Using Mergers to Test a Model of Oligopoly

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Abstract

This paper evaluates the efficacy 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 effects of two competitively problematic mergers. Using both pre and post-merger data, the actual price effects of both mergers are calculated using difference-in-difference and difference estimators. One merger was marginally anticompetitive while the second was competitively benign. The simulated prices across the two mergers are of the wrong rank-order: the anticompetitive merger was predicted to have small price effects while the benign merger was typically simulated to have larger price effects. The simulated price changes are close to the actual price changes for the anticompetitive merger but are typically much larger than actual price changes for the benign merger. Shifts in demand after the mergers occurred explain only a small part of the difference between simulated and actual price changes. Implausibly large marginal cost changes (over 15%) are required to equate actual and simulated price effects.

Governments are frequently forced to make policy decisions that have important impacts on the evolution of markets. Often these decisions must be made with limited information and time. U.S. horizontal merger enforcement provides a classic example. Because it is extremely costly to break up consummated mergers, virtually all analysis of mergers is prospective: government regulators forecast the price effects of prospective

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mergers and challenge mergers that are predicted to increase price[1]. Static oligopoly models and demand estimates are often used to simulate how a merger affects product prices. This technique is known as "merger simulation". Despite the tremendous amount of public and private resources dedicated toward analyzing horizontal mergers, very little research has evaluated the efficacy of these forecasting tools. One way to do so is to compare the *ex ante* predicted prices of mergers to direct *ex post* estimates of the actual changes.

This paper does just that and thus proposes a framework for improving the credibility of economic modeling during merger review. We observe data before and after two consumer product mergers were consummated. These mergers are particularly well suited to this type of analysis. The mergers took place in mature consumer products industries involving well known products. The first merger combined the ownership of the Pennzoil and Quaker State brands of passenger car motor oil. The second was the purchase of Log Cabin breakfast syrup by the owner of the Mrs. Butterworth brand. Because both mergers took place in markets with relatively few brands, it is possible to estimate relatively unrestricted demand systems. Both mergers appeared likely to be anticompetitive ex ante: the affected products were likely close substitutes, the products' market shares were relatively large as was overall market concentration.

The paper compares direct estimates of the impact of these mergers on consumer prices to a range of simulated price changes that are estimated using pre-merger data. We simulate the merger using a Bertrand pricing model with AIDS, linear, and logit demand estimated using standard techniques. The simulated price changes for the motor oil merger were small, typically less than 5 percent, while the actual price effects were on the order of 4 to 8 percent. The simulated price increases for the breakfast syrup merger are relatively large, typically 5% to 20%, while the merger itself did not result

[1]See Baer (1997) for a discussion of the costs of retrospective antitrust policy towards horizontal mergers.

in an increase in consumer prices. Thus, the merger simulations underestimate the price impact of a marginally anticompetitive merger and substantially overestimate the price effects of a competitively benign merger. We next examine what might be the source of the bias in the estimated price effects. First we examine the quality of the demand estimates used as inputs in the oligopoly model. Most of the estimated demand systems imply elasticities that appear reasonable. While the demand curves change between the pre- and post-merger periods, this change in demand does not explain a large portion of the difference between simulated and actual prices. Our results also suggest that implausibly large changes in marginal costs post-merger, more than 15 percent, would be necessary to equate simulated and actual prices. These costs changes are not plausible given the production technology that generates both motor oil or breakfast syrup. We then explore the sensitivity of the simulations to various assumptions on how consumers substitute to the outside goods.

The rest of this paper is structured as follows. Section II provides a brief description of the literatures relevant to our paper. Section III provides a brief description of U.S. horizontal merger review and provides some institutional detail about the syrup and motor oil mergers we study. Section IV describes the demand systems and techniques we use to simulate the price effects of the mergers. Section V compares the simulated price changes to actual price changes and evaluates different explanations for their differences. Section VI concludes.

1 Using Economics to Inform Policy Decisions

The need to make *ex ante* predictions to inform policy is the essence of U.S. antitrust enforcement. Merger review is one of the largest components of the U.S. antitrust enforcement budget. On average, each year the two federal antitrust agencies conduct 75 major investigations of horizontal mergers. By necessity, merger review is speculative: the antitrust agencies must make *ex ante* predictions about how a change in market structure will affect market prices and hence impact consumer welfare. Typically, there is little in the way of retrospective evidence that can be used to directly estimate the price effects of a merger.[2] Lawyers and economists analyze data in the form of market shares, marketing plans, and opinions of market participants (customers and, perhaps surprisingly, executives in the merging and rival firms) to infer whether a merger will harm consumer welfare. Clearly, this kind of decision making is largely subjective. While regulators use economic models to inform their understanding of the likely competitive effects of a merger, they ultimately must use qualitative evidence to predict if the change in market structure will harm consumers.

How should the government develop evidence to determine which mergers it should block and allow? One approach is to study the price impact of previously consummated mergers to determine what characteristics tend to generate price increases, e.g., measures of market concentration, the difficultly of entry, or factors that would facilitate collusive behavior. Surprisingly, given the large number of horizontal mergers that take place each year, relatively few papers examine the price effects of mergers. Because of the importance of institutional factors in merger analysis (there is unlikely a single "effect of a merger" across industries), virtually all merger retrospectives analyze one or a small number of mergers in the same (or similar) industries. The typical study examines a merger that was likely marginal; i.e., appeared to have a significant likelihood of increasing consumer prices, and determines if prices rose following the merger. These papers use one of two approaches to identify the price effect of the merger. Some researchers explicitly build a model that forecasts what equilibrium prices would have been "but-for" the merger see, e.g., GAO(2004). The other approach is to identify a control market to

[2] In rare circumstances antitrust agencies can examine entry and exit behavior in a pre-merger period to infer relationships between price and competition. The most well known recent example of this took place in the FTC's successful challenge of the proposed Staples/Office Depot merger (see, e.g., Ashenfelter, Ashmore, Baker, Gleason and Hosken (2006).

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] This paper tests a widely used structural model of oligopoly by using it to simulate mergers and comparing the simulated price changes to actual price changes. To compute the directly measured actual price changes, we use a subset of the same data and identification strategy that Ashenfelter and Hosken (2008) use to estimate the impact of merger on the prices charged by merging firms in the breakfast syrup and motor oil industries. This paper extends their analysis by estimating the effect of mergers on the pricing decisions of rival firms. Other studies in this literature include Borenstein's (1990), Kim and Singal 's (1993), Werden, Joskow and Johnson's (1991), and Peters's (2006) studies of airline mergers, Vita and Sacher's (2001) study of a California hospital merger, and Prager and Hannan's (1998), Focarelli and Panetta's (2003), and Sapienza's (2002) studies of banking mergers.[4] The other major industry where the price effects of mergers have been examined is the petroleum industry, see GAO (2004), Hastings and Gilbert (2005), Hastings (2004), Taylor and Hosken (2007), and Simpson and Taylor (2008). Finally, Barton and Sherman (1984) studied two consummated mergers in the microfilm industry that were subsequently challenged by the FTC and McCabe (2002) studied mergers amongst publishers of academic journals. All but one of these studies finds some evidence of price increases following the mergers they study.[5]

[3]See Pautler (2003) and Weinberg (2008) for an extensive review of this literature.

[4]Prager and Hannan and Focarelli and Panneta study the interest rate consumers earn on deposits. Thus, other things equal, a higher interest rate benefits consumers. To parallel the discussion of other studies of how mergers affect consumer prices, we refer to an interest rate falling as a price increase.

