Estimating Industry Conduct in Differentiated Products Markets*

The Evolution of Pricing Behavior in the RTE Cereal Industry

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Abstract

We estimate the evolution of competition in the ready-to-eat (RTE) cereal industry. To separately identify detailed patterns of industry conduct from unobserved marginal cost shocks, we construct novel instruments that interact data on rival firms' promotional activities with measures of products' relative isolation in the characteristics space. We find strong evidence for partial price coordination among cereal manufacturers in the beginning of our sample. Manufacturers' price coordination intensifies following a horizontal merger in 1993, with median manufacturer margins increasing from 20.8 to 38.1 percent over those implied by multiproduct Bertrand-Nash pricing, but eventually fully breaks down to multiproduct Bertrand-Nash pricing.

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1 Introduction

One of the central questions in industrial organization is to what extent firms exert market power. Product differentiation, as one source of market power, can lead to positive markups even if firms compete effectively with each other. In many industries, there are concerns that a low intensity of competition further contributes to high industry markups. Empirically disentangling legitimate from anti-competitive sources of market power is thus an important task. This task, however, is very difficult because neither the intensity of competition nor marginal cost, which is another price determinant, are commonly observed in the data.

A key identification problem in empirical industry models is thus to distinguish whether firms charge high prices because of anti-competitive behavior or because of high unobserved cost shocks. To separate the two channels, one needs to find suitable instruments that are correlated with markups but not with underlying cost shocks. Recently, Berry and Haile (2014) have shown that it is in principle possible to empirically discriminate between different oligopoly models by exploiting variation in market conditions.[1] In practice, however, many of the instruments based on this type of variation tend to be weak. The few studies that have focused on estimating *industry conduct*, as a measure of an industry's competitive intensity, have used alternative identification strategies, such as exploiting plausibly exogenous industry shocks.[2] Such identification strategies can already lead to important insights. However, they often require the researcher to focus on estimating the conduct of only a subset of firms and time periods, or to assume that the structure of conduct is invariant across time and firms.

In most cases, it is not clear a priori that the conduct in an industry follows such a pattern. The level of conduct might not only deviate from competition but also differ substantially over time and across firms. Not accounting for this heterogeneity can lead to inconsistent estimates of markups and marginal costs. Allowing for more flexible conduct specifications is thus likely to lead to more accurate predictions and more effective policy recommendations.

In this paper, we estimate detailed patterns of industry conduct that account for changes over time and heterogeneity across firms in the US RTE cereal industry. To do so, we employ a structural differentiated products demand model and a flexible conduct parameter framework on the supply side. To separately identify industry conduct and manufacturers' marginal costs, we propose novel instruments that exploit products' relative proximity in

[1] Examples of this type of variation are the number of firms, the set of competing products, or functions of their characteristics.

[2] For example, Miller and Weinberg (2017) consider a joint-venture as an exogenous shock to estimate a parameter that reflects how the behavior between the two leading firms in the US beer industry deviates from Bertrand-Nash pricing once one of them participates in the joint-venture. Ciliberto and Williams (2014) leverage a special feature of airport gate leasing contracts to estimate conduct as a function of multimarket contact in the airline industry.

the characteristics space interacted with information on rival firms' promotional activities, which we explain in detail below. Our paper contributes to the literature by incorporating an identification strategy based on variation in the characteristics space to estimate rich patterns of industry conduct. We focus on estimating the behavior of firms in the industry over time, and, in particular, on whether the behavior changes following important industry events. Specifically, we estimate the levels of conduct between firms before and after the 1993 Post-Nabisco merger, and following a massive wholesale price reduction by most cereal brands in 1996. Being able to accurately measure and explain the effects of such events is of key interest for competition policy.

Our results indicate that there are indeed substantial changes in industry conduct over time. We find partially cooperative levels of conduct between firms in the beginning of our sample, followed by a further increase in cooperation after the horizontal merger. When allowing our conduct parameters to differ across firms, we find that the pricing behavior of the smaller firms during these periods is more cooperative than that of the two market leaders, Kellogg's and General Mills. Finally, our estimates are consistent with a drastic change in industry conduct towards fully competitive behavior three and a half years after the merger.[3]

Section 2 introduces our data and provides detailed information about the RTE cereal industry and important industry events. We use scanner data from the Dominick's Finer Food (DFF) database. The database includes detailed information on DFF's supermarket stores located in the Chicago metropolitan area. In addition to detailed store-specific data on quantities, retail prices and temporary promotions, one convenient aspect of our data is that it contains information on wholesale prices. We analyze a five-and-a-half year span of data from 1991 until 1996. Our sample period includes several important events, most notably the Post-Nabisco merger in January 1993 and a period that began in April 1996 in which manufacturers greatly decreased wholesale prices, which the business press referred to as a *price war*. For brevity, we use this terminology for the remainder of this paper.

To motivate our structural model and our identification strategy, we conduct a series of reduced form regressions. We find that following the horizontal merger, prices increased significantly for the merging firms as well as for two other firms. However, three-and-a-half years later, almost all of the manufacturers greatly reduced their wholesale prices within only a few weeks which translated into shelf-price reductions of up to 18 percent for consumers

[3]Our results also relate to a long and extensive discussion regarding the underlying sources of market power of national cereal manufacturers. For example, Schmalensee (1978) argues that price competition is suppressed although firms might still partially compete via advertising and product entry. In contrast, Nevo (2001) finds that markups in the industry can be best explained solely by product differentiation and the profit-maximizing behavior of multiproduct firms.

(Cotterill and Franklin, 1999). These descriptive statistics provide the first evidence that the interaction between manufacturers significantly changed over our sample period.

Typically, it is not possible to disentangle the different explanations for the observed pricing patterns using only reduced form regression methods. Therefore, we introduce a structural empirical model in Section 3. On the demand side, we use a random coefficients nested logit (RCNL) model in the style of Berry *et al.* (1995) (henceforth, BLP) and Nevo (2001), allowing for detailed consumer heterogeneity. On the supply side, we use a flexible conduct parameter framework that specifies the degree of cooperation by a matrix of parameters that capture the degree to which firms internalize their rivals' profits.

We consider our approach as having significant advantages over simply assuming a particular form of industry conduct, as is often done in the literature. For example, the most commonly used assumption in such models is multiproduct Bertrand-Nash pricing. This form of conduct implies that a firm maximizes the total profits of its own product portfolio but fully competes with all rival firms' products. Such a specification limits the heterogeneity of markups over time and across firms by assumption. There is a growing interest in the heterogeneity of markups in both the macroeconomics and the trade literature, which usually rely on estimating output elasticities using a production function approach; see for example, De Loecker and Eeckhout (2017). Our approach allows us to estimate whether there is markup heterogeneity within an industry that can be attributed to heterogeneity in industry conduct.

Section 4 explains the details of our identification strategy. We exploit variation across markets in firm's markup incentives caused by temporary promotions for different products. The intuition is the following. In many consumer products industries, promotions are agreed upon between a manufacturer and a retailer several months in advance. This is done for various reasons, for example, a sufficient supply of the product must be ensured and promotional brochures must be printed.[4] Therefore, rivals' promotional activities in a given time period should be exogenous to innovations in a specific product's demand and supply shocks. We provide reduced form evidence that supports the implied timing assumptions. In particular, we show that wholesale prices react to cost shocks immediately, i.e., in the same month, whereas the promotional intensity of a product is not affected by contemporaneous shocks. The promotional intensity of a product 1 to 5 month in the future, however, is significantly affected by shocks today.

Furthermore, the promotional activities of a rival product will affect a product's own demand. While promotions typically come with a decrease in the retail price of a product, we

[4] In both Europe and the US, retailers often establish a planogram of promotions for an entire product category several months in advance.

show in reduced form regressions that –even when controlling for the lower retail price typically associated with promotional activities– promotions also have additional, nonmonetary effects on demand, for example, because of an increased coverage in a retailer's brochures, better shelf space, or in-store promotional signs for products "on sale". It is mainly these types of nonmonetary demand shifts that we exploit for our instruments to identify industry conduct. The shifts in competitive pressure by these promotion effects will be stronger the more consumers consider these products as substitutes. Therefore, firms have an incentive to adjust the markups of all their products accordingly. This is why we interact the number of rivals' promotions with the products' relative proximity in the characteristics space. The relative proximity feature is shared with the class of differentiation instruments recently proposed by Gandhi and Houde (2017). In contrast to their approach and to classic BLP instruments, we do not require product entry or exit to induce variation in the characteristics space. Instead, we exploit variation in products' promotional activities as shifters of firms' pricing and markup behavior. We conduct a series of weak identification tests for both our demand and our supply side estimations, and find that our proposed instruments indeed prove to be very powerful in identifying both consumers' price elasticities and manufacturers' industry conduct. The data required to construct our instruments are readily available for many consumer goods industries, and thus our empirical strategy has broad applicability.

Section 5 presents our main estimation results. We find strong evidence for partial coordination in the beginning of our sample period, and for an additional increase following the Post-Nabisco merger in 1993. When we restrict the conduct parameters to be equal across firms, our pre-merger conduct estimate of 0.277 indicates that a firm values US-$ 1 of its rivals' profits as much as US-$ 0.277 of its own profits. Furthermore, our estimates reveal that pre-merger, price-cost margins are 25.6 percent higher than under multiproduct Bertrand-Nash pricing. Following the merger, the estimated conduct increases to 0.454, implying a 42.7 percent median margin over that for multiproduct Bertrand-Nash pricing. Such an increase is, for example, consistent with a merger further facilitating coordination across firms in an industry.[5] When allowing the conduct parameters to differ across firms, we find that the small firms' internalization is higher than that of the two largest firms (Kellogg's and General Mills). The overall median margins are slightly lower in this model, at 20.8 and 38.1 percent over multiproduct Bertrand-Nash pricing pre- and post-merger, respectively. Moreover, towards the end of our sample period, for both specifications, we estimate conduct parameters close to 0, which is consistent with multiproduct Bertrand-Nash pricing.

[5] Throughout the paper, we use the term *coordination* to describe cooperative pricing behavior, in the sense that firms' internalize the effect of their pricing on rival firms' profits to various degrees. We use this term for conciseness, and do not suggest that our model parameters correspond to anti-competitive behavior in the sense of violating antitrust laws.

As a plausibility check, we compare the implied marginal costs obtained from our conduct models with those from a hypothetical multiproduct Bertrand-Nash pricing model and the evolution of several input prices (gas, electricity, various grains) during our sample period. Most notably, the Bertrand-Nash model predicts that manufacturers' marginal costs rise during the first half of our sample period and decrease sharply at the end of our sample period. This is in contrast to the substantial downward trend in input prices during the first 4 years and the sharp increase in input prices at the end of our sample period. Our conduct model, however, predicts marginal costs that roughly follow this pattern, in particular, a downward trend in the post-merger period and a significant increase in marginal costs during the price war period towards the end of our sample.

Furthermore, we extensively compare our results to those in the existing literature. Our demand estimates and the implied price elasticities are very much in line with previous studies on the RTE cereal industry. The key difference between the existing literature and our paper is that we allow for and find substantial heterogeneity in conduct and markups over time, especially during a period in our sample that has, to the best of our knowledge, not been studied using a structural model. We further discuss how our direct conduct estimation can allow for a more "fine-grained" estimation of markups that can also lead to more accurate counterfactual predictions and thus better policy recommendations.

We use our parameter estimates to conduct a series of counterfactual exercises in which we simulate how prices and consumer surplus would have evolved under different levels of industry conduct. First, if firms had competed via Bertrand-Nash pricing prior to the price war, consumer welfare would have increased by between US-$ 1.6 and 2.0 million per year for the markets in our data set. Furthermore, the median wholesale prices would have been 9.5 percent lower during the pre-merger period, and roughly 16.3 percent lower during the post-merger period. Second, if industry conduct had remained at the post-merger level during the price war, the median wholesale prices during the actual price war period would have been between 16.2 and 17.1 percent higher, with substantial heterogeneity across firms.

Our paper relates to several different strands in the literature. First, it relies on the theoretical literature on the identification of industry conduct and other structural elements of demand and supply in differentiated products models. Berry and Haile (2014) illustrate the potential to distinguish different oligopoly models in differentiated products industries by exploiting variation in market conditions. We show one way in which their arguments can be applied to real-world industry data and propose specific instruments that we find to be powerful for identifying detailed industry conduct patterns that are difficult to identify using established instruments.

Early work in the literature on industry conduct has mostly relied on estimating conjectural variations; see, for example Bresnahan (1982) and Lau (1982) for identification results when estimating conduct for the homogeneous good case. Corts (1999) critically discusses such approaches. He argues that the estimated parameters usually differ from the "as-if conduct parameters" and, therefore, that they do not necessarily reflect the economic parameters of interest. This critique is not applicable in our case because we estimate a structural model of the supply side. In a series of seminal papers, Nevo (1998) discusses the advantages and disadvantages of a direct conduct estimation compared to a non-nested menu approach. He argues that in practice, estimating detailed industry conduct directly using only a single demand rotator is impossible, and proposes the use of selection tests for a "menu" of pre-specified models; see, for example, Gasmi *et al.* (1992), Rivers and Vuong (1988), and Chen *et al.* (2007). One advantage of these approaches compared to a direct conduct estimation approach is the relatively easy computation of the test statistics. However, in some cases the statistical power of these tests can be relatively weak and difficult to assess; see, for example, Shi (2015) for a discussion. This can be especially problematic when several detailed conduct patterns are tested against each other.

Bresnahan (1987) estimates a structural model for both demand and supply to test whether multiproduct Bertrand-Nash pricing or full collusion better explains conduct in the US car industry around a price war in 1955. For 1954 and 1956, his results indicate a collusive industry outcome, and for 1955, they indicate multiproduct Nash pricing. Nevo (2001) estimates a detailed differentiated products demand model for the RTE cereal industry, and recovers marginal cost for a menu of pre-specified models, i.e., single-product Nash pricing, multiproduct Nash pricing, and joint profit maximization. He subsequently compares the different cost estimates with accounting data to select the most plausible specification, which he finds to be multiproduct Bertrand-Nash pricing. His sample period partly overlaps with the pre-merger period in our sample. For this period, our estimates are consistent with his results but provide additional insights. While our conduct parameters are much closer to multiproduct Nash than to full collusion, even small differences in conduct can have a considerable impact on the estimated price-cost margins. We find that under multiproduct Nash pricing, combined retailer and manufacturer gross margins would be 45%, but that after allowing for a flexible conduct specification, gross margins are around 55%.

There is a small but growing literature on the estimation of industry conduct in a structural conduct parameter framework. The two papers most closely related to ours are Miller and Weinberg (2017), and Ciliberto and Williams (2014).

Miller and Weinberg (2017) assess the effects of a joint-venture on industry pricing behavior in the beer industry. They focus on estimating a conduct parameter that measures the magnitude of mutual profit internalization between Anheuser-Busch InBev (ABI) and Miller-Coors after the Miller-Coors joint-venture. Their model assumes industry-wide Bertrand-Nash pricing before the joint-venture for all firms and throughout the sample period for all firms except ABI and MillerCoors. Their identification strategy exploits the joint-venture as an exogenous shock together with the assumption that ABI's marginal costs are not affected by the MillerCoors joint-venture. They find a positive profit internalization between ABI and MillerCoors following the joint-venture, indicating that it potentially facilitated price coordination. Instead of relying on the merger itself as an exogenous instrument, our identification considers variation in rival firms' promotional activities and information on the relative proximity of products in the characteristics space. This allows us to identify a richer pattern of industry conduct. For example, we are able to quantify changes in conduct over time and differences across firms without assuming a specific conduct in any time period. Ciliberto and Williams (2014) estimate industry conduct in the airline industry. Their focus is on modeling industry conduct as a function of the degree of multimarket contact between different airlines. They find that firms with a lower degree of multimarket contact cooperate less when setting ticket fares. The identification strategy relies on the probability of a certain route being served by an airline being correlated with the number of gates an airline operates at an airport, and the number of gates not being easily adjustable in the short-term. Their model assumes a time-invariant and proportional relationship between the degree of cooperation between airlines and their level of multimarket contact.[6]

2 Data and Industry Overview

In this section, we describe our data and provide background information on the US RTE cereal industry. In addition, we conduct a series of reduced form regressions to guide our structural model and motivate the construction of our instruments.

2.1 Data Sources

Our main data consist of scanner data from the DFF database. The database includes information on DFF supermarkets located in the Chicago metropolitan area and weekly

[6]Although our paper focuses on estimating industry conduct for general industry settings, it is further related to the ex-post analysis of mergers. Crawford *et al.* (2018) analyze the welfare effects of vertical integration in the US cable and satellite industry. They account for internalization effects using a structural bargaining model and find a less than optimal increase in internalization after a merger. Michel (2017) analyzes the internalization of horizontally merging firms' pricing externalities in a structural model, and finds a relatively rapid internalization for the first two years following the 1993 Post-Nabisco RTE cereal merger. Moreover, there is a growing literature focusing on the impacts of horizontal mergers on consumer surplus and industry prices; see, for example, Ashenfelter *et al.* (2013), and Björnerstedt and Verboven (2016).

information on product prices, quantities sold, temporary promotions, and 1990 census data on demographic variables for each store area. For our analysis, we use data from 58 DFF stores, which we define as the geographical market and focus on 26 brands from the 6 different nationwide manufacturers present in the industry from February 1991 until October 1996. All of the products are offered throughout the whole sample period and at all stores. There is no persistent entry of new products with a significant market share during our sample period. Therefore, we do not include these products. The database also includes data on in-store promotions, which DFF temporarily offers for different products. We explain this aspect in detail in the next subsection.

We complement the DFF data with input price data from the Thomson Reuters Datastream database and from the website www.indexmundi.com. The data include prices on commodities needed for the production of cereals such as sugar and various grains, and data on energy, electricity, and labor costs. Finally, we collect nutrition facts from the website www.nutritiondata.self.com and information on the different production and processing techniques for the different cereals. Throughout our analysis, we use deflated prices using a regional consumer price index.

We define a single unit of cereal as a 1 OZ serving of a specific brand. The total overall market size is defined as one serving per capita per weekday times the mean store-specific number of total customers.[7]

We are primarily interested in the interactions among the manufacturing firms. Observing a wholesale price measure rather than only the retail price allows for more precise inference regarding the manufacturing firms' marginal costs and markups. Specifically, we observe the retailer's average acquisition costs for each product at a given time. This variable reflects the inventory-weighted average of the percentage of the retail price that was paid to the producer. From this variable we compute average wholesale prices for a given period. Note that this measure gives the weighted average of the wholesale prices for the products in the inventory; see Chevalier *et al.* (2003) for a discussion of this variable.[8] For our estimation, the data are aggregated at the monthly level. Consequently, DFF's inventory stocking at low

[7]On average, our market size definition is very close to the specification of Meza and Sudhir (2010). We find the empirical results to be robust to using a time-variant market size specification, and to changing the market size by factors $\frac{1}{3}$,$\frac{1}{2}$, 2, and 3, respectively. The implied elasticities from the main model are relatively close to those from studies using regional level data from the same industry, as, for example, in Nevo (2001). The demand results for the alternative market specifications are available upon request. We treat our market size number as exogenous to the RTE cereal prices because cereals only amount to a relatively small fraction of supermarket purchases for most consumers.

[8]DFF uses the following formula to calculate the average acquisition costs (AAC): AAC(t+1) = (Inventory bought in t) Price paid(t) + (Inventory, end of t-l-sales(t)) AAC(t). From an economic perspective, the variable reflects the weighted profit share for each product in a period, minus the retailer's costs. Thus, it is a weighted average in terms of the time of purchase of the products in inventory and does not reflect a product's current replacement value.

wholesale prices for later dates should have a negligible effect on our wholesale price measure.

2.2 Industry Overview

The RTE cereal industry has been studied extensively; see, for example, Schmalensee (1978), Scherer (1979), and Nevo (2000b). At the end of our sample period, the industry had annual revenues of about US-$ 9 billion, which implies that almost 3 billion pounds of cereals were sold.

RTE cereals differ with respect to their observed and unobserved product characteristics, such as sugar and fiber content or package design. In the beginning of our sample period, the industry comprises 6 large nationwide manufacturers: Kellogg's, General Mills, Post, Nabisco, Quaker Oats, and Ralston Purina. It is common to classify the cereals into different groups, such as adult, family, and kids cereals. Kellogg's, which is the firm with the biggest market share, has a strong presence in all segments. General Mills is mainly present in the family and kids segments, whereas Post and Nabisco are strongest in the adult segment.

The products also differ in the type of main cereal grain and type of processing. The main types of cereal grains are corn, wheat, rice, and oats. The main production processes are flaking, puffing, shredding, and baking. We analyze the industry in a very mature state when no significant technological innovations occurred; therefore, we judge it safe to assume that production processes are constant over time.

On the retail level, RTE cereal products are primarily distributed via supermarkets. According to Nevo (2000b), more than 200 brands are available to consumers during the time span we analyze; however, the majority of of sales can be attributed to the 25 most popular brands. Table 4 in Appendix A summarizes the evolution of manufacturer market shares over our sample period. Although market shares vary over the different years in our sample, the industry structure is relatively stable. The two largest firms alone, i.e., General Mills and Kellogg's, cover around 75% of the market. The remainder of the market is split among the substantially smaller firms (Post, Nabisco, Quaker, and Ralston). We do not include private label products explicitly in our analysis because our main focus is on estimating the competitive interactions between national cereal manufacturers.[9]

An important feature of many consumer products industries is the prevalence and impor-

[9] In principle, it is straightforward to incorporate private label products into our analysis. The main challenge with private label products is that one has to model how profits are split in the vertical supply chain of a retailer that owns the private label products but also benefits from selling the national manufacturer brands. To keep the focus of our analysis on the strategic interaction among national cereal manufacturers, we follow most of the literature and pool private label brands into the outside good. We account for potential changes in the popularity of private label products in a reduced form by incorporating a time trend for the inside goods in the utility function of consumers, see the discussion in Section 4.3.

tance of temporary promotions. In our data, we observe four different forms of promotions: bonus buy, coupon, general, and price reduction. With regard to their effects on prices and consumer demand, the promotions in our sample can be classified into two different categories. First, general and explicit price reduction promotions result in lower retail prices for all consumers and usually, also in a lower wholesale price. To obtain coupon and bonus buy price reductions, consumers typically must exert extra effort, and these promotions on average result in a lower price reduction than the other promotions. The different promotion types are often accompanied by measures that increase consumers' awareness of a product, for example, by being included in a retailer's advertising brochure or because of better shelf space or additional in-store promotion signs. Both direct price effects and increased product exposure typically increase the demand for products "on sale" and tend to temporarily decrease demand for rival products.[10]

On November 12, 1992, Kraft Foods made an offer to purchase RJR Nabisco's RTE cereal line. The acquisition was cleared by the FTC on January 4, 1993. According to Rubinfeld (2000), the main concern of the antitrust authority regarding this merger was the strong substitutability in the adult cereal segment between Post's Grape Nuts cereal and Nabisco's Shredded Wheat, which would give the merging firms a non-trivial incentive to increase prices unilaterally. The merger did not lead to any product entry or exit or any changes to existing products. In fact, Nabisco cereals were even sold under the same brand names and in a packaging very similar to before the merger. Therefore, we abstract from product repositioning, as, for example, analyzed in Sweeting (2010) and Mazzeo *et al.* (2013), and treat the set of products as exogenous.

