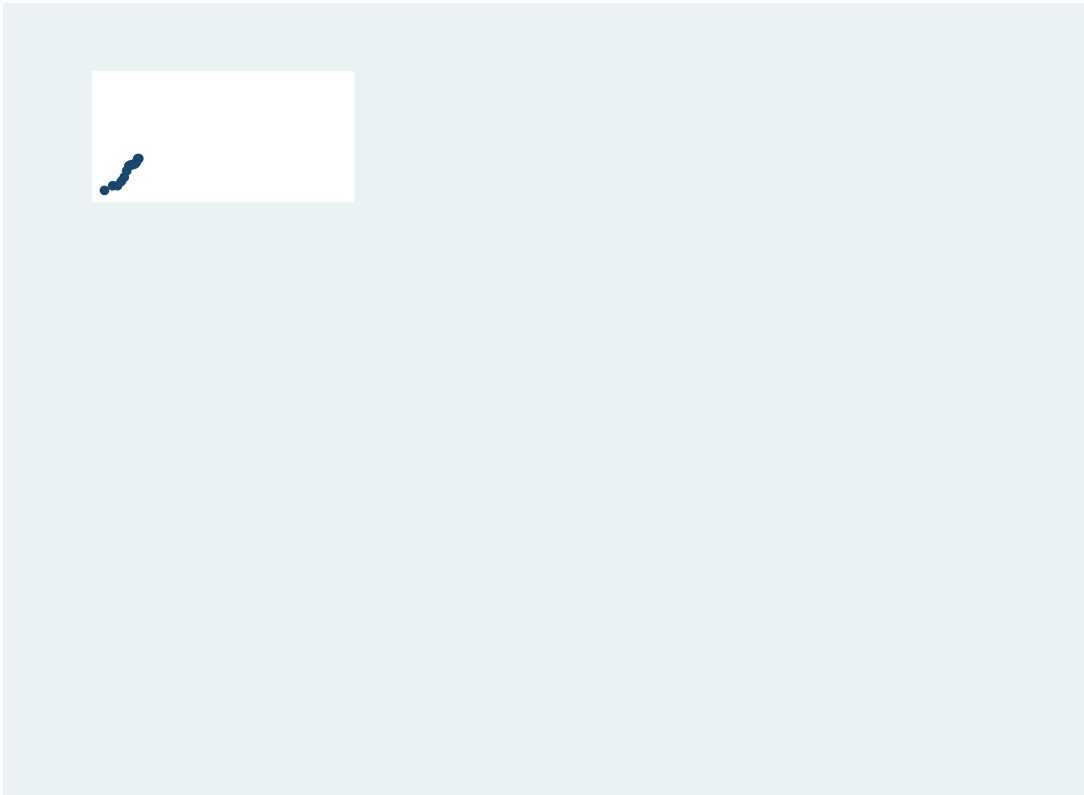
extremely wide confidence intervals. Because the underlying demand parameter estimates calculated with instrumental variables are often of sign inconsistent with these products being substitutes, it is unlikely that a researcher would use them to simulate a merger. This is the cause of the extremely large and sometimes negative price effects resulting from demand estimated with IV. The reason for the imprecise IV estimates is described below in our discussion of the demand estimates.

While the simulated and (to a much lesser extent) the estimated price changes vary across specification, the key findings are clear. The motor oil merger led to a small but significant price increase while the syrup merger left consumer prices unchanged. The simulated price effects reverse the rank order of the estimated price effect of the mergers. The syrup merger is predicted to have a significant (in some specifications a quite large) price increase, while the motor oil merger is predicted to have no or a small price increase. A policy maker relying solely on the results of the merger simulations would have made the

the data than the AID and linear systems. The OLS and IV results are similar both in terms of elasticities and simulated price e ects.

Simulating a merger requires that demand, costs, and the nature of competition do not change after the mergers occur. While not possible durin

prices one plus the percentage price e ects in column 2 of Table 2.