[5]Simpson and Taylor do not find a price increase in their study. Taylor and Hosken find an increase in wholesale gasoline prices that is not passed-thru as an increase in retail prices. Sapienza finds prices fall in regions with small changes in market concentration (suggesting efficiencies dominate), but that large changes in concentration are associated with increased prices. Focarelli and Panetta conclude that the anticompetitive effects of the mergers they examined were dissipated after three years by large cost savings resulting in lower consumer prices.

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, Leonard and Zona (1994), Werden and Froeb (1994), Nevo (2000), Epstein and Rubinfeld (2001), and Molnar (2008) have used this method to demonstrate how various mergers would affect prices. These papers all assume that firms compete in prices in differentiated product markets, but differ in the assumed model of demand used in the merger simulations. At one extreme, specific functional forms for demand such as Logit (see Werden and Froeb) or AIDS (see Epstein and Rubinfeld) are restricted and then calibrated. At the other, demand is estimated, often with retail scanner data. Hausman Leonard and Zona use data from the brewing industry to estimate a three-stage budgeting 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 effects across the models; i.e., even when the "true" demand model is not logit the logit still gives reasonable predictions of the price effect of a merger. For a detailed survey of simulation methods in merger analysis see Werden and Froeb (2006).

The difficulty in the structural approach is in building a reasonable behavioral model to use for policy simulation. Determining the validity of a structural model by testing the assumptions imposed by theory is not terribly informative. Because any model is a simplification of reality, with enough data any structural model will be statistically rejected by the data. A far more compelling test is to evaluate the model based on its ability to predict economic outcomes out of sample. Probably the most well known application of this approach was McFadden's (1977) evaluation of the logit random utility model in predicting consumers' transportation choices in the development of the Bay Area Rapid Transit system. More recently, a number of studies in labor and development economics have evaluated structural models by examining the model's ability to predict behavior on a data set not used in estimation. Todd and Wolpin (2006), Lise, Seitz and Smith (2005), and Kabowski and Townsend (2007) have taken advantage of a number of major policy experiment to validate behavioral models; i.e., using data from before the experiment to estimate the behavioral model and evaluating the model using data on the outcome of the experiment. However, because true experiments are very rare in economic applications, other out of sample approaches have been used. Keane and Wolpin (2007), for example, test a dynamic model of women's education, marriage, welfare, work, fertility decisions using a "hold out" sample build and estimate. The model is estimated using a sample from high welfare benefit states and evaluated using data from low welfare benefit states. All of these studies conclude that their modeling approaches are useful in predicting behavior. While not perfect, the predictions are close enough to the observed values to give policy makers comfort in using predictions from these models to inform policy.

Within industrial organization there have been two approaches to using out-of-sample predictions to test structural models. The first, Genesove and Mullin (1998), Clay and Troesken (2003), and Kim and Knittel (2006), test if indirect techniques of estimating marginal costs match up with direct measures of marginal cost.[6] The findings of this literature are somewhat mixed. Genesove and Mullin find the two measures of costs are close for more competitive modes of conduct, while both Clay and Troesken and Kim and Knittel find the indirect NEIO estimates overstate marginal costs on average.

The second approach, which is closest to our own, uses either changes in market structure or a natural experiment to evaluate the predictive power of structural models. Hausman and Leonard (2002) simulate how firms would change their prices after the introduction of a new product using data from the toilet paper industry. These indirect estimates of prices are then compared with direct estimates of the impact of the new product on prices. They find that the two sets of estimates are fairly close to one another. Rojas (2008) examines how well different models of competition explain the change in market prices resulting from a large increase in the excise tax for beer in the U.S.; i.e., a large common shock to marginal cost. His results suggest that both the Bertrand-Nash and Stackelberg models predict observed changes in price well, while collusion models do not.

Nevo's (2000) study of mergers in the ready-to-eat cereal industry and Peters (2006)

[6]The industries studied by these authors each had a production process known well enough to the authors such that marginal costs could be accurately and directly characterized.

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 observed in his data. Peters (2006) focus is in evaluating the efficacy of merger simulation by comparing the price predictions from six airline mergers simulations to actual price changes. He estimates both nested logit demand and the Generalized Extreme Value demand model of Bresnahan, Trajtenberg and Stern (1997). Across the six mergers in Peter's data, simulated price changes were on average 11 percentage points different from actual price changes with nested logit demand and 9 percentage points different from actual changes with GEV demand. Simulations using nested logit demand under-predicted actual price changes in all cases and GEV demand over-predicted demand in one-third of the mergers considered. Our paper differs from Peters in that it analyzes mergers in consumer product markets. Merger simulations are used most commonly in consumer product markets, where the threat of price-constraining entry is less likely to exist than in city-pair airline markets. We also calculate standard errors for the simulated price changes that explicitly account for demand being estimated (instead of known). Finally, we examine the price changes of not only the merging firms' brands, but of all firms in the market separately for evaluation purposes.

2 Institutional Merger Background

The U.S. antitrust laws forbid mergers that would reduce consumer welfare. Because of the difficulty and costliness of restoring competition following an anticompetitive merger, the U.S. Congress passed the Hart-Scott-Rodino (HSR) Act which requires firms to delay merging until the government has had the opportunity to determine if the merger is likely to harm consumers. After the merging parties file their proposed merger, the 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 investigation consists of a review of company documents, depositions of company executives, and interviews of competitors, customers, and other third parties with potentially useful information about the likely effects of the merger. In addition, the merging parties may make presentations describing why the proposed merger is unlikely to have anticompetitive effects. After the parties have complied with the second request (typically within two or three months, but sometimes six months or more), the government has thirty days to decide whether to block the transaction, accept some type of remedy (typically a divestiture of assets or modification of the transaction), or allow the merger to proceed.[9]

The DOJ's and FTC's 1992 Horizontal Merger Guidelines provide the analytic framework used by economists and lawyers to determine if mergers are likely to be anticompetitive.[10] The Guidelines set out five tasks for agency staff to conduct as part of the investigation. The staff must define a product market (the set of close substitutes to the

[7]Following the passage of the HSR act in 1976 all mergers valued at more than 15 million dollars in assets were required to file with the FTC and DOJ. The filing threshold was increased to 50 million dollars in February of 2001, and is now indexed to changes in GDP growth.

[8]The FTC's web site provides an example of a second request on its web site, www.ftc.gov.

[9]In most cases there is a thirty day waiting period in which the government can make its decision to challenge the transaction. However, in cash tender offers or bankruptcy cases the waiting periods are considerably shorter. The government has fifteen days for the preliminary investigation and ten days following the parties complying with the second request.

[10]The Merger Guidelines can be found at www.ftc.gov.

merging parties' products), define a geographic market (the narrowest area in which anticompetitive 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

[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, by how much.

2.1 Background on Pennzoil-Quaker State Merger and the Aurora Foods Acquisition

This paper uses two consumer product mergers to evaluate merger simulation techniques. The first merger combined the ownership of the Pennzoil and Quaker State brands of passenger car motor oil. The second was the purchase of Log Cabin breakfast syrup by the owner of the Mrs. Butterworth brand. These markets are particularly well suited to our analysis. The basic model used by antitrust economists to identify anticompetitive mergers assumes static competition in prices. The mergers studied in this paper took place in mature consumer products markets involving well known products, and with no recent entry or product repositioning of any importance.

