Estimating Industry Conduct Using Promotion Data*

The Evolution of Pricing Behavior in the U.S. RTE Cereal Industry

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Abstract

We estimate the evolution of competition in the ready-to-eat 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. After a merger in 1993 price coordination decreases to a level consistent with multiproduct Bertrand-Nash pricing. The last part of our sample is characterized by even more aggressive pricing implying median wholesale margins of less than 5%.

Keywords: Markups, Market Power, Conduct Estimation, Differentiated Products Markets
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1 Introduction

One of the central questions in industrial organization is to what extent and how firms exert market power. Empirically disentangling legitimate sources of market power, such as product differentiation, from anti-competitive behavior, such as coordinated pricing is thus an important task. Since neither the intensity of competition nor marginal cost, which is another price determinant, are commonly observed in the data, this task is very difficult, however.

In a seminal paper, Bresnahan (1982) showed for a homogeneous goods model how demand shifters and rotators can be used to distinguish different oligopoly models. Berry and Haile (2014) formalized this intuition for a general class of models with differentiated products and show 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, so that estimation-based inference about the competitive intensity of an industry remains challenging.

Most studies that estimate *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. These restrictions can lead to inconsistent estimates of markups and marginal costs.

In this paper, we estimate detailed patterns of industry conduct that account for changes over time and heterogeneity across firms in the U.S. 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 the characteristics space interacted with information on rival brands' promotions.

For our estimation, 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 advantage of our data is that it contains information on wholesale prices. We analyze a five-and-a-half year span of data from 1991 to 1996. Our sample period includes two important events; first, the Post-Nabisco merger in January 1993

[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 U.S. beer industry deviates from Bertrand-Nash pricing once one of them participates in the joint-venture.

and second, a period starting in April 1996 during which manufacturers massively decrease wholesale prices, which the business press referred to as a *price war*. A key focus of our application is to quantify how pricing behavior changes following these events.

To motivate our structural model and our identification strategy, we conduct a series of reduced form regressions. We find that after the merger most prices increased slightly and that during the price war period wholesale prices are 7% lower than in the pre-merger period. Moreover, we show that how firms react to rival firms' promotions changes significantly over time. We illustrate using a stylized model that these patterns can be interpreted as evidence that industry conduct changed over time.

Naturally, the observed pricing trends can be due to several reasons, in particular, changes in demand, marginal cost, and industry conduct. In order to disentangle these channels, we develop a structural empirical model. 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 models the degree of cooperation by a matrix of parameters that capture the degree to which firms internalize their rivals' profits. Compared to a model that simply assumes a particular form of industry conduct, for example, Bertrand-Nash pricing, as is often done in the literature, our model allows for substantially more heterogeneity of markups over time and across firms. Therefore, it is likely to lead to more accurate predictions and more effective policy recommendations.

The novel instruments that we use to identify industry conduct are based on information on rival brand's temporary promotions interacted with measures of proximity in the characteristics space. These instruments follow the logic of Berry and Haile (2014) and classical BLP-instruments in the sense that they capture variation across markets in the competitive pressure exerted by rival products' promotions and therefore shift firms' markups.

The shifts in competitive pressure induced by a rival brand's promotions should be stronger the more consumers consider these products as substitutes. Therefore, we interact the market-specific number of rivals' promotions with the products' relative proximity in the characteristics space. The relative proximity feature mirrors the logic of the differentiation instruments recently proposed by Gandhi and Houde (2019) to identify consumers' substitution patterns.

Even though promotions are clearly endogenously set by firms, promotional activities can be considered as sequentially exogenous. In almost all 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 advertising brochures must be printed. Therefore, rivals' promotional activities in a given time period are plausibly exogenous to innovations in product-specific demand

and supply shocks. We present extensive evidence from the marketing literature and reduced form evidence from our data that support the timing assumptions implied by our choice of instruments in Section 2.3 and Appendix A.7.

In contrast to typical BLP instruments, we do not require variation in the physical characteristics space, which is typically generated by product entry or exit, to construct a rich set of instruments. In addition, our empirical strategy does not rely on exogenous industry shocks. The data required to construct our instruments are readily available for many consumer goods industries, and thus our empirical strategy has broad applicability. Finally, we conduct a series of weak identification tests and find that our proposed instruments indeed prove to be very powerful in identifying firm conduct.

Our estimation results indicate that there are substantial changes in industry conduct over time. We find partially cooperative levels of conduct between firms in the beginning of our sample, with wholesale margins that are twice as large as those implied by Bertrand-Nash pricing.[3] After the Post-Nabisco merger conduct becomes more competitive and on average consistent with Bertrand-Nash pricing. When we allow our conduct parameters to differ across firms, we find that only the post-merger conduct of the smaller firms is consistent with Bertrand-Nash pricing, while the two market leaders, Kellogg's and General Mills still price more cooperatively. For the price war period, our estimates indicate that firms price even more aggressively with median wholesale margins of less than 5%.

Finally, we use our model to conduct a series of counterfactual simulations. First, we decompose the observed price changes post-merger into the unilateral and coordinated effects of the merger. We find that the unilateral effects of the merger are minimal and that almost all of the observed price changes can be attributed to a change in the conduct parameter. Second, we simulate how the industry would have evolved if the price war had not taken place. In this scenario, prices would have been 9% higher, and consumer surplus for the Chicago area during the 9 month of the price war period that our sample covers would have been US-$ 1 million lower, and the corresponding firm profits would have been US-$ 1.1 million higher.

Our paper relates to several strands of 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

[3]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.

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 on industry conduct has mostly relied on estimating conjectural variations for the homogeneous good case, see, for example Bresnahan (1982) and Lau (1982). 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. Nevo (1998) discusses the advantages and disadvantages of a direct conduct estimation compared to a non-nested menu approach for differentiated products industries. 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, Rivers and Vuong (2002) and the recent working paper by Duarte *et al.* (2022). One advantage of these approaches compared to an estimation-based approach is that testing generally imposes lower requirements on the strength of the moment conditions. A disadvantage of a testing-based approach is that it requires the researcher to prespecify a fixed set of conduct models to test against each other. Moreover, in some cases the statistical power of these tests can be relatively weak and difficult to assess; see, for example, Shi (2015). This can be especially problematic when several detailed conduct patterns are tested against each other. Backus *et al.* (2021) also propose a testing-based approach to empirically analyze industry conduct. They focus on distinguishing multiproduct Nash pricing from pricing patterns implied by the common ownership hypothesis using Nielsen data on the U.S. cereal industry from 2007 to 2016.

Our instruments can straightforwardly be incorporated into the testing-based approaches of Duarte *et al.* (2022) and Backus *et al.* (2021). In addition a key advantage of our instruments is that we find them powerful enough for an estimation-based approach, which allows for quantifying more fine-grained conduct patterns. This is particularly advantageous for settings, in which the conduct parameter can be given a micro-founded structural interpretation, such as when quantifying within-firm internalization patterns, as for example, analyzed by Michel (2017).

Our analysis also contributes to a broader 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. 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: 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. However, his data has a different geographical coverage (65 U.S. cities) than ours (only the Chicago area). For the pre-merger period, our estimates are overall consistent with his results, but we provide additional insights. While our markup estimates are closer to those implied by multiproduct Nash than those implied by 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 around 40%, but that after allowing for a flexible conduct specification, median gross margins in the pre-merger period are 52%. Most importantly, Nevo (2001) assumes a time-invariant conduct, while we find significant changes in the conduct parameter over time.

There is also a growing interest in quantifying the heterogeneity of markups in both the macroeconomics and the trade literature, which usually rely on the production function approach, see for example, De Loecker *et al.* (2020). In a similar spirit, Döpper *et al.* (2021) analyze over 100 consumer products categories to quantify the evolution of markups over time using a BLP-style demand inversion approach under the assumption of constant static Bertrand-Nash pricing. We consider our analysis complementary to this literature by allowing heterogeneity in industry conduct to drive markup heterogeneity across firms and time.

The two papers most closely related to ours are Miller and Weinberg (2017), and Ciliberto and Williams (2014), who also employ an estimation-based approach to quantifying industry conduct. 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 MillerCoors 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 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.[4]

2 Data and Industry Overview

In this section, we provide background information on the U.S. RTE cereal industry and describe our data. In addition, we conduct a series of reduced form regressions to provide evidence for changes in industry conduct over time and to guide our structural model.

2.1 Industry Overview

In the beginning of our sample period, 6 nationwide manufacturers dominate the U.S. RTE cereal industry. The two largest firms, 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). More than 200 brands are available to consumers during the time span we analyze; however, the majority of sales can be attributed to the 25 most popular brands.

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. 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. Table 5 in Appendix A.1 shows that the market is considered highly concentrated already before the merger, with an HHI of more than $2,500$. However, the merger did not lead to a significant increase in the HHI. Figure 1 in Appendix A.1 illustrates that prices of individual brands reacted heterogeneously to the merger. Kellogg's and Ralston increased prices the most, especially right after the merger. Wholesale prices of Post, Nabisco and Quaker increased only marginally and General Mills decreased them for many of its brands, especially starting in 1994.

In the spring of 1996, all cereal manufacturers massively decreased their wholesale prices nationwide. 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. Although we remain agnostic about the causes for the price war, there is anecdotal evidence that negative publicity and political pressure were important motivations for the price cuts. For example, in March 1995 two U.S. congressmen started a

[4] Although our paper focuses on estimating industry conduct for general industry settings, it is further related to the ex-post analysis of mergers, for example, Crawford *et al.* (2018), Ashenfelter *et al.* (2013), and Björnerstedt and Verboven (2016).

public campaign to reduce cereal prices, which received high media attention. This campaign was revived one year later right before the start of the large wholesale price cuts (Cotterill and Franklin, 1999). Figure 1 shows that the nationwide patterns are also present in our sample. 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 coordinated pricing rather than potential shifts in demand and marginal costs.

RTE cereals are distributed to private consumers via supermarkets. An important feature of many consumer packaged goods (CPG) industries is the presence of temporary promotions. A large literature in marketing and economics discusses manufacturers' and retailer's motivations for running promotions and how they are implemented in practice, see, for example, Anderson and Fox (2019) for an excellent survey of this literature.

In the following, we discuss several institutional features that motivate our model and our empirical strategy to quantify industry conduct. First, temporary promotions are large shifters of (short-run) demand, for example, because promotions induce brand-switching or incentivize consumers to buy additional units (Anderson and Fox, 2019, p.501). Promotions generate these demand shifts (and rotations) through both temporary reductions in a product's retail price and demand-enhancing non-monetary effects, for example, because of an inclusion in a retailer's advertising brochure, better shelf space allocation or additional in-store promotion signs, see, for example, Anderson and Simester (1998) for the importance of such sale-sign effects.

Second, promotions follow *sticky plans*, i.e., they are set at least several months in advance and almost never reversed (Anderson and Fox, 2019, p.541). This is to coordinate operations of the manufacturer and the retailer so that, for example, sufficient inventory is available during a promotion. Therefore, promotions usually cannot react to contemporaneous innovations in demand and cost shocks immediately, and can be considered sequentially exogenous.

Lastly, promotions are often funded via *trade spend* payments. In order to incentivize the retailer to pass-through a promotion for a specific product, its manufacturer will usually grant a discount on the wholesale price for all units sold during the promotion period, which is financed from a *trade spend budget*, that is typically fixed for a longer time horizon and considered to come from a separate manufacturer account than payments associated with base wholesale prices (Anderson and Fox, 2019, p.536). To ensure that the retailer does not free-ride on lower promotion wholesale prices without passing-through these discounts to consumers, manufacturers use detailed *contingent contracts* (Anderson *et al.*, 2017).[5] Therefore, both retail and net wholesale prices (wholesale prices after trade spend discounts) often

[5]For example, a manufacturer might require proof from the retailer that the agreed upon promotion activities were indeed implemented and that promotion-adequate quantities were sold during the promotion, for example, by providing scanner data.

move in parallel during a promotion period and this variation in wholesale prices does not reflect variation in a manufacturer's marginal cost of production.

A key feature that we exploit for our empirical strategy is that regular (base) wholesale prices and promotion prices are typically determined by two different price processes (Anderson *et al.*, 2017, p.536): While manufacturers use base prices to respond to changes in demand and supply conditions, the latter almost never seem to react significantly to economic forces but rather follow their predetermined sticky plans.

Even though our structural model will incorporate both base wholesale prices and promotional prices induced by trade spend discounts, the main strategic variable in our analysis will be the base wholesale price taking the trade spend patterns as exogenously given.

2.2 Data

Our main data come from the DFF scanner database covering the period from February 1991 to October 1996. It includes information on DFF supermarkets located in the Chicago metropolitan area and weekly 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 and focus on 27 brands from the six nationwide manufacturers. 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. We do not include private label products in our analysis, because our focus is on estimating the competitive interactions between national cereal manufacturers. In Appendix A.2 we provide additional details about the brands that we exclude from our analysis, in particular, the private label products in our data. We show that for DFF their overall quantity is negligible and unlikely to affect our analysis. The 27 brands included in our sample cover roughly 75% of all the cereals sold at DFF during our sample period.

Typically, each brand is offered in the form of two main UPCs (sizes) and temporarily features special UPCs that exhibit only small sales. For our estimation, we follow most of the literature and aggregate the data from the UPC-week to the brand-month level, mostly in order to alleviate concerns about measurement error and consumer stockpiling on a weekly level.

Information on temporary promotions is recorded on the UPC-store-week level, separately for two types of promotions: general price reduction sales and bonus buy/coupon promotions, i.e., we observe for how many weeks a given brand is on promotion within each month. We discuss detailed descriptives of the different promotion variables on several levels (UPC-week versus brand-month) in Appendix A.3. Within a month, promotions are usually highly correlated across DFF stores, even though there is some variation within the chain in a given month, see Figure 10 in Appendix A.3.

Most importantly, Figures 7 and 8 reveal that, even after aggregating the data to the brand-month level, there is substantial variation across brands and month in the observed promotion intensity, which is a significant shifter of consumers' demand. As we discuss in Section 4.1, our instruments for identifying industry conduct exploit this rich variation in promotion "breadth" (over brands and time) as observed demand shifters. While we observe the price promotion depth, i.e., by how much retail and wholesale prices decrease during a temporary promotion, we do not observe any depth measure of the non-monetary promotion components, such as the number of advertising brochures or shelf space allocation. We discuss the issue of promotion breadth versus promotion depth further in Appendix A.3.

A key advantage of the DFF data is that we observe the retailer's average acquisition costs for each product in each week. From this variable we compute a measure of wholesale prices for each brand and month. This variable is a weighted average of the wholesale prices for the products in the inventory; see Chevalier *et al.* (2003) for a discussion of this variable.[6] Under the assumption that the retailer cannot carry forward significant inventory from month to month, we judge this wholesale price measure to be a reasonable approximation to the actual wholesale price paid by the retailer.

An important point is that the observed wholesale prices contain *trade spend* discounts which are granted by manufacturers during a promotion period to incentivize the retailer to pass-through a promotion to the final consumer. As discussed extensively in Anderson and Fox (2019), trade spend discounts are unlikely to reflect variation in marginal costs of producing cereal; rather they are determined by sticky plans and complicated contingent contracts between manufacturers and retailers. Since our structural model will focus on base wholesale prices as manufacturers' strategic variable, we decompose the observed net wholesale price into base wholesale prices and trade spend payments.

For our main specification, we assume that manufacturers set base wholesale prices every month at the chain level, while wholesale price variation across weeks and store within a month are assumed to arise because of trade spend payments to incentivize promotions at specific stores. Therefore, we impute the base wholesale price for each brand-month observation from wholesale price information from adjacent non-promotion weeks in the same months. We provide the details of this computation, as well as several alternatives and robustness checks, in Appendix A.4.

We complement the DFF data with input price data for commodities, such as sugar and various grains, as well as gasoline and electricity prices from Thomson Reuters Datas-

[6]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 cost.

tream and from www.indexmundi.com. Finally, we collect nutrition facts from the website www.calorieking.com and information on the different production and processing techniques for the different cereals from manufacturer websites. Throughout our analysis we use prices deflated to 1991-USD.

2.3 Reduced Form Analysis

In the following, we use reduced form regressions to investigate the patterns in our data in more detail and to provide evidence for our hypothesis that firm conduct changed following the industry events that we analyze. Our analysis is based on the idea that the promotion of a rival product should have different effects on a brand's own price under competition and collusion. In general, the promotion of a rival product increases competitive pressure on a product because of two effects; first, demand-enhancing "sale sign" effects (through non-monetary channels), and second a retail price reduction that acts as a short-term marginal cost reduction (from the perspective of the retailer) triggered by a trade spend payment. In our application, the latter effect almost always dominates the first, so that promotions are not only associated with lower retail but also with lower net wholesale prices.