Table 5 shows that marginal cost decreases are necessary to equate simulated and actual prices when the simulations were larger and increases are necessary when the actuals are larger. The necessary marginal cost changes are implausibly large given the technology of artificial syrup and motor oil production. "Breakfast syrup" essentially has two ingredients: corn syrup and an artificial flavoring called sotolon. The marginal cost of production is essentially the marginal cost of these two i

on the "potential market size" in order to define the market share of the outside good (see, for example, Berry, Levinsohn and Pakes (1995), Nevo (2000), and Bass, Huang and Rojas (2008)). We assumed that the potential market size for

that is, these mergers might have resulted in small price increases.

The results of the merger simulations are mixed. Some of the simulations for the motor oil merger were very close to the actual observed price effects. However, the merger simulations for the syrup merger always over estimate the price effects of the merger, often substantially. Thus, the merger simulations generated price changes that were of the wrong rank order. If simulations were the only basis of antitrust decision making and policy makers attempted to block mergers expected to generate price changes larger than 5 percent, the models would have led to exactly the wrong conclusion in most specifications and both cases: challenge the syrup merger and pass the oil merger. We have been unable to identify an obvious source of bias in the merger simulations. Neither changes in demand or cost appear to be the source of the inaccuracies. While some of the demand estimates generated implausible elasticities and thus unexpectedly implausible simulated price changes, many of the estimated demand systems generate plausible elasticities still result in inaccurate simulations. There was no evidence in the demand estimations that would lead a researcher relying solely on pre-merger data to believe that merger simulations using these demand estimates would lead to incorrect merger simulations.

We do not want to overstate our conclusions regarding the efficacy of merger simulation. After all, we have studied only two mergers. However, our conclusions are similar to the most directly comparable study, Peters (2006), which analyzed the ability of merger simulation techniques to accurately predict the price effects of five mergers in the airline industry. In Peter's study each of the mergers resulted in a large price increase, between 7% and 30%. While each of his merger simulations predicted a significant price increase (a minimum of $3\% - 7\%$ depending on the demand specification), his simulations reversed the rank order of observed price effects. In his study the merger predicted to generate the largest price increase (Northwest/Republic) yielded the smallest observed price increase. Similarly the merger predicted to generate one of the smallest price increases (Continen-

tal/People's Express) generated the largest price increase.[20] Thus, like in our study, the
simulations generate relatively small price increases when the actual e ects were relatively

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Table 1: Pre-Merger Descriptive Statistics

Products	Price	Volume Share

Table 3: AIDS First Stage Regression Diagnostics

Endogenous Regressor	First Stage Robust Partial F-Stat	Shea's Partial R-squared
Pennzoil/Quaker State Merger		
$\log(\frac{X}{P})$	41.28	0.026
$\log(p_{Castrol\ TX})$	53.60	0.060
$\log(p_{HavolineF3})$	103.15	0.122
$\log(p_{Mobil})$	395.48	0.104
$\log(p_{Pennzoil})$	23.83	0.039
$\log(p_{PrivateLabel})$	26.19	0.031
$\log(p_{QuakerState})$	85.51	0.173
$\log(p_{ValvolineMV})$	33.33	0.120
Log Cabin/Mrs Butterworth Merger		
$\log(\frac{X}{P})$	23.83	0.027
$\log(p_{AuntJemima})$	1.68	0.002
$\log(p_{HungryJack})$	3.41	0.006
$\log(p_{LogCabin})$	3.41	0.006
$\log(p_{MrsButterworth})$	3.56	0.010
$\log(p_{PrivateLabel})$	2.28	0.006

Notes: **Authors' own calculations on IRI data. Oil statistics calculated on weekly data over 10 regions from 1/5/1997 until 11/29/1998. Oil prices are per quart. Syrup statistics calculated on weekly data over 49 regions from 10/27/1996 until 6/28/1997. Regions are listed in the appendix.**

Table 4: Estimated and Simulated Percentage Price Effects of Motor Oil and Syrup Merger Using Post-Merger Data

	Estimated Price Changes

Table 5: Percentage Marginal Cost Changes Required to Equate Actual and Simulated Post-Merger Prices