In April 1996, Post decreased the wholesale prices for its products nationwide by up to 20%, thereby also increasing its market share. This was followed by significant price cuts a few weeks later by the market leader Kellogg's and then by General Mills and Quaker. Cotterill and Franklin (1999) report an average decrease in the wholesale price of 9.66% across all products in the industry between April and October 1996, and an average 7.5% decrease in the retail price. These numbers suggest a systematic change in industry pricing for most products during this period.[11] One of the contributions of this paper is that we structurally estimate how much of the change in industry behavior is due to a breakdown of

[10]Many of the non-price effects of promotions are likely to be highly correlated with brand-specific advertising, i.e., it is conceivable that promotional activities and advertising capture very similar underlying drivers of consumer demand. While incorporating detailed advertising data could potentially provide additional insights, such data is unfortunately hard to obtain for a large part of our sample.

[11]In March 1995, two US congressmen started a public campaign to reduce cereal prices, which received relatively high media attention; this campaign was revived one year later right before the start of the substantial wholesale price cuts (Cotterill and Franklin, 1999). Although negative publicity and political pressure might be potential reasons for the price cuts, we remain agnostic about any causes for the price war.

coordinated pricing rather than potential shifts in demand or marginal costs.

2.3 Reduced Form Analysis

To investigate whether our data support anecdotal industry evidence and to guide our structural model, we run a series of reduced form regressions. In particular, we are interested in whether prices systematically changed following the merger and during the price war, and whether and how the promotions of rival brands affect manufacturers' pricing decisions. Figure 1 in Appendix A illustrates the evolution of wholesale and retail prices averaged over all stores during our sample period for some important brands.

We analyze the determinants of both wholesale and retail prices by estimating a series of OLS regressions. The level of observation is a product-store-month combination resulting in a sample size of $96,512$ observations.[12] Our dependent variables is $\log(p^w_{it})$, i.e., the logged wholesale price of brand i for store-market combination t.

The large data set allows us to control for a wide variety of fixed effects such as brand, store, and time fixed effects. Moreover, we include total market sales to control for overall industry shocks. For both dependent variables, i.e., wholesale prices and retail prices, our key regressors of interest are dummy variables for the post-merger and the alleged price war periods, and variables summarizing a brand's own and rival firms' promotional activities in a specific store and month.

In the baseline specification, we interact a post-merger indicator only with a dummy for the merging firms and a dummy for the non-merging firms, allowing the merging firms (Post and Nabisco) to react differently to the merger than the non-merging firms. In more detailed specifications, we use the post-merger indicator interacted with the dummies for every post-merger firm (KEL, RAL, QUA, GMI, and POSTNAB).

To motivate our identification strategy for industry conduct, we include several measures of the firm's own and rival brands' promotional activities as additional regressors. First, we provide descriptive evidence on the distribution of promotions across brands, stores, and time. Figure 2 in Appendix A reveals that there is significant variation in the number of promotional activities across time and that different brands tend be on promotion in different periods. Figure 3 illustrates that, although promotions are positively correlated across stores in the Chicago metropolitan area, there is also variation across stores. Overall, this rich pattern of variation is promising for constructing strong instruments.

For our regressions, we disaggregate the total promotional intensity into several variables. *Promo (own brand)* captures the number of promotions (general sales or price reduction-

[12] To investigate UPC-composition effects, we also ran our regressions on the UPC-zone-month level. These regressions resulted in very similar results and are available upon request.

based sales) conducted for a given brand in a given market. *Promo (same firm)* indicates the number of promotions a firm conducted for its products other than brand i in a given store and month. *Promo (rival firm)* captures the number of promotions conducted by all rival firms. Because the reaction to rivals' promotions is likely to be affected by the prevailing industry conduct, we allow the effect of rivals' promotions to differ in the pre-merger, post-merger, and the price war periods.

We conjecture that general and price reduction sales are typically more visible and appeal to a broader range of consumers than bonus buy and coupon promotions. Since the latter are usually more complicated promotions that have more restrictions and often require consumers to exert extra effort, we suspect their effects to be different from general sales and potentially much weaker. Therefore, in our baseline specification, we construct promotion regressors based only on general and price reduction promotions. In the second set of regressions, we include a measure summarizing bonus buy and coupon promotions conducted by the firm's own brand, the firm's other brands, and rival firms' brands. Appendix A provides additional results and presents the estimation equations for the reduced form regressions.

Table 5 in Appendix A summarizes the regression results when the dependent variable is the logged wholesale price. In the period following the Post-Nabisco merger, the merging firms increase their wholesale prices by 6% on average. Looking at the non-merging firms' reaction to the Post-Nabisco merger in detail (column 2), we find that Kellogg's and Ralston increase their wholesale prices by almost as much as the merging firms, while Quaker and General Mills slightly decrease their prices. Furthermore, during the price war period, the wholesale prices drop substantially for all firms by almost 10% on average.

Not surprisingly, general and price reduction promotions result in a strong decrease in wholesale prices. An additional promotion on average decreases the wholesale price by approximately 11%. In contrast, the cross-effects of promoting brands owned by the same firm are very small but positive, i.e., a brand's wholesale price increases slightly when other products owned by the same firm are on promotion. When including regressors that capture the intensity of bonus buy promotions (columns 3-4), our initial conjecture is confirmed, i.e., bonus buy promotions are associated with a substantially smaller (roughly 2%) reduction in wholesale prices.

Analyzing the effects of the promotions conducted by rival firms over time indicates important changes in how firms react to each other. In the early periods of our sample (i.e., pre-merger), the rival firms' promotions and wholesale prices for a given brand have a small but positive correlation both for general and bonus buy promotions. Following the merger, the effect becomes negative but remains very weak for general promotions, while the effect for bonus buy promotions remains positive and becomes stronger. During the price war period which starts approximately three and a half years after the merger, both general and bonus buy promotions have a substantial negative effect on rivals' wholesale prices.[13]

This pattern is consistent with significant changes in industry conduct over time. In a collusive industry, firms internalize each other's profits. Therefore, rivals' promotions are not guaranteed to result in complementary price cuts by a firm's brands. In contrast, in a competitive environment, prices should be strategic complements: Rivals' promotions increase competitive pressure and should go hand in hand with price cuts for a firm's own brands.

An essential prerequisite for our instruments to be able to work is that promotions affect demand patterns not only through the retail price but also through other channels, such as being more salient when being promoted inside a store. To investigate this channel, we regress the logged quantities sold on a series of brand, store, and time fixed effects, and statistics of own brand and rival firms' promotional activities. Table 6 in the Appendix summarizes the associated results. The main purpose of these quantity regressions is to illustrate that –even after controlling for the actual retail prices paid by consumers– the pattern of product-specific promotions in a market has a significant effect on consumer choices. In particular, both general promotions and bonus buy promotions for a brand increase consumer demand significantly. We interpret this as strong evidence for the presence of considerable non-price effects (advertising intensity, brochures, shelf space allocations, or promotional signs for products on sale) of promotional activities that shift consumer demand.

Overall, our reduced form regressions provide supporting evidence that, in our application, promotional measures indeed capture relevant shifters of manufacturers' markups and can therefore constitute a promising basis for instruments to identify industry conduct.

3 Empirical Model

The reduced form analysis presented in the previous section yields several important insights into the evolution of the RTE cereal industry in the 1990s. Most importantly, on average, there is a significant price increase following the Post-Nabisco merger, which is followed by a dramatic reduction in wholesale prices three-and-a-half years later. There are several potential reasons for observing this pattern. For example, consumers' preferences and willingness-to-pay may have shifted, resulting in changes in market power due to product differentiation. Alternatively, production costs may have changed over time. In addition, there may have

[13]The results for retail price regressions using the same specifications as those for wholesale prices are qualitatively similar and available on request. Prices increase substantially following the merger. When investigating the post-merger reaction in more detail, the same pattern as for wholesale prices emerges: the retail prices increase for two non-merging firms (Kellog's and Ralston) but remain constant for General Mills and Quaker. As expected, both wholesale and retail prices react strongly to promotions and decrease significantly during the price war period.

been changes in industry conduct. Generally, it is extremely difficult to disentangle these explanations using only reduced form regressions. To gain much more detailed insights into the different channels, we develop a structural model of the RTE cereal industry.

3.1 Demand Model

On the demand side, we estimate a random coefficients nested logit (RCNL) model with a specification that is similar to those in Nevo (2001) and Miller and Weinberg (2017). One key advantage of this model is that it allows for very flexible substitution patterns. An accurate estimation of own- and cross-price elasticities is crucial in our model since they are the most important determinants of a firm's pricing first-order conditions. Consequently, using incorrect or weakly identified demand estimates is likely to result in confounded estimates of both marginal costs and industry conduct.

There are J brands available in each market. We denote the number of markets, defined as a store-month combination, by T. Each market consists of a continuum of individual consumers. Individual i's indirect utility from consuming product j in market t is given by

$$u_{ijt} = x_j\beta_i + \alpha_i p^r_{jt} + \xi_{jt} + \epsilon_{ijt}, j = 1, .., J; t = 1, .., T, \tag{1}$$

where x_j denotes a K-dimensional vector of brand j's observable characteristics (including several layers of fixed effects), p^r_{jt} denotes the retail price of product j in market t, and ξ_{jt} is a brand-market specific quality shock that is unobservable to the researcher but observable to and equally valued by all consumers. In addition, we assume that ξ follows an AR(1)-process so that

$$\xi_{jt+1} = \iota^D\xi_{jt} + \nu^D_{jt+1}. \tag{2}$$

This specification allows for persistence in the structural demand error and, most importantly, enables us to form moment conditions based on the innovations in the process instead of its levels.

The coefficients β_i and α_i are individual-specific. They depend on the mean valuations, a vector of i's demographic variables, D_i, and their associated parameter coefficients Φ, that measure how preferences vary with demographics; therefore,[14]

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Phi D_i. \tag{3}$$

Finally, ϵ_{ijt} is an iid error term. We model this idiosyncratic error term with a nested logit structure, such that

$$\epsilon_{ijt} = \zeta_{igt} + (1-\rho)\tilde{\epsilon}_{ijt}, \tag{4}$$

where $\tilde{\epsilon}$ is an individual-product-market specific shock that follows an extreme value distribution, and ζ denotes an individual-product group-market specific shock that is drawn from the unique distribution that results in the compound error ϵ to follow an extreme value distribution. The nesting parameter ρ captures the amount of correlation between the product-specific shocks within the same product group g. In our application, the main reason for allowing for a nested logit specification is to obtain reasonable substitution patterns between the inside goods and the outside good. Therefore, we group all inside goods in one nest and the outside good in a separate nest.

Consumers who do not purchase any cereal product in a period choose the outside good. The indirect utility of consuming the outside good can be written as $u_{i0t} = \xi_0 + \phi_0 D_i + \epsilon_{i0t}$. Because only differences in utility are identified in discrete-choice models, we normalize ξ_0 to zero.

The vector of demand parameters θ_D consists of a linear part $\theta_1 = (\alpha, \beta)$, that affects each consumer identically, and a nonlinear part $\theta_2 = vec(\Phi)$. Analogously, the indirect utility of consuming a product can be decomposed into a mean utility δ_{jt} and a mean-zero random component $\mu_{ijt} + \epsilon_{ijt}$ capturing heterogeneity from demographics and unobserved taste shocks. The decomposed indirect utility can be expressed as $u_{ijt} = \delta_{jt}(x_j, p^r_{jt}, \xi_{jt}, \theta_1) + \mu_{ijt}(x_j, p^r_{jt}, D_i; \theta_2)$; with

$$\delta_{jt} = x_j\beta + \alpha p^r_{jt} + \xi_{jt}, \tag{5}$$

$$\mu_{ijt} = [p^r_{jt}, x_j]' * \Phi D_i, \tag{6}$$

where $[p^r_{jt}, x_j]$ is a $(K+1) \times 1$ vector of observable product characteristics.

Consumers buy either one unit of a single brand or take the outside good, and they choose

[14] In extensive robustness checks, we also experimented with persistent preference heterogeneity in the form of classical normally distributed taste shocks. While these models led to elasticities that were similar to our baseline demand specifications, the standard errors increased; therefore, we opted for a model with only demographic interactions, as, for example, in Goldberg and Hellerstein (2013) and Miller and Weinberg (2017).

the option that yields the highest utility. The model's market share predictions are obtained by integrating over all the shock distributions

$$s_{jt}(x_{.t}, p^r_{.t}, \delta_{.t}, \theta_2) = \int_{A_{jt}} dP^*_\epsilon(\epsilon) dP^*_D(D), \tag{7}$$

where $A_{jt}(x_{.t}, p^r_{.t}, \delta_{.t}, \theta_2) = \{(D_i, \epsilon_{it}) | u_{ijt} \geq u_{ilt} \forall l \in \{0, .., J\}\}$ denotes the set of consumers' shock realizations for which j yields the highest utility. For our RCNL specification, market share predictions are then given by

$$s_{jt} = \int_i \frac{\exp\big((\delta_{ijt} + \mu_{ijt})/(1-\rho)\big)}{\exp\big(I_{igt}/(1-\rho)\big)} \frac{\exp(I_{igt})}{\exp(I_{it})} dP_{it}, \tag{8}$$

where I_{igt} and I_{it} are the inclusive values of consumer i for product group g and all products respectively, and the integral is taken over the distribution of consumer types in market t, P_{it}. The inclusive value of the inside goods is $I_{i1t} = (1-\rho)\log\big(\sum_{j=1}^J \exp\left((\delta_{jt} + \mu_{ijt})/(1-\rho)\right)\big)$. Because of the normalization of the utility of the outside good to zero, $I_{i0t} = 0$, so the inclusive value across all products is given by $I_{it} = \log\left(1 + \exp(I_{i1t})\right)$.

As discussed in Section 2.2, temporary product- and store-specific promotions are important determinants of consumers' cereal choices through both direct price effects and indirect awareness effects that increase the attractiveness of products "on sale". Our model captures direct price reductions in the observed retail price p^r_{jt}. For our instruments to work it is essential that promotions have additional effects on consumer demand that do not work through the retail price. Our reduced form regressions in Table 6 in Appendix A illustrate that these effects exist and are significant in the cereal industry. While these effects can be generated through several channels, for example, retailers' advertising brochures, better shelf space because of promotions or in-store promotional signs, we incorporate the indirect effects of promotions in a relatively parsimonious way by including the number of promotions for a given brand in a given market as an additional product characteristic in the consumer's utility function. Note that our empirical strategy can accommodate that promotions may work through a variety of channels.[15] The essential restriction that we impose is that there is no direct promotion spillover, i.e., we require that a consumer does not receive a higher utility from consuming good A if brand B is on promotion. Put differently, while promotions of rival products affect the demand for a product indirectly by making the rival product

[15] For example, if one believes that promotions explicitly shift consumers' awareness of different products, one could estimate a demand model in the style of Sovinsky Goeree (2008). While the estimation of the demand model becomes much more involved and requires more data, for example, on product-market specific advertising expenditure, the estimation of the supply side parameters, which is the focus of this paper, is not fundamentally affected, and our identification strategy can be employed in a straightforward way.

more attractive –not only because of a lower price but also because of nonmonetary effects of promotions– rivals' promotions do not directly affect the utility from consuming a product.

We abstract from dynamic consumer behavior for several reasons. In principle, our supply model and our identification strategy can be combined with a dynamic demand model in the style of Hendel and Nevo (2006). However, dynamic models that allow for detailed high-dimensional heterogeneity are extremely computationally intensive. A dynamic model would therefore have to heavily compromise in this dimension. In our application, we judge accounting for detailed consumer heterogeneity to be more important for estimating consumers' substitution patterns than dynamic storage behavior. We use data at the month level for which dynamic behavior is arguably much less relevant than for weekly data. To further support our myopia assumption, we present evidence that storage behavior does not play a significant role in our sample. Specifically, we regress the quantities sold of a given brand in a given store-month combination on a brand's lagged promotional intensity. The associated results are displayed in column (3) of Table 6 in Appendix A. While current brand-specific promotions have a large effect on the quantities sold, lagged promotional activities for the same brand in the same store do not significantly affect demand in the current period.

3.2 Supply Model

The J brands in the industry are produced by $R \leq J$ firms. Each brand is produced by only one firm, but each firm can produce multiple brands. We model marginal costs as a linear function of a battery of fixed effects, observable cost factors w_{jt}, and a brand-market specific cost shock ω_{jt} that is unobserved by the researcher but known to the firms, so that

$$mc_{jt} = \underbrace{w_{jt}\gamma}_{\tilde{mc}_{jt}} + \omega_{jt}, \tag{9}$$

where γ is a vector of marginal cost parameters to be estimated, and $\tilde{mc}_{jt}$ denotes the part of the marginal cost that is attributed to observable cost shifters.[16] Analogous to our demand model, we allow for persistence in the unobserved cost shock and model ω as an AR(1)-process

$$\omega_{jt+1} = \iota^S \omega_{jt} + \nu^S_{jt+1}. \tag{10}$$

Our baseline cost specification implies that the production processes do not change over time, resulting in time-invariant marginal cost functions. For our application, we judge this

[16]For simplicity of notation, we omit index w for wholesale marginal costs.

to be a reasonable assumption since no technical innovations or relocations of production facilities occurred during our sample period. For a discussion on the types of time-varying cost functions our model can accommodate, for example, because of synergies following the merger, see Section 4.

In each market, the manufacturing firms set wholesale prices for their products, and the retailer sets a product-specific retail markup over the wholesale price. We assume linear wholesale prices that are not contingent on the overall quantity sold in a period. As in Goldberg and Hellerstein (2013), this results in a model of double marginalization in which manufacturers set their wholesale prices anticipating that the retailer takes these prices as given and optimally adjusts its retail prices.[17]

Focusing on data from a single retailer (DFF) allows us to observe detailed wholesale price data. The downside of this approach is that we cannot analyze substitution to different retailer chains. Given that cereals typically constitute only a small fraction of overall grocery expenses, we judge this channel to be much less important than the substitutability of different products within the same store. Slade (1995) finds that 90% of consumers do not compare the prices of different retailers on a week-to-week basis. Therefore, we do not expect that excluding other retailers will have a significant effect on our estimation results.

Henceforth, we denote a manufacturing firm simply as a firm. λ_{ijt} represents the degree to which brand i takes into account brand j's profits when setting its wholesale prices in market t. All λ_{ijt} can be arranged in an *internalization matrix* Λ_t. Consequently, Λ_t generalizes the ownership matrix of zeros and ones in classical BLP-models. We follow the literature (Miller and Weinberg, 2017; Ciliberto and Williams, 2014) in treating the elements of Λ as structural parameters. Black *et al.* (2004) and Sullivan (2017) illustrate how these parameters can be translated into the parameters of an underlying repeated game in which firms maximize their own discounted lifetime profits. Each λ_{ijt} is normalized to lie between 0 and 1, where 0 implies no internalization of firm j's profits by firm i, and 1 implies full internalization.[18]

[17] Testing different forms of vertical price-setting behavior, Sudhir (2001) finds evidence for such sequential price-setting behavior between manufacturers and retailers in the industry. Also see Villas-Boas (2007) for a framework to test for different forms of vertical relations using retail and input prices. Our model implies that each manufacturer sets store-specific wholesale prices. In principle, it is straightforward to estimate our model under various alternative assumptions, for example, under the assumption that firms set the same wholesale price for all stores or all stores within a pricing zone. We opted for a model of store-specific wholesale prices to capture that in reality, manufacturer-retailer contracts are often very high-dimensional. For example, they may specify additional payments for delivery or shelf space allocations, which are likely to vary across stores.

[18] Conceptually, our model can also accommodate either $\lambda > 1$ or $\lambda < 0$. Negative internalization parameters would imply that a firm derives a positive utility from "ruining" another firm. In the cereal industry, there is no evidence of such behavior. $\lambda > 1$ implies that a firm values its rivals' profits more than its own, which does not seem reasonable in our application. See Appendix F for the normalization details and for how this affects the computation of standard errors.

The manufacturer's objective function for product j in market t can be written as

$$\Pi_{jt} = (p_{jt}^w - mc_{jt})s_{jt}M_t + \sum_{k \neq j} \lambda_{jkt}(p_{kt}^w - mc_{kt})s_{kt}M_t, \tag{11}$$

where s_{jt} denotes the market share of brand j as defined in Equation (7), M_t denotes the market size, and p_{jt}^w denotes the wholesale price per unit of brand j in market t. Following the literature, we assume that marginal costs are common knowledge among firms but unobserved by the researcher.