Under static Bertrand-Nash competition, this is likely to lead to own price cuts when a rival brand goes on promotion, since prices are strategic complements. Under joint profit maximization, however, each brand will take into account an additional term, which contains a cross-derivative effect. If a rival promotion increases this cross-derivative enough, it is possible that a rival promotion generates an own-price increase, which is much less likely to occur under competition.

Therefore, how a firm reacts to a rival brand's promotion can be informative about the level of price competition in the market. We provide a more formal discussion of these effects using a stylized model as well as a numerical illustration using a logit model in Appendix A.5.

Table 7 in Appendix A.6 summarizes the results from linear regressions that apply the above logic by regressing wholesale prices on various measures of own-brand and rival promotions. The different columns differ in what promotional activity variables we include (columns 1 and 3 with only general promotions or 2 and 4 with both general and bonus buy promotions) and which wholesale price is analyzed (net wholesale prices (including trade spend) in columns 1 and 2 or base wholesale prices in columns 3 and 4).

First, we find that after the Post-Nabisco merger wholesale prices tend to increase for most firms, even though for many firms the total wholesale price increase is insignificant. Kellogg's and Ralston increase wholesale prices most by around 3% to 4%. General Mills is a notable exception and decreases prices in the post-merger period by 4% on average. During the price war period wholesale prices are roughly 10% lower than in the pre-merger period.

The effects of rival firms' promotions on wholesale prices change substantially across the three periods of our sample, which is in line with our hypothesis of changes in industry conduct and the results are similar across all specifications. In the pre-merger period rival firms' general promotions and wholesale prices have a large and positive correlation. After the merger this effect becomes smaller and insignificant. During the price war period general promotions have a large and significant negative effect on rivals' wholesale prices. Qualitatively, similar patterns hold for bonus buy/coupon promotions, although the coefficients are generally smaller and sometimes insignificant.

The effect of own-brand promotions is negative and significant for net wholesale prices (columns 1 and 2). Base wholesale prices are not significantly lower during promotion periods, see columns 3 and 4. This pattern is not surprising since the reported net wholesale prices include trade spend payments during promotion periods, while base wholesale prices do not include this discount.

In order to test formally whether the estimated changes over time are significant, we conduct several structural break tests for the "promotion passthrough" coefficients of both own and rival promotions for each of the four regression models in Table 7. Table 1 summarizes the results for total wholesale prices, which include trade spend payments.[7]

Each row tests the hypothesis that the promotion passthrough coefficient is constant over the three periods using F-tests. The first three rows correspond to testing the equality of rival promotions passthrough, which we can clearly reject in all models, even at the 1% level. In contrast, we cannot reject the equality of the passthrough coefficients of own-brand promotions over time.[8]

Overall, we interpret these results as strong evidence for our hypotheses that industry conduct changes over time.

3 Empirical Model

There are several potential reasons for observing the price increases following the Post-Nabisco merger and the large reduction in wholesale prices three-and-a-half years later. For example, consumers' preferences 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 been changes in industry conduct. To disentangle the different channels, we develop a structural model of the RTE cereal industry.

[7]The results for base wholesale prices are similar and summarized in Table 8 in Appendix A.6.

[8]In Appendix A.6, we provide additional structural break tests that do not assume that the the break point is known. Specifically, we conduct the structural break test of Bai and Perron (1998) on the price time series for each brand. Overall, these tests confirm that structural breaks in the passthrough of rival promotions occur around the months where the merger and the alleged price war happened.

Table 1: Structural Break Tests - Total Wholesale Prices

	$\beta(SE)$			$H_0 : pre = post = pw$	
	Pre-merger	Post-merger	Price war	F-statistic (df1,df2)	p-value
Promo (SG, rivals), model 1	8.7240	2.4414	-2.7381	11.0933 (2,1683)	0.0000
	(2.5680)	(0.8754)	(1.0324)		
Promo (SG, rivals), model 2	9.1778	2.2676	-2.3925	8.4951 (2,1677)	0.0002
	(2.8057)	(0.8784)	(1.1368)		
Promo (BC, rivals), model 2	-0.4443	2.5267	-0.7469	3.1954 (2,1677)	0.0412
	(0.8919)	(0.8857)	(1.9204)		
Promo (SG, own), model 1	-0.0022	-0.0019	-0.0012	1.8082 (2,1683)	0.1643
	(0.0007)	(0.0002)	(0.0003)		
Promo (SG, own), model 2	-0.0022	-0.0019	-0.0012	1.6309 (2,1677)	0.1961
	(0.0007)	(0.0002)	(0.0003)		
Promo (BB, own), model 2	-0.0002	-0.0003	-0.0004	0.4808 (2,1677)	0.6184
	(0.0001)	(0.0002)	(0.0003)		

Notes: The table summarizes the results from testing the equality of the own and rival promotion passthrough coefficients on total wholesale prices over time using F-tests.

3.1 Demand Model

On the demand side, we estimate a random coefficient 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 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.

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

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

where x_{jt} denotes a K-dimensional vector of brand j's observable characteristics (including brand fixed effects, year fixed effects, and month-of-the-year fixed effects), p^r_{jt} denotes the retail price of product j in market t. All physical product characteristics in x_{jt}, such as sugar and fiber content, are time-invariant and therefore collinear with brand fixed effects.

As discussed extensively in the marketing literature, temporary promotions are important determinants of consumers' cereal choices through both direct price effects and non-monetary effects that increase the attractiveness of products "on sale". Our model captures direct price reductions in the observed retail price p^r_{jt}. We find strong evidence for the non-monetary sale-sign effects in our data using reduced form regressions of sold quantities on promotion measures and other market characteristics; see Appendix A.7 for details. To capture the non-monetary effects in our demand model in a parsimonious way, we include the number of promotions for product j in market t in the vector of observable product characteristics x_{jt}, which constitutes the only time-varying product characteristic.

We capture brand-market specific quality shocks that are unobservable to the researcher but observable to and equally valued by all consumers by ξ_{jt}. In addition, we assume that ξ follows an AR(1)-process so that $\xi_{jt+1} = \iota^D \xi_{jt} + \nu^D_{jt+1}$. This specification allows for persistence in the structural demand error and, most importantly, enables us to form moment conditions based on the innovations of the process instead of its levels.

The coefficients β_i and α_i are individual-specific. They depend on the mean valuations (α, β), a vector of i's demographic variables, D_i, and Φ, a vector of parameters that measure how preferences vary with demographics, so that

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Phi D_i. \tag{2}$$

In our main specification we include only income as a demographic characteristic and interact it with the constant, price, sugar, and fiber.

Finally, ϵ_{ijt} is an iid error term, which we model with a nested logit structure, such that $\epsilon_{ijt} = \zeta_{igt} + (1-\rho)\tilde{\epsilon}_{ijt}$. The nesting parameter ρ captures the amount of correlation between the product-specific shocks within the same product group g. Our motivation for allowing for a nested logit structure 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.[9]

Consumers who do not purchase any cereal choose the outside good, the utility of which we normalize to ϵ_{i0t}.[10] Market share predictions are then given by

$$s_{jt} = \int_i \frac{\exp\big((\delta_{ijt} + \mu_{ijt})/(1-\rho)\big)}{\exp\big(I_{igt}/(1-\rho)\big)} \frac{\exp(I_{igt})}{\exp(I_{it})} dP_{it}, \tag{3}$$

where $\delta_{jt} = x_{jt}\beta + \alpha p^r_{jt} + \xi_{jt}$, $\mu_{ijt} = [p^r_{jt}, x_{jt}]' * \Phi D_i$, and I_{igt} and I_{it} are the inclusive values for consumer i from product group g and all products respectively, and the integral is taken over the distribution of consumer types in market t, P_{it}.

[9] Conceptually, grouping all inside goods into a nest is similar to including a random coefficient on the constant term.

[10] Potential changes to the quality of the outside good are captured by our time fixed effects.

3.2 Supply Model

The J brands in the industry are produced by R multiproduct firms.[11] We impose that wholesale marginal costs do not vary across stores and that manufacturers set a uniform wholesale price for all DFF stores for a specific brand in a given month; therefore, in our supply model a market is defined as a month instead of a month-store combination.[12]

We model wholesale marginal costs of producing cereals as a linear function of observable cost shifters w_{jt} and a brand-market specific cost shock ω_{jt}, that is unobserved by the researcher but known to the firms, so that $mc_{jt} = w_{jt}\gamma + \omega_{jt}$, where γ is a vector of marginal cost parameters to be estimated. In order to allow for flexible marginal costs, we include brand-half-year fixed effects and several input prices (for sugar, wheat, corn, oat, and rice) weighted with a cereal's content of each input in w_{jt}.[13] Analogous to our demand model, we allow for persistence in the unobserved cost shock and model ω as an $AR(1)$-process $\omega_{jt+1} = \iota^S \omega_{jt} + \nu^S_{jt+1}$.

Next, we describe the interplay between manufacturers and retailers, and the timing of promotion and price setting. It is important to note that we do not estimate the promotion part of the model. Rather we provide it to clarify our assumptions and to justify the validity of our identification strategy. The focus of our empirical supply model is on the setting of base wholesale prices.

In period $t-k$ (with $k \geq 1$), each manufacturer determines for each of its brands how often to put the brand on promotion. Furthermore, if product j is on promotion in period t, the manufacturer sets the trade spend payment td_{jt}, which incentivizes the retailer to implement the promotion strategy, also in period $t-k$. If brand j is not on promotion in period t, $td_{jt} = 0$.

We assume that manufacturers have an exogenously given target for promotional intensity, which could come from a separate, potentially dynamic optimization problem, that we do not model. Furthermore, we assume that manufacturers make a take-it-or-leave-it offer with trade spend payments such that, in equilibrium, the retailer always accepts the offer by the manufacturers.

Promotions have two effects in our model. First, they have perceived quality-enhancing effects via sale-sign effects that are captured by the inclusion of the brand-specific number of promotions in a market as an observable demand shifter in the consumer's utility function. Second, a promotion and the associated trade spend payment act as a temporary marginal

[11] Henceforth, we denote a manufacturing firm simply as a firm.

[12] Note that in contrast to many other retailers DFF engages in zone-level pricing so that retail prices need not be identical across different DFF stores.

[13] The brand-half-year fixed effects also pick up potential synergies arising from the Post-Nabisco merger. In a robustness check we also include a separate post-merger-merging firms dummy. The results are very similar and available upon request. For a more detailed discussion, see Appendix B.3.

cost reduction from the perspective of the retailer. This reduction has to be passed through to consumers in the form of a lower retail price in period t, because funds from the trade spend budget are released. The net effect of a brand's promotion on its total wholesale and retail price is determined by the sum of these two effects.[14]

In period t, a firm sets the base wholesale prices p^w_{jt} for all of its products j. We assume that retail prices are determined by the wholesale price plus a fixed markup, that is determined by the manufacturer and can differ across products and markets. The retailer is not allowed to respond independently to market conditions, however. Therefore, retail prices are given by $p^r_{jt} = p^{wb}_{jt} - td_{jt} + MU^r_{jt}$. The assumption of a fixed retailer margin is often used in the literature, see, for example, Miller and Weinberg (2017) and Backus *et al.* (2021), and several studies have rejected independent retail pricing models in favor of strategies, in which manufacturers have significant influence on retail prices, see, for example, Bonnet and Dubois (2010).

In order to model deviations from Bertrand-Nash pricing, we follow a *conduct parameter* approach similarly to Miller and Weinberg (2017) and Ciliberto and Williams (2014). We denote the degree to which brand i takes into account brand j's profits when setting its wholesale prices in market t by λ_{ijt}, which we treat as structural parameters. These parameters are arranged in an *internalization matrix* Λ_t, which generalizes the ownership matrix of zeros and ones in standard BLP-models. We do not restrict λ_{ijt} to lie between 0 and 1. Therefore, our model can also accommodate negative internalization parameters, which imply that a firm prices more aggressively than static Bertrand-Nash. A parameter $\lambda > 1$ would imply that a firm values its rivals' profits more than its own.

To keep the estimation tractable, we restrict the structure of Λ in an economically reasonable way. One of our primary goals is to quantify the evolution of conduct over time. Our structural break tests discussed in Section 2.3 suggest that pricing behavior indeed changed systematically across the pre-merger, the post-merger, and the price war period. Therefore, we estimate conduct parameters that change across but are constant within the three periods. We impose the standard assumption that after the merger, the merging firms fully internalize the profits of the other division.[15] 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. 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.

A key challenge for our model is that we need to capture within a tractable model, i.e.,

[14] In our data we find that the retail price decreasing effect almost always dominates the quality-enhancing effect of promotions, so that during a promotion net wholesale prices are lower than in non-promotion periods, see Section 2.3 and Appendix A.3.

[15] Our empirical strategy is flexible enough to incorporate models of partial within-firm internalization, as, for example, analyzed by Michel (2017), in a straightforward fashion.

a static model, that a manufacturer commits in advance to lower its wholesale price during a promotion by paying an additional trade spend payment to the retailer.[16] We incorporate this commitment by assuming that brand j maximizes the following profit function in each period t

$$\Pi_{jt} = (p_{jt}^{wb} - mc_{jt}) \underbrace{\sum_{g=1}^{G} w_t^g s_{jt}^g M_t^g}_{\tilde{s}_{jt}} + \sum_{k \neq j} \lambda_{jkt} (p_{kt}^{wb} - td_{kt} - mc_{kt}) \sum_{g=1}^{G} w_t^g s_{kt}^g M_t^g, \tag{4}$$

where s_{jt}^g is the market share of brand j in store g in month t, and $w_t^g = \frac{M_t^g}{\sum_l M_t^l}$ is the weight of store g in month t, which is computed as the share of the store-specific market size relative to the market size across all stores. $\tilde{s}_{jt}$ denotes the market share of brand j aggregated over all stores and p_{jt}^{wb} denotes the base wholesale price per unit of brand j in month t.

This setup implies that the manufacturer sets its base wholesale base price during a promotion period only to maximize its "base profit" and ignores the direct costs of the applicable trade spend payment td_{jt}. However, base wholesale prices are allowed to react in response to contemporaneous shocks to marginal cost and demand as well as rivals' promotions. These assumptions are consistent with the industry information discussed in Anderson and Fox (2019) and we provide supporting reduced form evidence from our data in Section 2.3 and Appendix A.7.

If brand j took into account its own trade spend commitment when setting its current base wholesale price, many models would predict a higher total wholesale price during a promotion than in a non-promotion period with exactly the same characteristics. Since such a prediction would violate what we observe in the data, namely, that the total wholesale price during a promotion decreases, we opt for our current model specification.

However, the firm takes into account that trade spend payments are going to be made for other brands that are on promotion and when it sets its base price it takes into account that the profits that it internalizes are also a function of rivals' trade spend payments.[17]

Given the complicated contingent contracts between manufacturers and retailers we judge our model setup a plausible and tractable approach to capture the commitment in a static model. For example, it seems plausible that the retailer can monitor the market conditions and knows what a "fair" base price, i.e., one that does not implicitly revert the trade spend

[16] We judge a static model to be a reasonable simplification because our data is aggregated to the monthly level, for which we believe that dynamic consumer behavior is much less relevant than for weekly data. In addition, the contingent contracts between manufacturers and the retailer typically are designed to prevent significant forward-buying by the retailer, see also our discussion in Appendix B.2.

[17] If we assumed that a firm does not take into account its rivals' trade spend payment, it would internalize only a part of the rivals' profits, which would lead to a peculiar definition of conduct. Since the conduct parameters are the central object of our model, we prefer to keep their interpretation as standard as possible, i.e., have them work on the total profits of rivals.

payment, is during a promotion period. Given the importance of promotions in almost all CPG industries, manufacturers are plausibly willing to commit to this type of pricing restriction in order to maintain a good relationship with the retailer.

Throughout, we treat the trade spend td_{jt} as exogenous and we do not model that firms could also adjust their promotions and trade spend as part of their conduct. Quantifying these aspects of firm behavior requires a substantially more complicated supply model, that considers endogenous promotions, trade spend, and base wholesale prices jointly. Such a model goes beyond the scope of this paper but is an interesting area for future research. We discuss the implications of this for the interpretation of our estimation results in Section 5.

Define $\Omega_{jkt} \equiv -\lambda_{jkt} * \frac{\partial \tilde{s}_{kt}}{\partial p^{wb}_{jt}}$, 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.[18] The FOC for brand j is given by

$$\tilde{s}_{jt} + td_{jt}\frac{\partial \tilde{s}_{jt}}{\partial p^{wb}_{jt}} + \sum_{k=1}^{J} \lambda_{jkt}(p^{wb}_{kt} - td_{kt} - mc_{kt})\frac{\partial \tilde{s}_{kt}}{\partial p^{wb}_{jt}} = 0. \tag{5}$$

The key difference to a a pricing FOC in a standard BLP supply model is the term $td_{jt}\frac{\partial \tilde{s}_{jt}}{\partial p^{wb}_{jt}}$ which comes from the fact that the firm does not consider the direct costs of the trade spend payment during a promotion period. This term will be zero by construction, if brand j is not on promotion. This FOC can be inverted as a function of the conduct matrix and the demand parameters to compute the vector of manufacturers' marginal costs of production for all products in market t.