Pennzoil's 1 billion dollar purchase of Quaker State in December of 1998 combined two of the leading brands of passenger car motor oil in the U.S. Table 1 reports average pre-merger prices per quart and revenue shares by market. While there were three types of motor oil sold in the U.S. at the time of the merger, conventional motor oil was the most common form, accounting for about 88% of sales revenue and 95% of the volume in our data. The other two types of motor oil were semi-synthetic and synthetic motor oils which were much higher performance and much more expensive ($2.50-$4.00 a quart

Hausman, Leonard, and Zona (1994) and Nevo (2000). A standard approach is to estimate demand using a linear, constant-elasticity model, or a variation of the AIDS model. Alternatively, an increasingly popular method of estimating demand uses the discrete choice model suggested by Berry (1994) and Berry, Levinson, and Pakes (1995), which has been applied by Nevo (2000) to a merger simulation.

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 effectively 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 a set of proprietary weights. The motor oil data comes from IRI's mass merchandiser channel, which covers 10 of the largest metropolitan areas in the U.S. The oil data is at the weekly frequency and begins on January 5, 1997 and ends on March 18, 2001. The syrup data comes from IRI's food channel, and contains complete observations across 49 different regions. The sample for the syrup industry starts on October 27, 1996 and ends on December 31, 2000. A list of the regions used in our analysis is included in the appendix.

We have aggregated the data up to the product level. Specifically, for the motor oil category we kept data on the three major weights of motor oil sold (10W30, 10W40 and

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 to the pre-merger data by choosing marginal costs such that the firms' pre-merger first-order conditions are satisfied for each brand. Assuming that demand, costs, and the nature of competition do not change, the post-merger equilibrium is simulated by changing the profit functions and solving the best response functions for the new equilibrium price vector.

The Almost Ideal Demand System was proposed by Deaton and Muellbauer (1980) and has been applied to merger analysis by Hausman, Leonard and Zona (1994) amongst others. The revenue share equations for each of the J products are given by:

$$s_{int} = \alpha_{in} + \beta_i \log(\frac{X_{nt}}{P_{nt}}) + \sum_{j=1}^{J} \gamma_{ij} \log(p_{jnt}) + \sum_{m=1}^{11} D_m M_t + \eta_{int} \tag{1}$$

$$P_{nt} = \prod_{j=1}^{J} p_{jnt}^{w_{jn}}$$

where s_{int} and p_{int} are, respectively, the share of sales and price of brand i in region n at time t, the α_{in} are fixed effects that allow brand share equation intercepts to vary across 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 η_{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 (1986)).

The conditional elasticities of demand for product i with respect to the price of product j are given by:

$$\epsilon_{ij} = \frac{\gamma_{ij} - \beta_i w_j}{s_i} - 1[i = j] \tag{2}$$

If aggregate demand for all products in the market is not unit inelastic, then unconditional elasticities of brand i with respect to price of brand j can be found by correcting the conditional elasticities by adding to them $(1+\epsilon)s_j$ where ϵ is the elasticity of over-all demand. Here, we follow Epstein and Rubinfeld (2001) and assume that $\epsilon = -1$.

Let $\mathcal{J}_f$ denote the set of products sold by firm f. Assuming an equilibrium exists and that it is supported by strictly positive prices, the necessary first-order condition for brand i owned by firm f from the static Bertrand game can be written as:

$$\sum_{j \in \mathcal{J}_f} \left(\frac{p_j - mc_j}{p_j}\right)\epsilon_{j,i}(p_1, ..., p_J)s_j(p_1, ..., p_J) + s_i(p_1, ..., p_J) = 0 \tag{3}$$

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 regions through the brand/region fixed effects, this is done separately for each regional market in the pre-merger data resulting in a different implied marginal cost for each brand in each region.

Merger changes the profit functions and thus the prices firms choose in the Bertrand game. Assume that marginal costs do not change. If firm F acquires new products $\mathcal{J}_g$, the merged firm's first-order conditions for all products $i \in \mathcal{J}_f \cup \mathcal{J}_g$ become:

$$\sum_{j \in \mathcal{J}_f} (\frac{p_j - mc_j}{p_j}) \epsilon_{j,i}(p_1, ..., p_J) s_j(p_1, ..., p_J) \tag{4}$$
$$+ \sum_{j \in \mathcal{J}_g} (\frac{p_j - mc_j}{p_j}) \epsilon_{j,i}(p_1, ..., p_J) s_j(p_1, ..., p_J) + s_i(p_1, ..., p_J)$$

The post-merger equilibrium price vector solves this new system of equations. For the AID system, this must be done numerically. This paper solves for the equilibria separately for each region using Newton's method to solve for a root of the first-order conditions. Pre-merger prices in each region are used as initial guesses in the Newton iterative scheme. The simulated price effects of the merger are calculated by taking the median percentage difference between post and pre-merger prices across regions.

Here the other demand systems studied in this paper are introduced. Linear demand has the advantage of yielding an analytical solution to the post-merger equilibrium. The system is specified as:

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

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 $d_{ij} = b_{ji}$ if product i and j are owned by the same firm and zero otherwise. Then the J pre-merger first order conditions are given by $a - Dmc + (B + D)p = 0$ and pre-merger marginal costs are given by $mc = D_{pre}^{-1}a + (D_{pre}^{-1}B + I)p_{pre}$. Let the new D matrix, D_{post} reflect the changed ownership structure after the merger occurs. Then the post-merger equilibrium is given by $p_{post} = (D_{post} + B)^{-1}(D_{post}mc - a)$.[15]

Logit demand forces the cross-price elasticity of brand i with respect to the price of brand j to be the same for all i via IIA and forces own-price elasticities to be proportional to price. However, logit demand remains popular in antitrust due to the quickness with which it can be calculated and its relatively thin data requirements. For applications of logit demand to merger simulations see Werden and Froeb (1994), Nevo (2000), who also estimates a BLP model of demand, and Molnar (2008). Like the Bertrand model with linear demand, it is known that a unique equilibrium exists under logit demand. Volume shares v_{int} are given by

$$v_{int} = \frac{\exp\left(x_{int}\beta - \alpha p_{int} + \xi_{int}\right)}{\sum_{k=1}^{I} \exp\left(x_{knt}\beta - \alpha p_{knt} + \xi_{knt}\right)} \tag{6}$$

$$\tag{7}$$

[15] Again, we use pre-merger average prices in each region as p_{pre}. Simulated prices are calculated for each region and the price effect is the median percentage change taken across the regions.

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 across markets, so our empirical specification follows Nevo (2000) and is given by

$$\ln v_{int} - \ln v_{0nt} = -\alpha p_{int} + x_{int}\beta + \xi_{int}\gamma + \Delta\xi_{int} \tag{8}$$

for brands $i = 1, ..., J$. Here, the ξ is a vector of brand dummies with element i equal to one and all other equal to zero and the x_{int} contains month dummies. To make our results more comparable to Nevo, who has quarterly scanner data on breakfast syrups, we estimate the discrete choice models on data aggregated up to the monthly frequency. The merger is simulated as follows: let Δ be the J by J matrix with element $\Delta_{ij} = \frac{\partial v_i}{\partial p_j}$ if the same firm owns both i and j. Then the first-order conditions can be written as $v + \Delta(p - mc) = 0$ and the marginal costs are given by $mc = \Delta^{-1}v + p$. The post-merger equilibrium is found numerically by solving the non-linear system of equations $v(p_{post}) + \Delta(p_{post})(p_{post} - mc) = 0$.

A measure of market potential is necessary in order to calculate the outside share in the logit model. Normalizing the mean utility of the outside good to be zero instead of normalizing on one of the inside goods allows a parallel increase in all prices to decrease demand. The size of the outside share has little effect on estimates of α, but does impact the magnitude of the implied elasticities and the simulated price effects of the merger. In our preferred specifications, we take the market potential for motor oil to be one oil change per person each three months and assume that it takes 5 quarts of oil for an oil change, and we take the market potential for maple flavored syrup *consumed at home* to 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:

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

[16] 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.