Products	AIDS		Linear		Logit	
	OLS	IV	OLS	IV	OLS	IV
Pennzoil/Quaker State Merger						
Pennzoil	-1.27	-75.25	2.67	5.37	2.99	2.78
Quaker State	-5.14	-67.17	-0.03	-1.50	9.01	8.36
Log Cabin/Mrs Butterworth Merger						
Log Cabin	-22.44	315.06	1.33	153.02	-10.02	-9.29
Mrs Butterworth	-23.81	599.74	-11.74	250.25	-18.46	-17.63

Notes: Authors' own calculations on IRI data. Actual price changes calculated with "di erence" estimator. Oil statistics calculated on weekly data over 10 regions from 1/5/1997 until 11/29/1998. Syrup statistics calculated on weekly data over 49 regions from 10/27/1996 until 6/28/1997. Regions are listed in the appendix.

Table 6: Simulated Percentage Price Changes with Di erent Overall Elasticities of De-mand with OLS AIDS at Bottom Stage

Products	e = −2	e = −1.67	e = −1.33	e = −1
Pennzoil/Quaker State Merger				
Pennzoil	0.08	0.53	1.27	2.59
	(-1.50, 1.15)	(-0.92, 1.77)	(-0.28, 3.26)	(0.08, 5.68)
Quaker State	2.14	2.92	4.32	7.49
	(-0.22, 4.46)	(0.83, 5.55)	(1.64, 8.20)	(2.81, 13.58)
	e = −2	e = −1.67	e = −1.33	e = −1
Log Cabin/Mrs Butterworth Merger				
Log Cabin	6.47	11.18	16.99	23.50
	(2.17, 12.37)	(5.04, 18.09)	(11.33, 29.16)	(14.84, 36.24)
Mrs Butterworth	6.31	10.39	15.45	21.58
	(1.97, 11.03)	(5.29, 16.64)	(9.72, 24.35)	(12.95, 34.53)

Notes: Authors' own calculations on IRI data. e is the elasticity of demand for aggregate oil or syrup corresponding to the top level of a two-stage budgeting pr())-1176.96(6)-5.89017())-1176.96(()3.4505(t)27.5365(w)23.6077

A Demand Elasticities for Oil and Syrup by Estimation Strategy

Table 1: Oil Elasticities, AIDS Model Estimated with OLS

Table 2: Oil Elasticities, AIDS Model Estimated with 2SLS

	Castrol GTX	Havoline	Mobil	Pennzoil	Private Label	Quaker State	Valvoline
CastrolGTX	-5.86	0.08	0.03	-0.45	0.06	0.36	0.03
	(0.38)	(0.28)	(0.48)	(0.39)	(1.01)	(0.21)	(0.29)
Havoline	-1.14	-6.74	2.10	-1.64	-6.62	-1.12	0.38
	(0.93)	(0.65)	(1.18)	(0.94)	(2.41)	(0.52)	(0.74)
Mobil	0.22	0.05	-8.73	-0.34	2.68	0.20	0.47
	(0.96)	(0.69)	(1.18)	(0.98)	(2.46)	(0.51)	(0.74)
Pennzoil	1.54	0.85	0.43	-1.76	1.00	0.94	0.92
	(0.23)	(0.16)	(0.28)	(0.23)	(0.58)	(0.13)	(0.18)
PrivateLabel	0.42	0.37	1.02	0.95	-3.49	0.35	0.45
	(1.24)	(0.86)	(1.55)	(1.26)	(3.15)	(0.66)	(0.96)
QuakerState	2.88	-0.77	3.53	2.99	-5.21	-5.30	0.31
	(0.78)	(0.57)	(0.99)	(0.80)	(2.01)	(0.42)	(0.61)
Valvoline	1.42	1.59	-0.79	1.07	4.64	0.67	-4.15
	(1.31)	(0.96)	(1.64)	(1.34)	(3.41)	(0.72)	(1.03)

Notes: Authors' own calculations on IRI data. Entry in row i and column j is the elasticity of brand i with respect to the price of brand j evaluated at grand means. Demand estimated on weekly data over 10 regions from 10/27/1996 until 11/29/1998. Regions are listed in the appendix. Standard errors in parentheses. Standard errors for elasticities were constructed by drawing from asymptotic distribution of demand parameters 1000 times. The estimator for the variance covariance matrix of the demand parameters is Newey-West with truncation parameter of 4. Demand share equations include month and region-brand fixed e ects. Instruments are average prices across other regions.