Plugging in the marginal cost function 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

$$\omega_{.t}(\theta_D, \gamma, \Lambda_t) = p^{wb}_{.t} - td_{.t} - w_{.t}\gamma - \Omega_t^{-1}\big(\theta_D, \Lambda_t, p^r_{.t}(p^w_{.t}), x_{.t}\big)\left(s_{.t}\big(\theta_D, p^r_{.t}(p^{wb}_{.t}), x_{.t}\big) + td_{.t} \cdot \frac{\partial \tilde{s}_{.t}}{\partial p^{wb}_{.t}}\right). \tag{6}$$

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

Two aspects, that are essential for our identification strategy, are noteworthy. First, we assume that firms cannot anticipate the innovations to marginal costs ν^S_t before period t. We judge this to be a reasonable assumption given that we include a detailed set of fixed effects in the marginal cost function so that the remaining cost shocks are plausibly hard to

[18]Note that the own-and cross wholesale price derivatives $\frac{\partial \tilde{s}_{kt}}{\partial p^{wb}_{jt}} = \frac{\partial \tilde{s}_{kt}}{\partial p^{r}_{jt}}$, because we assume a model of fixed retail margins. In a model with independent retailer pricing and double marginalization, the derivatives would depend on the exact assumption on the retailer behavior.

predict in advance. Second, contemporaneous promotions and trade spend are considered fixed by manufacturers and retailers, and they cannot be reversed. This is in line with the marketing literature on the institutional features of promotion setting and supported by our reduced-form regressions, see Section 2.3.

4 Identification & Estimation

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

4.1 Identification

The most novel instruments for both our demand and our supply estimation are based on rival brands' promotions interacted with measures of proximity in the characteristics space. These instruments follow the same logic as classical BLP instruments in the sense that they measure variation across markets in the competitive pressure exerted by rival products and therefore are correlated with firms' markups.

Our identification strategy for industry conduct builds on the intuition first proposed by Bresnahan (1982) for homogeneous product industries and generalized by Berry and Haile (2014) for differentiated products markets. Their main insight is that a sufficiently rich set of demand rotators allows the researcher to discriminate among different oligopoly models. In a differentiated products model such demand rotators can be based on variables that are often used as standard BLP-instruments, for example, summary statistics of the characteristics of rival products, the number of available products, or other market characteristics.

In practice, however, these variables often do not exhibit a lot of variation so that, from an econometric perspective, standard BLP-instruments are typically weak for identifying industry conduct. In addition, in many applications, including ours, the researcher does not even observe variation in the set of products offered, which makes these instruments collinear with brand fixed effects.

Compared to traditional instruments employed in the literature, our instruments have several advantages. First, we do not require the availability of exogenous industry shocks, such as ownership changes, to identify industry conduct. 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 market-level data sets used in empirical industrial organization or quantitative marketing; therefore, our empirical strategy can be easily applied to many markets and industries.

Before we discuss our specific instruments for both the demand and the supply model, we first discuss the general idea of our *promotion-differentiation* instruments and why they can serve as instruments on both the demand and the supply side. Formally, our promotion-differentiation instruments are defined as

$$z_{jt}^{x,k,w} = \sum_{i \in \mathcal{G}(j)} \mathbb{1}\left(|d_{ij,t}^{x}| < c_{k}^{x}\right) \cdot PROMO_{it}^{w}, \tag{7}$$

where x denotes a physical product characteristic, such as sugar or fiber content, $d_{ij,t}^{x}$ indicates how close products i and j are in dimension x, w denotes a type of promotion activities, for example, either *general* or *bonus buy*, and $\mathcal{G}(j)$ is the product portfolio that we consider for brand j. For example, we can consider either only the rival products owned by the same firm or all rival products owned by 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 some relative proximity measure. Since one typically has several options for x, k, w, and $\mathcal{G}$, this logic allows us to construct a large number of instruments, which can be used to identify rich patterns of industry conduct and consumers' substitution patterns.

Interacting the promotion intensity of rival brands with measures of the brands closeness in the characteristics space has a similar flavor as the differentiation instruments proposed by Gandhi and Houde (2019) for identifying consumers' substitution patterns. For our application, we find that an analogous logic yields powerful instruments for identifying industry conduct: 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;[19] therefore, basing the instruments on the activity of close rival products should result in stronger instruments than relying on average statistics of all available products.

In addition, our instruments need to be exogenous to the structural errors used to construct the moment conditions. Clearly, promotions are chosen by firms and are therefore endogenous. However, in almost all industries, including ours, decisions between retailers and manufacturers regarding whether a promotion for a particular market will occur in period t are made in advance, i.e., at the latest in $t-1$ and as we discuss in Section 2 and Appendix A.7 almost never reversed, while wholesale price can still be flexible.

Under this timing assumption and the standard assumption that physical product characteristics are exogenous, our promotion-differentiation instruments are plausibly exogenous to innovations in both the demand and marginal cost shocks, as long as firms cannot anticipate

[19] 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.

the shock innovations.

Given that we include several layers of fixed effects in both our demand and the marginal cost function, we judge it plausible that the structural supply errors for product j at time t are unknown and cannot be anticipated by any firm before period t. As an additional "safety measure" we replace the observed promotions in Equation (7) with predicted promotions from an auxiliary linear regression, in which we use one- and two-period lags of the brand-store specific promotions and lagged input prices for various grains (weighted by the cereal's grain contents), electricity and gas prices, as well as brand dummies as regressors.

We extensively discuss the supporting evidence for our timing assumptions in Section 2 and provide additional supporting reduced form evidence from our data in Appendix A.7.

Next, we describe the specific instruments that we use for our demand and supply estimation, respectively. Conceptually, our demand model does not differ significantly from most of those used in the literature. Our main concern is to use strong instruments for prices and market shares to precisely identify both consumers' price sensitivity and the substitution patterns determined by the demographic interaction parameters and the nesting parameter. To do so we construct several sets of instruments.

First, we include brand dummies, year dummies, and month-of-the-year dummies as included instruments for themselves. Second, as instrument for retail prices we compute predicted wholesale prices. We obtain the predictions from a linear regression of observed net wholesale prices on the following regressors: brand dummies, month-of-the-year dummies, store dummies, a linear-quadratic time trend, gasoline and electricity prices, and input prices (for sugar, corn, wheat, rice, and oats) weighted with a cereal's respective grain content. In essence, this instrument uses input prices as cost shifters as excluded instruments. An advantage of our price instrument compared to using all the excluded instruments in its raw form is that it combines the many variables more efficiently; therefore, our predicted wholesale prices have a flavor of Chamberlain's optimal instruments.[20]

Third, we instrument a brand's own promotion intensity in the current period, which we include as a demand shifter in the observed product characteristics x_{jt}, with a predicted promotion intensity in order to mitigate concerns that firms might be able to anticipate future demand shocks.[21] For this regression, We use one- and two-period lags of the brand-store specific promotions and lagged input prices for various grains (weighted by the cereal's grain contents), electricity and gas prices, as well as brand dummies as regressors.

Lastly, we employ a set of promotion-differentiation instruments as discussed above to identify the substitution patterns, see Equation (7). As product characteristics x we use

[20] Using predicted retail prices instead of wholesale prices led to very similar results.

[21] Given that we construct our moment conditions based on the innovations in the unobserved demand shocks, and that we include several layers of fixed effects, we judge this risk to be relatively minor in our application. The results using observed promotions instead of predicted ones are qualitatively similar and available upon request.

sugar and fiber content, for the distance $d^x_{ij,t}$ between products i and j along dimension x we use the 33%-percentile and the 66% percentile. Furthermore, we construct the instruments separately for (predicted) *general* and *bonus buy & coupon* promotions. Finally, we only consider only brands that are owned by rival firms. This results in eight promotion-differentiation instruments in total.

On the supply side, the identification of the parameters in the marginal cost function γ is standard. We use brand-half year dummies and (weighted) input prices for sugar, corn, wheat, oat, and rice as included instruments.

In order to identify the conduct parameters, we consider the following promotion-differentiation instruments. As product characteristics x we use sugar and fiber content, as distance $d^x_{ij,t}$ between products i and j along dimension x we use the the 33%-percentile and the 66% percentile. As for the demand instruments, we construct the instruments separately for (predicted) *general* and *bonus buy* promotions. Finally, we construct the instruments separately based on rival brands owned by the same firm and on rival products owned by rival firms. These four binary classifications allow us to compute up to $2^4 = 16$ promotion-differentiation instruments in total, which allow us to identify detailed conduct patterns.[22]

4.2 Estimation Algorithm

We estimate our model using the generalized method of moments (GMM) similarly to the seminal work by BLP and the subsequent literature. Following most of the literature, we estimate demand and supply parameters in two steps.

Demand estimation. Since our demand estimation is relatively standard, we relegate the details of the estimation algorithm to Appendix **??**. The key difference to many other studies is that we base our moment conditions on the innovation of the unobserved marginal cost shock and not its levels.[23] Our GMM estimator for the demand parameters θ^D minimizes the following objective function

$$\hat{\theta}_D = \arg\min_{\theta} \nu^D(\theta)' Z_D \hat{W}_D^{-1} Z_D' \nu^D(\theta), \tag{8}$$

where $\hat{W}_D^{-1}$ is an estimate of the efficient weighting matrix based on parameter estimates obtained from a first-stage estimation with a 2SLS weighting matrix $E[Z_D' Z_D]^{-1}$ and Z_D denotes the demand side instruments discussed in Section 4.1 and Appendix D.

[22] Note that in our main specification we do not exhaust all 16 instruments, because the full set of instruments results in collinearity problems. Specifically, we drop several instruments that are based on only rival brands owned by the same firm, namely those based on fiber content, as well as the 33%-percentile-sugar-based ones.

[23] Similar approaches are used by Lee (2013) and Schiraldi (2011).

Supply estimation. For the supply estimation we generalize the BLP-approach from a binary ownership matrix to a flexible conduct matrix. For a given guess for the supply side parameters $\theta_S = (\gamma, \lambda, \iota^S)$, we solve the stacked first-order conditions, given by Equation (5), for the unobserved cost shock ω for each brand and month. Afterwards, we compute the innovations in the marginal cost shocks ν_S as a function of the backed out ω-vector and the $AR1$-parameter guess ι^S. Similarly to our demand estimation, we exploit orthogonality conditions between ν_S and a set of instruments Z_S described in Section 4.1 and Appendix D. The GMM estimator of our supply side parameter is given by

$$\hat{\theta}_S = \arg\min_{\theta_S} \nu^S(\theta_S, \hat{\theta}_D) Z_S' \hat{W}_S^{-1} Z_S' \nu^S(\theta_S, \hat{\theta}_D), \tag{9}$$

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. We relegate additional details of the construction of our dynamic panel moments and potential alternative moments for both the demand and supply estimation to Appendix D.

5 Results

5.1 Demand Estimates

Table 2 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 in the consumer's utility function. Furthermore, we interact a consumer's income with preferences for the constant, price, sugar, and fiber content. In addition, we group all inside goods into one nest and the outside good as a separate nest.[24]

All of our demand coefficients are precisely estimated and significant. The signs of the estimates for mean preferences are reasonable. The price coefficient is negative and highly significant, and ceteris paribus, consumers prefer cereals with lower sugar and lower fiber content. Our estimated price-income coefficient is positive and significant indicating that high-income consumers are less price-sensitive. The constant-income interaction is negative so that high-income consumers have a lower preference for cereals overall. The demand

[24]We experimented extensively with alternative demand specifications that include additional demographic interactions and normally distributed random coefficients. The results are qualitatively similar, in particular, in terms of the implied price elasticities, which are the most important output of our demand model. Our larger demand models resulted in higher standard errors for some of the additional parameters, especially for the normally distributed random coefficients, which we attribute to the fact that our data contain information on only one local market and one retailer. We also estimated specifications that include interactions between a dummy for households with small children (less than 10 years old) with the preference for sugar and experienced similar precision issues, which we attribute to the fact that within our data we observe relatively little variation in the share of family's with children across DFF stores.

Table 2: RCNL Demand Estimates: Main Specification

	Mean	Income
Constant	0.1782***	−2.8007***
	(0.0548)	(0.2217)
Price	−15.4745***	14.9522***
	(0.2410)	(0.9195)
Sogginess	0.1643***	
	(0.0188)	
Sugar	−0.1592*	1.3494***
	(0.0823)	(0.3524)
Fiber	−0.6056***	0.5358***
	(0.0230)	(0.1565)
Promotions	0.6073***	
	(0.0451)	
Nesting parameter	0.3806***	
	(0.0693)	
AR(1) Coeff	0.8491***	
	(0.0317)	

*Notes: The estimation includes product-, month-of-the-year, and year fixed effects. Standard errors are in parentheses. *, **, and *** denote significance at the 10-, 5-, and 1-percent level, respectively. Number of observations: 100,224.*

for both sugar and fiber in cereals is positively correlated with income and both income interactions are significant.

Promotions have a positive and highly significant effect on consumers' purchase probabilities even after controlling for the lower retail price during a promotion. Finally, the error terms for the inside goods are substantially correlated as the positive and significant nesting parameter (0.3806) indicates.

Table 14 and Table 15 in Appendix E display the implied median price elasticities over all markets. The own-price elasticities are negative for all products with a median across markets and brands of roughly −4.5. While our elasticities imply somewhat more elastic demand than some other studies on the industry, for example, Nevo (2000b, 2001), one should keep in mind that we are using a different sample, with data from only one local market, the Chicago area, and one retailer, DFF, while most other studies use data from several U.S. cities and several retailers.

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 high among the signature products of Kellogg's, for example, between *Corn Flakes* and *Frosted Flakes*. 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*

Rice Krispies, and *Quaker Cap'n Crunch*, or among low-sugar cereals, such as *GM Cheerios*, *Nabisco Shredded Wheat* and *Quaker Oats*. Finally, the diversion to the outside good is on average 45%.

Overall, we judge our model to be economically meaningful and to have a good fit with 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 0.04 percent of our observations.

5.2 Supply Estimates

On the supply side we focus on two different specifications. In our "small" model, we estimate three 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.[25] 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 the pre-merger and the post-merger period 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. Because of our relatively short sample for the price war period (only 9 months) we estimate only one conduct parameter for the price war period; therefore, our large model features five conduct parameters. This specification allows us to capture that industry leaders might have different pricing incentives than smaller competitors.

For our small model, we find significant internalization between firms pre-merger, with an estimate of 0.6417, see Table 3. If interpreted structurally, this parameter indicates that a firm values US-$ 1 profit of a rival firm as much as US-$ 0.6417 of its own profits. For the post-merger period, the conduct parameter decreases to 0.1784, which is not statistically different from zero. Therefore, the estimated pricing behavior in the post-merger period is consistent with static Bertrand-Nash pricing. In the price war period, the conduct parameter drastically decreases further, with an estimate that is negative (-1.42) and is significantly lower than 0. We perform several additional t-tests to confirm that the conduct parameters are statistically different from perfect collusion, i.e., a conduct parameter of one, and that they are statistically different over time. For the small model, we clearly reject both hypotheses. Table 18 in Appendix E summarizes these results.

When interpreting our results with respect to policy recommendations, several caveats

[25] Motivated by our tests for structural breaks with an unknown date, we set the start of the effective post-merger period to April 1993, which is three months after the Post-Nabisco merger is consummated. Analogously, we set the start of the price war period to February 1996, which is two months earlier than what the business press mentions as the start of the nation-wide price war, see Appendix A.6 for additional details.

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. Instead, the focus of our model is to detect and measure systematic changes in industry pricing patterns associated with these events.

Third, our model focusses on conduct in base wholesale prices and takes promotions as given. Endogenizing promotions would require a much more complicated dynamic supply model. In our reduced form regressions we find that the trade spend payment associated with a single promotion activity does not statistically change over time, see Section 2.3. However, there is a slight increase in the total number of promotional activities over time, especially during our price war period. As a consequence, base prices and promotions move in parallel in our application, i.e., as base wholesale prices become more competitive, we also observe more promotions. Therefore, we argue that the qualitative trend in conduct that we find should be robust to endogenizing the promotion part of our model.