Therefore, marginal cost must be backed out via the model's first-order conditions. The first-order condition for product j with respect to its own price can be written as

$$s_{jt} + \sum_{k=1}^{J} \lambda_{jkt}(p_{kt}^w - mc_{kt}) \frac{\partial s_{kt}}{\partial p_{jt}^w} = 0. \tag{12}$$

Define $\Omega_{jkt} \equiv -\lambda_{jkt} * \frac{\partial s_{kt}}{\partial p_{jt}^w}$, which combines information on consumers' price elasticities and firms' internalization behavior, and let Ω_t be the stacked version of Ω_{jkt} with j in the rows and k in the columns. Given the demand parameters θ_D, the vector of manufacturers' marginal costs of production for all products in market t, $mc_{.t}$, conditional on the ownership matrix Λ^t, is

$$mc_{.t}(\theta_D, \Lambda_t, p_{.t}^r, p_{.t}^w, x_{.t}) = p_{.t}^w - \Omega_t^{-1}\big(\theta_D, \Lambda_t, p_{.t}^r(p_{.t}^w), x_{.t}\big)s_{.t}\big(\theta_D, p_{.t}^r(p_{.t}^w), x_{.t}\big). \tag{13}$$

Rearranging and plugging in the marginal cost function from Equation (9) allows us to write the vector of structural cost shocks for all products in market t, $\omega_{.t}$, as a function of the model parameters and observed data, so that

$$\omega_{.t}(\theta_D, \gamma, \Lambda_t) = p_{.t}^w - \tilde{mc}_{.t}(\gamma, w_{.t}) - \Omega_t^{-1}\big(\theta_D, \Lambda_t, p_{.t}^r(p_{.t}^w), x_{.t}\big)s_{.t}\big(\theta_D, p_{.t}^r(p_{.t}^w), x_{.t}\big). \tag{14}$$

This structural cost shock forms the basis of our moment conditions to estimate the supply parameters.

In most BLP-style models, Λ is fully assumed. One of the key contributions of this paper is to flexibly estimate industry conduct as captured by the parameters within Λ. In principle, our empirical strategy is general enough to treat Λ non-parametrically, i.e., let its parameters vary freely across local markets, time, and products. However, a fully flexible conduct matrix for a specific market t consists of J^2 parameters. To keep the estimation tractable, we restrict the structure of Λ in an economically reasonable way.

Throughout the paper, we assume that the underlying conduct is identical across all geographical markets for a given time period. This rules out cases in which manufacturing firms collude in some stores and compete in others. For the cereal industry, we judge this to be a reasonable restriction, that allows us to focus in detail on variation in conduct over time and across firms. Moreover, we assume that each firm internalizes all products of a rival firm equally, so that our internalization parameters are not product- but firm-specific.

One of our primary goals is to quantify the evolution of conduct over time, in particular over three different periods: the pre-merger period (February 1991 - December 1992), the post-merger period (January 1993 - April 1996), and the price war period (after April 1996). Throughout, we estimate conduct parameters that change across but are constant within periods. We employ the standard assumption that after the merger, merging firms fully internalize the profits of the other division. In our baseline specification, we assume that all firms internalize all rivals' profits to the same degree. In a more detailed specification, we allow different firms to internalize differently.

Example for Λ: industry with three firms For illustrational purposes, assume that there are 3 single-product firms. If each firm equally internalizes its pricing externalities on every rival, the pre-merger conduct matrix is given by

$$\Lambda^{Pre} = \begin{pmatrix} 1 & \lambda^{Pre} & \lambda^{Pre} \\ \lambda^{Pre} & 1 & \lambda^{Pre} \\ \lambda^{Pre} & \lambda^{Pre} & 1 \end{pmatrix}.$$

If firms 1 and 2 merge, the conduct matrix post-merger changes to

$$\Lambda^{Post} = \begin{pmatrix} 1 & 1 & \lambda^{Post} \\ 1 & 1 & \lambda^{Post} \\ \lambda^{Post} & \lambda^{Post} & 1 \end{pmatrix}.$$

This matrix reflects that the merging firms fully internalize their profits post-merger. Moreover, this specification allows for non-merging firms to change their behavior as well. For example, if the merger resulted in increased industry-wide price coordination, then we expect λ^{Post} to be higher than λ^{Pre}. Finally, during the price war period, the conduct matrix evolves to

$$\Lambda^{PW} = \begin{pmatrix} 1 & 1 & \lambda^{PW} \\ 1 & 1 & \lambda^{PW} \\ \lambda^{PW} & \lambda^{PW} & 1 \end{pmatrix}.$$

If the price war leads firms to price competitively, then we expect λ^{PW} to be very close to zero.

Because we observe a horizontal merger in our sample, it is worth discussing how potential cost synergies could affect our estimation results. Note that we do not use the ownership change as an instrument, so that the occurrence of synergies would in principle not pose a problem. Our identification strategy would lead to biased estimates only if our instruments are correlated with the innovations in the structural cost shock ν^S. This would be the case if there are synergies that are absorbed into the innovations of the unobservable cost shock and these synergy effects are systematically related to our (promotion and relative proximity based) instruments for manufacturers' markups. For example, our instruments would be invalid if following the merger, Post and Nabisco have systematically lower cost shock innovations, and rival firms anticipate these future shocks and therefore systematically change their promotional activities. Given that we include a battery of fixed effects in the marginal cost function (see Section 4.3) and construct our moments based only on the innovations instead of the levels of the cost shocks, we argue that our error term ν_{jt}^S contains only shocks that are hard for j's rivals to anticipate when setting their promotions for period t in period $t-1$. Furthermore, we are not aware of any industry evidence for these kinds of shifts in manufacturers' strategies after the merger, nor do we find any support for such behavior in our data.

We have not found evidence suggesting that the Post-Nabisco merger caused significant marginal cost synergies. Moreover, cost synergy considerations have not been of significant importance during the merger case.[19] In addition, merger-related savings in fixed costs have no effect on firms' pricing because fixed costs do not affect the first-order conditions. An example of such savings is costs for administrative staff or rent for office space. Similarly, savings in financing costs due to a larger firm size should not affect the marginal costs of production in the short run.

We explicitly rule out synergies due to the increased bargaining power of the merged firm with suppliers of inputs. Because the production facilities of the different firms are geographically separated, the need to use different suppliers of wheat, sugar, and energy seems reasonable. In addition, there are no factory closures within the first five years of the merger. Nabisco's main production facility in Naperville, Illinois, continues to produce the

[19]See Rubinfeld (2000) for a detailed description of the arguments brought forward in the merger case. Synergies are not mentioned as an argument in favor of the merger but rather the discussion focused heavily on the consumers' substitution patterns between different cereals, which we estimate in detail. A potential non-synergy rationale for the merger was a reduction in debt for Nabisco's former parent company, RJR Nabisco. After the 1988 leveraged buyout of RJR Nabisco, which at this time was the largest leveraged buyout of all time, the ownership group accumulated substantial debt. Divesting different branches of the company such as the RTE cereal branch was thus a strategy to reduce the overall debt level.

same products after the merger as before. Moreover, the merging firms' products use different production technologies. Post's products primarily require flaking and baking processes, while Nabisco's products mainly rely on shredding.

To address potential remaining concerns about merger-related synergies, we include a post merger-merging firm dummy in the marginal cost function.[20]

4 Identification & Estimation

In this section, we describe which variation in the data identifies consumer demand, manufacturers' marginal costs, and industry conduct. Furthermore, we describe how we construct our instruments and the estimation algorithm.

4.1 Identification of Supply Parameters

Intuitively, one can think of the identification strategy in two steps: first, decomposing observed wholesale prices into a marginal cost term and a markup component, and second, backing out the conduct parameters from the identified vectors of marginal costs and markups. Once these two vectors are identified, the identification of industry conduct is relatively straightforward. Intuitively, conduct will be identified from the covariation of manufacturer markups within a given market and by how this covariation differs across markets with different characteristics. Formally, the first step involves decomposing observed prices, such that $p_{jt} = mc_{jt}(w_{jt}, \omega_{jt}) + MU_{jt}(\mathcal{I}_t)$ where $MU_{jt} = (p_{jt} - mc_{jt})$ denotes the markup of product j in market t, and $\mathcal{I}_t$ captures all relevant demand and cost shifters that affect the markups in market t. Suppose for now that we have identified the markup terms for all brands j and markets t. In the simple case of two firms with one product each, the system of first-order conditions for market t can be written as

$$p_1 = mc_1 + \underbrace{\left(\frac{\partial s_1}{\partial p_1}\right)^{-1} \left[s_1 + \lambda_{12}(p_2 - mc_2)\frac{\partial s_2}{\partial p_1}\right]}_{MU_1} \tag{15}$$

$$p_2 = mc_2 + \underbrace{\left(\frac{\partial s_2}{\partial p_2}\right)^{-1} \left[s_2 + \lambda_{21}(p_1 - mc_1)\frac{\partial s_1}{\partial p_2}\right]}_{MU_2}. \tag{16}$$

[20] As a robustness check, we also estimate our model treating the merging firms' cost functions as constant over time. The results for the two specifications are qualitatively identical and quantitatively very similar, see Appendix C.

Prices p and market shares s are observed in the data and the partial derivatives of shares with respect to prices are a function of the demand parameters but not of the supply parameters. If all marginal costs, or alternatively all markup terms MU_{jt}, are identified, the only unknown parameters in the system are the conduct parameters $\lambda = (\lambda_{12}, \lambda_{21})$. The estimation of λ can then be thought of as picking the parameter values $\hat{\lambda}$ such that they solve Equations (15) and (16) given the values of the demand parameters, prices, shares, and marginal costs.

Therefore, the primary difficulty on the supply side is to separately identify manufacturer markups from unobserved marginal cost shocks. Finding good instruments to identify markups, and therefore industry conduct, is complicated by two factors. First, many instruments used in practice turn out to be weak. For example, the classical BLP moment conditions, which are based on aggregate functions of rival products' characteristics, are often too crude and not able to strongly identify conduct parameters. Second, in many applications, one does not observe variation in the set of products offered which makes many instruments collinear with brand fixed effects. In the following, we propose a novel set of instruments that rely only on standard market-level data and help addressing these issues.

To address the problem of weak instruments, we construct measures of products' relative isolation in the characteristics space. Gandhi and Houde (2017) illustrate that differentiation instruments, which exploit products' relative isolation, perform well in identifying heterogeneous consumer preferences. For our application, we find that instruments that are based on similar proximity measures are also very powerful for identifying industry conduct. More specifically, we construct several variables that capture how similar the characteristics of two products are to each other, for example, with respect to their sugar or fiber content.

To overcome the problem of a constant product space, we interact our isolation measures with information on the promotional activities of rival firms. Intuitively, our instruments count the number of promotions by rival firms in a given market but only consider those rival products that are "close enough" according to our relative proximity measures described above.

Typically, one can compute several proximity measures, and one often observes several types of promotions. This allows us to construct multiple instruments for industry conduct. For example, if we compute 3 different proximity measures and observe 2 types of promotions, we can rely on 6 different instruments. Appendix B.1 provides the details on how we specify the instruments in our application.

For our instruments to be valid, they must satisfy two conditions. First, they must be correlated with the endogenous regressor. When estimating firm conduct, we effectively need to instrument firms' markups. How many and which rival products are on promotion affects the competitive pressure exerted on a product. When any substitute product of j is on sale, consumers become more likely to choose it over product j compared to when there is no promotion. The firm owning product j should consider this when setting the prices and markups of its brands. We provide extensive evidence for these effects in Section 3.

Second, the instruments must be exogenous to the structural error used to construct the moment conditions. Clearly, promotions are chosen by firms and are therefore endogenous. However, in many industries, including ours, decisions between retailers and manufacturers regarding whether a promotion for a particular product-store combination will occur in period t are made in advance, i.e., at the latest in $t-1$. Generally, these decisions are unlikely to be reversed due to operational and logistical issues; for example, advertising brochures have to be printed, and a higher product supply than usual has to be delivered to the different stores.[21]

Note that we include brand, store, and seasonal fixed effects in the marginal cost function and that we use only the innovation in the structural cost shock to construct our moment conditions. Therefore, it seems very plausible that the structural supply errors for product j at time t are unknown and cannot be anticipated by any firm before period t. Consequently, they should be uncorrelated with other brands' promotional activities that are decided in $t-1$ at the latest.

The key restriction we make is that while firms decide in period $t-1$ or before whether a promotion occurs in period t, they do not simultaneously determine the wholesale price. While one could in principle relax this timing assumption, the essential requirement for our instruments to work is that the promotion patterns are fixed before the wholesale prices are set.[22] Formally, we require that wholesale prices $p^w_{jt} = f(\mathcal{I}_t)$, where $\mathcal{I}_t$ denotes all information available in period t, for example, all contemporaneous demand and cost shifters. In contrast, the number of promotions in period t $Promo_{jt} = f(\mathcal{I}_{t-1})$, where $\mathcal{I}_{t-1}$ contains only information available up to $t-1$. Shocks that cause $\mathcal{I}_{t-1}$ to be different from $\mathcal{I}_t$ provide the variation in the data necessary to make our instruments for identifying industry conduct work. In all other regards, we can be agnostic regarding the reason why the retailers and manufacturers agree to place products on promotion.[23] Thus, rival firms' promotional periods should affect

[21] This is a pattern observed in many consumer products industries in many different countries. In some countries, it is even known several months in advance at which retailer which brands will be on promotion, and this is common knowledge across the different manufacturers.

[22] A subtle additional requirement is that after the promotion pattern for period t is determined, but before the wholesale prices for period t are set, product-specific (demand or supply) shocks occur that lead two firms with identical promotion patterns today to charge different wholesale prices in the next period. This assumption is similar to common assumptions in the literature on production function estimation; see, for example, the extensive discussion in Ackerberg *et al.* (2015).

[23] There is a theoretical literature on why promotions occur in the first place; see, for example, Lal and Matutes (1994) on using promotions as loss-leadership and Varian (1980) and Villas-Boas (1995) for a price-discrimination rationale regarding different consumers.

firm j's pricing but should not be correlated with j's structural cost shocks.

Because there is little hard evidence on the structure of the contracts between manufacturers and retailers, we provide support from the data for these timing assumptions. If our timing assumptions are satisfied, one would expect that wholesale prices react to demand and cost shocks immediately. In contrast, if promotions are predetermined, they should not react to contemporaneous shocks. Instead, one would expect that promotions adjust with a lag. We investigate these hypotheses in a series of reduced form regressions. Specifically, we regress wholesale prices on various cost shifters that should affect the pricing decisions of manufacturers, in particular, input prices for sugar, rice, and corn weighted by the respective content in a given product, the gasoline price interacted with a production facility's distance to the Chicago area, and the electricity price interacted with the main methods of production (flaking and shredding). Throughout, we control for a series of fixed effects on the brand, store, and month level. Afterwards, we conduct analogous regressions with the number of contemporaneous promotions for a given brand in a given market as the dependent variable. Finally, we repeat this regression, replacing the contemporaneous promotion intensity measure with the number of promotions in future periods (1 to 6 months into the future). The associated results are summarized in Table 7 in Appendix B.2. Column (1) reveals that wholesale prices indeed react to shocks in the same month. The weighted grain prices and gasoline prices significantly affect wholesale prices.[24] Column (2) displays that the number of promotions in the current month is not significantly affected by any of the cost shifters. Finally, columns (3) to (8) illustrate that the number of promotions in the future is, however, significantly affected by cost shocks today.

The observed patterns seem reasonable and are consistent with firms being able to react to different types of shocks in different ways. For example, grain prices today affect the promotional intensity one and two months in the future, the gasoline price interacted with factory distances affects promotional intensity 2 to 3 months from today, and electricity prices have an effect on the number of promotions 3 to 5 months into the future. As another sanity check, column (8) reveals that the effect of cost shifters on promotions vanishes after 6 months. Overall, we interpret these regressions as providing strong support for the validity of our timing assumptions. Note that the staggered effect of different cost shifters does not invalidate our instruments. Instead, all that matters is that it takes time for promotions to be adjusted so that they are plausibly uncorrelated with the innovations in the structural cost shock that we use in our moment conditions.

To verify that our supply side instruments are indeed very powerful for identifying the

[24] The coefficients of electricity prices exhibit high standard errors and are therefore insignificant.

conduct parameters, we conduct a series of weak IV and weak identification tests. We report these results in Appendix B.3.

Several advantages of our identification strategy are noteworthy. First, our instruments do not require the availability of exogenous industry shocks, such as ownership changes. Second, they do not rely on variation in the set of products offered or changes in products' physical characteristics. Finally, the information necessary to construct our instruments is available in many data sets used in empirical industrial organization or quantitative marketing; therefore, our empirical strategy can be easily applied to many consumer products industries.

4.2 Identification of Demand Parameters

Conceptually, our demand model does not differ significantly from most of those used in the literature. Our primary concern is that the estimated conduct parameters will depend crucially on the estimated demand elasticities. This results in two challenges for our demand model. First, we require realistic and flexible substitution patterns among the inside goods and between the inside goods and the outside good. Therefore, simple logit models are unlikely to describe the full picture. Second, a recent and growing strand of the literature has highlighted that many demand instruments commonly used in BLP-type models are weak. Weak instruments are likely to result in imprecise and very sensitive estimates of substitution patterns. Because reliable price elasticities and substitution patterns are the key inputs from the demand side to our supply model, it is extremely important to use strong instruments.

Our instruments for identifying heterogeneity in consumer preferences and the nesting parameter are based on the logic of classical BLP instruments. However, we address the issues of weak instruments by building on the concept of *differentiation instruments* recently introduced by Gandhi and Houde (2017). Differentiation instruments, which are a function of a product's relative isolation in the physical characteristics space, cannot be employed in our application since the set of products and their physical characteristics do not vary across markets. Therefore, we interact measures of products' relative proximity in the characteristics space with the number of promotions of rival products.[25] The increased promotion intensity of product j's rival will make that rival more attractive –not only through a lower price but also through the advertising and awareness effects that we documented in Section 2.3– and so shift the markup of product j. Moreover, because of the predetermined nature of promotional activities, for which we provide evidence in the previous subsection and Appendix B.2, rival

[25] Essentially, one can interpret the number of market-specific promotions as a nonphysical product characteristic that varies across markets. Also, see Pinkse and Slade (2004) for a semiparametric approach to estimating demand elasticities using the distance between brands in the characteristics space in the UK beer market.

products' promotions should be uncorrelated with the innovations in the demand shocks of product j. This logic results in instruments that are conceptually very similar to the instruments for identifying industry conduct that we described in the previous subsection.

The implied key restrictions are twofold. First, and analogous to our argument on the supply side, we require that the innovations in the structural demand errors in period t cannot be anticipated by firms before period t. Given that we include a battery of fixed effects in the utility function of consumers, it seems reasonable that the innovations in the demand errors capture only highly idiosyncratic shocks that are hard to anticipate for national cereal manufacturers. Second, we cannot accommodate promotional spillover effects. These would occur if the promotions of product j's rivals affect the utility of product j directly. Given that promotional activities in the cereal industry are highly brand-specific and do not reference rival products, it seems very plausible that they affect the demand for product j only indirectly by making the rival products more attractive.

As instruments for potentially endogenous retail prices in the demand equation, we exploit input price variation over time interacted with product characteristics. The economic assumption is that input price variation should be correlated with variation in retail prices but not with consumers' preferences for unobservable product characteristics. Because of the absence of any major variation in the production processes, for example, due to firms' relocating their production facilities, and because our data covers only one metropolitan area, the relation between observed cost shifters, such as input prices, and retail prices can be opaque and statistically weak. Therefore, we exploit data on wholesale prices, as, for example, proposed by Chintagunta *et al.* (2003). We use predicted instead of actual wholesale prices to account for the possibility that a manufacturer's wholesale price could be correlated with a transitory demand shock. We calculate predicted wholesale prices as the fitted values from a linear regression of observed wholesale prices on a wide variety of fixed effects and observed demand and cost characteristics. We explain how we construct this regression in detail in the next subsection.

To ensure the power of our demand instruments, we conduct extensive checks to ensure that our model does not suffer from weak identification. We run a battery of first-stage F-tests and rank deficiency tests of the first-stage based on ideas in Cragg and Donald (1993) and Kleibergen and Paap (2006). The details and results are presented in Appendix B.3.

4.3 Estimation Algorithm

We estimate our model using the generalized method of moments (GMM) similarly to the seminal work by BLP and the subsequent literature. We estimate demand and supply parameters in two steps. Given our large data set, we judge the gain in efficiency from estimating both parts jointly to be less important than the gains in computational speed from estimating demand and supply separately.

Demand estimation For a given guess of the nonlinear demand parameters, we solve the BLP contraction mapping to back out the mean utility levels δ for each brand, store and month to match the model's predicted market shares to the observed data. Then, we compute the structural demand shocks ξ for a given value of the linear demand parameters. Afterwards, we regress ξ_{t+1} on ξ_t using auxiliary OLS regressions to compute the predicted innovations ν^D of the ξ-process. Finally, we interact the implied demand shocks with a set of suitable demand instruments Z_D. Based on the identification arguments from the previous section, we choose Z_D such that at the true demand parameter values θ_{D0}, the innovations in the demand shock are uncorrelated with Z_D. The moment conditions for the demand model can be written as

$$E[Z_D'\nu^D(\theta_0)] = 0. \tag{17}$$

In our main specification, Z_D contains the following variables. First, we include brand dummies and month-of-the-year (henceforth, month-year) dummies to capture potential seasonal effects in cereal demand, and the total number of a brand's promotions in a given market.[26] In addition, X and Z_D contain a linear-quadratic time trend that controls for long-term industry trends. Second, our main specification includes predicted wholesale prices as brand-specific cost shifters to identify the price coefficient. In our linear hedonic wholesale price regression, we use the following regressors: brand dummies; month-year dummies; store fixed effects; a time trend; input prices for wheat, corn, sugar, rice, oats, electricity, and gasoline; and the number of a brand's own and rival firms' promotions. Third, Z_D includes instruments based on the number of rivals' promotional activities interacted with the relative proximity in the characteristics space as described in the previous subsection. In particular, we use both the number of general promotions and bonus buy promotions and interact them with the relative proximity of the two products with respect to sugar content, fiber content, and sogginess. A detailed description of how these instruments are computed is provided in Appendix B.1. We regard these instruments as the most important for identifying the demographic interaction coefficients.

Our GMM estimate for the demand parameters minimizes the following objective function

[26] Since in our application, product characteristics do not change across markets, we follow Nevo (2001) and do not include exogenous product characteristics x in the estimation directly. Instead, we back out mean preferences for each time-invariant product characteristic by regressing the estimated brand fixed effects on these characteristics.

$$\hat{\theta}_D = \arg\min_{\theta} \nu^D(\theta)' Z_D \hat{W}_D^{-1} Z_D' \nu^D(\theta), \tag{18}$$

where $\hat{W}_D^{-1}$ is an estimate of the efficient weighting matrix

$$W_D^{-1} = E[Z_D' \nu^D(\theta_{D0}) \nu^D(\theta_{D0})' Z_D]^{-1}$$

based on parameter estimates obtained from a first-stage estimation with a 2SLS weighting matrix $E[Z_D' Z_D]^{-1}$. As proposed by Nevo (2001), we profile out all linear parameters contained in δ so that we have to optimize numerically only over the nonlinear coefficients.