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

where $\log(\bar{p}_{j\neg nt}) = \frac{1}{N-1}\sum_{m\neq n}\log p_{jmt}$. The first stage for the linear model is completely analogous. The deflated expenditure term in the AIDS and the per capita expenditure term in the linear model were instrumented using averages of those variables across other regions as well. This leaves each equation exactly identified in the AID and linear demand systems. We use average prices to instrument for the single price regressor in the logit model, except we follow Nevo (2000) and use not only average prices in the current period but average prices in all periods as instruments.

The second approach follows Hausman, Leonard and Zona (1994) and estimates the demand systems using OLS. This will be valid if prices in the demand system are predetermined, perhaps because retailers do not adjust their prices within a week and have constant marginal costs.

As demonstrated in Equation 4 the simulated price changes are a highly nonlinear function of estimated demand parameters and may not be accurately approximated by the delta method. For that reason, we use a parametric bootstrap to calculate confidence intervals for the simulated prices corresponding to each demand system instead of the delta method. We take 1000 draws from the asymptotic distribution of each demand systems estimator, calculate the simulated price change for each draw, and construct 90 percent confidence intervals from the empirical distribution of the bootstrapped price changes. The variance-covariance estimator for the AID and linear demand systems is Newey and West (1987) allowing for fourth order serial dependence in the error terms. The variance-covariance matrix for the logit demand systems is heteroskedasticity robust as implemented by Nevo (2000).

4 Results

In this section of the paper we present the empirical results of the study. We first estimate the actual price effects from the motor oil and breakfast syrup mergers using two 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:

$$\log(p_{int}) = \alpha_{in}^{dd} + \delta^{dd} PostMerger_t + \beta^{dd} Branded_i * PostMerger_t + \sum_{m=1}^{11} \gamma_m^{dd} M_t + \epsilon_{int}^{dd} \tag{10}$$

where the α_{in} are region/product specific fixed effects, $PostMerger_t$ is a dummy variable equal to one if observation t is after the merger date, $Branded_i$ is a dummy variable equal to one if product i is not a private label product. The M_t are month dummies that account for monthly seasonal effects. The coefficient β^{dd} measures the percentage change in branded product i's price relative to the percentage change in private label product prices after the mergers. Our sample differs slightly from Ashenfelter and Hosken (2008) because the products studied in this paper were not available in all regions included in their sample and the AID and linear demand systems require a balanced panel. However, our basic approach follows theirs and the reader is referred to that paper for details and robustness checks.

We next drop the private label comparison group and calculate the actual price effects by comparing average prices before and after the mergers using what we call the "difference" estimator. The specification is given by:

$$\log(p_{int}) = \alpha_{in}^{d} + \beta^{d} PostMerger_{t} + \sum_{m=1}^{11} \gamma_{m}^{d} M_{t} + \epsilon_{int}^{d} \tag{11}$$

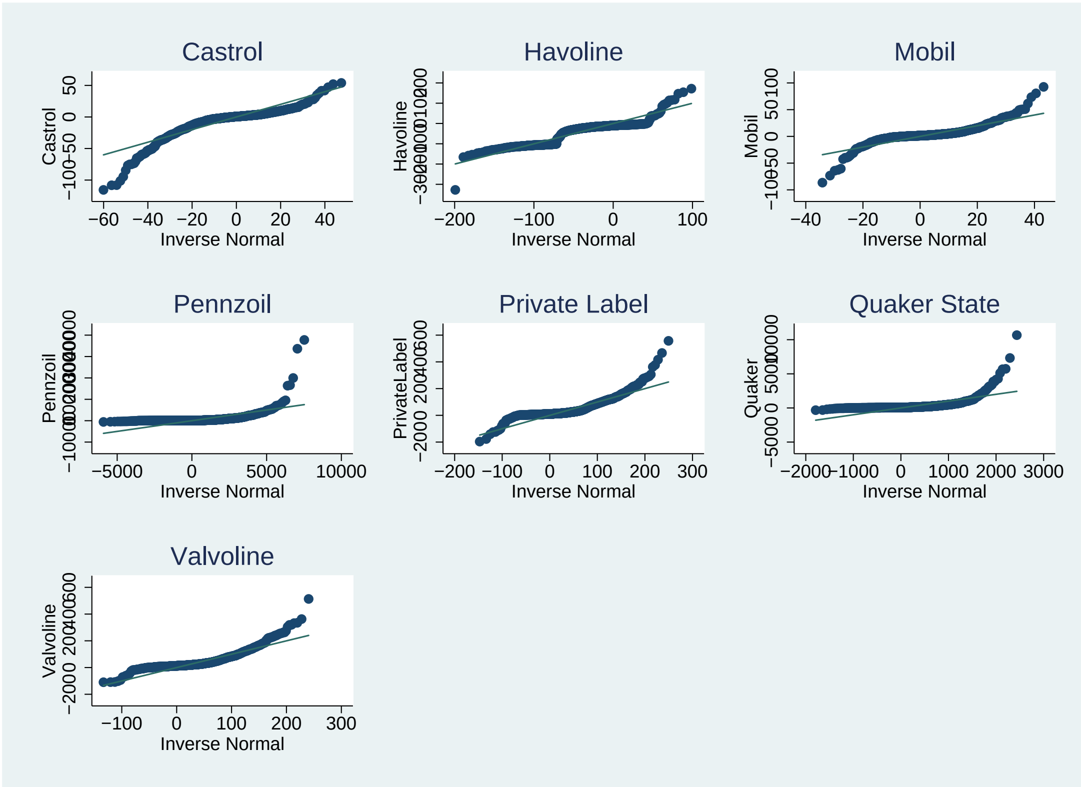
Columns 1 and 2 of Table 2 present the actual price effects of the motor oil and syrup mergers calculated with two different methods. The merging firms' brands are in bold font. Standard errors clustered on time are in parentheses. Column 1 presents difference-in-difference estimates of the price effects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

The motor oil merger had moderate but statistically significant price effects. 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 effect.

Columns 3 through 8 of Table 2 present the simulated price effects 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 effects 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

[18]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



Notes: QQ plots constructed by taking 1000 draws from asymptotic distribution of 2SLS estimator of AIDS demand system parameters and simulating the merger for each draw.

changes against the quantiles of the normal distribution. If the sampling distribution were normal, the points in the graph would all lie on a straight line. The sampling distribution is not normal because occasionally a draw from the demand parameters sampling distribution causes the simulation to divide by some number close to zero. This is why we do not use the delta method to estimate standard errors.

OLS performed much better than IV in our data. The results with demand estimated with OLS are both typically closer to the actual price effects and have smaller confidence intervals. The results from instrumental variables are very large in magnitude and have

positive cross-price elasticities. Accordingly, within each functional form we use the specification that provides the most plausible elasticities. The full specification for each demand system is given in the footnote of Tables 1 through 10 in the appendix.

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 wrong policy decision: block the syrup merger and possibly allow the motor oil merger. The results of the syrup simulation, however, are not surprising: virtually any oligopoly model with few firms selling differentiated products with that are close substitutes ought to lead to large price increases after a merger.