Table 3: Conduct Estimates: Model Comparison

	Small Model			Large Model		
	Pre-merger	Post-merger	Price War	Pre-merger	Post-merger	Price War
All Firms	0.6417***	0.1784	−1.4238***			−1.3784***
	(0.1178)	(0.1323)	(0.4315)			(0.4684)
KE and GM				0.6322***	0.4638**	
				(0.1695)	(0.1904)	
Other Firms				0.7189***	−0.0635	
				(0.2049)	(0.1936)	
MC Prod	0.0957	0.1252	0.1391	0.0947	0.1233	0.1390
Manuf MU	0.4141	0.1879	0.0448	0.4148	0.1869	0.0484

Notes: The table displays the conduct estimates for both the small and the large conduct specification. Standard errors are in parentheses and account for two-step estimation. The last two rows display estimated medians of manufacturer marginal costs and wholesale margins across brands and months. Number of observations: 1,728.

At first sight, the estimated conduct pattern might seem surprising. Many standard models, for example, a Cournot model with homogeneous products, would predict that collusion becomes more sustainable after a merger. These theoretical predictions do not carry over to a more general setting with product differentiation and asymmetric firms, in which it is possible that a merger makes coordinated pricing harder to sustain; see, for example, Davis (2006). In addition, it could be that price coordination became harder for exogenous reasons that we do not model. The merger could simply have been an attempt by Post and Nabisco to sustain the existing price coordination in a different form. The negative conduct parameter in the price war period might be surprising as well, because it implies that firms price more aggressively than static Bertrand-Nash at the end of our sample period. In order to put our conduct estimates better into perspective we translate them into the implied markups, see the last row of Table 3 for industry-level statistics and Table 17 in Appendix E for product-specific wholesale price-cost margins over time.

Consistent with the conduct parameter estimates, markups are very heterogeneous across brands and most products experience considerable changes in markups over time. In the pre-merger period, wholesale margins are almost twice as large as the ones implied by static Bertrand-Nash pricing by roughly 50%. After the merger, our estimated margins are relatively close to Bertrand-Nash margins. In the price war period median wholesale margins are less than 5%. This indicates that pricing strategies during the price war are closer to marginal cost pricing than to Bertrand-Nash, even though there is heterogeneity across brands, with General Mills charging the highest margins and Kellogg's pricing even slightly below marginal costs, see Table 17.

The median marginal costs implied by our models are US-$ 0.125 per serving under the assumption of multiproduct Nash pricing. For our small conduct specification, marginal cost estimates in the pre-merger period are substantially lower (US-$ 0.096) and increase over time to US-$ 0.125 and US-$ 0.139 in the post-merger and price war period, respectively.[26]

The results for our large model are in line with the results from the small model. There two notable differences, however. First, for the small firms pre-merger pricing is not statistically different from perfectly coordinated pricing, i.e., a conduct parameter of one. Second, during the post-merger period we find evidence for static Bertrand-Nash pricing only for the smaller firms, while we reject the null hypothesis that the conduct parameter is zero for the large firms (Kellogg's and General Mills). Overall, conduct of the large firms is relatively stable across the pre- and post-merger periods, while it changes significant more for the smaller firms, see Table 18 in Appendix E.

For the small and the large model the Sargan-Hansen test statistics have p-values of 0.27 and 0.38, respectively; therefore, we do not reject the null hypothesis of the joint validity of the moment conditions for either model.

6 Counterfactual Simulations

We use our structural model to simulate how changes in the underlying industry conduct would affect consumer surplus and manufacturers' pricing. First, we decompose the price changes in the post-merger period into the *unilateral* and *coordinated* effects of the merger.

[26]This marginal cost evolution is consistent with public remarks by Kellogg's that production costs increased during this time period, see, for example, https://www.nytimes.com/1993/08/10/business/consumers-wake-up-to-increases-in-cereal-prices.html.

To do so, we start by simulating the industry assuming that the Post-Nabisco merger is not consummated but conduct changes as estimated, i.e., the parameter decreases from 0.64 to 0.18. Afterwards, we simulate the industry in the post-merger period assuming that the post-merger conduct remains at the pre-merger level and that the Post-Nabisco merger takes place. Second, we simulate the industry in the price war period assuming that the price war does not occur, i.e., firms continue to price as in the post-merger period.

Table 4 summarizes our results for changes in total wholesale prices, retail prices, consumer surplus, sold quantities, and firm profits.[27] All statistics are averages over all markets in the respective period analyzed.[28]

Table 4: Summary of Counterfactual Results

	CF1 Post merger	CF2 Post merger	CF3 Post merger	CF4 Price War
Δ p_w (in %)	6.7881	6.8136	−0.5378	8.8484
Δ p_r (in %)	6.8109	6.8370	−0.4991	8.8662
Δ CS (total, in mio-USD)	−1.9392	−1.9461	0.2066	−1.0189
Δ quantities (total, in mio-oz)	−18.9519	−19.0255	2.1498	−10.0006
Δ firm profit (total, in mio-USD)	1.0641	1.0693	−0.0823	1.1016

Notes: CF1 = No merger and no conduct change in post-merger period. CF2 = Merger and no conduct change in post-merger period. CF3 = No merger and conduct change in post-merger period. CF4 = Same conduct as in post-merger in price war period.

The first three columns summarize the results from our post-merger counterfactuals. We use column 1 as a benchmark in which both the ownership structure and the estimated conduct parameter remain unchanged in the post-merger period compared to the pre-merger period. In this scenario prices increase significantly, by roughly 7%, consumer surplus decreases by US-$ 2 million, and total firm profits increase by US-$ 1 million over the two years of our post-merger period.[29]

Column 2 and 3 reveal that almost all of the change in the post-merger period is due to the change in industry conduct and not the unilateral effects of the Post-Nabisco merger. If the Post-Nabisco merger is consummated but post-merger conduct remains at the pre-merger level of 0.64 instead of the estimated 0.18, prices increase only marginally more compared to the case in column 1, see column 2. Analogously, consumer surplus and profit changes are almost identical to the ones in column 1. If conduct changes as estimated, but the merger

[27] 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.

[28] The results in Table 4 are based on our small model. In terms of average statistics, both the small and the large conduct model yield relatively similar results. Results using the large model are available upon request.

[29] Recall that our sample only includes data from the Chicago metropolitan area. Under the assumption that our sample is representative for the U.S. as a whole, one can scale up the numbers for consumer surplus, quantities, and profits in Table 4 by the share of the population in Chicago relative to the U.S. population (roughly 3% in 1995) to obtain a back-of-the-envelope statistic for the impact of our industry events on the national level.

does not occur, prices are only marginally lower than in the observed data, by 0.5%, see Column 3. Consumer surplus and firm profits remain almost the same as in the observed data as well.

In summary, our post-merger counterfactuals provide evidence that coordinated effects can be much more important than unilateral effects for quantifying the effects of a merger, and that, at least in our application, coordinated effects can also be negative in the sense that conduct post-merger can be more aggressive than before the merger.

A general caveat with this counterfactual is that we cannot establish that the merger causes the change in conduct. Our estimates only indicate that the post-merger period coincides with a period of more competitive conduct. It could well be that there are unobserved factors that make coordinated pricing harder to sustain and therefore also motivate Post and Nabisco to pursue the merger.

Our last counterfactual confirms that firms in the price war period price very aggressively. If conduct in the price war period remains at the post-merger level of 0.18, which is statistically not different from zero, both retail and wholesale prices are 9% higher. Consumer surplus is lower by roughly US-$ 1 million and firm profits are US-$ 1.1 million higher when aggregated over the price war period, which we define as the last nine months of our sample.

7 Conclusion

In this paper, we estimate the evolution of competition in the U.S. 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 conduct parameters is based on the idea that rivals' promotions act as sequentially exogenous demand rotators and 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 in 1993 and second, a period of large wholesale price cuts in 1996. Our estimation results suggest that in the beginning of our sample period, the industry was characterized by substantial price coordination, with wholesale margins that are almost twice as large as those implied by static Bertrand-Nash pricing. After the Post-Nabisco merger, price coordination decreased to a level that is on average not statistically different from Nash pricing. When allowing conduct to differ across firms, we find that only the small firms revert to Nash pricing, while the industry leaders (Kellogg's and General Mills) continue to exhibit a conduct parameter larger than zero. Our conduct estimates for the last months of our sample period are consistent with a shift in firms' behavior to even more aggressive pricing with median wholesale margins of less than 5%.

These results indicate that a significant percentage of the markups of national cereal manufacturers during the the early 1990s can be attributed to cooperative industry behavior, and most importantly, that there are substantial changes in conduct over time.

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 promising area for future research. Our empirical strategy and the rich set of instruments that we propose are likely to be easy 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 well for estimating markups in such high-dimensional models. In addition, our instruments can straightforwardly be incorporated into testing-based approaches to quantify industry conduct, as, for example, proposed by Backus *et al.* (2021) and Duarte *et al.* (2022).

Recently, there has also been an increased interest in the evolution of markups over time from a macroeconomic perspective. De Loecker *et al.* (2020) 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 both 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 Data Management and Reduced Form Evidence

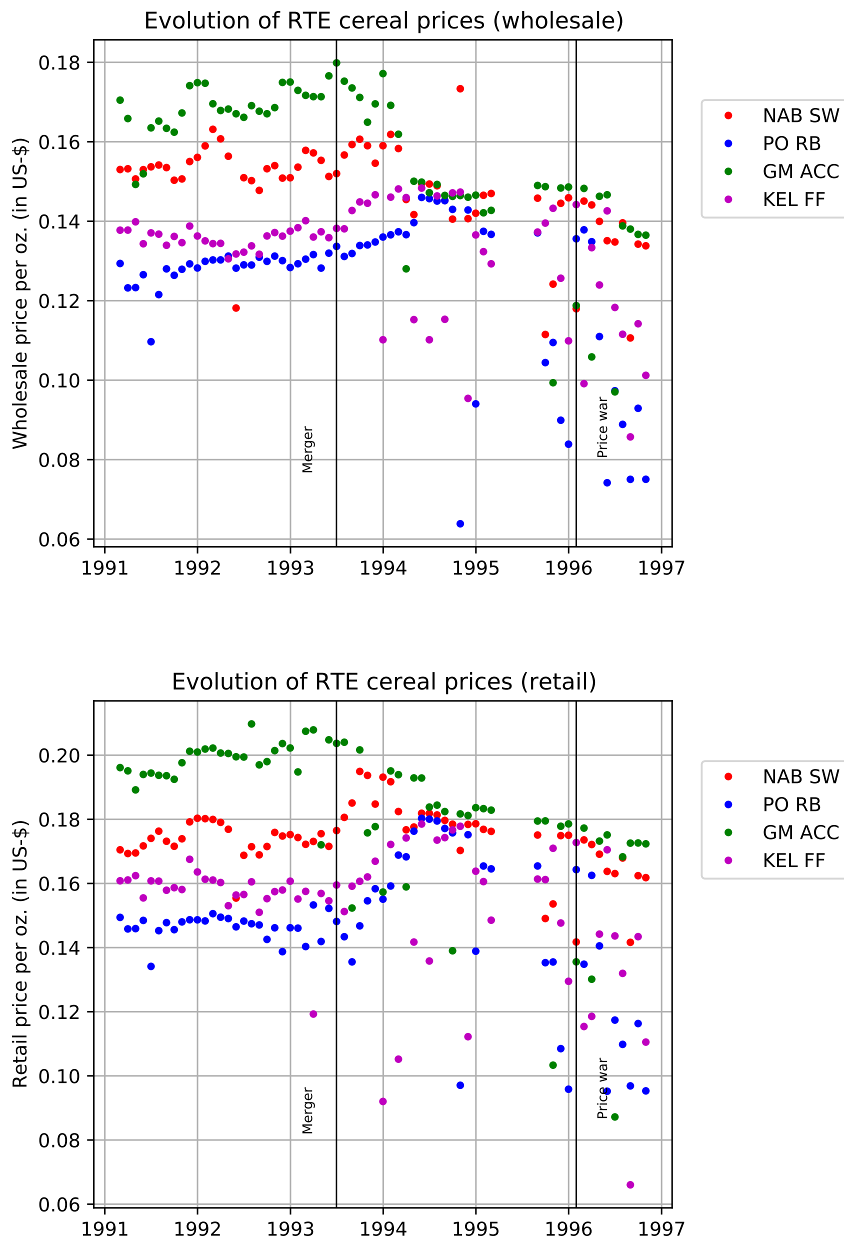
A.1 Market Shares and Price Evolution

Table 5: Market share evolution

	GMI	KEL	POS	NAB	QUA	RAL	HHI
1991	32.2	47.1	7.8	0.9	8.8	3.3	3400
1992	29.4	47.7	9.7	1.5	8.7	3.0	3317
1993	27.9	48.8	8.9	0.0	11.0	3.4	3367
1994	25.1	49.1	9.8	0.0	12.8	3.1	3311
1995	33.3	43.9	10.8	0.0	9.0	3.1	3243
1996	27.3	49.9	10.5	0.0	9.7	2.6	3447

Notes: The table summarizes the firm-specific volume-based market shares across all stores in our data set for each year, as well as the Herfindahl-Index (HHI). 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.

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 General Mills Apple Cinnamon Cheerios.

A.2 Details on Sample Selection and Role of Private Label Products

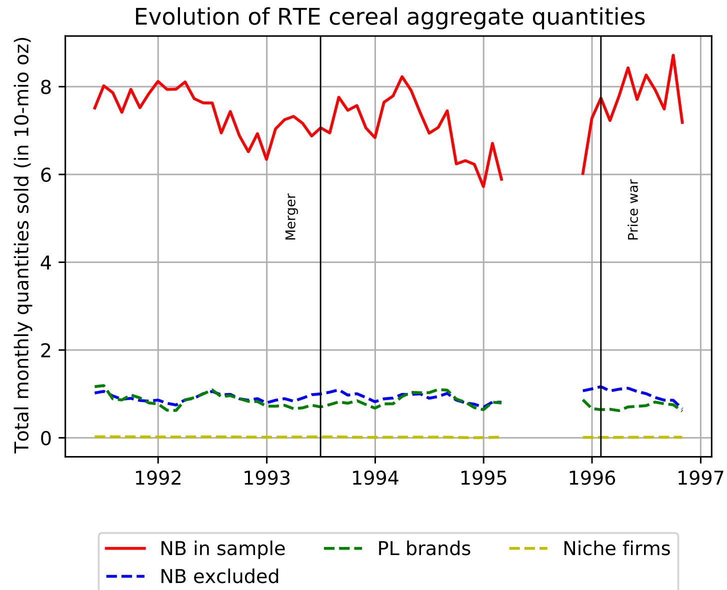
In this appendix, we provide background information on the evolution of various products that we pool into the outside good. We start by discussing what fraction of the overall cereal market is captured by our data. Afterwards, we present statistics on the evolution of prices and quantities of various product groups in the cereal segment that we exclude from our sample. Based on these descriptive statistics we justify the exclusion of these products and argue that our sample selection does not affect the essence of our estimation results.

The 27 brands in our sample cover roughly 75% of the overall sales in the cereal category at DFF stores. The remaining 25% of cereal sales can be attributed to the following product groups: (1) national niche manufacturers, (2) niche brands by the large national manufacturers, (3) private label cereals, and (4) products that we judge to be in a separate market from RTE cereals. With this product selection, we cover a larger share than other studies on the same industry and time period. For example, the sample of Nevo (2001, 2000b) covers only slightly more than 50% of the total cereal sales. The key difference between his data and ours is that our data only covers one retailer and one local market, while Nevo's data covers several regions and retailers. We include all brands from his sample and in addition add three brands from the national manufacturer *Ralston*. In the following, we discuss the role of each of the excluded product groups in more detail.

First, our data cover two national manufacturers *Sunbelt* and *Kashi*. Both firms maintain a focus on homemade-style, environmentally friendly produced products almost exclusively marketed to health-conscious consumers.[30] In addition to having only a minuscule share of the market (see Figure 2) and low availability, we argue that for many consumers these products are considered as separate from the traditional RTE cereal market that we analyze.

[30]Most of their products fall into the category of whole wheat or oat cereals and granolas. Most of Kashi's products are also certified organic.