Supply estimation For the estimation of the marginal cost parameters γ and the conduct parameters λ, we generalize the algorithm by BLP to allow for the profit internalization matrix Ω to be estimated rather than assumed.

For a given parameter guess for the supply side parameters $\theta_S = (\gamma, \lambda)$, we solve the stacked first-order conditions, given by Equation (12), for the unobserved cost shock ω for each brand, store and month

$$\omega(\theta_S, \hat{\theta}_D) = p^w - \tilde{mc}(\theta_S) - \Omega^{-1}(\theta_S, \hat{\theta}_D)s.$$

Similar to our demand estimation, we exploit orthogonality conditions between the innovations in the structural cost term ω and a set of instruments Z_S. We back out the innovations in the structural cost shocks using auxiliary OLS regressions of ω_{t+1} on ω_t. The moment conditions of the supply model can then be written as

$$E[Z_S' \nu^S(\theta_{S0}, \hat{\theta}_D)] = 0. \tag{19}$$

Our supply side instruments consist of the following variables. First, they include brand dummies, month-year dummies, and store fixed effects to control for persistent cost differences, for example, due to different delivery costs for different locations or seasonal effects. Second, we include exogenous cost shifters. In our main model, we include only the electricity price in the Midwest region to avoid quasi-collinearity problems between different commodity prices. Finally, we include products' relative distance in the characteristics space interacted with rivals' promotion intensity as discussed in the previous subsection. While the first two sets of moments identify the parameters of the marginal cost function, the last one identifies the conduct matrix. The objective function of our supply side estimation is given by

$$\hat{\theta}_S = \arg\min_{\theta_S} \nu^S(\theta_S, \hat{\theta}_D) Z_S' \hat{W}_S^{-1} Z_S' \nu^S(\theta_S, \hat{\theta}_D), \tag{20}$$

where $\hat{W}_S$ is an estimate of the asymptotically efficient weighting matrix based on parameters obtained from the first-stage estimation using the 2SLS weighting matrix. As for the demand estimation, we profile out the linear parameters contained in the marginal cost function and search nonlinearly only for the conduct parameters.

5 Results

5.1 Demand Estimates

Table 1 displays the estimation results for our main demand specification. We include mean parameters for a constant, price, sogginess, sugar content, fiber content, and the total number of a brand's promotions in a given market. Furthermore, we interact consumer demographics with observed product characteristics. Specifically, we interact a dummy for households with small children (less than 10 years old) with the preference for sugar and a consumer's income with preferences for price and fiber content.

Table 1: RCNL Demand Estimates: Main Specification

	Mean	Children	Income
Constant	−2.1043***		
	(0.0066)		
Price	−9.4674***		0.7491***
	(0.0967)		(0.1825)
Sogginess	0.2202***		
	(0.0018)		
Sugar	−1.0145***	3.1400***	
	(0.0048)	(0.1456)	
Fiber	−0.0383***		−0.1074***
	(0.0022)		(0.0299)
Promotions	0.2662***		
	(0.0146)		
Nesting parameter	0.4758***		
	(0.0859)		

Notes: The estimation includes product- and month-year fixed effects and a linear-quadratic time trend. Standard errors are in parentheses. Number of observations: 96512.

All of our demand coefficients are precisely estimated and highly significant, and the signs of the estimates for mean preferences seem reasonable. The price coefficient is highly negative, and ceteris paribus, consumers prefer cereals with higher sugar and less fiber content. Our estimated price-income coefficient is positive and significant indicating that high-income consumers are less price-sensitive. Households with small children have a stronger preference for cereals with a higher sugar content, which is consistent with popular kids' cereals having higher sugar content. Finally, the demand for fiber in cereal is negatively correlated with income and significant, potentially because high-income consumers prefer to consume fiber from other food sources.

We experimented extensively with alternative demand specifications that include additional demographic interactions and normally distributed random coefficients. The results are qualitatively similar. In particular, the implied price elasticities, which are the most important output of our demand model, are very similar to those of our main specification. However, larger demand models generally resulted in higher standard errors for some of the additional parameters, especially for the normally distributed random coefficients.[27]

Table 11 and Table 12 in Appendix C show the median price elasticities over all markets for our main demand specification. The own-price elasticities are highly negative for all products. Moreover, our estimated substitution patterns exhibit significant variation across brands. The median cross-price elasticities are all positive, which is consistent with products being imperfect substitutes. Our estimates reveal that the cross-price elasticities tend to be particularly high among the signature products of Kellogg's (*Corn Flakes* and *Frosted Flakes*) and General Mills' (*Cheerios* and *Honey Nut Cheerios*). In addition, we generally observe strong substitution among products with similar characteristics, for example, among sugary cereals, such as *Kellogg's Frosted Flakes*, *Kellogg's Smacks*, and *Quaker Cap'n Crunch*. Furthermore, our substitution patterns also seem to capture well that consumers may have a preferred type of cereal so that they substitute more strongly within this type than with another type of cereal. For example, for the different *Raisin Bran* brands in our sample produced by Post, General Mills, and Kellogg's, the median cross-price elasticities are usually the highest to the other raisin bran products, which we think is a reasonable pattern.[28] Overall, our estimated substitution patterns are relatively similar to those of previous demand studies on the cereal industry using similar models but different instruments, such as Nevo (2001).

In general, we judge our model to be economically meaningful and to have a good fit with

[27] These results are available from the authors upon request.

[28] Specifically, most substitution from Post RB occurs to Kellogg's RB, substitution from GM RNB is highest to Post RB, and consumers of Kellogg's RB are most likely to substitute to Post RB.

the observed data. The distribution of implied marginal costs based on the estimated demand elasticities seems reasonable. For example, under hypothetical multiproduct Bertrand-Nash pricing our model predicts negative marginal costs only for less than 0.035 percent of our observations. We further illustrate that the effect of the structural error terms ξ is small and not systematic. A series of figures in Appendix D shows that in general, when setting the ξ errors to zero, our model predictions are close to the observed data on several levels. For example, our graphs suggest that when we predict aggregate sales for the whole Chicago area or for specific stores or market shares of individual brands, our prediction error is modest and nonsystematic.

5.2 Supply Estimates

On the supply side, we focus on two different specifications. In our "small" model, we estimate 3 conduct parameters that reflect the level of conduct in each period, i.e., one parameter pre-merger, one post-merger, and one for the price war period. For this model specification we impose symmetry across all firms, such that each firm internalizes every rival's profit to the same degree. In our "large" model we let the conduct vary across firms. For each period (pre-merger, post-merger, and price war), we estimate two distinct parameters capturing the potentially different internalization behavior of the two largest firms, Kellogg's and General Mills, and the smaller firms, i.e., Post, Nabisco, Ralston, and Quaker. Consequently, our large model estimates 6 conduct parameters. This specification allows us to capture the fact that industry leaders might have very different incentives to internalize rival firms' profits than smaller competitors. However, we remain agnostic about which type of firm cooperates more.

Table 2 presents the estimation results from our main specification, in which we account for a synergy dummy in the merging firms' cost function following the merger. The estimates are very similar to those of the baseline specification that abstracts from cost synergies, see Table 15 in Appendix C.[29]

For our small model, there is significant internalization between firms pre-merger, with an estimate of 0.277. Intuitively, this parameter indicates that a firm values US-$ 1 profit of a rival firm as much as US-$ 0.277 of its own profits. This parameter further increases to 0.454 following the merger. Consistent with our descriptive evidence, in the price war period, the industry conduct drastically decreases, with an estimated conduct parameter that is very close to 0. While the pre- and post-merger conduct parameters are highly significant, the

[29] When interpreting our results with respect to policy recommendations, two caveats should be noted. First, we do not suggest that such estimates necessarily provide evidence that cereal manufacturers violated antitrust laws. Second, we do not claim that the merger or the price war actually caused the shifts in industry conduct.

conduct parameter in the price war period is not significantly different from 0.

When allowing for heterogeneity in the internalization behavior of different firms, we find considerable differences across firms. Pre-merger, the small firms with a parameter of 0.404 already internalize rivals' profits substantially more than the large firms (0.127). For the large firms, the conduct parameter in the pre-merger period is significantly different from 0 only at the 10%-level. Following the merger, the degree of internalization increases and is statistically significant for all firms, and remains higher for small firms (0.624) than for large firms (0.309). During the price war period, the estimated parameters revert to very close to 0 for all firms, indicating behavior that is consistent with Bertrand-Nash price competition during the price war. These results are broadly consistent with the descriptive and reduced form evidence presented in Section 2.

Table 2: Conduct Estimates: Model Comparison

	Small Model			Large Model		
	Pre-merger	Post-merger	Price War	Pre-merger	Post-merger	Price War
All Firms	0.2766***	0.4535***	0.0001			
	(0.0316)	(0.0101)	(0.0012)			
Large Firms				0.1269*	0.3094***	0.0038
				(0.0648)	(0.0633)	(0.0107)
Small Firms				0.4043***	0.6236***	0.0192
				(0.0208)	(0.0403)	(0.0358)

Notes: The table entries reflect the conduct estimates for both the small and the large conduct specification. Standard errors are in parentheses and account for two-step estimation. Number of observations: 96512.

Table 13 in Appendix C summarizes the marginal cost estimates for our two conduct specifications, and under the assumption of multiproduct Nash pricing. In the cost function, we account for product fixed effects, month-year (seasonal) dummies, store fixed effects, a time trend, and electricity prices as a proxy for aggregate production costs. To control for potential cost synergies after the merger, we further incorporate a merging firms-post-merger dummy in the marginal cost function. The time trend and price of electricity generally have a positive sign but are insignificant. The insignificant time trend is consistent with production processes being relatively constant over time. We experimented with several additional cost shifters, for example, commodity (wheat, corn, rice, oats, and sugar) spot prices interacted with a brand's specific grain content. These specifications yielded very similar results. However, we did not obtain significant coefficients on the additional variables, most likely because of high correlation in commodity prices, and because of potential commodity price hedging by manufacturers, which makes observed spot prices only weak proxies for manufacturers' economic marginal cost shifters. The estimates of the post-merger-merging-firms dummy indicate a very small and insignificant decrease in the merging firms' marginal cost after the merger.

Finally, we allow manufacturers' marginal cost to depend on the number of general promotions and bonus buy promotions as additional cost shifters. These variables should capture that promotions could, for example, lead to scale economies in shipping, or other types of cost savings. We find a significant negative effect on manufacturers' marginal cost for the number of brand- and market-specific general promotions but only an insignificant negative effect for the number of bonus buy promotions. Despite of several insignificant coefficients, our marginal cost specification explains a large portion (73%) of the variation in marginal costs across brands, stores, and time because most of our fixed effects are large and highly significant.

For the large specification, the signs and absolute magnitudes of the parameters are similar to those for the small specification. The cost parameters do not change considerably when we do not include a synergy dummy for the merging firms following the merger, as shown in Table 16 in Appendix C. For the small and the large model, we obtain J-statistics of 14.04 and 9.12 respectively, so that the Hansen-Sargent test does not reject the null hypothesis of the joint validity of the moment conditions at the 1%-level for either model.

A very important and policy-relevant issue is to determine the extent to which industry conduct translates into the markups of individual products. Table 14 in Appendix C compares product-specific median (across markets) price-cost margins for both of our conduct specifications. In addition, we compute the implied margins under multiproduct Nash pricing which we use as a competitive benchmark.[30]

Both specifications lead to markups that are considerably higher than those implied by Bertrand-Nash pricing before the price war period. General Mills and Kellogg's products have higher markups in the small specification than in the large specification, while the opposite is true for the smaller firms' products. Again, this is likely to occur because General Mills and Kellogg's internalize their pricing externalities less in the large model than in the small model, while the opposite is true for the small firms.

The median marginal costs implied by our models are US-$ 0.107 per serving under multiproduct Nash pricing, US-$ 0.085 for the small conduct specification, and US-$ 0.089 for the large conduct specification. Over the whole sample period, our estimated median margins are 33 percent (small specification) and 29.4 (large specification) percent higher than those implied by multiproduct Nash pricing. In the small specification, the median

[30] Recall that multiproduct Nash pricing implies that each firm maximizes the profits of its own product portfolio and that all of the markups can be attributed to product differentiation rather than to cooperative behavior.

margins increase from 25.6 percent over multiproduct Nash pricing in the pre-merger period to 42.7 percent in the post-merger period. These numbers are slightly lower for the large model, with an increase in median margins over Nash pricing from 20.8 percent pre-merger to 38.1 percent in the post-merger period.[31] Our estimates imply that, over our whole sample period, 24.8 percent (small specification) and 22.7 percent (large specification) of the median markup can be attributed to cooperative industry behavior.[32]

Table 17 in Appendix C displays the median price-cost margins decomposed for both different brands and different time periods. Consistent with the model parameter estimates, markups are very heterogeneous across brands and most products experience considerable changes in markups over time.

As a final validation of our estimates, we compare marginal cost predictions from our two conduct models with the ones obtained under the assumption of multiproduct Nash pricing. Figure 4 in Appendix C illustrates the evolution over time of the median marginal costs implied by the three different models. Several observations are noteworthy. Under the assumption of multiproduct Bertrand-Nash pricing, we obtain an inverse u-shaped evolution of marginal costs. The predicted costs increase during the pre-merger period and for another year after the merger. They remain roughly constant until shortly before the price war and decline substantially afterwards. The implied marginal costs from our conduct models exhibit a different pattern. While they also increase over the pre-merger period, marginal costs decrease considerably during the post-merger period and increase again during the price war period, and the qualitative predictions from our small and large models are very similar.

Ideally, one would like to compare these predicted marginal costs to an observed counterpart. Unfortunately, it is extremely hard to obtain such measures from observed data. Therefore, we plot the evolution of several important input prices (corn, wheat, rice, oat, sugar, electricity and gasoline) in the bottom panel of Figure 4. Even though input prices are not a perfect proxy for economic marginal costs, their general development seems much more consistent with the cost predictions from our conduct models. For example, during most of the post-merger period, many input prices are considerably lower compared to the pre-merger and price war periods, and there is a sharp increase in input prices shortly before and during the price war.[33] Overall, these patterns seem difficult to reconcile with the marginal costs predicted by a multiproduct Nash model. We believe that these results provide further

[31]We compute the median margin over Nash pricing for a given conduct specification as the difference between the median margins under this conduct specification and under multiproduct Nash pricing, divided by the median margin under Nash pricing.

[32]We compute the fraction of the markups that is attributed to cooperative behavior for a given conduct specification as the difference between the median margins under this conduct specification and under Nash pricing, divided by the median margin under the conduct specification.

[33]Sugar constitutes an exception as its price drops monotonically (except for a short period in 1994).

support for our conduct specifications.

Relationship to other industry studies Because the RTE cereal industry has been studied extensively, it is useful to relate our results to those in the literature. The works of Nevo (2000b) and Nevo (2001) are of particular interest. Nevo (2000b) simulates the effects of different hypothetical horizontal mergers using only pre-merger data. Assuming multiproduct Bertrand-Nash pricing before and after the merger, he finds that, in the absence of considerable cost synergies for the merging firms, the merger between Post and Nabisco leads to an increase in prices and a decrease in consumer surplus. Our focus is mainly on estimating the conduct between different manufacturers over time, and accounting for potential changes in conduct. Most importantly, in our model specifications, increases in markups can not only be explained by the "unilateral effects" of the merger but also by a more cooperative industry conduct in the post-merger period ("coordinated effects").

Nevo (2001) measures market power in the RTE cereal industry. His sample contains data from 65 US cities covering a period from 1988 to 1992. Time-wise, this partially overlaps with our pre-merger period. On the demand side, our estimates of the median own- and cross-price elasticities are very close to his. This is the case despite his use of Hausman (1996)-style instruments based on prices from other regions, and different data with a slightly different product set.[34] An additional difference on the demand side is that we use a nested random coefficient logit model rather than a random coefficient logit model to capture a richer substitution pattern between the inside products and the outside good. We consider the similarity of the implied coefficients as an additional validation of our demand estimates.

To select among different forms of industry conduct, Nevo (2001) compares the recovered marginal cost for different pre-specified conduct assumptions with accounting cost data under the assumption of vertical integration, i.e., joint profit maximization between retailers and manufacturers. Comparing three different conduct assumptions (single-product Nash, multiproduct Nash, and joint ownership of all products), he finds that multiproduct Nash pricing provides the best fit to the industry accounting data, resulting in a combined retailer-manufacturer price-cost margin of 42.2 percent compared 35.8 percent under single-product Nash and 72.6 percent under joint ownership of all brands. For the part of our sample period that overlaps with his sample period, i.e., the pre-merger period, the estimated markups from both of our conduct models are closer to his multiproduct Nash specification than to the other two considered options. However, our results indicate a significantly positive but moderate level of cooperative conduct during this period. For the pre-merger period, we find implied median gross margins for retailer and manufacturers combined of 53.7 percent

[34] Most notably, we additionally include products from the manufacturer Ralston.

for the small conduct model, and of 52.1 percent for the large model.[35] As discussed above, comparing the implied marginal costs for the different models with input price data yields supporting evidence that for our sample, our conduct specifications yield a more accurate industry description than multiproduct Nash pricing.

Comparing our results with those from a pre-specified menu of conduct specifications also relates to the question of why direct conduct estimation might be useful in the first place. First, accounting data as a measure of marginal cost is not necessarily very fine-grained, and it is not always clear how it relates to marginal cost. Thus, while it might enable a distinction among different relatively distant conduct assumptions, it is more difficult to use when considering different forms of conduct that are relatively close to each other. For example, already for a conduct parameter of 0.1, a significant part of the markups can be due to cooperative behavior between firms. Another alternative to comparing the recovered marginal cost to accounting data is the use of non-nested statistical tests; see, for example, Rivers and Vuong (1988), Chen *et al.* (2007), and Shi (2015). While in principle, it is possible to compare conduct specifications that are relatively close to each other, the statistical power of these tests is often hard to assess. This is even more problematic when one is interested in estimating conduct patterns, that potentially change over time and across firms. For these reasons, we believe that a direct estimation of industry conduct can contribute to a better understanding of markups and marginal costs in differentiated products industries.

6 Counterfactual Simulations

In this section, we use our estimated parameters from the structural model to simulate how two different changes in the underlying industry conduct would affect consumer surplus and manufacturers' pricing behavior.

First, we examine how these two measures would change if the firms were competing a la multiproduct Bertrand-Nash pricing before the price war. Table 3 shows the associated results. As a measure of consumer surplus, we estimate the compensating variation, i.e., the dollar value for which consumers would have been equally well off in both the observed industry state and the counterfactual simulation. Both the small and large conduct model

[35] Assuming multiproduct Nash pricing, we find an implied gross margin for the pre-merger period of 45.2 percent, which is slightly higher than Nevo's (2001) for the same assumption. Note that Nevo recovers the gross margin under the assumption of joint maximization of retailer and manufacturers profits, while we use the assumption that manufacturers and retailers maximize profits independently, which results in double marginalization. This is fully consistent with the slightly higher gross margin for our multiproduct Nash specification compared to his in the same time period. Also note that while the implied margins of both our small and large models are considerably higher than Nevo's, they still lie within his estimated 95 percent confidence interval for the implied margins under multiproduct Nash pricing. The lower and upper bound of his 95% confidence interval are 29.1 percent and 55.8 percent respectively.

Table 3: Counterfactual Simulation 1: Change to multiproduct Bertrand-Nash pricing

	Small Model		Large Model	
	Pre-merger	Post-merger	Pre-merger	Post-merger
Δ consumer surplus (in US-$ mio.)	2.3	5.3	3.2	6.3
Δprice All Firms (in %)	−9.5	−15.7	−9.4	−16.9
Δprice GM (in %)	−8.5	−15.3	−7.6	−14.8
Δprice RAL (in %)	−10.8	−16.8	−25.4	−25.7
Δprice KEL (in %)	−8.3	−13.5	−8.3	−13.8
Δprice POSNAB (in %)	−13.7	−18.6	−27.6	−27.4
Δprice QUA (in %)	−13.5	−22.8	−30.9	−34.1

Notes: The table entries reflect the results from the counterfactual simulations for both the small and the large conduct specification. The simulations compute the changes in consumer surplus and wholesale prices before the price war period when all firms play according to multiproduct Nash pricing instead of the estimated conduct.

yield relatively similar results. We find that if firms had played according to multiproduct Bertrand-Nash pricing instead of our estimated conduct, before the price war, consumers in our sample would have been between US-$ 1.6 million and US-$ 2.0 million per year better off. Consistent with the changes in industry conduct over time, the counterfactual simulations indicate that under multiproduct Nash pricing, the median wholesale prices across all firms would have been between 9.4 and 9.5 percent lower in the pre-merger period and between 15.7 and 16.9 percent lower in the post-merger period. When considering firm-specific prices, we find that Kellogg's would have had the lowest predicted wholesale price decrease, while the decrease would be the largest for Post-Nabisco and Quaker.

Second, we examine how consumer welfare and pricing would have changed if the price war had never occurred, i.e., if the conduct had remained the same as before the price war period. Table 18 in Appendix C shows the associated results. We find that without the price war, consumers would have been between US-$ 0.7 million and US-$ 0.8 million worse off during this period, which spans the last 6 months of our sample. The median wholesale price responses of each manufacturer differ between the small and large conduct models. While for the small model, the predicted price responses are relatively homogeneous, for the large model, the wholesale price responses are generally higher for small firms than for large firms. This is fully consistent with the higher conduct parameters for small firms in the large model.

7 Conclusion

In this paper, we estimate the evolution of competition in the RTE cereal industry using a structural model of demand and supply. Our empirical strategy is flexible enough to accommodate detailed patterns of industry conduct; in particular, we allow levels of conduct to vary both across time and firms.

To overcome the identification problem of separating marginal costs from industry conduct, we construct novel instruments that interact measures of products' relative isolation in the characteristics space with data on rival firms' temporary and market-specific promotional activities. Intuitively, our identification of the supply parameters is based on the idea that a firm's markups react much more strongly to the promotions of a competing product that is close in the characteristics space than to those of a more distant product; and this relationship should be stronger the more competitive the industry is.