Under a unilateral effects theory the antitrust agencies focus on the impact on the prices of the merging firms products. However, the full solution to the Bertrand model calculated in this paper predicts prices for all products in the model. Thus an additional test of the oligopoly model is a comparison of the full vector of simulated and estimated price changes. The actual and simulated price changes for the rival firms' brands are in normal font in Table 2. Almost all brands controlled by the non-merging firms increased their price as well. Quaker State had the second highest price increase of all seven brands and Pennzoil had the sixth highest. Havoline experienced a decline in price. The remaining columns present the full simulated equilibria by demand specification and estimation procedure. When the demand estimates imply the products are substitutes, the prices of the non-merging firms' brands increase as well. The findings are clear and reinforce the results for the merging brands: again the simulations reverse the rank order of the actual price effects. Most all of the oil brands produced by rivals had a moderate actual price effect and small simulated price effect. For the syrups, brand by brand the entire simulated post-merger equilibrium price change is larger than the actual price change with only two exceptions.

4.1 Explaining the Differences Between Actual and Simulated Price Changes

In the remainder of this section we investigate four potential reasons for the differences between actual and simulated price changes. First we discuss the quality of the demand estimates to determine if the inputs into the merger simulations are obviously flawed. We next examine the extent to which the simulated price changes are inaccurate due to changes in demand or changes in marginal costs after the mergers occurred. Finally, we explore the sensitivity of the analysis to different assumptions on the ability of consumers to substitute towards outside goods. In terms of the continuous demand models this means examining how changing the elasticity of over-all category demand for oil or syrup affects the merger simulations. For the discrete choice model, we examine how changing the definition of total market potential affects the simulations.

Demand estimates are a key ingredient for merger simulations. Tables 1 through 10 in the appendix present elasticities evaluated at grand means over region and time for each demand system and each estimation technique. In general, the OLS estimates look reasonable. The own-price elasticities are bigger than one with the exception of private label oils from linear demand and private label syrups from logit demand. This may be because the private label category is very different from the other brands and not a unique product in itself. Instead, IRI's private label brand is an aggregate of various store brands. The syrup own-price elasticities are typically between 1 and 2 for AIDS and logit demand and are much larger with linear demand, ranging from 3 to 5. The oil own-price elasticities are much more elastic, typically between 3 and 7. Again, linear demand yields larger elasticities. The larger elasticities for the oil brands relative to syrup is one reason why the oil merger yielded smaller simulated price changes.

The cross-price elasticities from the demand systems estimated with OLS are virtually all positive. The only exception are some of the cross elasticities with respect to private label products. While negative cross-price elasticities for products thought to be substitutes are common in empirical work (Nevo (2000), for example, mentions that this is a problem in his experience with AIDS models), this is not a serious issue in the OLS results in our data.

The IV results look much worse for linear demand and AIDS, particularly for the syrups. The cross-price elasticities are often negative and the own-price elasticities are too large to be credible. The reason is that the instruments are not strongly correlated with the endogenous prices. Table 3 presents first-stage diagnostics for the AIDS models. Column 1 reports first stage robust partial F-stats of joint significance of the instruments. The F-stats for the syrup prices are quite small. Because there are multiple endogenous regressors, however, it is better to use a measure of instrument relevance for multivariate models such as Shea's (1997) partial R-squared or the measures of Stock, Wright and Yogo (2002). Column 2 of Table 3 presents Shea's partial R-squared. Shea's partial R-squared is small for the oil merger and extremely small for the syrup merger. This explains the large standard errors for the syrup demand parameters, elasticities, and also provides an explanation for many parameters having unexpected sign.

The logit results with IV look much more reasonable. This is not surprising as logit demand has only one endogenous regressor and estimating demand requires much less of the data than the AID and linear systems. The OLS and IV results are similar both in terms of elasticities and simulated price effects.

Simulating a merger requires that demand, costs, and the nature of competition do not change after the mergers occur. While not possible during actual merger review, we next use the post-merger data to test these assumptions and determine whether changes in these primitives can account for the discrepancy between simulated and actual price effects. Chow tests for parameter stability of the AIDS model reject the null of stability at the .05 level. Accordingly, we use demand estimated on the post-merger data to simulate the price effects. The results are in Table 4. For ease of presentation, we present only the results for the merging firms. In some cases the post-merger demand yields slightly more accurate simulations than pre-merger demand. The IV results are much more precise for motor oil, but are still extremely imprecise for syrup. Further, the rank order is still incorrect with simulated oil price changes smaller than syrup price changes. Only a small amount of the difference between simulated and actual price changes can be accounted for by demand shifting after the mergers occurred.

Thus far it has also been assumed that marginal costs do not change after the mergers. The required marginal cost changes for simulated price effects to match actual price effects were calculated and are presented for the merging firms in Table 5. To illustrate how these numbers were calculated, consider the linear demand system stacked in matrix notation as in Werden (1996), $q = a - Bp$, where B is a J by J matrix of demand slope parameters, and a is a J dimensional vector of demand intercepts and shifters. Let D_{pre} be a matrix with element $d_{ij} = b_{ji}$ if products i and j are owned by the same firm and zero otherwise before the merger. Then the first-order conditions can be written as $mc_{pre} = D_{pre}^{-1}a + (D_{pre}^{-1}B + I)p_{pre}$, where p^{pre} is the pre-merger equilibrium price vector. Let D_{post} be the post-merger D matrix, then $mc_{post} = D_{post}^{-1}a + (D_{post}^{-1}B + I)p_{post}$ where p_{post} is the actual post-merger price vector found by multiplying the pre-merger average prices one plus the percentage price effects 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 ingredients, packaging, and power. There is no reason to believe the cost would drop by the approximate 18 percent necessary to equate simulated and actual price changes for syrup. In most cases, marginal cost increases are needed for the simulations to explain the actual price changes of motor oil. These can also be quite sizable: for example, marginal costs would have to increase by 9 percent for the simulated price changes with logit demand to match the actual price effects.

In order to estimate consumer substitution patterns, Hausman and Leonard (2002) estimate a multi-stage budgeting program with AIDS at the bottom level and constant elasticity demand at the top. In this model consumers first allocate expenditures toward motor oil, syrup, and all other expenditure categories, and then allocate expenditures to the various brands within each category. Thus far, we have assumed that the top level of demand has elasticity of -1. This assumption was relaxed and Table 6 presents simulated price effects of the two mergers with different values of the elasticity of demand for overall oil and syrup. As the top-level demand becomes more elastic, the simulated prices decrease in magnitude. The USDA reports an estimate of -1.3 for the overall demand of breakfast syrups.[19] An overall elasticity of -2.6 is required to generate a price effect of log cabin equal to the difference estimate of the actual effect.

In order to estimate the logit demand system it is conventional to make assumptions

[19] Aggregate demand elasticities by product category are stored on the USDA's webpage. These specific numbers were taken by the USDA from Bergtold, Akobundu and Peterson (2004) and Helen and Willett (1986).

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 syrup consumed at home was one serving per person per month, and that the potential market size for motor oil was five-thirds a quart per month. While our assumptions on total market potential are justifiable, they are to some extent arbitrary. Here we consider other potential market sizes. Specifically, we re-simulate the merger using a total of four potential market sizes for the oil and syrup markets. We take the potential market size for syrup consumed at home to be one serving per day, one serving per week, one serving per two weeks, and on per month per person. We take the potential market size for passenger car motor oil purchased directly by consumers to be $2\frac{1}{3}$, $1\frac{2}{3}$, 1, and $\frac{1}{3}$ a quart per month. The results are in Table 7.