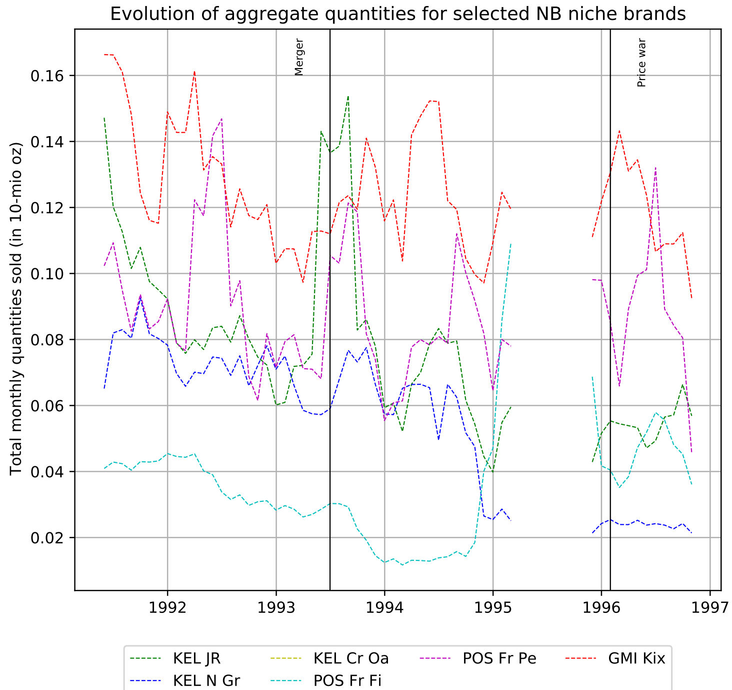
Figure 2: Evolution of aggregate quantities for different product groups



Notes: The figure displays the evolution of the aggregate quantities sold for the NB included in our sample, NB brands excluded, private label brands and brands from niche manufacturers, respectively.

Second, overall, our data contains information on over 200 brands by the national cereal manufacturers that were offered at some point during our sample period in some stores. However, none of these products achieved a significant presence in the market. A typical product in this subsample has only a very small market share (typically less than 1% of the total inside good share) and is available in only about 15% of the week-store combinations (most likely due to the product being only offered in an experimental phase). When considering all these brands together, their sales represent less than 15% of the national brands in our sample.

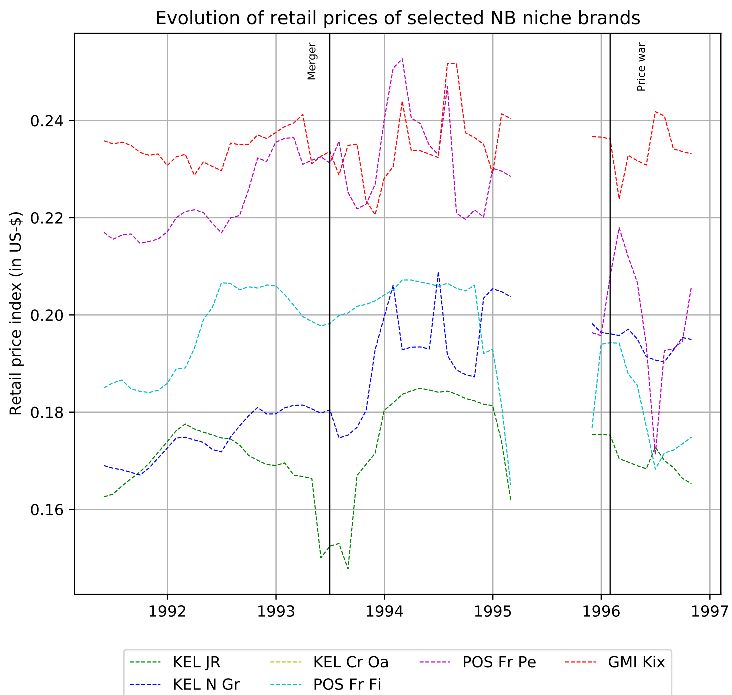
Figure 3: Evolution of aggregate quantities: Selected NB niche brands



Notes: The figure displays the evolution of the aggregate quantities sold for selected niche brands (by major national manufacturers) that are excluded from our sample.

Therefore, while there is in principle a huge set of products that we could incorporate in the model, this "right tail" is extremely scattered and the associated price and quantity data is likely to be measured with significant measurement error, which in our experience makes it hard to extract meaningful information from these products. Figure 3 illustrates the quantity evolution of the most popular niche brands by the national manufacturers. Overall, the shares exhibit significant fluctuations around a relatively stable mean. In addition, Figure 4 illustrates the price evolution of the niche brands of the national manufacturers. While these brands roughly follow the same trends as our in-sample brands (a slight increase post-merger and a drop in the price war period), prices are more volatile. Therefore, we believe that we do not miss any important trends in the industry by excluding these brands. Instead, restricting the sample to well-established brands helps us to keep measurement error in our sample reasonably low.

Figure 4: Evolution of average prices: Selected NB niche brands

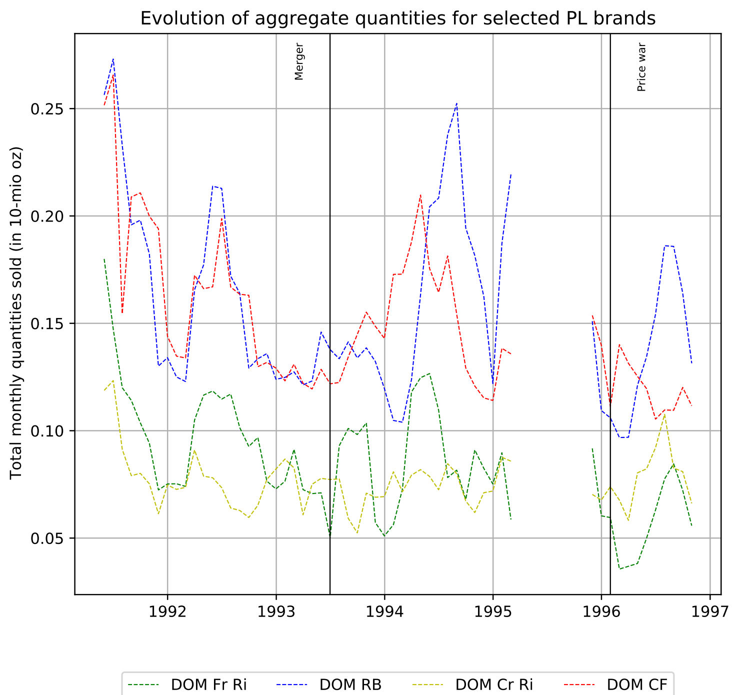


Notes: The figure displays the evolution of the average (retail) prices of selected niche brands (by major national manufacturers) that are excluded from our sample.

Third, our data contain information on about 15 private label DFF cereals. Figure 2 illustrates that private label cereals at DFF stores did arguably not play a very important role during our sample period with combined private label sales amounting to less than than a 15% of the sales of the national brands in our sample. Most importantly, the evolution of private label quantities remains reasonably stable over time.[31] Note that in order to accommodate any remaining concerns about changes in the outside good, we include year-dummies for the inside goods in our demand model, see Section 3.

[31]On the national level private label products gained more importance during our sample period. As illustrated in Figure 2 this trend is not observed at DFF stores, however.

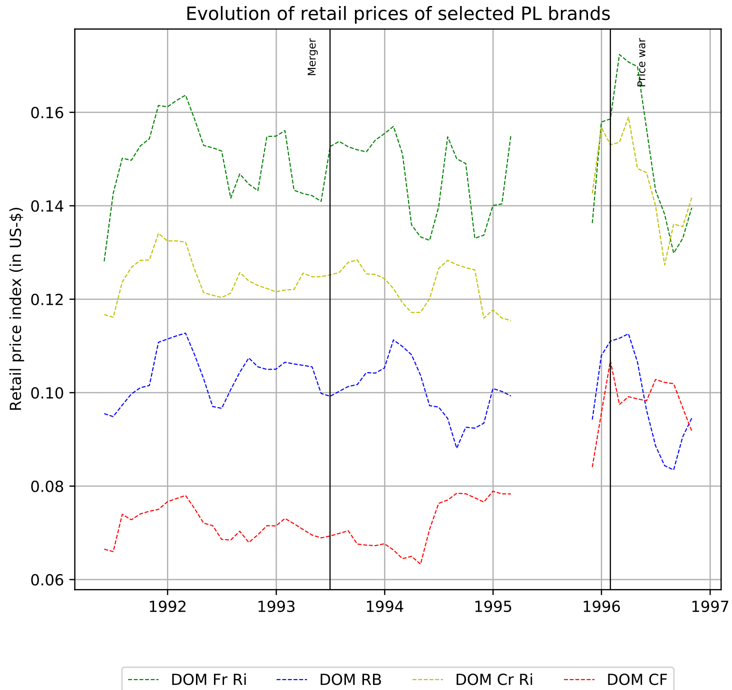
Figure 5: Evolution of aggregate quantities: Selected PL brands



Notes: The figure displays the evolution of the aggregate quantities sold for selected PL brands that are excluded from our sample.

Figure 5 provides more information on the evolution of the quantities of the four most popular private label brands at DFF. There is some evidence that some private label brands gained market share in the post merger period, for example, DOM Raisin Bran and DOM Corn Flakes between 1994 and 1995. However, the quantity evolution is fairly volatile, and relatively flat for other private label brands.

Figure 6: Evolution of average prices: Selected PL brands



Notes: The figure displays the evolution of the average (retail) prices of selected PL brands that are excluded from our sample.

Figure 6 displays the evolution of prices for the most important private label brands. In line with the aggregate quantity evolution discussed above, there is not an obvious trend in the price evolution. As Figure 6 indicates, during the price war period the private label brands on average did not decrease their prices in response to the national brands' price cuts.

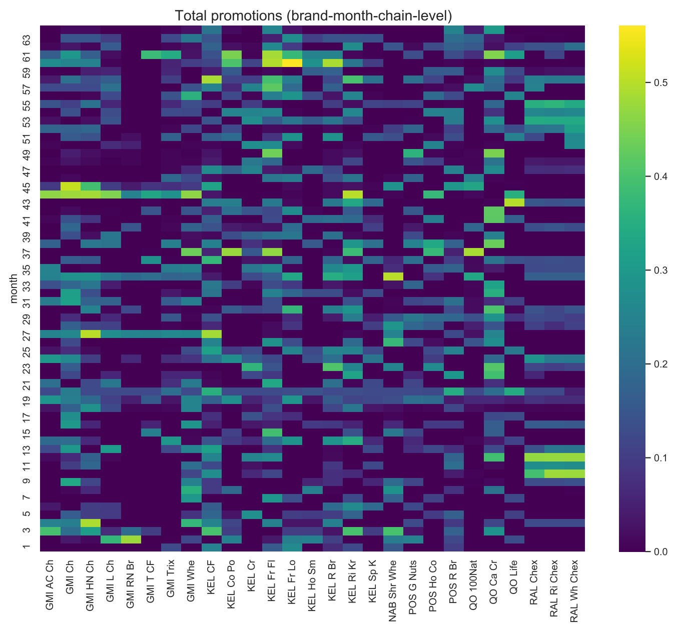
Fourth, a small share of the products officially labeled as *cereal sales* comes from products that most consumers would not consider a suitable substitute to RTE cereals, for example, Pop Tarts.

A.3 Distribution of Promotional Activities and Prices

In this appendix, we describe several characteristics of our promotion data and how these patterns provide us with suitable variation to construct markup shifting instruments to identify industry conduct.

Figures 7 and 8 illustrate the distribution of the total promotion intensity for each product at different levels of aggregation using heatmaps. For the illustration, we scale the promotion intensity to lie between zero and one with zero indicating that a product is never on promotion, and one denoting that the product was on promotion at every opportunity (time period, store, and UPC). In all heatmaps, brighter colors indicate a higher promotional intensity than darker ones.

Figure 7: Distribution of promotional activities on month-brand level



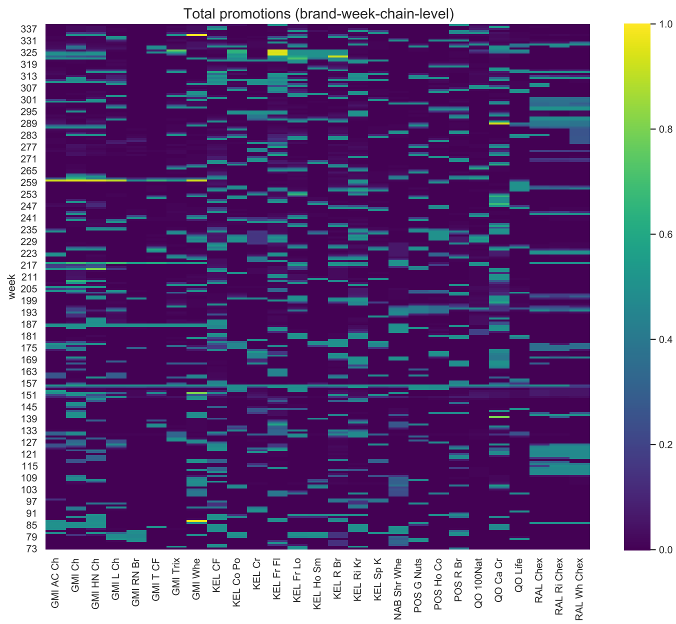
Notes: The figure displays a heatmap of the distribution of the total promotion intensity for each brand over time aggregated over all stores in our sample on a monthly level.

In Figure 7 we plot the total number of promotional activities aggregated over all UPCs for a given brand and all 58 stores in our sample for each brand-month combination. This figure illustrates that, even though promotions are often a weekly activity, there is substantial variation in promotional activity both across time and brands at the brand-month aggregation level, which is the aggregation level that we use for our structural estimation. While some firms (General Mills and Ralston) tend to coordinate promotions across their brands, others (Kellogg's, PostNabisco, and Quaker) put brands on promotion somewhat asynchronously.

In Figure 8 we plot the total number of promotions for each brand-store combination for each week in our sample. Qualitatively, we observe the same patterns as with the monthly aggregation; therefore, we argue that we do not lose significant variation in our promotion variables, when aggregating to the monthly level.

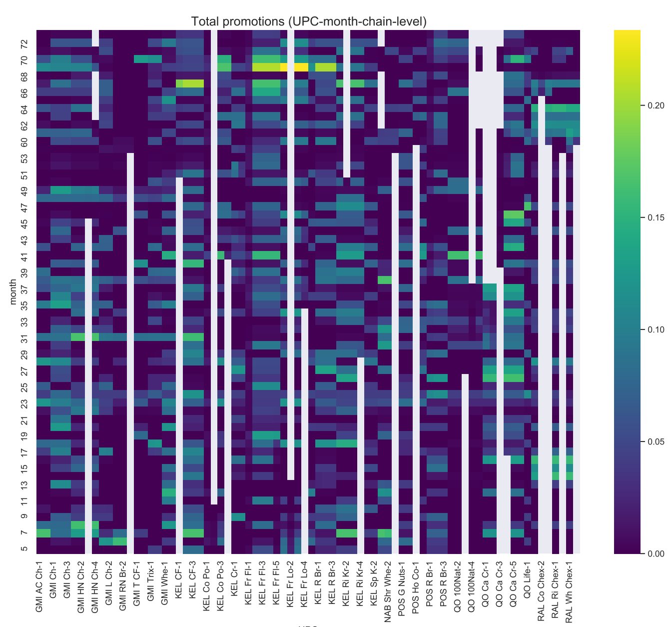
In Figure 9 we disaggregate our measure of promotion intensity to the UPC level for each month, aggregated over all stores. Most importantly, we observe that different UPCs of the same brand have a strong tendency to be on promotion at the same time in DFF stores; therefore, we argue that UPC composition effects do not substantially affect the use

Figure 8: Distribution of promotional activities on weekly-brand level



Notes: The figure displays a heatmap of the distribution of the total promotion intensity for each brand over time aggregated over all stores on a weekly level.

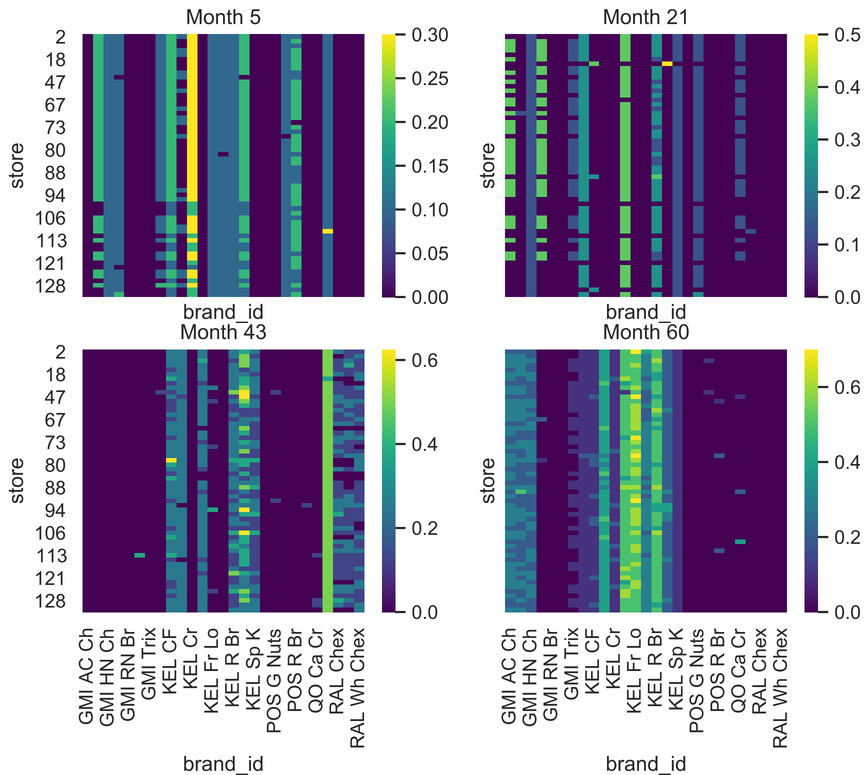
Figure 9: Distribution of promotional activities across stores on UPC-month level



Notes: The figure displays a heatmap of the distribution of the total promotion intensity for each UPC-month combination over time aggregated over all stores.

of promotional intensity to construct our instruments.