Our empirical strategy has several attractive features that allow it to be applied to many other industries. First, it does not rely on exogenous industry shocks, such as ownership changes, to identify industry conduct. Second, our instruments can be used even if there is no product entry or exit during the sample period. Third, the required data are available in many standard data sets for a broad range of consumer goods industries. Finally, a series of weak identification tests indicates that our instruments indeed are very powerful for identifying flexible patterns of industry conduct in contrast to many commonly used BLP-style instruments.

We use our model to shed new light on two important industry events during the 1990s: first, the Post-Nabisco merger and second, a period of large wholesale price cuts in 1996. Our estimation results suggest that in the beginning of our sample period in 1991, the industry was characterized by moderate levels of price coordination which increased significantly for all firms after the Post-Nabisco merger in January 1993. For the pre-merger and the post-merger periods, our model predicts price-cost margins that are higher than those implied by multiproduct Nash pricing by 20.8 and 38.1 percent, respectively. These numbers indicate that a significant percentage of the markups of national cereal manufacturers during the first half of the 1990s can be attributed to cooperative industry behavior. Our conduct estimates for the last months of our sample period are consistent with a shift in firms' behavior to multiproduct Nash pricing. Our results thus suggest that while product differentiation alone can explain the largest portion of the price-cost margins, for a long time cooperative behavior further increased markups even more. Moreover, we find that such behavior was more prevalent for small firms than for large firms.

A well-known critique of conduct parameter models in general is that the estimated parameters ultimately constitute only a reduced form approximation to a more structural model of firm behavior, for example, in the form of a repeated game. While the development of such a framework goes beyond the scope of this paper, it is a very promising area for future research. Our empirical strategy and the rich set of instruments that we propose are likely to be easy to apply and to adapt to these more complicated settings. In particular, a structural repeated game model is likely to contain more parameters than ours. The empirical results from our application provide first evidence that our instruments may work very well for estimating markups in such high-dimensional models.

Recently, there has been an increased interest in the evolution of markups over time from a macroeconomic perspective. De Loecker and Eeckhout (2017) document a substantial increase in markups from 1980 onwards for the US economy by using a production function approach. They attribute this pattern mainly to a sharp increase in the markups of already high-markup firms within the different industries. Our approach can be seen as complementary to this literature. By focusing on estimating competitive interactions between firms within an industry, one can gain detailed insights into the extent to which potentially heterogeneous conduct and differentiated consumer preferences can explain firms' markups.

Our model can be readily applied to estimate supply side patterns in many important industries because many standard data sets contain the information required for our estimation strategy. Comparing estimated conduct levels across industries can lead to a better understanding of the determinants of anti-competitive firm behavior, which is still a relatively open question with important implications for competition policy.

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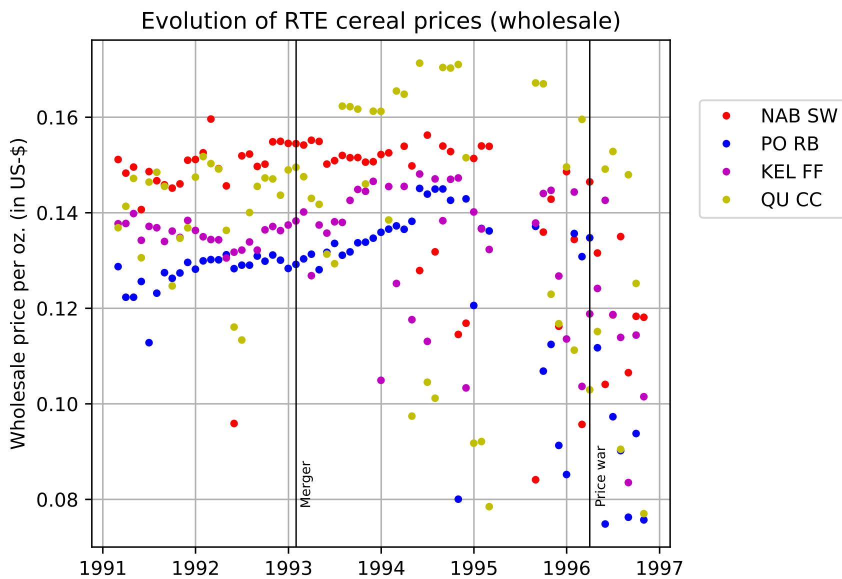
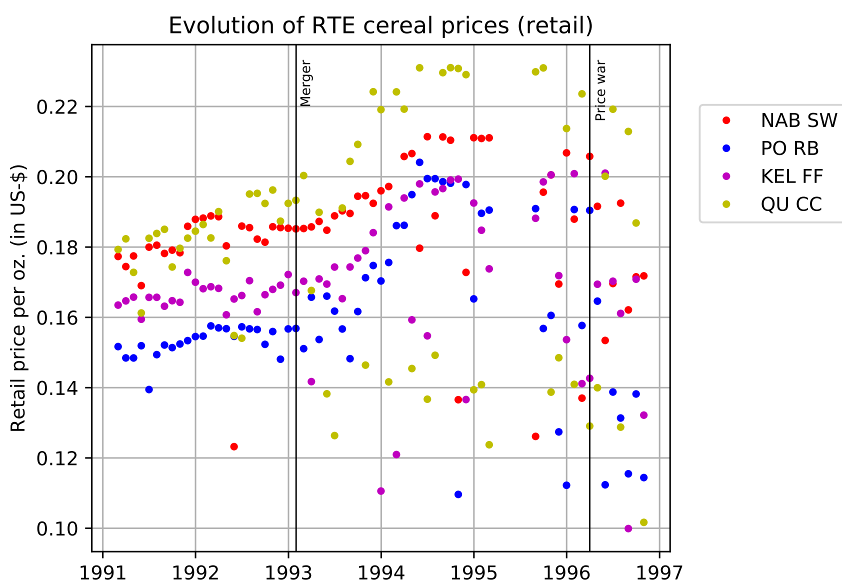
A Reduced Form Estimations and Additional Details

A.1 Reduced Form Estimation Equations

In this section, we provide the estimation equation for our baseline reduced form regressions of the log wholesale price $\log(p^w_{ist})$ in Table 5. $PromoG$ denotes the number of general promotions for a given product in a given market. The superscript indicates which promotions are included. *own* considers only promotions for the same product, *firm* denotes the promotions

Figure 1: Evolution of RTE cereal prices





Notes: The two figures display the evolution of the average wholesale and retail prices, respectively, across all stores over time for selected brands. The brands are Nabisco/Post Shredded Wheat, Post Raisin Bran, Kellogg's Frosted Flakes, and Quaker Cap'n Crunch.

Table 4: Market share evolution

	GMI	KEL	POS	NAB	QUA	RAL
1991	32.4	46.1	7.9	3.1	7.2	3.4
1992	30.0	46.3	10.1	3.9	6.6	3.1
1993	28.9	47.0	11.6	0.0	8.9	3.6
1994	25.8	48.3	12.3	0.0	10.4	3.3
1995	31.9	43.8	14.4	0.0	6.8	3.1
1996	27.5	48.1	13.5	0.0	8.1	2.7

Notes: The table summarizes the firm-specific volume-based market shares (in percent) across all stores in our data set for each year. From 1993 onwards, Post's market shares include those of Nabisco. GMI stands for General Mills, KEL for Kellogg's, POS for Post, NAB for Nabisco, QUA for Quaker, and RAL for Ralston.

of all other products owned by the same firm, and *rival* captures the number of rival firms' products' promotions. We also allow for different rival effects pre-merger (pre), post-merger before the price war ($post$), and during the price-war (pw). $\mathbb{1}_{Post}^{POSNAB}$, $\mathbb{1}_{Post}^{nomerge}$, and $\mathbb{1}_{PW}$ represent dummy variables for the merging firms post-merger, the non-merging firms post-merger, and a price war dummy for all firms, respectively. Furthermore, $Sales\_Tot$ indicates the total quantity of cereals sold in a given store and month. Finally, κ_i and κ_s denote brand and store fixed effects, respectively. Our baseline wholesale price equation can thus be written as

$$\begin{aligned}\log(p^w_{ist}) =& \beta_1 PromoG^{own}_{ist} + \beta_2 PromoG^{firm}_{ist} + \beta_3 PromoG^{riv,pre}_{ist} + \beta_4 PromoG^{riv,post}_{ist} \\ &+ \beta_5 PromoG^{riv,pw}_{ist} + \beta_6 \mathbb{1}_{Post}^{POSNAB} + \beta_7 \mathbb{1}_{Post}^{nomerge} + \beta_8 \mathbb{1}_{PW} \\ &+ \beta_9 Sales\_Total_{st} + \kappa_i + \kappa_s + \epsilon_{ist}\end{aligned}$$

where i, s, and t denote brands, stores, and months respectively. The second column in Table 5 substitutes the post-merger non-merging dummy with firm-specific post-merger dummies. The last two models add the *bonus buy* promotion variables, $PromoB$, in addition to the general promotion variables. We estimate the same model using the log retail price, $\log(p^r_{ist})$, as the dependent variable and obtain similar estimates. These results are available upon request.

A.2 Distribution of Promotional Activities

Figures 2 and 3 illustrate the distribution of the promotional intensity across different brands, stores, and time. In Figure 2, we plot the total number of promotional activities aggregated

Table 5: Reduced form analysis: Wholesale prices

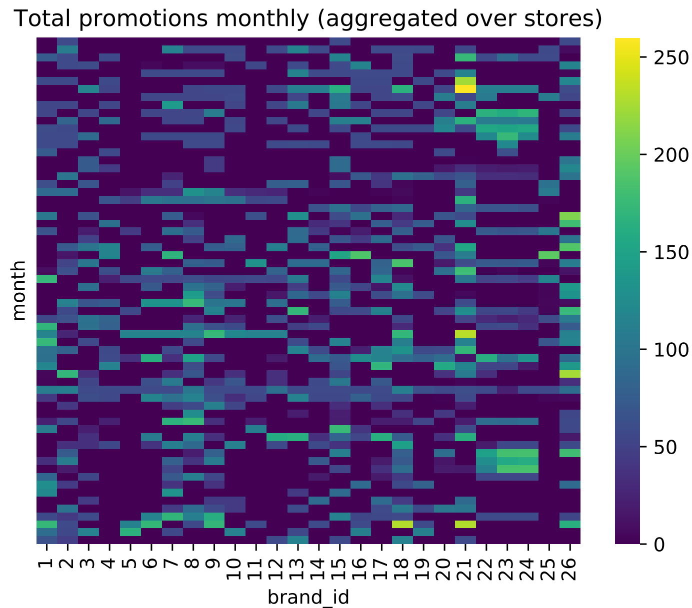
	(1) Baseline	(2) Firm detailed	(3) Baseline w/ BB	(4) Firm detailed w/ BB
Promo (own brand)	-0.1099***	-0.1093***	-0.1116***	-0.1111***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Promo (same firm)	0.0007*	0.0009**	0.0021***	0.0022***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Promo pre-merger (rivals)	0.0029***	0.0024***	0.0026***	0.0023***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Promo post-merger (rivals)	-0.0019***	-0.0017***	-0.0010*	-0.0008
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Promo price war (rivals)	-0.0071***	-0.0082***	-0.0054***	-0.0068***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Post-merger non-merging	0.0182***		0.0124**	
	(0.0022)		(0.0046)	
Post-merger POSTNAB	0.0609***	0.0584***	0.0511***	0.0436***
	(0.0023)	(0.0023)	(0.0049)	(0.0049)
Price war period	-0.0983***	-0.0936***	-0.0869***	-0.0854***
	(0.0015)	(0.0015)	(0.0017)	(0.0017)
Post-merger KEL		0.0515***		0.0413***
		(0.0021)		(0.0041)
Post-merger RAL		0.0501***		0.0376***
		(0.0027)		(0.0054)
Post-merger QUA		-0.0176***		-0.0273***
		(0.0026)		(0.0052)
Post-merger GMI		-0.0284***		-0.0394***
		(0.0025)		(0.0048)
BB (own brand)			-0.0217***	-0.0220***
			(0.0009)	(0.0009)
BB (same firm)			0.0051***	0.0045***
			(0.0002)	(0.0002)
BB pre-merger (rivals)			0.0009***	0.0008***
			(0.0001)	(0.0001)
BB post-merger (rivals)			0.0014***	0.0018***
			(0.0003)	(0.0003)
BB price war (rivals)			-0.0053***	-0.0040***
			(0.0003)	(0.0003)
Observations	96512	96512	96512	96512
R-square	0.76	0.76	0.77	0.77

Notes: All estimations include brand and store fixed effecs. Columns (2) and (4) allow for the post-merger reaction to differ across firms. Promo (same firm) describes the number of promotions of other products in a market that belong to the same firm. Promo (rivals) describes the number of promotions of other products in a market that do not belong to the same firm. Pre, post, and PW stand for pre-merger, post-merger, and price war period, respectively. BB stands for bonusbuy and coupon promotions, while all promo variables without BB reflect general and price reduction promotions.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

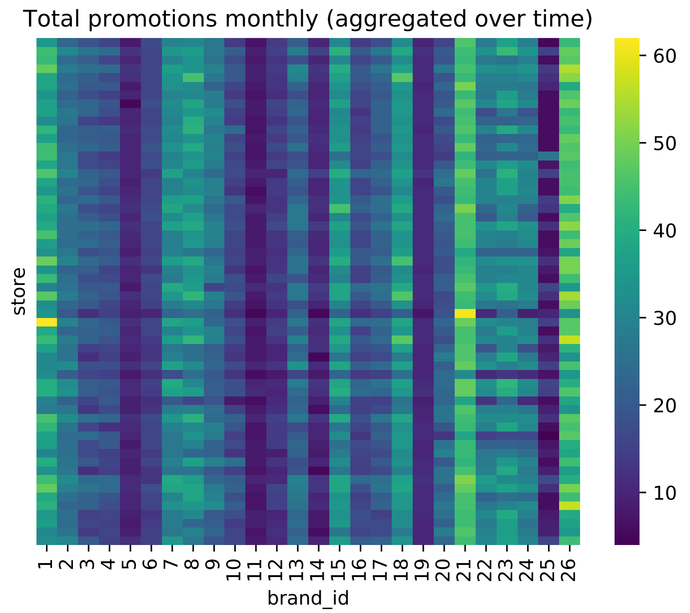
over all 58 stores in our sample for each brand-month combination. In Figure 3 we plot the total number of promotions for each brand-store combination aggregated over all months in our sample. In both figures, brighter colors indicate a higher promotional intensity than darker colors.

Figure 2: Distribution of promotional activities I



Notes: The figure displays a heatmap of the distribution of the total number of promotions for each brand over time aggregated over all stores in our sample.

Figure 3: Distribution of promotional activities II



Notes: The figure displays a heatmap of the distribution of the total number of promotions aggregated over time for each brand-store combination.

Table 6: Reduced form analysis: Quantities sold

	(1) Baseline	(2) Baseline w/ BB	(3) BB & lagged promos
Log Retail Price	-1.8089***	-1.8139***	-1.8393***
	(0.1230)	(0.1231)	(0.1258)
Promo (own brand)	0.1761***	0.1757***	0.1705***
	(0.0257)	(0.0252)	(0.0247)
BB (own brand)	0.0861***	0.0848***	0.0845***
	(0.0093)	(0.0096)	(0.0082)
Promo (same firm)	-0.0048	-0.0037	-0.0030
	(0.0036)	(0.0033)	(0.0031)
Promo pre-merger (rivals)	-0.0085	-0.0034	-0.0008
	(0.0059)	(0.0033)	(0.0039)
Promo post-merger (rivals)	-0.0072***	-0.0070***	-0.0073***
	(0.0017)	(0.0017)	(0.0015)
Promo price war (rivals)	-0.0260*	-0.0253*	-0.0244*
	(0.0101)	(0.0102)	(0.0098)
BB pre-merger (rivals)		-0.0056	-0.0035
		(0.0043)	(0.0043)
BB post-merger (rivals)		0.0021	0.0023
		(0.0018)	(0.0018)
BB price war (rivals)		-0.0168	-0.0196
		(0.0163)	(0.0160)
Promo (own brand, lag 1)			-0.0200
			(0.0108)
BB (own brand, lag 1)			-0.0092
			(0.0076)
Promo (own brand, lag 2)			0.0070
			(0.0115)
BB (own brand, lag 2)			0.0026
			(0.0079)
Promo (own brand, lag 3)			0.0103
			(0.0106)
BB (own brand, lag 3)			-0.0081
			(0.0103)
Promo (own brand, lag 4)			0.0029
			(0.0120)
BB (own brand, lag 4)			0.0059
			(0.0064)
Observations	96512	96512	90480
R-square	0.83	0.83	0.83

Notes: All estimations include brand, store, and month fixed effecs. Promo (same firm) describes the number of promotions of other products in a market that belong to the same firm. Promo (rivals) describes the number of promotions of other products in a market that do not belong to the same firm. BB stands for bonusbuy and coupon promotions, while all promo variables without BB reflect general and price reduction promotions. Column (2) adds rival firms' BB promotions as regressors. Column (3) adds lags of a brand's promotions as regressors.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Construction of Instruments and Testing for Weak Identification

B.1 Details of Computation of Instruments

Our instruments for manufacturer markups, that identify industry conduct, consist of two parts. First, we construct proximity measures that describe how close each pair of products is in the characteristics space. Second, we compute a market-specific measure of the intensity of each product's rivals' promotional activities.

The first component is motivated by the fact that the effect of a rival product's promotions on another product's demand should strongly depend on the proximity of the two products in the characteristics space. A close rival product going on sale will exert much more competitive pressure than a very distant product on sale. For example, demand for Post's Raisin Bran should be affected much more by promotions of Kellogg's Raisin Bran than by promotions for Quaker Oats. For instance, the degree of closeness can be described by whether the difference between two products in terms of a specific characteristic, for example, sugar content, is in the first, second, third etc. decile of all differences in terms of that characteristic.[36]

More specifically, define $d_{ij}^x \equiv x_i - x_j, i \neq j$ as the difference in the product characteristic x between products i and j. Let $C^x = \{c_1^x, .., c_v^x\}$ denote v equally spaced percentiles of the entire distribution of characteristics differences d_{ij}^x with respect to product characteristic x.

The second part of our instruments is motivated by the fact that the pattern of promotions shifts the competitive pressure in a market. Denote by $PROMO_{it}^G$ and $PROMO_{it}^{BB}$ the number of general promotions and bonus buy promotions respectively for product i in market t. We compute our instruments by interacting these promotion measures with our proximity measures for the corresponding product-pairs. For a continuous product characteristic x, our instruments $z_{jt}^{x,k,w}$ can then be computed as

$$z_{jt}^{x,k,w} = \sum_{i \notin \mathcal{F}(j)} \mathbb{1}\left(|d_{ij,t}^x| < c_k^x\right) \cdot PROMO_{it}^w,$$

where k indicates the percentile of closeness, w denotes the type of promotions, i.e., either *general* or *bonus buy*, and $\mathcal{F}(j)$ is the product portfolio of the firm owning brand j. This results in $v * 2$ potential instruments per continuous product characteristic x. Intuitively, our instruments count the number of different types of promotions conducted by rivals in a given market but only consider promotions of rival products that are close according to our

[36]Similar ideas underlie the construction of *differentiation instruments* to identify consumer substitution patterns in Gandhi and Houde (2017).

definition above. The analogous instruments for a binary product characteristic, for example, whether a cereal is soggy in milk or not, can be computed as

$$z_{jt}^{x,k,w} = \sum_{i \notin \mathcal{F}(j)} \mathbb{1}(|d_{ij,t}^{x}| = k) \cdot PROMO_{it}^{w},$$

which leads to at most $2 * 2$ instruments per binary product characteristic.

In our application, we use sugar and fiber content as continuous characteristics, and the binary variable sogginess. For the sugar- and fiber-based instruments we use the 33.33 percentile of the respective distribution of characteristic differences as the cutoff value c_k. For the binary variable sogginess, we only consider promotions of rivals that fall in the same sogginess category, i.e., $k = 0$. Computing our instruments based on other closeness definitions, such as using deciles instead of terciles, resulted in very similar estimation results.

B.2 Reduced Form Evidence for Validity of Assumptions

In this appendix, we present reduced form evidence for the timing assumptions that we employ for our identification strategy. Essentially, we require that wholesale prices in period t are a function of all information available in period t, so that $p_{jt}^{w} = f(\mathcal{I}_t)$, where $\mathcal{I}_t$ denotes all information available in period t, i.e., all relevant demand and cost shocks. In contrast, the number of promotions in period t, $Promo_{jt} = f(\mathcal{I}_{t-1})$, where $\mathcal{I}_{t-1}$ contains only information available up to $t-1$. Shocks that cause $\mathcal{I}_{t-1}$ to be different from $\mathcal{I}_t$ provide the variation in the data necessary to make our instruments for identifying industry conduct work.

Column (1) in Table 7 summarizes the results from regressing logged wholesale prices on various cost shifters to illustrate that wholesale prices react immediately to contemporaneous cost shocks. Column (2) highlights that promotions in the current period are not affected by contemporaneous cost shocks, which provides evidence that promotional activities are not adjusted immediately. Columns (3) to (7) show that future promotions are affected by cost shocks today, however. Therefore, while promotions are clearly endogenous, Table 7 provides evidence that they are likely to be sequentially exogenous to future innovations in manufacturers' marginal cost shocks.