Simulated price changes are monotonically decreasing in the potential market size, as in Bass, Huang and Rojas (2008). Changing the market potential has very little impact on estimates of the logit price coefficient. However, larger potential market sizes implies smaller shares of the inside goods and these shares enter the elasticity and post-merger pricing formulas directly. When the potential market size for store-bought syrup is one serving per person per day, the merger has a very small impact on prices (less than 1 percent for the merging firms' brands). When the potential market size is one serving per person per week, the price effects increase to 1.4 and 1.7 percent for the merging brands. For the oil estimates, while the size of the price effect is decreasing in the potential market size, the simulated price changes are small for all market sizes that we have considered.

In many specifications the simulated price changes are close to the actual price changes from the oil merger. Further, the simulations correctly predicted that the price of Quaker State would increase by a larger amount than the price of Pennzoil. The results from the syrup merger are, however, more discouraging. If antitrust decisions had to be made strictly on the basis of merger simulations, this merger would likely have been challenged even though it was ultimately not anticompetitive. These results are even more striking given that *a priori* there is no reason to believe the syrup simulations would perform badly while the oil simulations would be fairly accurate. We find that the simulated price changes are sensitive to both the functional form of demand and the estimation strategies, with the IV results performing poorly in our data for the continuous choice models. While the demand estimates changed after the mergers occurred, these changes explain a small fraction of the difference between simulated and actual price changes. Marginal cost changes necessary to equate simulated and actual price changes are both implausibly large and asymmetric across firms that, given the technology of oil and syrup production, likely face the same marginal cost curves.

5 Conclusions

Structural models of oligopoly with information on consumer's substitution patterns allow antitrust economists to perform merger simulations. Given the legal necessity of prospective merger review in the U.S., the ability of structural models to simulate the price effects of mergers would be extremely valuable. The mergers studied in this paper were selected because they appeared to be, *ex ante*, ideal for the assumptions required for successful merger simulation. There was no recent history of entry or exit in either market. Because there were relatively few products in either market, it was not necessary to place many restrictions on the demand systems required for merger simulations. Both industries were mature, suggesting that shocks to demand (through advertising or growth) either pre or post-merger should be relatively unimportant. Similarly, given the production technology of both motor oil and syrup large shocks to marginal cost, particularly costs affecting a specific firm in the industry, were unlikely. Finally, because of the small number of firms participating in both industries, these mergers may have been on the enforcement margin;

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 (Continental/People's Express) generated the largest price increase.[20] Thus, like in our study, the simulations generate relatively small price increases when the actual effects were relatively large and large price increases when the actual price effects were relatively small. Based on the available evidence, current merger simulation technology does not appear to be a reliable enough tool to play a primary roll in antitrust enforcement.

Despite these shortcomings, some of our findings should be viewed as supportive of the potential of using structural models to forecast market outcomes. We find that the linear and logit demand models yield simulated price effects that are "close" to actual price effects. For decision making that does not require precise estimates of market outcomes, this approach may provide reasonable forecasts. The closeness of the merger simulation to observed price effects in some cases the oil results in particular suggests that these simulations are providing some useful information about pricing incentives. Each year the economy generates many experiments (in the form of consummated mergers) that can be used by researchers to develop and validate better tools to simulate the price effects of mergers. To our knowledge, there has been very little work up until now that examines the ability of these techniques to forecast the changes in price induced by a large change in market structure. Given the revolutionary changes taking place in demand estimation and structural models of oligopoly, new applications to merger review seem a fruitful area of research.

[20] Peters (2006), Table 3 p 641.

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Table 1: Pre-Merger Descriptive Statistics

Products	Price				Volume Share			
	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard Deviation	Minimum	Maximum
Pennzoil/Quaker State Merger								
Pennzoil	1.20	0.12	0.37	1.38	0.32	0.16	0.03	0.87
Quaker State	1.24	0.15	0.60	1.76	0.09	0.08	0.01	0.63
Castrol GTX	1.23	0.13	0.53	1.51	0.18	0.10	0.03	0.79
Havoline F3	1.11	0.13	0.60	2.04	0.09	0.07	0.01	0.51
Mobil	0.95	0.07	0.76	1.26	0.10	0.09	0.01	0.59
Private Label	0.85	0.07	0.68	1.57	0.08	0.03	0.01	0.21
Valvoline	1.19	0.13	0.60	1.53	0.14	0.12	0.01	0.71
Log Cabin/Mrs Butterworth Merger								
Log Cabin	1.82	0.21	1.25	2.44	0.22	0.07	0.05	0.79
Mrs. Butterworth	1.93	0.15	1.10	2.50	0.19	0.08	0.04	0.62
Aunt Jemima	1.94	0.20	0.51	2.56	0.20	0.10	0.01	0.78
Hungry Jack	1.76	0.16	1.08	2.20	0.07	0.05	0.01	0.53
Private Label	1.10	0.20	0.73	2.18	0.32	0.10	0.06	0.68

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. Syrup prices are per pint. Regions are listed in the appendix.

Table 2: Estimated and Simulated Percentage Price Effects for Merging and Rival Firms' Products

	Estimated Price Changes		**Simulated Price Changes**					
	Difference in Difference	**Difference**	AIDS		**Linear**		**Logit**	
Products			OLS	IV	OLS	IV	OLS	IV
Pennzoil/Quaker State Merger								
Castrol GTX	8.05	6.77	1.19	-1.36	0.26	0.05	0.00	0.00
	(1.78)	(1.46)	(0.52, 1.99)	(-37.95, 11.43)	(0.01, 0.58)	(-0.23, 0.41)	(0.00, 0.00)	(0.00, 0.00)
Havoline	-4.32	-6.43	0.78	-27.82	0.36	-0.67	0.00	0.00
	(1.54)	(1.54)	(0.27, 1.37)	(-116.00, -4.67)	(0.04, 0.82)	(-2.84, 1.13)	(0.00, 0.00)	(0.00, 0.00)
Mobil	7.48	5.45	0.21	3.12	0.16	0.11	0.00	0.00
	(1.25)	(1.11)	(-0.01, 0.51)	(-9.30, 25.37)	(0.02, 0.34)	(-0.14, 0.50)	(0.00, 0.00)	(0.00, 0.00)
Pennzoil	3.71	1.95	2.59	216.17	0.40	1.55	0.05	0.04
	(1.91)	(1.79)	(0.08, 5.68)	(25.19, 3272.03)	(-0.16, 1.04)	(0.58, 3.86)	(0.04, 0.06)	(0.03, 0.05)
Private Label	-	-2.14	1.41	24.49	0.16	-0.01	0.00	0.00
	-	(0.67)	(-0.20, 4.30)	(3.25, 167.30)	(-0.99, 1.58)	(-0.79, 0.73)	(0.00, 0.00)	(0.00, 0.00)
Quaker State	7.65	5.63	7.49	115.79	4.12	5.10	0.16	0.15
	(1.53)	(1.45)	(2.81, 13.58)	(26.14, 1094.64)	(1.60, 7.21)	(1.02, 12.15)	(0.14, 0.19)	(0.12, 0.17)
Valvoline	5.60	3.78	0.78	32.75	0.42	0.47	0.00	0.00
	(2.61)	(1.93)	(0.02, 1.49)	(1.02, 169.87)	(0.07, 0.79)	(0.10, 1.46)	(0.00, 0.00)	(0.00, 0.00)
Log Cabin/Mrs Butterworth Merger								
Aunt Jemima	-0.35	0.80	4.84	44.81	0.67	1.97	0.15	0.15
	(0.94)	(0.57)	(2.55, 8.22)	(-143.35, 125.98)	(0.31, 1.23)	(-44.03, 45.68)	(0.14, 0.18)	(0.13, 0.18)
Hungry Jack	-0.28	1.25	2.51	62.85	0.63	21.90	0.06	0.06
	(0.90)	(0.53)	(0.18, 6.19)	(-194.18, 190.444)	(-0.73, 2.67)	(-51.69, 54.87)	(0.05, 0.06)	(0.05, 0.07)
Log Cabin	1.40	2.74	23.50	-63.60	2.73	-60.21	5.92	5.78
	(1.40)	(0.74)	(14.84, 36.24)	(-152.90, 364.84)	(1.46, 4.35)	(-105.83, 98.37)	(5.25, 6.78)	(4.99, 6.89)
Mrs Butterworth	-2.08	-0.74	21.58	-235.18	4.42	-89.75	7.56	7.38
	(1.22)	(0.63)	(12.95, 34.53)	(-384.56, 798.41)	(3.03, 6.54)	(-172.50, 159.21)	(6.70, 8.65)	(6.37, 8.79)
Private Label	-	1.11	6.65	-62.41	1.41	-32.85	0.54	0.53
	-	(0.29)	(2.81, 10.29)	(-287.64, 344.23)	(0.48, 2.73)	(-56.20, 65.69)	(0.48, 0.62)	(0.46, 0.63)