Figure 10: Distribution of promotional activities across stores on monthly level



Notes: The figure displays a heatmap of the distribution of the total promotion intensity for each brand-store combination for a given month.

Finally, we illustrate the coordination of promotions across different local markets (stores). Figure 10 highlights that promotions are often very similar across different stores, i.e., products tend to go on promotion at the same time. However, this correlation is not perfect, in particular for Kellogg's brands. We take this as evidence that, even though our main variation in promotion intensity occurs over time and across brands, there is some variation across stores, which provides an additional layer of variation to use our instruments for the demand estimation at the month-store-brand level.

In the following, we provide additional descriptive statistics on promotion frequency (promotion breadth) and promotional price changes (promotion depth) at the chain-month-brand level. Table 6 compares the statistics across the different brands in our sample. The first four columns show the share of no-promotion months, the average retail price, the average (total) wholesale price, as well as the average retail margin during months, in which the specific brand is not on promotion in any DFF store. Columns 5 to 13 of Table 6 present the analogous variables for the subset of months in which a given brand is on promotion in at least one store and week during a given month. In addition, we compare the following variables across brands: the share of months in which the brand is on promotion at least in one store and week (Share) as a measure of the extensive margin of promotion breadth, the average share of store-week units that participate in the promotion conditional on some promotion taking place during this month (Pr Int) as a measure of the intensive margin of promotion breadth, the average retail discount, i.e., by how much retail prices are lower on average during a promotion period than during a non-promotion period, and the analogous average (total) wholesale price discount. We interpret the latter two variables as a measure of the monetary depth of a promotion.[32] Finally, we compare the average time between the promotion activities (Avg spell), and the average duration of a promotion (Avg dur).

Overall, we find significant heterogeneity across brands in how often a product is promoted. While the average brand is promoted roughly 60% of the time at least somewhere within the DFF chain, a few General Mills brands (Raisin Nut Bran and Total Cornflakes) are relatively rarely promoted and several Kellogg's products, for example, Cornflakes and Frosted Flakes, are on promotion somewhere at DFF nearly 90% of all months. Most importantly, we do not observe very significant trends in these numbers over time, see also Figure 7. Conditional on being on promotion, there is some variation across brands in the overall promotion breadth intensity (see column Pr Int) with the average brand being on promotion in roughly 25% of all store-week bins. However, there is significant heterogeneity. For example, several sugary cereals (Quaker Cap'n Crunch and Kellogg's Frosted Flakes) are on average on sale in more than 33% of all store-week combinations conditional on being on promotion at DFF. In contrast, several brands that are marketed as healthy cereals (Kellogg's Special K and Quaker Oats) tend to be promoted less heavily with an average intensity of 0.18 and 0.16, respectively.

We interpret our measures of retail and wholesale price discounts as a measure of promotional depth. On average, retail prices are roughly 10% lower during promotion periods. However, there is some heterogeneity across brands. While some of the rare-promoters (General Mills Raisin Nut Bran and Total Cornflakes) hardly reduce prices, some popular kids

[32]Unfortunately, we do not observe any information on the non-monetary depth of promotions, such as the prominence on the retailer's shelf space, or advertising intensity.

cereals (Quaker Cap'n Crunch and Kellogg's Cornpops) decrease retail prices by almost 15% on average during a promotion. Similar patterns are observed for wholesale price discounts although they are slightly less pronounced than the ones for retail prices. The smaller share of promotion periods for some brands translates into longer spells between two promotional activities. While rare promoters on average wait three to five months after the end of one promotion until the next one occurs, frequent promoters only exhibit no-promotion gaps of one to two months on average. Consistent with this pattern, frequent promoters on average conduct "uninterrupted promotions for more than six months, while rare promoters incur promtoion stretches of two months or less. This duration variable should be interpreted with caution, however, because by construction it suffers fro a time aggregation issue. For example, in our monthly data it is possible that a brand goes on promotion only in the first week of every month, but not during the remaining three weeks of each month, which our comparison would pick up at an interrupted promotion stretch. In contrast, a brand that goes on promotion for four uninterrupted weeks in month 1, and is not in promotion in any week of month 2 will be recorded as a promotion duration of only one month.[33] Given that our instruments mostly exploit variation in total promotion breadth, as measured by the number of total promotion activities on the chain-month level, we judge this problem to be of little relevance for our identification strategy. In addition, it is important to keep in mind that we use the promotion data mostly to construct our instruments, which need to satisfy the familiar relevance and exogeneity conditions. However, our instruments need not be perfect, i.e., they can contain measurement error without affecting the consistency of our parameter estimates.

[33]The analogous descriptive statistics on a weekly level look similar and do not provide much additional insights. They are available upon request.

Table 6: Comparison of non promo and any-promo periods (monthly data)

Brand	No-promotion periods				Any-promotion periods								
	Share	Avg p^r	Avg p^w	Avg rm	Share	Pr Int	Avg p^r	p^r disc.	Avg p^w	p^w disc.	Avg rm	Avg spell	Avg dur
GMI AC Ch	0.45	0.19	0.16	0.19	0.55	0.28	0.18	0.90	0.15	0.94	0.13	2.00	2.50
		(0.01)	(0.01)	(0.04)		(0.25)	(0.03)		(0.02)		(0.17)	(1.11)	(1.87)
GMI Ch	0.19	0.20	0.17	0.17	0.81	0.33	0.18	0.91	0.16	0.93	0.08	1.22	5.22
		(0.01)	(0.01)	(0.03)		(0.24)	(0.03)		(0.02)		(0.16)	(0.44)	(3.87)
GMI HN Ch	0.28	0.19	0.16	0.17	0.72	0.31	0.17	0.91	0.15	0.95	0.10	1.21	2.57
		(0.01)	(0.01)	(0.04)		(0.26)	(0.02)		(0.02)		(0.13)	(0.43)	(1.70)
GMI L Ch	0.38	0.22	0.18	0.18	0.62	0.24	0.20	0.91	0.17	0.93	0.11	2.30	4.00
		(0.01)	(0.02)	(0.06)		(0.21)	(0.03)		(0.03)		(0.14)	(1.42)	(3.16)
GMI RN Br	0.67	0.18	0.15	0.17	0.33	0.19	0.17	0.98	0.15	1.00	0.12	3.10	2.10
		(0.01)	(0.01)	(0.03)		(0.24)	(0.01)		(0.01)		(0.12)	(2.60)	(1.20)
GMI T CF	0.67	0.24	0.20	0.17	0.33	0.23	0.23	0.96	0.20	0.98	0.13	4.56	2.33
		(0.01)	(0.02)	(0.03)		(0.25)	(0.02)		(0.02)		(0.10)	(4.19)	(1.22)
GMI Trix	0.31	0.25	0.21	0.17	0.69	0.19	0.22	0.91	0.20	0.94	0.11	1.90	3.70
		(0.01)	(0.01)	(0.02)		(0.19)	(0.03)		(0.03)		(0.16)	(2.56)	(2.00)
GMI Whe	0.16	0.18	0.14	0.19	0.84	0.27	0.16	0.93	0.14	0.95	0.13	1.00	5.44
		(0.01)	(0.00)	(0.02)		(0.25)	(0.02)		(0.02)		(0.13)	(0.00)	(7.16)
KEL CF	0.09	0.12	0.10	0.17	0.91	0.32	0.11	0.96	0.10	0.96	0.07	0.83	8.00
		(0.01)	(0.01)	(0.02)		(0.25)	(0.02)		(0.02)		(0.23)	(0.41)	(7.27)
KEL Co Po	0.45	0.22	0.19	0.17	0.55	0.29	0.19	0.88	0.17	0.90	0.08	2.33	2.83
		(0.01)	(0.01)	(0.04)		(0.25)	(0.03)		(0.02)		(0.17)	(1.30)	(1.85)
KEL Cr	0.38	0.22	0.18	0.16	0.62	0.24	0.21	0.96	0.17	0.94	0.13	1.92	3.33
		(0.01)	(0.01)	(0.04)		(0.20)	(0.02)		(0.02)		(0.10)	(1.31)	(2.35)
KEL Fr Fl	0.12	0.16	0.14	0.16	0.88	0.35	0.15	0.93	0.13	0.95	0.07	1.17	6.17
		(0.01)	(0.00)	(0.03)		(0.27)	(0.02)		(0.01)		(0.23)	(0.75)	(6.88)
KEL Fr Lo	0.30	0.23	0.19	0.16	0.70	0.31	0.19	0.87	0.17	0.90	0.01	1.80	4.00
		(0.01)	(0.01)	(0.10)		(0.26)	(0.04)		(0.03)		(0.21)	(1.55)	(2.54)
KEL Ho Sm	0.59	0.19	0.16	0.18	0.41	0.24	0.17	0.91	0.15	0.91	0.10	2.64	1.86
		(0.01)	(0.01)	(0.04)		(0.17)	(0.02)		(0.02)		(0.13)	(1.82)	(1.03)
KEL R Br	0.11	0.15	0.13	0.17	0.89	0.25	0.14	0.93	0.12	0.97	0.09	1.00	7.17
		(0.01)	(0.00)	(0.05)		(0.23)	(0.02)		(0.02)		(0.17)	(0.63)	(6.11)
KEL Ri Kr	0.12	0.18	0.15	0.18	0.88	0.30	0.17	0.94	0.15	0.96	0.09	1.00	8.00
		(0.01)	(0.01)	(0.01)		(0.27)	(0.02)		(0.02)		(0.16)	(0.58)	(11.97)
KEL Sp K	0.44	0.22	0.19	0.17	0.56	0.18	0.21	0.94	0.18	0.94	0.13	1.80	2.40
		(0.01)	(0.00)	(0.03)		(0.14)	(0.03)		(0.02)		(0.11)	(0.86)	(1.59)
NAB Shr Whe	0.48	0.18	0.15	0.18	0.52	0.29	0.17	0.98	0.15	1.00	0.15	2.64	3.00
		(0.01)	(0.01)	(0.05)		(0.26)	(0.01)		(0.01)		(0.07)	(1.69)	(2.00)
POS G Nuts	0.47	0.13	0.11	0.19	0.53	0.25	0.13	0.95	0.10	0.95	0.13	1.65	2.00
		(0.01)	(0.01)	(0.02)		(0.16)	(0.01)		(0.01)		(0.08)	(0.70)	(1.22)
POS Ho Co	0.45	0.22	0.18	0.18	0.55	0.26	0.19	0.90	0.17	0.91	0.07	2.08	2.69
		(0.02)	(0.01)	(0.03)		(0.21)	(0.04)		(0.03)		(0.21)	(1.26)	(2.56)
POS R Br	0.17	0.16	0.13	0.16	0.83	0.22	0.14	0.91	0.12	0.91	0.12	1.14	4.57
		(0.01)	(0.01)	(0.05)		(0.19)	(0.02)		(0.02)		(0.13)	(0.69)	(2.57)
QO 100Nat	0.41	0.14	0.12	0.17	0.59	0.16	0.12	0.91	0.10	0.90	0.12	3.57	4.86
		(0.01)	(0.01)	(0.03)		(0.23)	(0.02)		(0.02)		(0.18)	(2.44)	(5.34)
QO Ca Cr	0.17	0.19	0.15	0.23	0.83	0.38	0.16	0.84	0.13	0.89	-0.01	1.50	5.67
		(0.01)	(0.01)	(0.04)		(0.29)	(0.03)		(0.03)		(0.28)	(0.84)	(4.80)
QO Life	0.55	0.15	0.12	0.18	0.45	0.27	0.14	0.92	0.11	0.92	0.12	2.62	2.23
		(0.01)	(0.01)	(0.04)		(0.25)	(0.01)		(0.02)		(0.11)	(1.61)	(1.59)
RAL Chex	0.45	0.23	0.18	0.22	0.55	0.31	0.21	0.92	0.17	0.90	0.12	2.25	2.67
		(0.01)	(0.01)	(0.04)		(0.23)	(0.03)		(0.03)		(0.17)	(1.06)	(1.61)
RAL Ri Chex	0.47	0.23	0.19	0.20	0.53	0.31	0.21	0.93	0.17	0.90	0.13	2.23	2.62
		(0.01)	(0.01)	(0.03)		(0.25)	(0.03)		(0.03)		(0.17)	(1.01)	(1.39)
RAL Wh Chex	0.41	0.17	0.14	0.22	0.59	0.30	0.16	0.93	0.12	0.90	0.16	1.92	2.92
		(0.01)	(0.01)	(0.04)		(0.26)	(0.02)		(0.02)		(0.17)	(0.86)	(1.55)
Average	0.36	0.19	0.16	0.18	0.64	0.27	0.17	0.92	0.15	0.93	0.10	1.98	3.88
		(0.01)	(0.01)	(0.04)		(0.23)	(0.02)		(0.02)		(0.15)	(1.26)	(3.27)

Notes: Comparison of descriptive statistics of chain-level price and promotion variables across promotion and no-promotion periods months. SD in parentheses.

A.4 Computation of Base Wholesale Prices and Trade Spend Payments

In this appendix, we provide the details on how we compute our measure of base wholesale prices from the observed wholesale prices, which include trade spend payments during a promotion period. Formally, let p_{jt}^{wb} be the base wholesale price of brand j in market t, and let p_{jt}^{w} denote the net (or total) wholesale price, which includes a trade spend discount td_{jt}, of brand j in market t.

Note that for brand-market combinations in which there is no promotion, the trade spend payment is by construction zero and we assume that we observe base wholesale prices in the data, so that $p_{jt}^{wb} = p_{jt}^{w}$. During a promotion period, we assume that the manufacturer pays a constant trade spend payment td_{jt} per unit sold, so that $p_{jt}^{w} = p_{jt}^{wb} - td_{jt}$.

For our main specification, we compute the base wholesale prices from the wholesale price data on the UPC-week level. We assume that each brand sets a base wholesale price for each month, and that variation in the wholesale price during a promotion-week is due to a trade spend payment and that the base wholesale price during a promotion week does not systematically differ from the base wholesale price in the surrounding weeks.

Therefore, we impute the base wholesale price for a UPC in a given store during a promotion week as the average between the observed wholesale price during the weeks immediately before and immediately after the promotion. After having computed the base wholesale prices on the UPC-store-week level, we aggregate them to the brand-month level. In order to obtain the trade spend payments we subtract the observed net wholesale prices from the imputed base wholesale prices.[34]

Note that we do not explicitly model how manufacturers set trade spend payments and budgets. In line with industry evidence (Anderson and Fox, 2019), we implicitly assume that the trade spend payments that are granted to the retailer come from a separate fixed trade spend budget, which the manufacturers consider to be sunk. We discuss the implications for the interpretation of our estimation results in Section 5.

We experimented extensively with alternative ways of computing the trade spend variable and base wholesale prices. For example, by imputing base wholesale prices on the brand-month level instead of the week-UPC level and or by computing base wholesale prices using the predictions from flexible linear regression models. Overall, these approaches led to very similar trade spend values and did not affect the results of our structural estimation significantly.

[34]Note that we cannot separately identify the trade spend td_j and a potential short-run deviation in the base wholesale price p_{jt}^{wb} during a promotion period. It could in principle be that the actual trade spend discount granted to the retailer is higher than estimated and at the same time the base wholesale price p_{jt}^{wb} is also higher than in non-promotional periods because of potential quality-enhancing of promotions. Because we cannot separate these effects, we assume that manufacturers commit to not change the base wholesale price because of a promotion relative to the surrounding non-promotion periods for the same brand at the same store, see also our discussion in Section 3 for how we incorporate this feature into our structural model.