B.3 Weak Identification

In the following, we illustrate that our instruments have power for identifying both demand and supply parameters. Compared to traditional first-stage diagnostics for linear IV regressions, testing for weak identification in our model is more complicated for several reasons. First, our models are highly non-linear and contain multiple endogenous regressors. Second,

Table 7: Reduced form evidence supporting our timing assumptions

	(1) Log Wholesale Price	(2) Promo in t	(3) Promo in $t+1$	(4) Promo in $t+2$	(5) Promo in $t+3$	(6) Promo in $t+4$	(7) Promo in $t+5$	(8) Promo in $t+6$
Weighted sugar price	1.4630***	-0.9881	-3.5065	-5.8884**	-5.7979**	-5.1888**	-4.1342*	-2.7413
	(0.5128)	(1.9384)	(2.2934)	(2.3610)	(2.4394)	(2.0418)	(2.0252)	(2.0482)
Weighted rice price	0.0108*	0.0264	0.0315*	0.0336*	0.0252	0.0161	0.0183	0.0306
	(0.0062)	(0.0250)	(0.0176)	(0.0169)	(0.0164)	(0.0190)	(0.0199)	(0.0277)
Weighted corn price	0.0075***	0.0237	0.0411***	0.0446***	0.0361	0.0415***	0.0243*	0.0193
	(0.0010)	(0.0213)	(0.0092)	(0.0079)	(0.0224)	(0.0091)	(0.0120)	(0.0128)
Distance X gas price	0.1013**	0.2155	0.2844	0.3920*	0.4732**	0.1454	0.1370	0.4189
	(0.0459)	(0.3665)	(0.2615)	(0.2174)	(0.2111)	(0.2307)	(0.2630)	(0.2615)
Elec. price X Flaking	0.0414	-0.1796	0.0105	0.1808	0.1786	0.4285**	0.2428	0.0251
	(0.0397)	(0.1734)	(0.2139)	(0.2613)	(0.1803)	(0.2029)	(0.2088)	(0.2280)
Elec. price X Shredding	0.0380	-0.0474	0.1271	0.4349	0.9905***	1.6795***	1.1773**	0.2957
	(0.0280)	(0.1740)	(0.2998)	(0.3426)	(0.2257)	(0.4951)	(0.5127)	(0.4102)
Observations	96512	96512	95004	93496	91988	90480	88972	87464
R-square	0.78	0.16	0.15	0.16	0.16	0.16	0.15	0.15

Notes: The table summarizes OLS results from regressing the wholesale price (Column 1) and the number of brand- and market-specific promotions at different points in time (Columns 2 for contemporaneous promotions, Columns 3 to 8 for promotions up to 6 months into the future) on various contemporaneous cost shifters. All estimations include brand, store, and month fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

even if instruments and endogenous regressors are correlated enough to result in a decently large F-statistic[37], the instruments can still be weak enough to result in very sensitive estimates and high standard errors.

In order to overcome the first problem, we adapt a testing procedure recently proposed by Gandhi and Houde (2017) for demand models. The main idea is to linearize the nonlinear BLP-model around the estimated parameter values using a first-order Taylor expansion. After the model is linearized, one can employ generalizations of the well-known F-statistics to test for identification of single parameters. While traditional F-tests test the null hypothesis of complete non-identification of a single parameter, rank deficiency tests as developed by Cragg and Donald (1993) and Kleibergen and Paap (2006) can be adopted to test for alternative hypotheses, such as underidentification or weak identification of single parameters or the model as a whole.

General procedure In the following, we describe a general procedure to test for various degrees of lack of identification and weak instruments based on Gandhi and Houde (2017). To the best of our knowledge, this procedure has so far not been used to test for weak identification of conduct parameters.

The starting point is a first-order Taylor expansion of the structural error $\kappa(\theta)$ as a function of the parameters around the true parameter vector θ_0

$$\kappa_{jt}(\theta) = \kappa_{jt}(\theta_0) + \sum_{k=1}^{K}(\theta_k - \theta_{0k})\frac{\partial \kappa_{jt}(\theta_0)}{\partial \theta_k} + \upsilon_{jt} \tag{21}$$

$$= \kappa_{jt}(\theta_0) + J_{jt}(\theta_0)b + \upsilon_{jt} \tag{22}$$

where J denotes the Jacobian stacking all the partial derivatives with respect to each parameter θ_k, b stacks the differences $\theta_k - \theta_{k0}$ and υ are higher-order residuals. When taking conditional expectations of the above equation with respect to the proposed instruments Z, $\mathbb{E}(\kappa(\theta_0)|Z)$ disappears and when evaluated at $\theta = \theta_0$ the Jacobian term becomes zero.

In order to have strong identification, we require $\mathbb{E}(\kappa(\theta)|Z)$ to be large for $\theta \neq \theta_0$. Therefore, we test whether the Jacobian of the objective function reacts strongly to the instruments (analogous to an F-test in linear GMM). Note that this test can be applied equally well to both demand and supply models.[38] For a given model, we proceed in the following steps.

[37] A popular rule-of-thumb criterion is that the F-statistic is larger than 10.

[38] We present the test for a general non-linear model and apply the same procedure for testing weak identification of our demand and supply model. The only difference between the two is in the definition of the structural error κ and potentially the choice of the instruments $A(Z)$. In our demand and supply models κ corresponds to ν^D and ν^S, respectively.

1. Estimate the model using a set of instruments $A(Z)$ to get the parameter estimates $\hat{\theta}$.

2. Compute the Jacobian of the structural error κ evaluated at $\hat{\theta}$. For the linear parameters, the derivative has an analytical form. For nonlinear parameters, the derivatives have to computed numerically.

3. Run a linearized first-stage-regression for each dependent variable, i.e., for each endogenous regressor, on the exogenous regressors X and the excluded instruments $A(Z)$.

$$\frac{\partial \kappa_{jt}(\hat{\theta})}{\partial \theta_k} = X_{jt}\pi_{1k} + A_j(Z_t)\pi_{2k} + \epsilon_{jtk} \tag{23}$$

   In our demand model, there are K endogenous variables corresponding to the K partial derivatives $\frac{\partial \nu^D}{\partial \theta_k}$ of the innovations in the structural demand shocks with respect to the non-linear preference parameters. In our supply model, the number of nonlinear parameters is equal to the number of estimated conduct parameters.

4. Test joint significance of π_{2k} using an appropriate F-test for each of the K first-stage regressions. This step is a generalization, of standard F-tests in linear IV regressions. Wright (2003) shows that at the true parameter value θ_0, one can use the same test logic for the linearized first-stage regressions. Moreover, he shows that the same remains valid when evaluating the test at $\hat{\theta}$. For example, the null hypothesis $H_0 : \pi_{2k} = 0$ corresponds to complete non-identification of θ_k.

An important question is which F-test to use in Step 4. Standard F-tests, as reported by most linear IV regression software packages, can provide a first starting point. However, in models with multiple endogenous regressors, conventional F-tests can easily result in falsely rejecting non-identification. Angrist and Pischke (2008) (henceforth, AP) propose a modified F-statistic that corrects for the presence of multiple endogenous regressors by profiling out the effects of the other $K-1$ endogenous regressors and using only the variation in the projection residual when running the first-stage regression. This test statistic has been further refined by Sanderson and Windmeijer (2016) (henceforth, SW) and we report their version of the F-statistic for testing for weak identification of a single regressor in row *Robust AP-SW-F-statistic* in Tables 8 to 10.

While single equation F-tests provide insights on whether a particular endogenous regressor is correlated with our instruments, these F-statistics need not be informative about identification of the model as a whole. In order to test whether all first-stage regressions are jointly significant, we combine the first-stage coefficients of all K regressions into a $dim\big(A(Z)\big) \times K$

matrix Ψ. Underidentification of the model is equivalent to Ψ being rank-deficient. Therefore, a natural choice for the null hypothesis of underidentification is $H_0 : rk(\Psi) = K - 1$. A convenient and robust way to test for rank deficiency is to analyze the smallest singular value of Ψ. If the smallest singular value is statistically different from zero, we can reject underidentification. This logic has been formalized by Cragg and Donald (1993) and Kleibergen and Paap (2006) (henceforth, KP). Intuitively, testing the rank of Ψ is equivalent to testing the local GMM-identification condition, which requires that the $K \times K$-matrix $\mathbb{E}\left[G_0' W G_0\right]$ with $G_0 = \frac{\partial g(\theta_0)}{\partial \theta}$ has full rank. Noting that in our models $g(\theta) = \kappa(\theta) \cdot Z$ yields $G_0 = Z' \frac{\partial \kappa(\theta)}{\partial \theta}$. The matrix of first-stage coefficients $\Psi = (Z'Z)^{-1} Z' \frac{\partial \kappa(\theta)}{\partial \theta}$ contains the same information as $[G_0' W G_0]$ (up to a scaling factor that does not affect the rank). Therefore, testing the rank of Ψ is equivalent to testing the local identification condition of our GMM model.

Even when we can reject underidentification of our model, i.e., Ψ has full rank, the model may still be weakly identified. Endogenous regressors and excluded instruments might be correlated but only weakly, which can result in Ψ having full rank but being close to singular. In such a case, estimation is likely to perform poorly. For example, estimates will be very sensitive to the selection of moments and the objective function can have several local minima. A suitable statistic to examine this type of weak identification of the model is the Cragg-Donald Wald statistic. Stock *et al.* (2002) discuss several definitions of performing poorly in various settings. For our models, we focus on the maximum relative bias as a measure for the performance of our instruments. If the Cragg-Donald Wald statistic exceeds the critical value we can reject the null hypothesis that our IV estimator has a bias of more than 5% (or 10%, or 20%) compared to the OLS estimator.[39]

Weak identification on the demand side Table 8 summarizes the results of our weak identification tests for the demand model.

All standard first-stage F-statistics are substantially larger than 10. When examining the robust AP-SW F-test we see a substantial drop in the statistic for the price coefficient α; therefore, controlling for multiple endogenous regressors is important. All of the test statistics remain larger than the critical values by at least a factor of 6. The KP-χ^2-statistic for underidentification is very large with a p-value of less than 0.00001. Therefore, we can strongly reject underidentification of the model. The Kleibergen-Paap F-statistic generalizes

[39] A minor practical problem is that the critical values tabulated by Stock *et al.* (2002) are only available for rather special cases such as having only up to 3 endogenous regressors. Both our demand and supply model contain more nonlinear parameters. Therefore, we cannot formally compare our Cragg-Donald Wald statistic to the appropriate critical values. In our experience, models that seem robust and reasonable, i.e., results in estimates that are not sensitive to minor changes in the moments and that have low standard errors, should result in substantially larger test statistics than the critical values tabulated by Stock *et al.* (2002) for one or two endogenous regressors. Therefore, we judge the practical problem of not having the critical values readily available as not crucial.

Table 8: Weak IV Tests: Demand Model

	$\frac{\partial \nu^D}{\partial \alpha} = p$	$\frac{\partial \nu^D}{\partial \Pi_1}$	$\frac{\partial \nu^D}{\partial \Pi_2}$	$\frac{\partial \nu^D}{\partial \Pi_3}$	$\frac{\partial \nu^D}{\partial \rho}$
Robust F-statistic	193.55	87.05	52.74	71.94	93.16
Robust AP-SW-F-statistic	127.88	155.06	65.20	159.80	93.16
KP χ^2-statistic	254.16				
KP χ^2-p-value	0.00				
KP F-statistic	28.53				

Notes: The Kleibergen-Paap (KP) χ^2-statistic tests the null hypothesis of underidentification. The KP F-statistic is a heteroskedasticity-robust version of the Cragg-Donald F-statistic testing the null hypothesis of weak identification.

the F-statistic by Cragg and Donald (1993) to models with heteroskedastic error terms. The KP F-statistic for weak identification exceeds 28. Consequently, we can not only reject underidentification but also weak identification of our demand model very strongly.

Weak identification on the supply side Table 9 and 10 summarize the results from testing for weak identification in our supply models. Table 9 focuses on the small specification with 3 conduct parameters. Table 10 displays the results for the more detailed specification with 6 conduct parameters.

Table 9: Weak IV Tests: Supply Model 1

	$\frac{\partial \nu^S}{\partial \lambda_1}$	$\frac{\partial \nu^S}{\partial \lambda_2}$	$\frac{\partial \nu^S}{\partial \lambda_3}$
Robust F-statistic	212.87	370.35	195.53
Robust AP-SW-F-statistic	120.68	186.12	128.81
KP χ^2-statistic	925.67		
KP χ^2-p-value	0.00		
KP F-statistic	94.85		

Notes: The Kleibergen-Paap (KP) χ^2-statistic tests the null hypothesis of underidentification. The KP F-statistic is a heteroskedasticity-robust version of the Cragg-Donald F-statistic testing the null hypothesis of weak identification.

First, we investigate the F-statistic of classical first stage regressions. We regress the endogenous variables, i.e., the derivatives of the innovations in the structural cost shocks ν^S with respect to the nonlinear (conduct) parameters, on our excluded instruments which are based on rivals' promotion activities interacted with relative proximity of products in the characteristics space. In all cases, the F-statistics massively exceed the rule-of-thumb critical value of 10. Next, we report F-statistics that take into account the presence of multiple

Table 10: Weak IV Tests: Supply Model 2

	$\frac{\partial \nu^S}{\partial \lambda_1}$	$\frac{\partial \nu^S}{\partial \lambda_2}$	$\frac{\partial \nu^S}{\partial \lambda_3}$	$\frac{\partial \nu^S}{\partial \lambda_4}$	$\frac{\partial \nu^S}{\partial \lambda_5}$	$\frac{\partial \nu^S}{\partial \lambda_6}$
Robust F-statistic	198.07	266.29	226.14	356.56	146.79	115.57
Robust AP-SW-F-statistic	43.33	63.32	83.41	62.40	28.22	47.64
KP χ^2-statistic	113.36					
KP χ^2-p-value	0.00					
KP F-statistic	11.17					

Notes: The Kleibergen-Paap (KP) χ^2-statistic tests the null hypothesis of underidentification. The KP F-statistic is a heteroskedasticity-robust version of the Cragg-Donald F-statistic testing the null hypothesis of weak identification.

endogenous regressors as initially proposed by Angrist and Pischke (2008) and refined by Sanderson and Windmeijer (2016). While the F-statistics generally become smaller by a factor of approximately 2 in the small model and by a factor of 2 to 5 in the large model, they still consistently exceed the critical values by several orders of magnitude. We take this as strong evidence that our instruments shift the endogenous regressors substantially and therefore constitute strong instruments.

Finally, we analyze rank deficiency of the full matrix of first stage coefficients. For both supply models, we can strongly reject the null hypothesis of underidentification with KP-statistics of 926 and 113, respectively, resulting in p-values of less than 0.0001 for both models.

We also look at the KP-F-statistic, which is a heteroskedasticity-robust version of the Cragg-Donald Wald-statistic for weak identification. For the small model with 3 conduct parameters the test statistic is 95. This is substantially larger than the critical values computed by Stock *et al.* (2002) even in conservative cases such as when we allow for a 5% maximal IV bias relative to NLS at the 5%-significance level. For our large supply model with 6 conduct parameters, the KP F-statistic is substantially smaller pointing to more detailed conduct models being more difficult to identify with a fixed set of instruments. Nonetheless, the test statistic significantly exceeds the rule-of-thumb critical value of 10. Therefore, we conclude that even our larger supply model does not suffer from weak identification problems.

C Additional Estimation Results

Demand elasticities In our random coefficient nested logit model, consumers' own- and cross-price elasticities can be computed according to the following formulas.

$$\eta_{jkt} = \begin{cases} \frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt} \left(\dfrac{1}{1-\rho} - s_{ijt} - \dfrac{\rho}{1-\rho} s^c_{ijt} \right) dP_D(D) & \text{for } j = k \\ -\frac{p_{kt}}{s_{jt}} \int \alpha_i \left(s_{ijt} + \dfrac{\rho}{1-\rho} s^c_{ijt} \right) s_{ikt} dP_D(D) & \text{for } j \neq k, \end{cases}$$

where s^c_{ijt} denotes the market share of product j among consumers of type i conditional on i choosing one of the inside goods and integration is taken with respect to the distribution of consumer demographics D.

Market share generation For our estimations, we include all package sizes between 10 and 32 ounces for the different products in our sample, and calculate aggregated quantities and the average price per ounce for each product. We obtain market shares for the inside goods by dividing aggregate quantities by our measure of the market size described in the main text. The remainder, i.e., 1 minus the sum of inside market shares per market, yields the market share of the outside good. We exclude five weeks in 1995 from our sample because of a substantial amount of missing data in the DFF database during these weeks.

Table 11: Median Elasticities RCNL Model (Part 1)

	NAB ShW	PO RBr	PO GNu	PO HCb	GM RNB	GM ACC	GM Whe	GM Che	GM HNC	GM LCh	GM TCF	GM Tri	KE FrL
NAB Shred Wheat	-3.644	0.076	0.094	0.018	0.049	0.031	0.077	0.237	0.122	0.049	0.039	0.024	0.038
PO Raisin Bran	0.115	-3.177	0.089	0.021	0.053	0.042	0.072	0.208	0.138	0.061	0.034	0.031	0.051
PO Grape Nuts	0.115	0.072	-2.672	0.020	0.047	0.035	0.071	0.219	0.124	0.053	0.040	0.027	0.043
PO Honey Comb	0.040	0.032	0.037	-3.022	0.028	0.043	0.034	0.107	0.101	0.068	0.044	0.046	0.068
GM RaisinNutBran	0.091	0.064	0.072	0.023	-3.474	0.041	0.061	0.184	0.128	0.062	0.040	0.035	0.055
GM ApplCin Cheer	0.049	0.043	0.044	0.030	0.034	-3.018	0.040	0.119	0.118	0.075	0.040	0.049	0.074
GM Wheaties	0.104	0.064	0.079	0.020	0.045	0.035	-3.342	0.206	0.121	0.054	0.042	0.029	0.045
GM Cheerios	0.097	0.057	0.074	0.020	0.041	0.032	0.063	-3.520	0.113	0.052	0.045	0.028	0.042
GM HonNut Cheer	0.071	0.053	0.059	0.025	0.039	0.044	0.052	0.158	-3.210	0.066	0.042	0.039	0.061
GM Luck Charms	0.047	0.039	0.043	0.029	0.032	0.047	0.039	0.117	0.111	-3.249	0.043	0.047	0.071
GM Tot CoFlakes	0.044	0.025	0.037	0.022	0.024	0.029	0.036	0.120	0.082	0.051	-3.071	0.032	0.046
GM Trix	0.035	0.030	0.033	0.029	0.027	0.045	0.031	0.095	0.100	0.071	0.042	-3.225	0.073
KE Froot Loops	0.039	0.036	0.037	0.030	0.031	0.049	0.035	0.103	0.110	0.075	0.041	0.050	-3.037
KE Special K	0.048	0.028	0.040	0.023	0.026	0.030	0.037	0.126	0.086	0.052	0.052	0.033	0.047
KE Frost Flakes	0.052	0.042	0.047	0.028	0.034	0.047	0.042	0.125	0.115	0.071	0.042	0.045	0.069
KE Corn Pops	0.032	0.030	0.031	0.031	0.027	0.049	0.030	0.088	0.102	0.075	0.040	0.052	0.079
KE Raisin Bran	0.110	0.081	0.085	0.022	0.051	0.043	0.069	0.200	0.139	0.063	0.035	0.033	0.055
KE Corn Flakes	0.084	0.050	0.065	0.021	0.038	0.034	0.057	0.180	0.110	0.054	0.047	0.030	0.046
KE Honey Smacks	0.039	0.046	0.040	0.034	0.036	0.060	0.036	0.096	0.130	0.089	0.035	0.058	0.091
KE Crispix	0.045	0.026	0.038	0.023	0.025	0.029	0.036	0.120	0.084	0.051	0.052	0.033	0.047
KE Rice Krispies	0.054	0.031	0.045	0.022	0.028	0.031	0.041	0.135	0.090	0.052	0.052	0.032	0.046
RAL Chex	0.055	0.031	0.045	0.022	0.028	0.031	0.040	0.135	0.091	0.052	0.052	0.032	0.046
RAL Wheat Chex	0.113	0.069	0.084	0.020	0.047	0.034	0.069	0.215	0.122	0.053	0.041	0.027	0.042
RAL Rice Chex	0.043	0.024	0.037	0.022	0.024	0.028	0.034	0.116	0.080	0.049	0.052	0.031	0.045
QU Quaker Oats	0.095	0.065	0.075	0.023	0.045	0.041	0.063	0.189	0.128	0.061	0.040	0.034	0.053
QU Capn Crunch	0.049	0.044	0.044	0.030	0.035	0.051	0.040	0.118	0.119	0.076	0.040	0.049	0.075
Outside good (div.)	0.455	0.461	0.443	0.393	0.422	0.388	0.431	0.448	0.418	0.393	0.411	0.379	0.391

Notes: Cell entries i (indexing row), j (indexing column) give the percent change in market share of brand i associated with a one percent change in the price of j. Each entry represents the median of the elasticities across the 3712 markets. The last row displays the predicted diversion to the outside good, i.e., the percentage of consumers who substitute from a specific inside good to the outside good (as a percentage of all who substitute away) when a product increases its price.