Table 3: Oil Elasticities, Linear Model Estimated with OLS

	Castrol GTX	Havoline	Mobil	Pennzoil	Private Label	Quaker State	Valvoline
CastrolGTX	-4.27	0.62	0.36	0.61	0.10	0.33	0.80
	(0.31)	(0.15)	(0.17)	(0.13)	(0.15)	(0.28)	(0.14)
Havoline	0.57	-4.48	0.37	1.36	-0.26	0.55	0.63
	(0.35)	(0.54)	(0.35)	(0.42)	(0.30)	(0.33)	(0.26)
Mobil	0.34	0.41	-6.81	0.81	-0.85	0.37	0.39
	(0.20)	(0.19)	(0.36)	(0.19)	(0.22)	(0.18)	(0.16)
Pennzoil	0.82	0.40	0.00	-4.47	0.41	0.30	0.24
	(0.15)	(0.11)	(0.14)	(0.59)	(0.14)	(0.12)	(0.11)
PrivateLabel	0.18	0.16	0.17	0.36	-0.37	-0.05	0.09
	(0.14)	(0.09)	(0.13)	(0.17)	(0.15)	(0.09)	(0.10)
QuakerState							

Table 4: Oil Elasticities, Linear Model Estimated with 2SLS

Table 5: Oil Elasticities, Logit Model Estimated with OLS

	Castrol GTX	Havoline	Mobil	Pennzoil	Private Label	Quaker State	Valvoline
CastrolGTX	-2.925	0.005	0.004	0.015	0.003	0.004	0.010
	(0.267)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Havoline	0.009	-2.512	0.004	0.015	0.003	0.004	0.010
	(0.001)	(0.223)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Mobil	0.009	0.005	-2.232	0.015	0.003	0.004	0.010
	(0.001)	(0.001)	(0.279)	(0.001)	(0.000)	(0.000)	(0.001)
Pennzoil	0.009	0.005	0.004	-2.855	0.003	0.004	0.010
	(0.001)	(0.001)	(0.000)	(0.261)	(0.000)	(0.000)	(0.001)
PrivateLabel	0.009	0.005	0.004	0.015	-1.971	0.004	0.010
	(0.001)	(0.001)	(0.000)	(0.001)	(0.180)	(0.000)	(0.001)
QuakerState	0.009	0.005	0.004	0.015	0.003	-2.815	0.010
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.257)	(0.001)
Valvoline	0.009	0.005	0.004	0.015	0.003	0.004	-2.814
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.257)

Notes: Authors' own calculations on IRI data. Entry in row i and column j 2u27 (n2539)-1.26 033587 54 7 74820 581 959 6 991

Table 6: Oil Elasticities, Logit Model Estimated with IV

	Castrol GTX	Havoline	Mobil	Pennzoil	Private Label	Quaker State	Valvoline
CastrolGTX	-3.444	0.006	0.004	0.018	0.004	0.005	0.012
	(0.364)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)
Havoline	0.010	-2.957	0.004	0.018	0.004	0.005	0.012
	(0.001)	(0.313)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)
Mobil	0.010	0.006	-2.628	0.018	0.004	0.005	0.012
	(0.001)	(0.001)	(0.278)	(0.002)	(0.000)	(0.001)	(0.001)
Pennzoil	0.010	0.006	0.004	-3.361	0.004	0.005	0.012
	(0.001)	(0.001)	(0.000)	(0.356)	(0.000)	(0.001)	(0.001)
PrivateLabel	0.010	0.006	0.004	0.018	-2.321	0.005	0.012
	(0.001)	(0.001)	(0.000)	(0.002)	(0.246)	(0.001)	(0.001)
QuakerState	0.010	0.006	0.004	0.018	0.004	-3.314	0.012
	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.351)	(0.001)
Valvoline	0.010	0.006	0.004	0.018	0.004	0.005	-3.312
	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.351)