A.5 Model-based Intuition for Reduced Form Regressions

In this appendix, we consider a stylized version of our supply model, developed in Section 3, with two single-product firms. Firms set base wholesale prices (p_j^{wb}) taking a specific value of the trade spend (td_j), retail markup (mu_j^r), and marginal costs of production (mc_j) as given. Potential price coordination among firms is captured by the conduct parameter λ. Equilibrium base wholesale prices will be characterized by the following first order conditions.

$$p_1^{wb} = mc_1 - \left(\frac{\partial s_1}{\partial p_1^r}\right)^{-1} \cdot s_1 - \lambda \frac{\partial s_2}{\partial p_1^r} \left(\frac{\partial s_1}{\partial p_1^r}\right)^{-1} \left(p_2^{wb} - td_2 - mc_2\right)$$
$$p_2^{wb} = mc_2 - \left(\frac{\partial s_2}{\partial p_2^r}\right)^{-1} \cdot s_2 - \lambda \frac{\partial s_1}{\partial p_2^r} \left(\frac{\partial s_2}{\partial p_2^r}\right)^{-1} \left(p_1^{wb} - td_1 - mc_1\right),$$

where $p_j^r = mu_j^r + p_j^{wb} - td_j$. From the above equations, it is clear that the value of λ has an effect on equilibrium wholesale prices. Next, we analyze how wholesale base prices changes when a rival firm goes on promotion and how this reaction depends on the level of price coordination λ. For illustrational purposes, we consider two cases assuming that firm 2 goes on promotion:

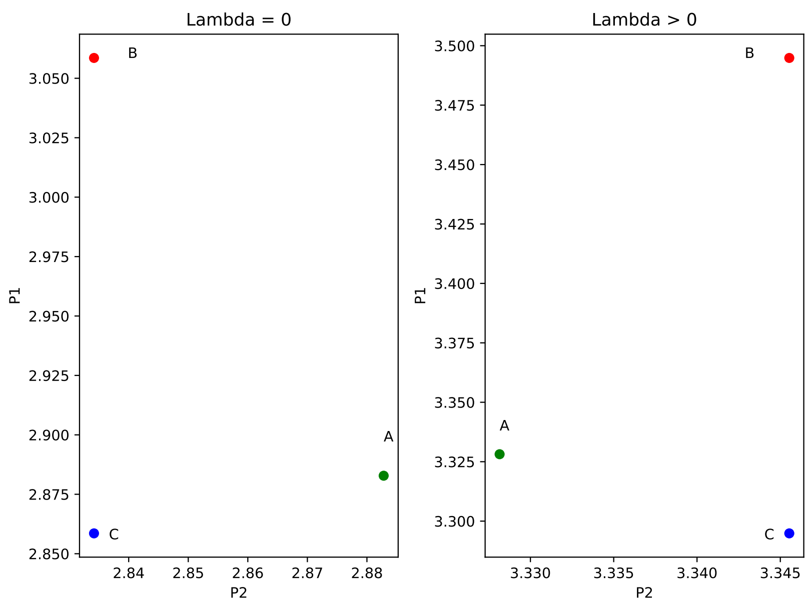
1. Competition ($\lambda = 0$): A rival promotion has several effects. First, it decreases s_1 –both through sale-sign demand effects which make the product on promotion more attractive and through a reduction in p_2^r (as td_2 increases). A promotion can either increase or decrease $\frac{\partial s_1}{\partial p_1^r}$ so that the overall effect of the rival promotion is ambiguous. However, we judge it likely –and consistent with our data– that a promotion of product 2 will make demand for product 1 more elastic so that the the wholesale price for product 1 should decrease under competitive conduct. More importantly, the own price derivative is not crucial for comparing the differential effects under competition and collusion, because this term enters both terms equally.

2. Collusion ($\lambda > 0$): The same effects as in the case of $\lambda = 0$ remain. However, there is an additional term present: $\left(p_2^{wb} - td_2 - mc_2\right) \frac{\partial s_2}{\partial p_1^r}$, which is likely to also be affected by a rival promotion. By construction a promotion of firm 2 decreases $(p_2^{wb} - td_2 - mc_2)$, because td_2 increases. However, it is possible that $\frac{\partial s_2}{\partial p_1^r}$ increases relatively more due to a promotion of firm 2. This can result in firm 1 increasing its price. Therefore, it is more likely that a promotion of firm 2 leads to an increase in the wholesale price of firm 1, if the firms engage in coordinated pricing.

A natural caveat with the above reasoning is that every potential change in prices can be rationalized by flexible changes in the own- and cross-derivatives of the demand function. This motivates us to estimate a structural model to disentangle the differential effects of changes in demand and strategic pricing incentives.

To conclude this section, we provide a numerical illustration of the above reasoning for a parametrized logit demand model, which can generate the patterns discussed above. Let the utility from good j be $u_j = V_j - \alpha p_j^r + \epsilon_j$, $mc_1 = mc_2 = 0.1$, $mu_1^r = mu_2^r = 0$. Furthermore, we assume that during a promotion of firm 1 trade spend increases to 0.20. The effects of the promotion of firm 1 on wholesale base and net prices are illustrated in Figure 11. The left and right panel indicate the effect under $\lambda = 0$ and $\lambda = 0.5$, respectively. During a promotion of firm 1 the wholesale base price equilbrium moves from point A to point B. Under competition, we observe that firm 2's wholesale base prices reduce, while they increase under coordinated pricing, i.e., $\lambda > 0$. Finally, point C visualizes the net wholesale prices that the retailer will face after the trade spend payment is taken into account. Consistent with the patterns in our data, firm 1's net wholesale price is smaller than the initial base wholesale price in point A.

Figure 11: Illustration of effects of rival promotion on wholesale prices



Notes: Left panel = no internalizacion of rival profits. Right panel = internalization of rival profits.

A.6 Reduced Form Results

Testing for structural breaks with unknown dates. As an additional robustness check, we also conduct structural break tests without assuming that the dates fo the structural break are known using the test proposed by Bai and Perron (1998). Specifically, we regress the log of net wholesale prices on the regressors used in Table 7 and test for changes in the effect of rival promotions' passthrough on a brand's own wholesale price. Since the test by Bai and Perron (1998) is designed for a single time-series, we run the regression separately for

Table 7: Reduced form analysis: Wholesale prices

	(1) Net - Only SG	(2) Net - SG BC	(3) Base - Only SG	(4) Base - SG BC
Post-merger KEL	0.0465***	0.0319*	0.0678***	0.0569***
	(0.0132)	(0.0142)	(0.0076)	(0.0079)
Post-merger RAL	0.0473	0.0371	0.0403***	0.0283*
	(0.0261)	(0.0258)	(0.0109)	(0.0114)
Post-merger QUA	0.0196	0.0197	0.0458***	0.0415***
	(0.0200)	(0.0201)	(0.0093)	(0.0095)
Post-merger GMI	-0.0476***	-0.0678***	-0.0234**	-0.0336***
	(0.0124)	(0.0152)	(0.0075)	(0.0080)
Post-merger POSTNAB	0.0149	-0.0002	0.0547***	0.0458***
	(0.0160)	(0.0186)	(0.0092)	(0.0105)
Price war period	-0.0928***	-0.1003***	-0.0696***	-0.0709***
	(0.0189)	(0.0196)	(0.0141)	(0.0142)
Promo (SG, own), pre-merger	-0.0022***	-0.0022**	-0.0004	-0.0004
	(0.0007)	(0.0007)	(0.0002)	(0.0002)
Promo (SG, own), post-merger	-0.0019***	-0.0019***	0.0001	0.0001*
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Promo (SG, own), price war	-0.0012***	-0.0012***	0.0000	0.0000
	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Promo (same firm), pre-merger	0.0000	0.0000	0.0002**	0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Promo (same firm), post-merger	0.0001**	0.0001**	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Promo (same firm), price war	0.0000	0.0001	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Promo (SG, rivals), pre-merger	8.7240***	9.1778**	1.2889	1.1669
	(2.5680)	(2.8057)	(1.7064)	(1.7078)
Promo (SG, rivals), post-merger	2.4414**	2.2676**	0.1696	0.3296
	(0.8754)	(0.8784)	(0.5366)	(0.5372)
Promo (SG, rivals), price war	-2.7381**	-2.3925*	-3.7304***	-3.8676***
	(1.0324)	(1.1368)	(0.8482)	(0.9311)
Promo (BB, own), pre-merger		-0.0002***		-0.0001*
		(0.0001)		(0.0000)
Promo (BB, own), post-merger		-0.0003*		0.0001
		(0.0002)		(0.0001)
Promo (BB, own), price war		-0.0004		0.0003*
		(0.0003)		(0.0001)
Promo (BC, rivals), pre-merger		-0.4443		0.5734
		(0.8919)		(0.3664)
Promo (BC, rivals), post-merger		2.5267**		1.4505**
		(0.8857)		(0.4546)
Promo (BC, rivals), price war		-0.7469		0.9354
		(1.9204)		(1.1007)
Observations	1728	1728	1728	1728
R-square	0.75	0.76	0.90	0.91

Notes: SG = general promotion, BC = bonus buy. Aggregated data at chain level.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 8: Structural Break Tests - Base Wholesale Prices

	$\beta(SE)$			$H_0 : pre = post = pw$	
	Pre-merger	Post-merger	Price war	F-statistic (df1,df2)	p-value
Promo (SG, rivals), model 3	1.2889	0.1696	-3.7304	8.6456 (2,1683)	0.0002
	(1.7064)	(0.5366)	(0.8482)		
Promo (SG, rivals), model 4	1.1669	0.3296	-3.8676	8.1656 (2,1677)	0.0003
	(1.7078)	(0.5372)	(0.9311)		
Promo (BC, rivals), model 4	0.5734	1.4505	0.9354	1.4511 (2,1677)	0.2346
	(0.3664)	(0.4546)	(1.1007)		

Notes: The table summarizes the results from testing the equality of the own and rival promotion passthrough coefficients on base wholesale prices over time using F-tests.

each brand. After having set the total number of structural breaks to find, the test provides the dates at which the tested coefficient changes. We focus on three specifications in which we allow for 1, 2, and 3 structural breaks during our whole sample period, respectively.

Figure 12 summarizes the associated results. Each panel corresponds to a different version of the test, in which we allow for a different number of breaks (either 1, 2, or 3). The x-axis displays the months of our sample. The y-axis denotes the number of brands for which we detect a structural break in each month.

Overall, we find that the tests predict structural breaks around the time of our industry events, i.e., the merger and the start of the price war. In particular, we find that a large number of brands exhibits a structural break in the passthrough of rivals' promotions in the beginning of 1996. Specifically, we find that the majority of brands exhibits a structural break in February 1996, which is two months earlier than what the business press usually proclaims as the start of the nation-wide price war. Therefore, in our main specification we set the start of the price war period to February 1996.

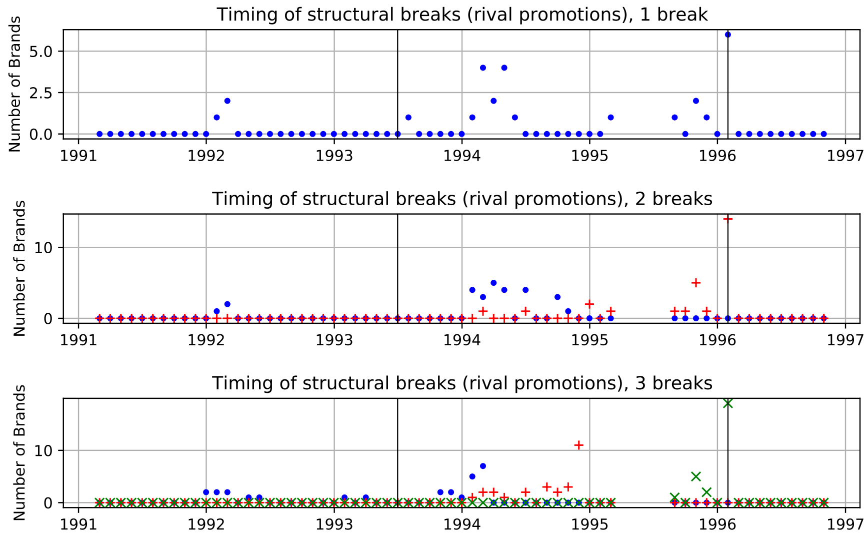
For the structural break after the merger our predictions are less clear, and we use the month in which we detect the first structural break following the merger as the effective date of the merger. This corresponds to defining the start of the post-merger period as April 1993, which is three months after the merger is consummated.[35]

A.7 Reduced Form Evidence for Validity of Modeling Assumptions

In this appendix, we present reduced form evidence for the modeling assumptions that we rely on for our identification strategy.

[35] As a robustness check, we also estimated our structural model with slightly different period definitions. These results are overall very similar and available upon request.

Figure 12: Unknown Structural Break Dates: Summary of Bai and Perron (1998)-Test Results



Notes: The figure summarizes for how many brands the test by Bai and Perron (1998) detects a structural break in any given month. Panel 1, 2, and 3 corresponde to tests in which we allow for 1, 2, and 3 structural breaks in the effect of rival promotions on (net) wholesale prices, respectively.

Timing Assumptions. The essential timing assumption in our model is that promotions in period t are set at the latest in period $t-1$, while (base) wholesale prices for period t are flexible until period t.[36]

Formally, we require that base wholesale prices $p_{jt}^{wb} = f(\mathcal{I}_t)$, where $\mathcal{I}_t$ denotes all information available in period t, i.e., all contemporaneous demand and cost shifters. In contrast, the number of promotions (and trade spend payments) 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.

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. A testable implication of this timing assumption is that wholesale prices in period t should be a function of all information available in period t, and that the number of promotions in period t, is only a function of information available up to $t-1$. This implies that, if our timing assumptions are satisfied, one would expect that wholesale base prices react to demand and cost shocks immediately. In addition, if promotions are predetermined, they should not react to contemporaneous shocks. Instead, one would expect that promotions adjust with a lag.

[36] 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).

We investigate these hypotheses in a series of reduced form regressions. Specifically, we regress both base and net wholesale prices on several 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 in the Chicago area (3-months-moving average). Throughout, we control for a series of fixed effects on the brand and month level, and we run the regressions on the chain level. Afterwards, we conduct analogous regressions with the number of contemporaneous promotions on the brand-month level 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 9.

Column (1) summarizes the results from regressing logged (net) wholesale prices on various cost shifters to illustrate that wholesale prices react immediately to contemporaneous cost shocks. Column (2) repeats the regression with base wholesale prices as the dependent variable and we find almost identical significance patterns as in Column (1).

Column (3) reveals that promotions in the current period are not affected by contemporaneous cost shocks, which provides evidence that promotional activities are not adjusted immediately. Columns (4) to (9) show that future promotions are affected by cost shocks today, however. Therefore, while promotions are clearly endogenous, Table 9 provides evidence that they are plausibly sequentially exogenous to future innovations in manufacturers' marginal cost shocks.

These patterns 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 two to six months from today, and electricity prices have an effect on the number of promotions four to six months into the future. Overall, we interpret these regressions as 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.