Table 12: Median Elasticities RCNL Model (Part 2)

	KE SpK	KE FFl	KE CPo	KE RBr	KE CFl	KE HSm	KE Cri	KE RKr	RA Che	RA WCh	RA RCh	QU QO	QU CCr
NAB Shred Wheat	0.063	0.119	0.026	0.166	0.131	0.009	0.031	0.112	0.016	0.025	0.017	0.074	0.038
PO Raisin Bran	0.056	0.148	0.037	0.187	0.119	0.017	0.028	0.099	0.014	0.023	0.015	0.078	0.052
PO Grape Nuts	0.064	0.128	0.031	0.158	0.124	0.012	0.032	0.112	0.016	0.023	0.018	0.070	0.043
PO Honey Comb	0.068	0.143	0.059	0.076	0.076	0.019	0.035	0.106	0.015	0.010	0.020	0.040	0.055
GM RaisinNutBran	0.064	0.145	0.041	0.146	0.111	0.016	0.032	0.109	0.015	0.019	0.018	0.065	0.052
GM ApplCin Cheer	0.063	0.163	0.063	0.103	0.081	0.023	0.032	0.100	0.014	0.012	0.017	0.049	0.064
GM Wheaties	0.067	0.129	0.033	0.144	0.120	0.012	0.034	0.116	0.016	0.021	0.019	0.066	0.043
GM Cheerios	0.071	0.121	0.031	0.127	0.119	0.010	0.036	0.121	0.017	0.020	0.020	0.061	0.039
GM HonNut Cheer	0.066	0.149	0.048	0.123	0.099	0.018	0.033	0.109	0.015	0.016	0.018	0.057	0.055
GM Luck Charms	0.066	0.153	0.060	0.092	0.080	0.020	0.034	0.104	0.015	0.012	0.019	0.046	0.060
GM Tot CoFlakes	0.078	0.107	0.038	0.059	0.081	0.009	0.041	0.123	0.017	0.010	0.024	0.034	0.037
GM Trix	0.065	0.149	0.065	0.073	0.069	0.021	0.033	0.099	0.014	0.009	0.018	0.038	0.058
KE Froot Loops	0.063	0.158	0.066	0.084	0.073	0.023	0.032	0.097	0.014	0.010	0.018	0.043	0.063
KE Special K	-2.960	0.111	0.039	0.066	0.086	0.010	0.040	0.124	0.017	0.011	0.024	0.037	0.038
KE Frost Flakes	0.066	-2.386	0.058	0.099	0.085	0.020	0.034	0.106	0.015	0.013	0.019	0.049	0.059
KE Corn Pops	0.062	0.155	-2.779	0.073	0.065	0.023	0.032	0.093	0.013	0.008	0.017	0.038	0.062
KE Raisin Bran	0.057	0.151	0.040	-3.005	0.116	0.018	0.028	0.100	0.014	0.022	0.015	0.076	0.054
KE Corn Flakes	0.073	0.124	0.034	0.113	-1.937	0.011	0.037	0.124	0.017	0.018	0.021	0.056	0.042
KE Honey Smacks	0.056	0.188	0.079	0.110	0.070	-3.008	0.028	0.085	0.012	0.010	0.015	0.051	0.077
KE Crispix	0.079	0.108	0.038	0.062	0.083	0.010	-2.826	0.124	0.017	0.011	0.024	0.035	0.037
KE Rice Krispies	0.079	0.113	0.037	0.073	0.092	0.010	0.041	-2.463	0.018	0.013	0.024	0.041	0.039
RAL Chex	0.079	0.113	0.037	0.073	0.091	0.010	0.041	0.127	-3.212	0.013	0.024	0.040	0.039
RAL Wheat Chex	0.066	0.126	0.030	0.150	0.124	0.011	0.033	0.115	0.016	-3.415	0.018	0.069	0.041
RAL Rice Chex	0.079	0.103	0.037	0.057	0.081	0.009	0.041	0.124	0.018	0.010	-2.829	0.033	0.036
QU Quaker Oats	0.064	0.144	0.040	0.148	0.113	0.016	0.032	0.109	0.015	0.020	0.017	-2.623	0.051
QU Capn Crunch	0.063	0.163	0.064	0.102	0.080	0.023	0.032	0.099	0.014	0.012	0.017	0.049	-2.676
Outside good (div.)	0.410	0.446	0.379	0.440	0.435	0.373	0.412	0.427	0.410	0.430	0.406	0.427	0.436

Notes: Cell entries i (indexing row), j (indexing column) give the percent change in market share of brand i associated with a one percent change in the price of j. Each entry represents the median of the elasticities across the 3712 markets. The last row displays the predicted diversion to the outside good, i.e., the percentage of consumers who substitute from a specific inside good to the outside good (as a percentage of all who substitute away) when a product increases its price.

Table 13: Marginal Cost Estimates: Model Comparison

	Small model	Large model	MP Nash
Time Trend	0.0010	−0.0002	
	(0.0392)	(0.0585)	
Elec. Price	0.0151	0.0134	
	(0.0758)	(0.1707)	
General Promo	−0.1597***	−0.1599***	
	(0.0182)	(0.0548)	
BB Promo	−0.0236	−0.0250	
	(0.0230)	(0.0410)	
Synergy Dummy	−0.0153	−0.0214	
	(0.2632)	(0.5758)	
Median MC	0.085	0.089	0.107
Mean MC	0.081	0.083	0.101
Median PCM	0.439	0.427	0.330
Mean PCM	0.439	0.427	0.356
Med. PCM pre	0.417	0.401	0.332
Med. PCM post	0.468	0.453	0.328
Med. PCM pw	0.342	0.345	0.342

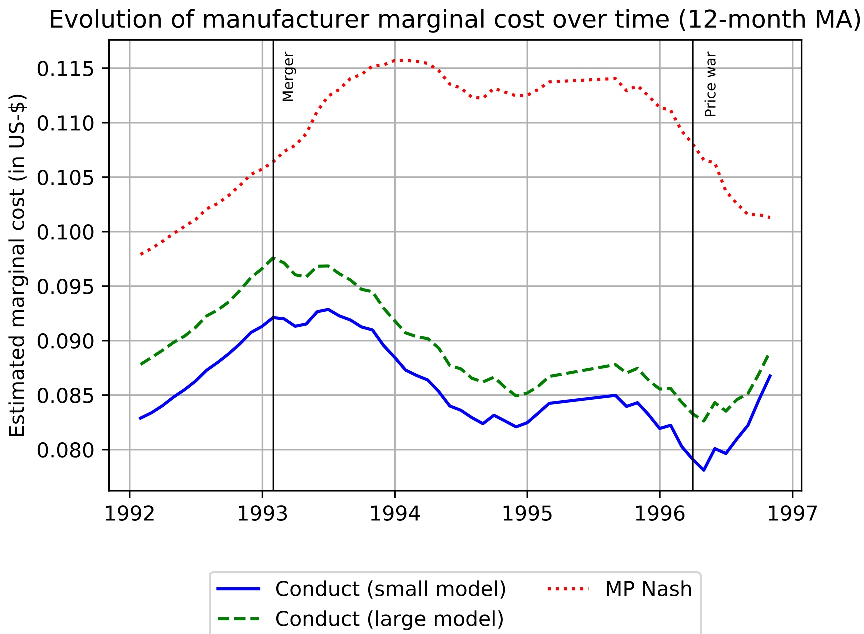
Notes: The table entries reflect the marginal cost estimates from our small conduct model, the large conduct model, and under Bertrand-Nash pricing. For time-specific median price-cost margins, pre refers to pre-merger period, post to post-merger period, and pw to price war period. All estimations include brand fixed effects, store fixed effects, and month-year fixed effects. Standard errors are in parentheses and account for two-step estimation. Number of observations: 96512.

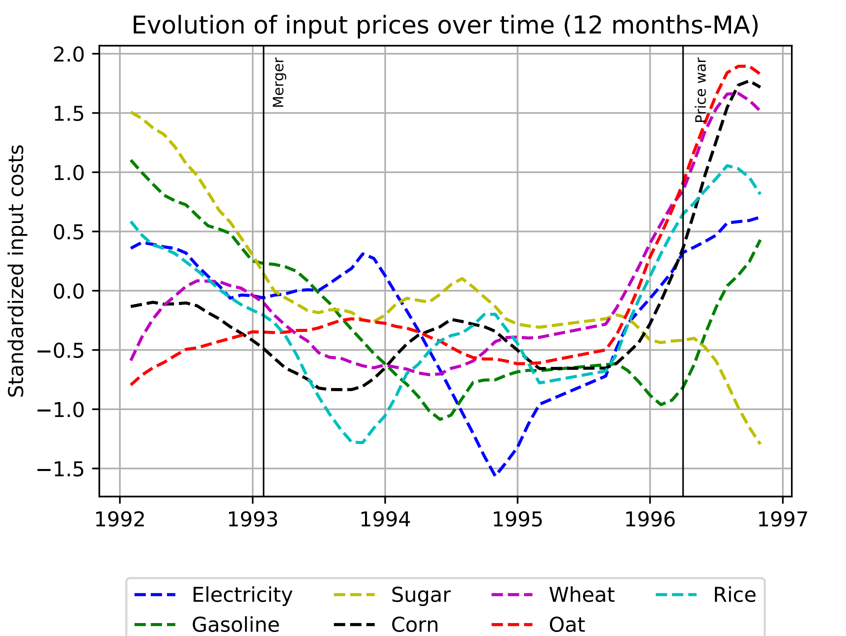
Table 14: Brand-specific PCM accounting for synergies

	Small model	Large model	MP Nash
NAB Shred Wheat	0.38	0.41	0.25
PO Raisin Bran	0.44	0.48	0.30
PO Grape Nuts	0.51	0.55	0.35
PO Honey Comb	0.37	0.40	0.26
GM RaisinNutBran	0.43	0.39	0.32
GM ApplCin Cheer	0.45	0.40	0.33
GM Wheaties	0.44	0.40	0.33
GM Cheerios	0.38	0.34	0.29
GM HonNut Cheer	0.43	0.38	0.32
GM Luck Charms	0.40	0.36	0.30
GM Tot CoFlakes	0.37	0.34	0.29
GM Trix	0.37	0.33	0.28
KE Froot Loops	0.45	0.42	0.38
KE Special K	0.43	0.40	0.36
KE Frost Flakes	0.56	0.52	0.47
KE Corn Pops	0.47	0.44	0.40
KE Raisin Bran	0.51	0.47	0.42
KE Corn Flakes	0.71	0.66	0.60
KE Honey Smacks	0.52	0.48	0.43
KE Crispix	0.46	0.43	0.38
KE Rice Krispies	0.51	0.48	0.43
RAL Chex	0.34	0.38	0.24
RAL Wheat Chex	0.39	0.44	0.26
RAL Rice Chex	0.35	0.39	0.26
QU Quaker Oats	0.51	0.57	0.34
QU Capn Crunch	0.43	0.47	0.31

Notes: The table entries reflect the brand-specific median (across markets) price-cost margins for both the small and large model specification and for multiproduct Bertrand-Nash pricing.

Figure 4: Evolution of predicted marginal costs for different model specifications





Notes: The top figure displays the evolution of the estimated manufacturer marginal costs over time predicted by three different models. The figures is based on the median over all brands and stores for a given month and a moving average over a rolling 12-months window. The bottom figure displays the evolution of the 12-months moving average of various input prices over time.

Table 15: Conduct Estimation without Synergies: Model Comparison

	Small Model			Large Model		
	Pre-merger	Post-merger	Price War	Pre-merger	Post-merger	Price War
All Firms	0.2867***	0.4409***	0.0096			
	(0.0219)	(0.0061)	(0.0072)			
Large Firms				0.2178***	0.3921***	0.0140
				(0.0313)	(0.0125)	(0.0211)
Small Firms				0.6524***	0.6599***	0.0032
				(0.0306)	(0.0277)	(0.0110)

Notes: The table entries reflect the conduct estimates for both the small and the large conduct specification. Standard errors are in parentheses and account for two-step estimation. Number of observations: 96512.

Table 16: Marginal Cost Estimates without Synergies: Model Comparison

	Small model	Large model	MP Nash
Time Trend	0.0010	0.0020	
	(0.0429)	(0.0156)	
Elec. Price	0.0123***	0.0194***	
	(0.0046)	(0.0035)	
General Promo	−0.1589***	−0.1605***	
	(0.0132)	(0.0052)	
BB Promo	−0.0242***	−0.0228***	
	(0.0034)	(0.0038)	
Median MC	0.085	0.082	0.107
Mean MC	0.081	0.076	0.101
Median PCM	0.438	0.463	0.330
Mean PCM	0.438	0.463	0.356
Med. PCM pre	0.421	0.455	0.332
Med. PCM post	0.463	0.481	0.328
Med. PCM pw	0.344	0.344	0.342

Notes: The table entries reflect the marginal cost estimates from our small conduct model, the large conduct model, and under Bertrand-Nash pricing. For time-specific median price-cost margins, pre refers to pre-merger period, post to post-merger period, and pw to price war period. All estimations include brand fixed effects, store fixed effects, and month-year fixed effects. Standard errors are in parentheses and account for two-step estimation. Number of observations: 96512.

Table 17: Time-Brand specific PCM without synergies

	Small model Pre-merger	Small model Post-merger	Small model Price War	Large model Pre-merger	Large model Post-merger	Large model Price War	MP Nash
NAB Shred Wheat	0.36	0.41	0.29	0.46	0.48	0.29	0.25
PO Raisin Bran	0.43	0.46	0.40	0.56	0.56	0.40	0.30
PO Grape Nuts	0.49	0.54	0.41	0.63	0.64	0.40	0.35
PO Honey Comb	0.36	0.38	0.30	0.47	0.45	0.29	0.26
GM RaisinNutBran	0.42	0.46	0.31	0.40	0.45	0.31	0.32
GM ApplCin Cheer	0.42	0.48	0.32	0.40	0.47	0.32	0.33
GM Wheaties	0.43	0.47	0.29	0.41	0.46	0.29	0.33
GM Cheerios	0.35	0.41	0.27	0.34	0.40	0.27	0.29
GM HonNut Cheer	0.40	0.46	0.30	0.38	0.45	0.31	0.32
GM Luck Charms	0.38	0.42	0.29	0.37	0.41	0.29	0.30
GM Tot CoFlakes	0.36	0.39	0.28	0.35	0.38	0.28	0.29
GM Trix	0.35	0.39	0.28	0.34	0.38	0.28	0.28
KE Froot Loops	0.44	0.47	0.43	0.43	0.46	0.43	0.38
KE Special K	0.43	0.44	0.36	0.42	0.43	0.36	0.36
KE Frost Flakes	0.55	0.58	0.52	0.54	0.57	0.52	0.47
KE Corn Pops	0.46	0.49	0.44	0.45	0.48	0.44	0.40
KE Raisin Bran	0.50	0.53	0.45	0.49	0.52	0.45	0.42
KE Corn Flakes	0.73	0.70	0.58	0.71	0.69	0.58	0.60
KE Honey Smacks	0.51	0.52	0.48	0.50	0.52	0.48	0.43
KE Crispix	0.46	0.47	0.37	0.45	0.46	0.37	0.38
KE Rice Krispies	0.52	0.51	0.43	0.51	0.50	0.43	0.43
RAL Chex	0.34	0.36	0.22	0.45	0.42	0.22	0.24
RAL Wheat Chex	0.38	0.42	0.23	0.53	0.51	0.23	0.26
RAL Rice Chex	0.35	0.37	0.23	0.46	0.43	0.23	0.26
QU Quaker Oats	0.46	0.56	0.36	0.63	0.67	0.36	0.34
QU Capn Crunch	0.41	0.47	0.30	0.54	0.56	0.29	0.31

Notes: The table entries reflect the brand-specific median price-cost margins for both the small and large model specification for the pre-merger, post-merger, and price-war periods, respectively, and for multiproduct Bertrand-Nash pricing over the whole sample.

Table 18: Counterfactual Simulation 2: No price war

	Small Model No price war	Large Model No price war
Δ consumer surplus (in US-$ mio.)	-0.7	-0.8
Δprice All Firms (in %)	16.2	17.1
Δprice GM (in %)	15.9	14.9
Δprice RAL (in %)	14.7	23.0
Δprice KEL (in %)	13.9	14.0
Δprice POSNAB (in %)	21.7	34.2
Δprice QUA (in %)	24.2	38.5

Notes: The table entries reflect the results from the counterfactual simulations for both the small and the large conduct specification. The simulations compute the changes in consumer surplus and wholesale prices when all firms continue to play according to the before price-war conduct instead of changing their conduct in the price-war period.

D Goodness-of-Fit Graphs

In this appendix, we provide several representative graphs to illustrate that our demand model fits the data reasonably well. We compare the observed data for market shares to our model predictions at various levels of aggregation. Our model predictions are computed using the estimated demand parameters and setting the structural error terms ξ to zero. Figure 5 displays observed and predicted brand-level market shares for two representative brands averaged across all stores over time. Figure 6 displays a comparison of predicted and observed total, i.e., aggregated over all brands, cereal sales for two representative stores over time.[40] In both figures, the prediction error is small and non-systematic. In particular, we examine whether our demand model is able to capture the effects of promotions on consumer demand in a reliable and robust way. To do this we construct our goodness-of-fit graphs separately for promotion and no-promotion periods. For the promotion graphs, we aggregate our predictions only over observations that indicate a brand-market combination that is on promotion. For the no-promotion graphs, we only aggregate over brand-market combinations that are not on promotion. Figures 7 to 10 illustrate that a similar pattern as for the aggregated figures prevails. Most importantly, the prediction errors for the separate promotion and no-promotion samples remain small and reasonably non-systematic.

[40] Additional results, such as the corresponding graphs for other stores or brands, are available from the authors upon request.

Figure 5: Goodness-of-fit: Brand-level market shares

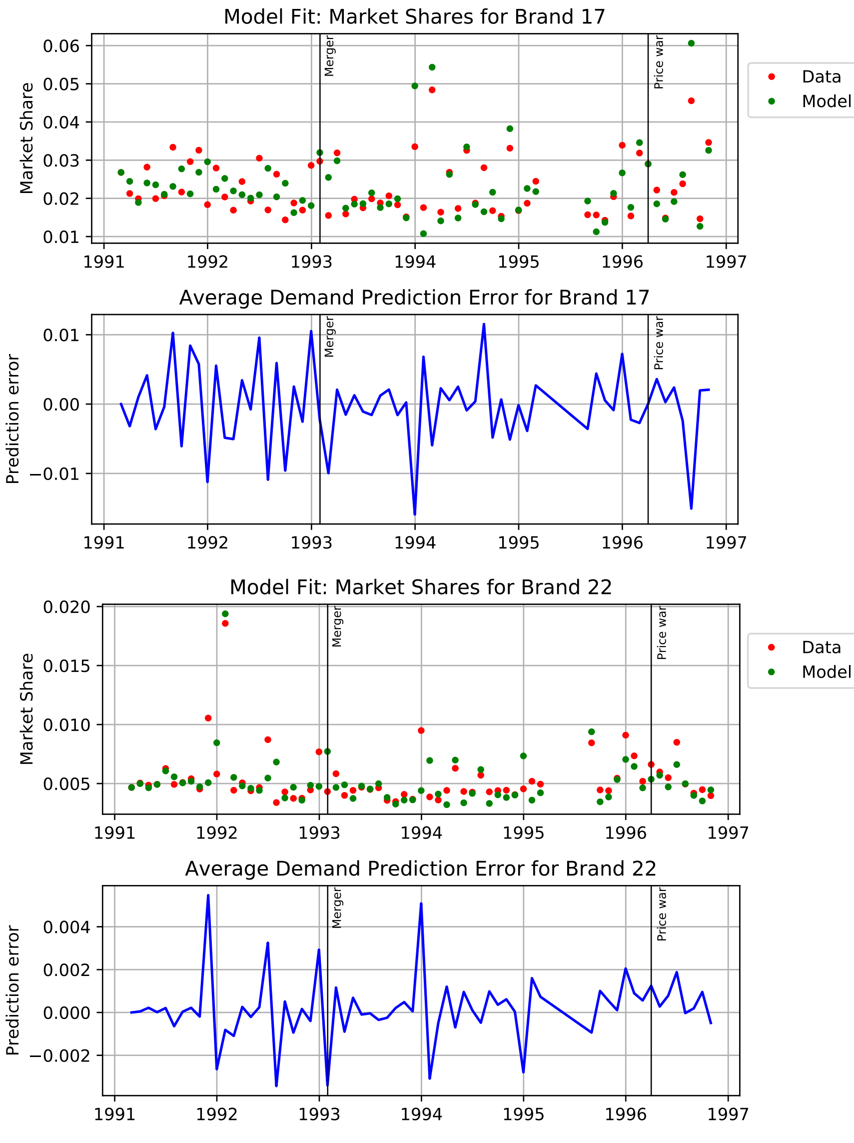


Figure 6: Goodness-of-fit: Store-level sales

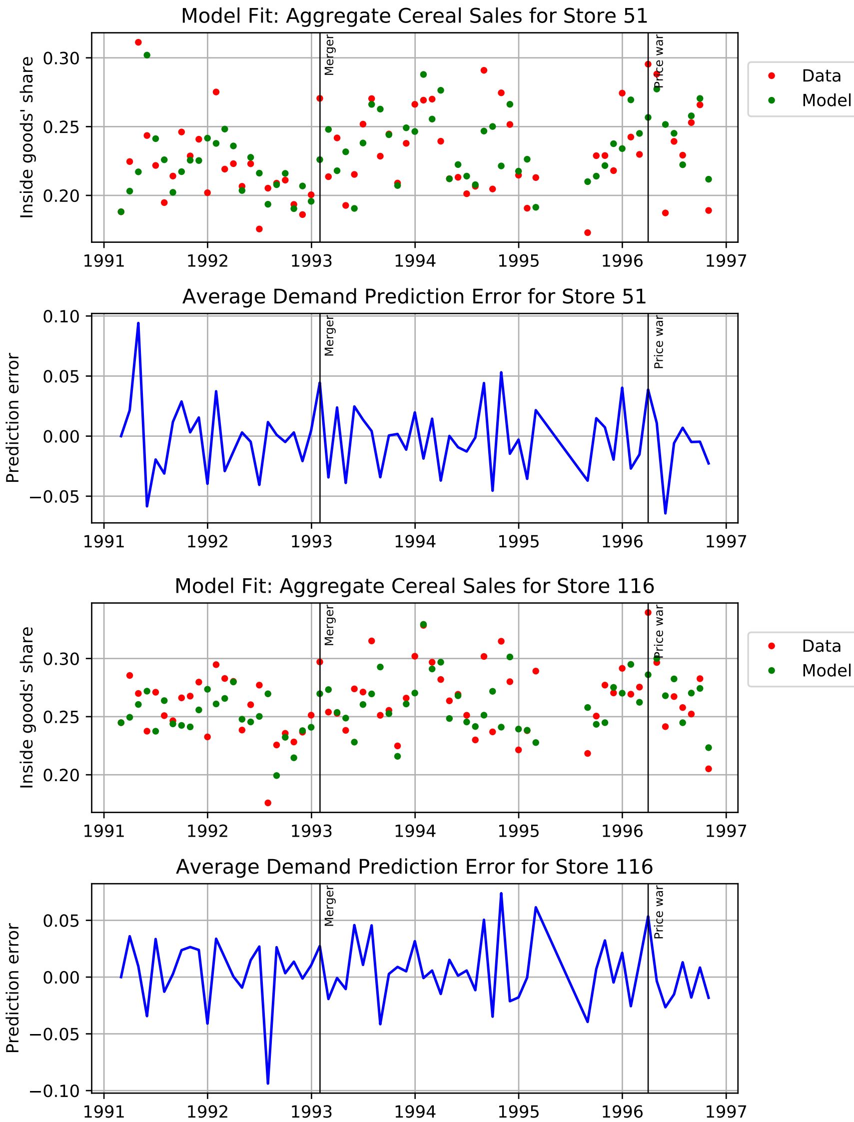


Figure 7: Goodness-of-fit: Brand-level market shares (promotion periods)