Notes: Authors' own calculations on IRI data. Clustered standard errors are in parentheses below difference in difference and difference estimates. 90 percent confidence intervals in parentheses under simulated price changes. Confidence intervals were constructed through drawing from asymptotic distribution of demand parameters and simulating distribution for each draw. Variance-covariance matrices of demand estimators are Newey-West with truncation parameter of 4, except logit which is Eicker-White. Oil statistics calculated on weekly data over 10 regions from 10/28/1996 until 12/1/1998. Syrup statistics calculated on weekly data over 49 regions from 10/28/1996 until 6/28/1997. Logit results calculated on monthly data over the same time periods. Regions are listed in the appendix.

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
$\log(p_{Castrol_GTX})$	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		**Simulated Price Changes**					
	Difference in Difference	**Difference**	**AIDS**		**Linear**		**Logit**	
Products			OLS	IV	OLS	IV	OLS	IV
Pennzoil/Quaker State Merger								
Pennzoil	3.71	1.95	6.28	2.41	2.23	1.06	0.07	0.27
	(1.91)	(1.79)	(4.19, 9.49)	(0.98, 3.93)	(1.78, 3.49)	(0.34, 2.11)	(0.06, 0.08)	(-0.59, 1.10)
Quaker State	7.65	5.63	11.75	6.14	5.04	4.30	0.26	1.10
	(1.53)	(1.45)	(6.29, 21.56)	(3.60, 8.83)	(2.32, 7.77)	(1.70, 5.69)	(0.23, 0.31)	(-2.37, 4.38)
Log Cabin/Mrs Butterworth Merger								
Log Cabin	1.40	2.74	20.31	2.65	3.34	-0.20	6.72	7.08
	(1.40)	(0.74)	(13.65, 30.85)	(-41.69, 86.23)	(2.54, 7.56)	(-47.80, 84.05)	(5.84, 7.82)	(5.98, 8.74)
Mrs Butterworth	2.08	-0.74	15.78	-2.08	3.50	7.13	8.48	8.94
	(1.22)	(0.63)	(10.47, 23.26)	(-121.96, 329.38)	(2.55, 8.03)	(-166.06, 141.98)	(7.38, 9.88)	(7.55, 11.03)

Notes: Authors' own calculations on IRI data. Clustered standard errors are in parentheses below difference in difference and difference estimates. 90 percent confidence intervals in parentheses under simulated price changes. Oil statistics calculated on weekly data over 10 regions from 12/6/1998 until 10/28/2000. Syrup statistics calculated on weekly data over 49 regions from 7/6/1997 until 3/8/1998. Logit results calculated on monthly data over the same time periods. Regions are listed in the appendix.

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

	Simulation Model					
	AIDS		Linear		Logit	
Products	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 "difference" 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 Different Overall Elasticities of Demand 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 program. 90 percent confidence intervals in parentheses. 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. Syrup prices are per pint. Regions are listed in the appendix.

Table 7: Simulated Percentage Price Changes with Different Outside Shares for IV Logit

Products	$2\frac{1}{3}$ Quarts per Month	$1\frac{2}{3}$ per Month	1 per Month	$\frac{1}{3}$ per month
Pennzoil/Quaker State Merger				
Pennzoil	0.008	0.024	0.040	0.056
	(0.007, 0.01)	(0.021, 0.029)	(0.034, 0.048)	(0.048, 0.068)
Quaker State	0.027	0.083	0.139	0.195
	(0.023, 0.034)	(0.071, 0.101)	(0.119, 0.167)	(0.166, 0.236)
	1 Serving per Day	4 per Month	2 per Month	1 per Month
Log Cabin/Mrs Butterworth Merger				
Log Cabin	0.19	1.43	2.89	5.78
	(0.17, 0.22)	(1.30, 1.67)	(2.60, 3.36)	(4.99, 6.89)
Mrs Butterworth	0.22	1.66	3.42	7.38
	(0.20, 0.25)	(1.51, 1.94)	(3.07, 3.96)	(6.37, 8.79)

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

A Demand Elasticities for Oil and Syrup by Estimation Strategy

Table 1: Oil Elasticities, AIDS Model Estimated with OLS

	Castrol GTX	Havoline	Mobil	Pennzoil	Private Label	Quaker State	Valvoline
$CastrolGTX$	-3.17	0.55	0.90	0.45	0.14	0.55	0.72
	(0.28)	(0.11)	(0.15)	(0.08)	(0.15)	(0.15)	(0.11)
$Havoline$	0.53	-4.65	0.65	0.46	-0.45	0.63	0.53
	(0.17)	(0.28)	(0.20)	(0.14)	(0.26)	(0.13)	(0.12)
$Mobil$	0.42	0.33	-7.09	0.41	-0.78	0.26	0.24
	(0.22)	(0.17)	(0.29)	(0.13)	(0.27)	(0.18)	(0.17)
$Pennzoil$	0.45	0.21	0.29	-1.81	-0.04	0.13	0.17
	(0.07)	(0.06)	(0.08)	(0.08)	(0.09)	(0.05)	(0.06)
$PrivateLabel$	0.20	0.22	0.41	0.17	-1.00	0.03	0.12
	(0.10)	(0.10)	(0.16)	(0.09)	(0.31)	(0.08)	(0.10)
$QuakerState$	1.15	-0.19	0.89	0.24	0.27	-3.44	0.22
	(0.28)	(0.19)	(0.24)	(0.18)	(0.25)	(0.31)	(0.17)
$Valvoline$	0.51	0.73	0.37	0.54	0.42	0.10	-3.07
	(0.33)	(0.25)	(0.30)	(0.25)	(0.35)	(0.30)	(0.22)

Notes: Authors' own calculations on IRI data. Standard errors in parentheses. 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 parameter of 4. The AIDS share equations contain month and year dummies, and region-product specific fixed effects. Demand estimated on weekly data over 10 regions from 10/27/1996 until 11/28/1998. Regions are listed in the appendix.

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 effects. 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)
$QuakerState$	0.96	-0.34	0.71	0.28	0.39	-3.16	0.33
	(0.34)	(0.17)	(0.22)	(0.33)	(0.22)	(0.30)	(0.17)
$Valvoline$	1.07	0.85	0.86	1.17	-0.09	0.43	-3.49
	(0.27)	(0.17)	(0.24)	(0.31)	(0.16)	(0.29)	(0.69)

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 1/5/1997 until 11/29/1998. Prices are per quart. Regions are listed in the appendix. Standard errors for elasticities were constructed by bootstrapping grand means and drawing from asymptotic distribution of demand parameters 1000 times and constructing elasticity for each draw. The estimator for the variance covariance matrix of the demand parameters is Newey-West with truncation parameter of 4. Demand equations include month, year dummies, time trends and region-brand fixed effects.