Notes: Authors' own calculations on IRI data. Entry in row i and column j is the elasticity of brand i with respect to the price of brand j. Standard errors in parentheses. Standard errors for elasticities were constructed by drawing from asymptotic distribution of demand parameters 1000 times. The

Table 7: Syrup Elasticities, AIDS Model Estimated with OLS

	Aunt Jemima	Hungry Jack	Log Cabin	Mrs. Butterworth	Private Label
AuntJemima					

Table 8: Syrup Elasticities, AIDS Model Estimated with 2SLS

Table 10: Syrup Elasticities, Linear Model Estimated with 2SLS

	Aunt Jemima	Hungry Jack	Log Cabin	Mrs. Butterworth	Private Label
AuntJemima	-15.78	0.72	-2.39	1.07	-0.27
	(9.49)	(25.36)	(4.65)	(6.18)	(7.67)
HungryJack	-0.12	-14.13	-5.70	-2.06	-4.40
	(2.23)	(5.28)	(1.13)	(1.86)	(2.31)
LogCabin	10.34	-3.56	-6.29	3.94	-3.95
	(9.07)	(20.73)	(4.23)	(5.67)	(6.69)
MrsButterworth	3.36	4.02	7.00	-3.67	4.81
	(4.39)	(11.97)	(2.47)	(3.54)	(4.20)
PrivateLabel	0.89	-1.01	1.90	1.76	-4.56
	(1.17)	(5.22)	(1.11)	(1.17)	(1.50)

Notes: Authors' own calculations on IRI data. Entry in row i and column j is the elasticity of brand i with respect to the price of brand j. Standard errors in parentheses. Standard errors for elasticities were constructed by drawing from asymptotic distribution of demand parameters 1000 times. The estimator for the variance covariance matrix of the demand parameters is Newey-West with truncation nkeppaudhiteDemanDehatidnestimdate720068-t4KT50hate)-3v82982(agi3.74ilotd(on-5.82332(n)25.575(t)3.48504(d)-3d74105(b)1.485

Table 11: Syrup Elasticities, Logit Model Estimated with OLS

	Aunt Jemima	Hungry Jack	Log Cabin	Mrs. Butterworth	Private Label
AuntJemima	-1.98	0.41	0.24	0.35	0.33
	(0.16)	(0.03)	(0.02)	(0.03)	(0.03)
Hungry					

Table 12: Syrup Elasticities, Logit Model Estimated with 2SLS

	Aunt Jemima	Hungry Jack	Log Cabin	Mrs. Butterworth	Private Label
AuntJemima	-2.02	0.42	0.25	0.36	0.33
	(0.18)	(0.04)	(0.02)	(0.03)	(0.03)
HungryHu					

B IRI Scanner Data Regions for Motor Oil and Breakfast Syrup

The motor oil data came from IRI's mass merchandiser channel and included the following Metropolitan Statistical Areas:

1. Chicago

2. Dallas/Fort Worth

3. Houston

4. Los Angeles

5. Minneapolis

6. New York, New York

7. Phoenix

8. San Diego

9. San Francisco/Oakland

10. Baltimore/Washington

The syrup data came from IRI's food channel and included the following Metropolitan Statistical Areas:

1. Atlanta

2. Birmingham

3. Bu alo

4. Charlotte

5. Chicago

6. Cincinnati

7. Cleveland

8. Columbus

9. Dallas/Fort Worth

10. Denver

11. Des Moines

12. Detroit

13. Grand Rapids

14. Green Bay

15. Harrisburg

16. Houston

17. Indianapolis

18. Jacksonville

19. Kansas City

20. Knoxville

21. Little Rock

22. Louisville

23. Memphis

24. Miami

25. Milwaukee

26. Minneapolis

27. Mississippi

28. New Orleans

29. Nashville

30. Oklahoma City

31. Omaha

32. Orlando

33. Peoria

34. Philadelphia

35. Phoenix

36. Pittsburgh

37. Portland

38. Raleigh

39. Richmond

40. Roanoke

41. San Antonio

42. South Carolina

43. Seattle

44. Saint Louis

45. Syracuse

46. Tampa

47. Toledo

48. Baltimore/Washington

49. West Texas