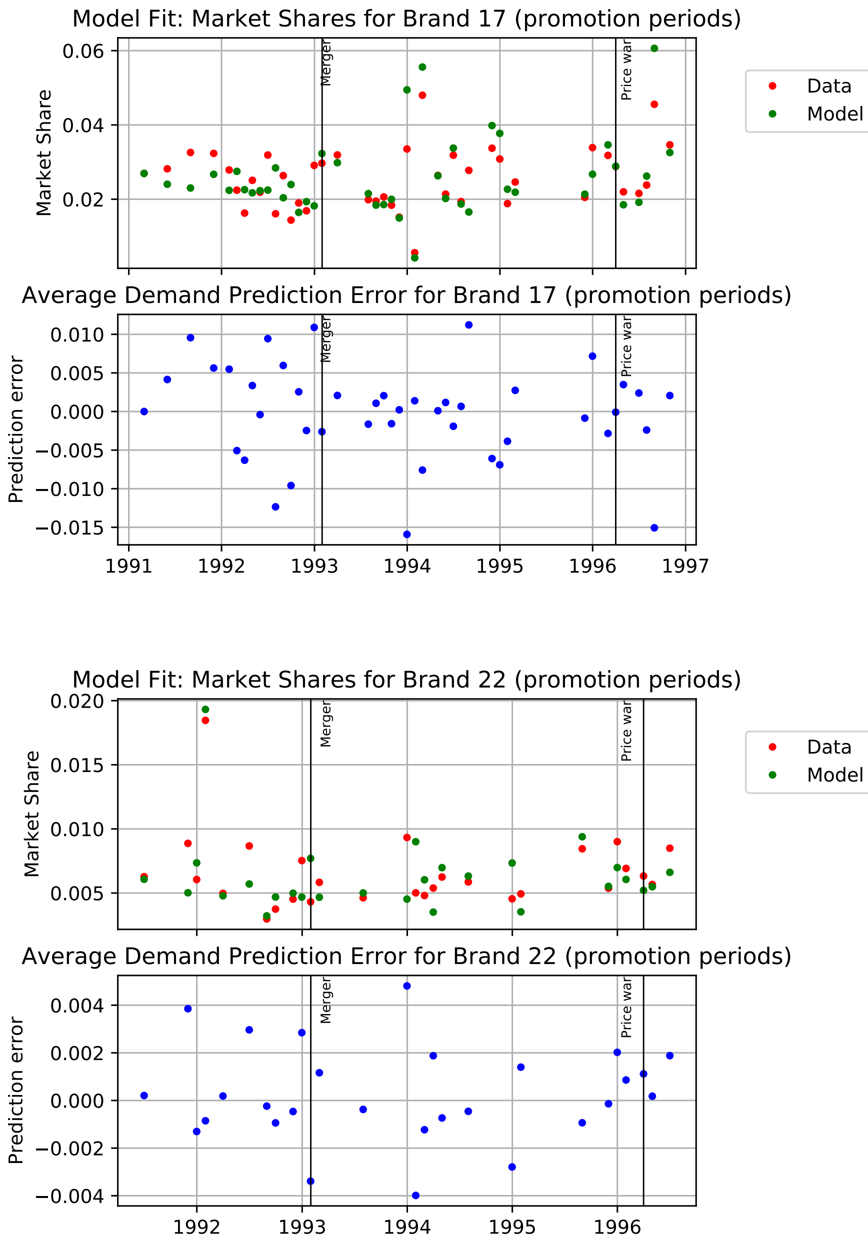


Figure 8: Goodness-of-fit: Brand-level market shares (non-promotion periods)

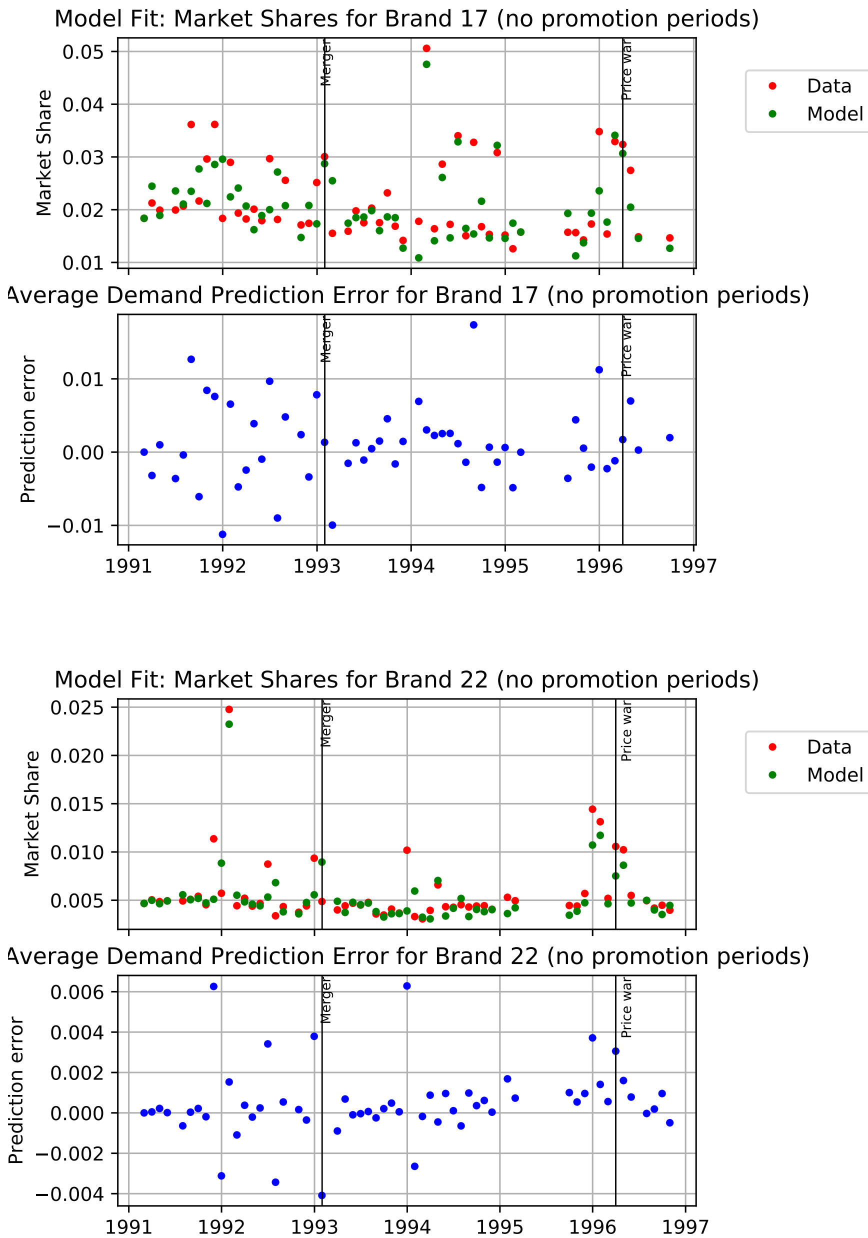


Figure 9: Goodness-of-fit: Store-level sales (promotion periods)

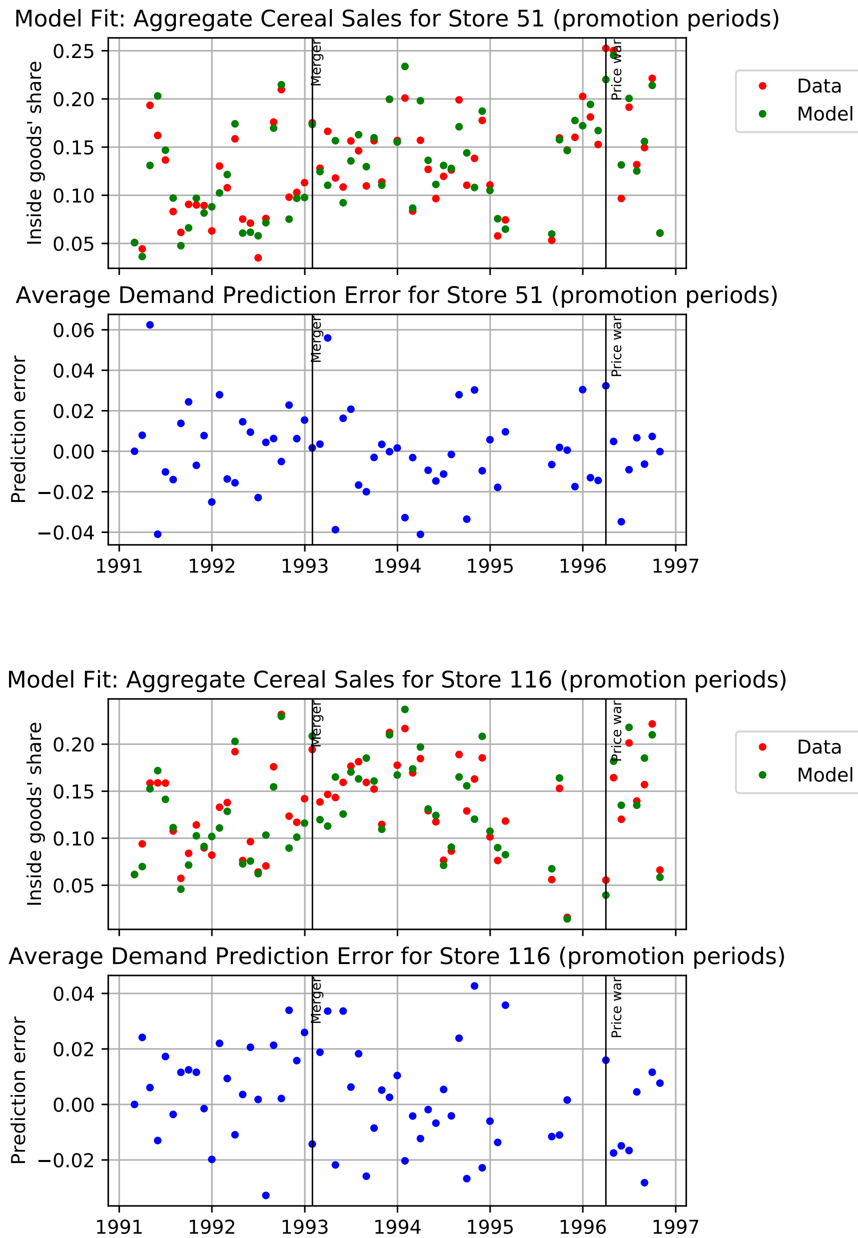
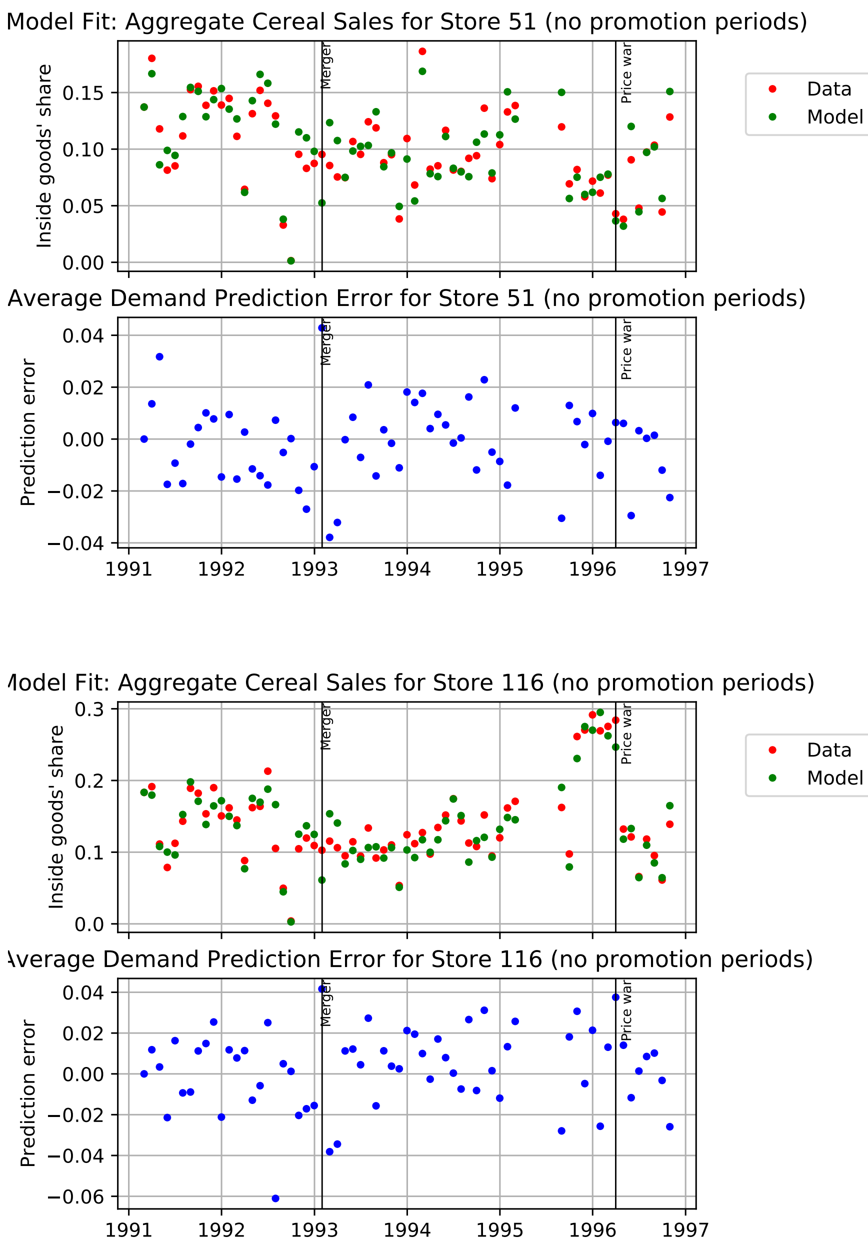


Figure 10: Goodness-of-fit: Store-level sales (non-promotion periods)



E Numerical Details of the Estimation Algorithm

In this appendix, we provide numerical details about our estimation algorithm and the software routines used. We estimate the demand side and the supply side in two steps. In principle, it is possible to estimate demand and supply jointly, which generally leads to efficiency gains because it exploits cross-model restrictions and correlations. We choose to estimate the models separately for several reasons. Joint estimation is computationally more intensive and with our very large sample we do not suffer from imprecise parameter estimates. Moreover, we found that using different optimization algorithms for demand and supply resulted in slightly more robust estimates.

Demand side For estimating our demand model, we use the nested fixed point routine proposed by BLP. Random coefficient demand models can be numerically difficult and computationally intensive to estimate as extensively discussed by Knittel and Metaxoglou (2014). Appropriate choices of optimizers and tolerance levels for such highly nonlinear models are crucial, see also the online appendix of Goldberg and Hellerstein (2013). In our baseline model, we estimate 4 non-linear coefficients capturing heterogeneity across different demographic consumer types and the nesting parameter. We also estimate much larger demand models with up to 12 non-linear parameters to perform extensive robustness checks.[41]

When computing the model's market share predictions, we simulate 500 consumers per market using Halton draws. Train (2000) demonstrates that Halton draws can be much more efficient in simulating the integral over the consumer population than naive random sampling. In line with the recommendations of Knittel and Metaxoglou (2014) and Dubé *et al.* (2012), we set the convergence criterion for the contraction mapping very tight. We stop the mapping, when the sup-norm of the change in the mean utilities δ between two iterations is less than 10^{-9}.

For minimizing the GMM objective function, we use a Nelder-Mead line search algorithm.[42] As stopping criterion for a minimum of the GMM objective function value we set

[41] Generally, we find that our baseline demand model provides a good fit to the data. The larger models result in very similar price elasticities which are the most important output of the demand estimation. Detailed results are available on request.

[42] Ideally, one would like to use a more efficient gradient-based optimizer. To exploit the full power of gradient-based optimization methods, we would have to compute the gradient of the objective function analytically, however. For a random coefficient model without nests the gradient has a closed-form solution, see, for example, Nevo (2000a). Unfortunately, a nested random coefficient model does not have a tractable closed-form gradient. Among others, we estimated random coefficient models without nests. For these models, we found that the gradient-based optimizer *SOLVOPT* is very powerful and robust in minimizing the GMM objective function compared to other gradient- and non-gradient based algorithms. In an extensive simulation study, Knittel and Metaxoglou (2014) report similar experiences.

the norm of the gradient of the objective functions to 10^{-6}. By using multiple starting values, we verify that the obtained minimum of the GMM function is indeed a global minimum.

Supply side For the estimation of the supply model, we generalize the algorithm proposed by BLP to allow for a flexible ownership/internalization matrix. The algorithm can be decomposed into four steps (2.-5.) as follows.

1. **Estimate the demand parameters θ and compute $\frac{\partial s()}{\partial p}$ to compute aggregate own- and cross-price elasticities as described in the previous paragraph.**

2. **Pick a guess for the non-linear supply parameters $vec(\Lambda)$.**

3. **Back out marginal costs given a guess for $vec(\Lambda)$, and $\frac{\partial s()}{\partial p}$ from the demand estimation.** Combining the price elasticities from Step 1 and the pick of $vec(\Lambda)$ from Step 2, we can compute marginal costs for each product and market. Since our marginal cost functions are linear, we can profile out the marginal cost parameters γ using linear IV regressions, as suggested by Nevo (2000a) for demand models. This step allows us to compute the unobservable marginal cost shock ω for each product and market and obtain the innovations of the shock process, ν^S, by auxiliary AR(1)-OLS regressions.

4. **Compute supply-side GMM objective function.** Based on the values for ν^S backed out in Step 3, we compute the supply side moments which are based on orthogonality conditions between the stacked ν^S and vectors of appropriate instruments. Finally, we aggregate the moment conditions to obtain the GMM criterion function for the parameter guess $vec(\Lambda)$.

5. **Repeat steps 2-4 until GMM objective function is minimized.**

Compared to the demand model, the supply side is computationally lighter because it does not require solving a contraction mapping for every parameter guess. Because we have to invert the system of firms' pricing FOCs, the analytical computation of the gradient of the GMM function is difficult. Since gradient-based optimization easily loses its power when gradients have to be computed numerically, we revert to non-gradient methods for estimating our supply model.

We find that a finite-descent accelerated random search (ARS) algorithm, as proposed by Appel *et al.* (2004), is very efficient and results in robust estimates in our application. Especially for our larger supply models with a high number of (non-linear) conduct parameters, ARS typically outperforms other non-gradient based approaches such as the simplex-based Nelder-Mead algorithm. For the ARS routine, we use a contraction factor of 2 and a convergence criterion of 10^{-8}.

F Standard Error Adjustments

Two-step standard errors adjustment Because we estimate demand and supply in separate steps, we have to account for the two-step nature of our estimation when computing the standard errors of the supply parameters. The correction takes into account the sensitivity of the supply moments with respect to the demand estimates and their variance. The general procedure for obtaining standard errors in this setting is outlined, for example, by Wooldridge (2010, Chapter 12.5.2). The asymptotic variance-covariance matrix of the GMM estimator for the supply side parameters $\hat{\theta}_S$ can be written as

$$var(\hat{\theta}_S) = \left[J_S(\hat{\theta}_S, \hat{\theta}_D)' W_S J_S(\hat{\theta}_S, \hat{\theta}_D)\right]^{-1} J_S(\hat{\theta}_S, \hat{\theta}_D)' W_S S_S W_S J_S(\hat{\theta}_S, \hat{\theta}_D) \left[J_S(\hat{\theta}_S, \hat{\theta}_D)' W_S J_S(\hat{\theta}_S, \hat{\theta}_D)\right]^{-1},$$

where $J_S(\cdot)$ denotes the Jacobian of the l_2 supply side moments with respect to the k_2 supply parameters, W_S is the supply side weighting matrix and S_S denotes the $l_2 \times l_2$ matrix containing the outer product of the l_2 supply side moments $g_{\nu^S}(\cdot) = \nu^S(\hat{\theta}_S, \hat{\theta}_D) Z_S$.

When demand and supply parameters are estimated in two separate steps, the standard formula underestimates the variance of the supply side parameters. In order to obtain correct standard errors, S_S has to be modified to take into account the sensitivity of the supply moments with respect to the demand parameters. In our model, S_S has to be replaced with

$$\tilde{S}_S = \left[g_{\nu^S}(\hat{\theta}_S, \hat{\theta}_D) + F g_{\nu^D}(\hat{\theta}_S, \hat{\theta}_D)\right] \left[g_{\nu^S}(\hat{\theta}_S, \hat{\theta}_D) + F g_{\nu^D}(\hat{\theta}_S, \hat{\theta}_D)\right]',$$

where g_{ν^S} contains the $l_2 \times n$ supply moments and g_{ν^D} contains the $l_1 \times n$ demand moments both evaluated at the estimated parameter values $(\hat{\theta}_D, \hat{\theta}_S)$. The sensitivity of the supply moments with respect to the demand parameters is captured by the $l_2 \times l_1$ matrix F

$$F = J_{SD}(\hat{\theta}_S, \hat{\theta}_D) \left[J_{DD}(\hat{\theta}_S, \hat{\theta}_D)' W_D J_{DD}(\hat{\theta}_S, \hat{\theta}_D)\right]^{-1} J_{DD}(\hat{\theta}_S, \hat{\theta}_D)' W_D,$$

where $J_{SD}(\cdot)$ contains the derivatives of the l_2 supply moment conditions with respect to the k_1 demand parameters evaluated at the estimated demand and supply parameters. $J_{DD}(\cdot)$ denotes the derivatives of the l_1 demand moments with respect to the k_1 demand parameters and W_D is the $l_1 \times l_1$ is the weighting matrix used in the demand estimation.

Delta method standard error adjustment We use an exponential transformation to restrict our conduct parameters λ to lie between 0 and 1. We estimate a parameter λ_e such that the actual model parameter is

$$\lambda = g(\lambda_e) = \frac{exp(\lambda_e)}{1 + exp(\lambda_e)}.$$

The standard GMM variance formula provides us with an estimate of the standard errors of λ_e. In order to compute standard errors for our actual conduct parameters λ, we apply the delta method which states that the variance of a continuous function $g(\cdot)$ of a random variable X is given by

$$var\big[g(X)\big] = \big[g'(X)\big]^2 var\big(X\big).$$

The derivatives of our functional transformation with respect to the estimated parameter λ_e are

$$g'(\theta) = \frac{exp(\lambda_e)}{1 + exp(\lambda_e)} - \frac{exp(\lambda_e)^2}{[1 + exp(\lambda_e)]^2} = \frac{exp(\lambda_e) + exp(\lambda_e)^2 - exp(\lambda_e)^2}{[1 + exp(\lambda_e)]^2} = \frac{exp(\lambda_e)}{[1 + exp(\lambda_e)]^2}.$$