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

	Castrol GTX	Havoline	Mobil	Pennzoil	Private Label	Quaker State	Valvoline
CastrolGTX	-6.47	0.46	0.15	0.08	-0.49	0.16	0.19
	(0.44)	(0.28)	(0.74)	(0.59)	(1.82)	(0.31)	(0.45)
Havoline	0.78	-5.83	6.08	2.69	-14.00	0.67	1.95
	(1.30)	(1.01)	(2.65)	(2.10)	(6.42)	(1.16)	(1.16)
Mobil	0.29	0.41	-9.63	0.36	3.24	0.64	0.78
	(0.51)	(0.35)	(1.16)	(0.77)	(2.44)	(0.40)	(0.48)
Pennzoil	0.64	0.51	-2.14	-7.34	4.92	0.88	0.15
	(0.58)	(0.43)	(1.08)	(1.45)	(2.42)	(0.46)	(0.56)
PrivateLabel	-0.36	-0.06	0.78	0.26	-4.21	-0.55	-0.18
	(0.44)	(0.32)	(0.80)	(0.76)	(1.86)	(0.33)	(0.41)
QuakerState	2.25	-1.43	4.37	3.59	-7.68	-8.27	0.26
	(1.00)	(0.69)	(1.77)	(1.47)	(4.29)	(0.80)	(0.91)
Valvoline	1.38	1.60	0.31	2.27	1.62	0.35	-4.65
	(0.45)	(0.37)	(0.52)	(0.58)	(1.01)	(0.33)	(0.91)

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 parameter of 4. Demand estimated on weekly data over 10 regions from 1/5/1997 until 11/29/1998. Prices are per quart. Regions are listed in the appendix. Demand equations include month, year dummies, and region-brand fixed effects.

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 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 parameter of 4. Demand estimated on monthly data over 10 regions from 1/5/1997 until 11/29/1998. Prices are per quart. Regions are listed in the appendix. Logit demand includes brand dummies and month dummies to capture seasonal effects.

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 estimator for the variance covariance matrix of the demand parameters is Newey-West with truncation parameter of 4. Demand estimated on monthly data over 10 regions from 1/5/1997 until 11/29/1998. Prices are per quart. Regions are listed in the appendix. Logit demand includes brand dummies and month dummies to capture seasonal effects.

Table 7: Syrup Elasticities, AIDS Model Estimated with OLS

	Aunt Jemima	Hungry Jack	Log Cabin	Mrs. Butterworth	Private Label
AuntJemima	-1.86	-0.01	0.32	0.32	-0.08
	(0.06)	(0.09)	(0.07)	(0.09)	(0.07)
HungryJack	0.27	-2.62	-0.29	0.68	0.29
	(0.17)	(0.29)	(0.22)	(0.28)	(0.23)
LogCabin	0.21	0.11	-1.93	0.43	0.15
	(0.05)	(0.09)	(0.07)	(0.09)	(0.07)
MrsButterworth	0.42	0.30	0.47	-2.35	0.34
	(0.06)	(0.11)	(0.08)	(0.10)	(0.08)
PrivateLabel	0.17	0.18	0.34	0.26	-1.53
	(0.12)	(0.21)	(0.15)	(0.20)	(0.16)

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 parameter of 4. Demand estimated on weekly data over 49 regions from 10/27/1996 until 6/28/1997. Regions are listed in the appendix. AIDS share equations include month dummies, equation specific time trends, and region/product specific fixed effects.

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

	Aunt Jemima	Hungry Jack	Log Cabin	Mrs. Butterworth	Private Label
AuntJemima	-4.91	2.51	-0.68	-0.78	-0.32
	(3.26)	(2.30)	(2.02)	(1.45)	(1.50)
HungryJack	-3.32	-7.27	-8.76	-1.65	-0.78
	(6.46)	(4.67)	(4.67)	(3.34)	(4.21)
LogCabin	1.65	0.72	-5.52	1.82	-0.42
	(2.63)	(2.07)	(1.75)	(1.36)	(1.71)
MrsButterworth	3.42	-0.45	6.24	-1.84	2.88
	(4.40)	(3.25)	(2.86)	(2.16)	(2.76)
PrivateLabel	0.16	-0.78	2.86	0.23	-2.76
	(4.30)	(3.45)	(2.76)	(2.14)	(2.70)

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 parameter of 4. Demand estimated on weekly data over 49 regions from 10/27/1996 until 6/28/1997. Regions are listed in the appendix. AIDS share equations include month dummies, and region/product specific fixed effects.

Table 9: Syrup Elasticities, Linear Model Estimated with OLS

	Aunt Jemima	Hungry Jack	Log Cabin	Mrs. Butterworth	Private Label
AuntJemima	-5.16	-0.16	2.13	0.53	-0.53
	(0.06)	(0.11)	(0.07)	(0.09)	(0.08)
HungryJack	0.77	-2.97	-0.33	0.82	0.24
	(0.20)	(0.35)	(0.25)	(0.31)	(0.26)
LogCabin	1.57	0.14	-4.44	1.64	0.12
	(0.06)	(0.10)	(0.07)	(0.10)	(0.07)
MrsButterworth	0.88	0.40	0.86	-4.48	0.23
	(0.07)	(0.12)	(0.09)	(0.11)	(0.08)
PrivateLabel	0.35	0.18	0.48	0.32	-1.10
	(0.13)	(0.24)	(0.17)	(0.20)	(0.17)

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 parameter of 4. Demand estimated on weekly data over 49 regions from 10/27/1996 until 6/28/1997. Regions are listed in the appendix. Demand equations include month dummies and region/product specific fixed effects.

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 parameter of 4. Demand estimated on weekly data over 49 regions from 10/27/1996 until 6/28/1997. Regions are listed in the appendix. Demand equations include month dummies and region/product specific fixed effects.

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)
HungryJack	0.27	-1.65	0.24	0.35	0.33
	(0.02)	(0.13)	(0.02)	(0.03)	(0.03)
LogCabin	0.27	0.41	-1.87	0.35	0.33
	(0.02)	(0.03)	(0.15)	(0.03)	(0.03)
MrsButterworth	0.27	0.41	0.24	-1.90	0.33
	(0.02)	(0.03)	(0.02)	(0.15)	(0.03)
PrivateLabel	0.27	0.41	0.24	0.35	-0.96
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)

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. 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 heteroskedasticity robust. Demand estimated on monthly data over 49 regions from 10/27/1996 until 6/28/1997. Regions are listed in the appendix. Logit demand includes brand dummies and month dummies to capture seasonal effects.

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)
HungryJack	0.28	-1.68	0.25	0.36	0.33
	(0.03)	(0.15)	(0.02)	(0.03)	(0.03)
LogCabin	0.28	0.42	-1.92	0.36	0.33
	(0.03)	(0.04)	(0.18)	(0.03)	(0.03)
MrsButterworth	0.28	0.42	0.25	-1.94	0.33
	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)
PrivateLabel	0.28	0.42	0.25	0.36	-0.98
	(0.03)	(0.04)	(0.02)	(0.03)	(0.09)

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 parameter of 4. Demand estimated on weekly data over 49 regions from 10/27/1996 until 6/28/1997. Regions are listed in the appendix. Logit demand includes brand dummies and month dummies to capture seasonal effects.

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. Buffalo
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