Non-monetary effects of promotions on consumer demand. To investigate the presence of non-monetary *sale-sign* effects of promotions on consumer demand, 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 10 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

Table 9: Reduced form evidence supporting our timing assumptions

	(1) log_whprice_mon	(2) log_whbase_mon	(3) sale_total_mon	(4) sale_tot_lead1	(5) sale_tot_lead2	(6) sale_tot_lead3	(7) sale_tot_lead4	(8) sale_tot_lead5	(9) sale_tot_lead6
sugar_g_price	0.00171***	0.000667***	-0.00162	-0.00486**	-0.00563***	-0.00462***	-0.00343*	-0.00181	-0.00446**
	(3.85)	(2.58)	(-0.90)	(-2.07)	(-3.17)	(-3.29)	(-1.99)	(-0.99)	(-2.21)
corn_g_price	0.00000649	0.00000915***	0.0000299	0.0000842**	0.0000667*	0.0000340	0.0000293	-0.00000273	0.0000622
	(1.46)	(3.63)	(0.85)	(2.35)	(1.79)	(1.16)	(0.79)	(-0.09)	(1.22)
rice_g_price	0.00000653**	0.00000445***	0.00000715	0.0000340***	0.0000247**	0.0000279	0.0000402***	0.0000144	0.00000958
	(2.54)	(3.59)	(0.61)	(9.00)	(2.49)	(1.18)	(6.32)	(1.03)	(0.80)
distance_gasoline	0.000938**	0.00149***	-0.00224	-0.0000700	0.00335**	0.00392**	-0.000525	-0.00691***	-0.00727***
	(2.37)	(6.46)	(-1.56)	(-0.05)	(2.28)	(2.12)	(-0.29)	(-4.31)	(-5.47)
electricity_chi3			0.00137	-0.00119	0.000293	0.00259	0.00592*	0.00722**	0.00782***
			(0.91)	(-0.68)	(0.16)	(1.11)	(1.79)	(2.69)	(4.03)
Observations	1728	1728	1728	1701	1674	1647	1620	1593	1566
R-square	0.73	0.91	0.10	0.09	0.09	0.09	0.09	0.09	0.10

t statistics in parentheses
Notes: Aggregated data at chain level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table 10: Reduced form analysis: Quantities sold

	(1) Baseline	(2) Baseline w/ BB	(3) Lagged promos
Log Retail Price	-1.7703***	-1.7727***	-1.7959***
	(0.1032)	(0.1444)	(0.1054)
Promo (SG, own), pre-merger	0.0029**	0.0028*	0.0027**
	(0.0009)	(0.0012)	(0.0010)
Promo (SG, own), post-merger	0.0028***	0.0027***	0.0026***
	(0.0005)	(0.0006)	(0.0005)
Promo (SG, own), price war	0.0018*	0.0018*	0.0018*
	(0.0008)	(0.0007)	(0.0007)
Promo (BB, own), pre-merger	0.0014***	0.0014***	0.0015***
	(0.0003)	(0.0003)	(0.0003)
Promo (BB, own), post-merger	0.0021***	0.0022***	0.0021***
	(0.0004)	(0.0003)	(0.0004)
Promo (BB, own), price war	-0.0000	-0.0000	0.0000
	(0.0005)	(0.0006)	(0.0005)
Promo (same firm), pre-merger	0.0001	0.0002	0.0000
	(0.0004)	(0.0004)	(0.0005)
Promo (same firm), post-merger	-0.0003*	-0.0003*	-0.0002*
	(0.0001)	(0.0001)	(0.0001)
Promo (same firm), price war	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)
Promo (SG, rivals), pre-merger	-31.5933**	-30.5942*	-29.1837**
	(10.0523)	(11.4010)	(10.3511)
Promo (SG, rivals), post-merger	-6.9483**	-6.5275**	-6.7376*
	(2.2062)	(1.8434)	(2.5658)
Promo (SG, rivals), price war	-4.1028*	-6.1626	-6.1113**
	(1.8599)	(3.5360)	(2.1132)
Promo (BC, rivals), pre-merger		-2.7141	-2.3016
		(1.6815)	(1.8548)
Promo (BC, rivals), post-merger		-4.3486*	-4.3669
		(2.0383)	(2.8780)
Promo (BC, rivals), price war		7.3440*	7.3302
		(3.1963)	(4.7883)
Promo (SG, own), lag 1			-0.1107
			(0.0640)
Promo (BB, own), lag 1			-0.0863
			(0.0574)
Promo (SG, own), lag 2			-0.0101
			(0.0512)
Promo (BB, own), lag 2			-0.0628
			(0.0523)
Promo (SG, own), lag 3			-0.0265
			(0.0709)
Promo (BB, own), lag 3			-0.0285
			(0.0503)
Promo (SG, own), lag 4			0.0199
			(0.0548)
Promo (BB, own), lag 4			0.0500
			(0.0491)
Observations	1728	1728	1620
R-square	0.89	0.90	0.90

Notes: All estimations include brand fixed effecs and a linear-quadratic time trend. 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 Discussion of Model Setup and Assumptions

In this appendix, we provide additional examples and discuss several assumptions of our model setup.

B.1 Example of Conduct Matrix with Three Firms

In order to illustrate the role of the conduct parameter matrix in our model, assume that there are three 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 engage in static Bertrand-Nash pricing, we expect λ^{PW} to be zero.

B.2 Static Demand

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 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 promotional intensity in previous months. The associated results are displayed in column (3) of Table 10 in Appendix A.7. 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.

B.3 Discussion of Potential Synergies

Note that we do not use the ownership change as an instrument, so that the occurrence of synergies does in principle not pose a problem for our empirical analysis. 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, in particular, brand-half year fixed effects, 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. 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.[37] 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

[37] 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.

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 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 estimate a robustness check in which we include a post merger-merging firm dummy in the marginal cost function. The results are unaffected and available upon request.

B.4 Consumers' Retailer Choice

We focus on data from a single retailer, i.e., DFF. This allows us to exploit available 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.

B.5 Market Size Definition and Computation of Market Shares

We define a unit of cereal as a 1 ounce 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 that visit a DFF store per month.[38]

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. The remainder, i.e., one minus the sum of the inside market shares for a given 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.

[38]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 demand results for the alternative market specifications are available upon request.

C Weak Identification Tests

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, even if instruments and endogenous regressors are correlated enough to result in a decently large F-statistic, the instruments can still be weak enough to result in very sensitive estimates and high standard errors.[39]

In order to overcome the first problem, we adapt a testing procedure recently proposed by Gandhi and Houde (2019) 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 (2019). 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

$$\kappa_{jt}(\theta) = \kappa_{jt}(\theta_0) + \sum_{k=1}^{K}(\theta_k - \theta_{0k})\frac{\partial \kappa_{jt}(\theta_0)}{\partial \theta_k} + \upsilon_{jt} \tag{10}$$

$$= \kappa_{jt}(\theta_0) + J_{jt}(\theta_0)b + \upsilon_{jt}, \tag{11}$$

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

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

(analogous to an F-test in linear GMM). Note that this test can be applied equally well to both demand and supply models.[40] For a given model, we proceed in the following steps.

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 be 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 $A(Z)$.

$$\frac{\partial \kappa_{jt}(\hat{\theta})}{\partial \theta_k} = X_{jt}\pi_{1k} + A_j(Z_t)\pi_{2k} + \epsilon_{jtk} \tag{12}$$

   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 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 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 11 to 13.

[40] 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.

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.[41]

Weak identification of the demand model. Table 11 summarizes the results of our weak identification tests for the demand model.

[41] 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 11: Weak IV Tests: Demand Model

	$\frac{\partial \nu^D}{\partial \alpha} = p$	$\frac{\partial \nu^D}{\partial \Pi_1}$	$\frac{\partial \nu^D}{\partial \Pi_2}$	$\frac{\partial \nu^D}{\partial \Pi_3}$	$\frac{\partial \nu^D}{\partial \Pi_4}$	$\frac{\partial \nu^D}{\partial \rho}$	$\frac{\partial \nu^D}{\partial \iota}$
Robust F-statistic	59.02	18.21	37.53	35.05	25.58	71.77	193.75
Robust AP-SW-F-statistic	31.20	15.56	22.75	26.52	22.71	22.26	74.64
KP χ^2-statistic	292.97						
KP χ^2-p-value	0.00						
KP F-statistic	10.63						

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.

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 most parameters; therefore, controlling for multiple endogenous regressors is important. All of the test statistics remain larger than the critical values. 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 the F-statistic by Cragg and Donald (1993) to models with heteroskedastic error terms. The KP F-statistic for weak identification exceeds 10. Consequently, we can not only reject underidentification but also weak identification of our demand model.

Weak identification on the supply side Table 12 and 13 summarize the results from testing for weak identification in our supply models. Table 12 focuses on the small specification with three conduct parameters. Table 13 displays the results for the more detailed specification with five conduct parameters.

Table 12: Weak IV Tests: Supply Model 1

	$\frac{\partial \nu^S}{\partial \lambda_1}$	$\frac{\partial \nu^S}{\partial \lambda_2}$	$\frac{\partial \nu^S}{\partial \lambda_3}$	$\frac{\partial \nu^S}{\partial \iota^S}$
Robust F-statistic	2612.06	6475.77	33659.89	13647.03
Robust AP-SW-F-statistic	2426.63	6110.19	33113.59	7410.76
KP χ^2-statistic	1373.15			
KP χ^2-p-value	0.00			
KP F-statistic	1987.61			

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.

Table 13: Weak IV Tests: Supply Model 2

	$\frac{\partial \nu^S}{\partial \lambda_1}$	$\frac{\partial \nu^S}{\partial \lambda_2}$	$\frac{\partial \nu^S}{\partial \lambda_3}$	$\frac{\partial \nu^S}{\partial \lambda_4}$	$\frac{\partial \nu^S}{\partial \lambda_5}$	$\frac{\partial \nu^S}{\partial \iota^S}$
Robust F-statistic	1988.10	5149.33	4406.99	4406.99	14760.91	4475.72
Robust AP-SW-F-statistic	1569.03	4912.15	2867.24	3303.71	4799.31	2853.11
KP χ^2-statistic	1309.38					
KP χ^2-p-value	0.00					
KP F-statistic	1164.05					

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 brands' 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 by orders of magnitude. Next, we report F-statistics that take into account the presence of multiple endogenous regressors as initially proposed by Angrist and Pischke (2008) and refined by Sanderson and Windmeijer (2016). While the F-statistics generally become smaller, they still consistently exceed the critical values substantially. We take this as strong evidence that our instruments shift the endogenous regressors sufficiently 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 $1,373$ and $1,309$, respectively, resulting in p-values of less than 0.0001 for both models.

We also compute 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 three conduct parameters the test statistic is $1,988$. This is significantly 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 five conduct parameters, the KP F-statistic is smaller. Nevertheless, the test statistic exceeds the rule-of-thumb critical value of 10 by orders of magnitude. Therefore, we conclude that even our larger supply model does not suffer from weak identification problems.

D Details on Estimation Algorithm

In this appendix, we provide additional details on our estimation algorithm, which generalizes the typical BLP approach to using a flexible set of dynamic panel moments similarly to Lee (2013) and Schiraldi (2011). The key generalization on the supply side is that we use a flexible conduct matrix instead of a binary ownership matrix when backing out marginal costs. In addition, we provide numerical details about our estimation algorithm and the software routines used. As most other papers, we estimate the demand side and the supply side in two steps.[42]

Demand estimation. For a given guess of the nonlinear demand parameters, i.e., four demographic interaction parameters, one nesting parameter, and one $AR1$-parameter, 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.

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 Monte Carlo sampling. In line with the recommendations of Dubé *et al.* (2012) and Conlon and Gortmaker (2020), 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^{-12}.

As first 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. Since in our application, product characteristics do not change across markets, we cannot include the time-invariant product characteristics, such as sugar and fiber content, in the profiling matrix directly. Instead we follow Nevo (2001) and back out mean preferences for each time-invariant product characteristic by regressing the estimated brand fixed effects on these characteristics.

After having computed the levels of the structural demand errors ξ, we compute the innovations ν^D of the ξ-process as a function of the $AR1$-parameter. Finally, we interact ν^D with the instruments Z_D discussed in Section 4.1.

In order to improve the efficiency of our estimation, we build on insights from the dynamic panel literature, see, for example, Arellano and Bover (1995) and Blundell and Bond (1998). In particular, we include our excluded instruments (predicted wholesale prices and rival-promotion-based differentiation instruments) not only in levels but also in first differences. Moreover, we interact the predicted own promotion variable, the rival-promotion-based in-

[42]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. Because of our reasonably large sample, we judge the efficiency gains to be less important than the robustness associated with a two-step estimation.

struments in levels and first differences with dummies for our three time periods (pre-merger, post-merger, price war). In addition, in order to identify the $AR1$-parameter of the ξ-process, we include one- and two-period lags of the implied mean utilities δ in Z_D similarly to Lee (2013).

For minimizing the GMM objective function, we use a Nelder-Mead line search algorithm.[43] As stopping criterion for the Nelder-Mead routine we set both the step size in the parameter and the change in the function value to 10^{-6}. By using multiple starting values, we verify that the obtained minimum of the GMM function is indeed a global minimum.

We also estimate larger demand models with up to 12 non-linear parameters as robustness checks. Generally, we find that our baseline demand model provides a good fit to the data. The larger models result in similar price elasticities. However, larger models exhibit significantly larger standard errors and we prefer to use a smaller model, that is more precisely estimated, rather than a potentially noisy large model. We conjecture that with our data, that only relies on data from one retailer and one local market, it is hard to exploit sufficient variation to estimate much larger random coefficient models precisely.

Supply estimation. 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 five steps (2.-6.) 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 above.**

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

3. **Back out marginal costs given a guess for the conduct parameters in Λ, and $\frac{\partial s()}{\partial p}$ from the demand estimation.** Combining the price elasticities from Step 1 and the parameter guess for Λ from Step 2, we compute the implied production marginal costs for each product and market based on Equation (5). Since our marginal cost functions are linear, we can profile out the marginal cost parameters γ using 2SLS regressions, as suggested by Nevo (2000a). This step allows us to compute the unobservable marginal cost shock ω for each product and market.

4. **Compute innovations in ω-process.** Next, we compute the innovations of the shock process, ν^S as a function of the parameter guess for ι^S and the backed-out vector of

[43] We also estimated our demand model with a gradient-based optimizer and obtained identical results. Dubé *et al.* (2012) discuss that gradient-based optimization of BLP-style models can have substantial advantages. To exploit the full power of gradient-based optimization methods, one has to compute the gradient of the objective function, ideally analytically. For a random coefficient model without nesting parameters and $AR1$-parameters, the gradient of the demand model has a closed-form solution, see, for example, Nevo (2000a). For a nested random coefficient model with dynamic panel moments the gradient is more complicated. Even though the gradient of our model is still tractable, we found the Nelder-Mead approach to comparable to the gradient-based optimization in terms of speed.

unobserved marginal cost shocks ω.

5. **Compute supply-side GMM objective function.** Based on the values for ν^S backed out in Step 4, we compute the supply side moments which are based on orthogonality conditions between ν^S and the instruments discussed in Section 4.1. Finally, we aggregate the moment conditions to obtain the GMM criterion function for the parameter guess $vec(\Lambda, \iota^S)$. Analogously to our demand estimation, we build on the insights from the dynamic panel literature to improve the efficiency of our estimation. Specifically, we include our promotion-differentiation instruments not only in levels but also in first differences. Finally, we also include one- and two-period lagged marginal costs as instruments to identify the $AR1$-parameter in the ω-process.

6. **Repeat steps 2-5 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. Similarly as for the demand side, we did not experience significant advantages of using a gradient-based optimization in our application. Therefore, we revert to derivative-free Nelder-Mead simplex method for estimating our supply model as well.[44] We use the same stopping criterion as for our demand estimation.

D.1 Standard Error Adjustments

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

[44] As for the demand model, we also estimate our supply model using gradient-based methods and using different starting values to ensure that we find the global minimum of the objective function.

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.

E 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.

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

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.

Table 14: 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	-4.551	0.057	0.080	0.036	0.045	0.052	0.070	0.206	0.145	0.065	0.065	0.043	0.075
PO Raisin Bran	0.026	-3.524	0.074	0.036	0.043	0.050	0.065	0.197	0.140	0.064	0.063	0.043	0.073
PO Grape Nuts	0.030	0.060	-4.140	0.033	0.046	0.052	0.077	0.214	0.147	0.055	0.061	0.037	0.068
PO Honey Comb	0.023	0.049	0.060	-4.229	0.040	0.046	0.058	0.175	0.128	0.061	0.059	0.041	0.068
GM RaisinNutBran	0.025	0.054	0.069	0.035	-4.057	0.050	0.065	0.196	0.139	0.065	0.064	0.044	0.075
GM ApplCin Cheer	0.024	0.052	0.065	0.034	0.042	-4.133	0.063	0.192	0.137	0.064	0.062	0.043	0.072
GM Wheaties	0.027	0.056	0.082	0.035	0.045	0.053	-4.369	0.207	0.144	0.063	0.064	0.043	0.073
GM Cheerios	0.025	0.053	0.071	0.035	0.043	0.050	0.066	-4.325	0.142	0.064	0.063	0.043	0.074
GM HonNut Cheer	0.025	0.053	0.068	0.035	0.042	0.050	0.064	0.198	-4.040	0.064	0.062	0.043	0.073
GM Luck Charms	0.019	0.041	0.045	0.029	0.034	0.039	0.048	0.150	0.111	-3.412	0.052	0.035	0.062
GM Tot CoFlakes	0.022	0.047	0.055	0.033	0.038	0.045	0.056	0.172	0.126	0.061	-4.520	0.041	0.069
GM Trix	0.018	0.040	0.044	0.029	0.033	0.038	0.047	0.147	0.108	0.053	0.051	-3.776	0.060
KE Froot Loops	0.022	0.047	0.055	0.031	0.038	0.043	0.055	0.167	0.123	0.057	0.057	0.038	-3.922
KE Special K	0.025	0.052	0.068	0.035	0.042	0.049	0.062	0.190	0.137	0.064	0.062	0.043	0.073
KE Frost Flakes	0.028	0.059	0.095	0.034	0.045	0.052	0.074	0.213	0.146	0.059	0.062	0.040	0.071
KE Corn Pops	0.025	0.053	0.068	0.034	0.042	0.048	0.064	0.188	0.136	0.063	0.062	0.042	0.074
KE Raisin Bran	0.027	0.057	0.085	0.035	0.045	0.052	0.070	0.207	0.145	0.062	0.063	0.042	0.074
KE Corn Flakes	0.029	0.057	0.137	0.026	0.041	0.046	0.076	0.199	0.131	0.042	0.047	0.026	0.052
KE Honey Smacks	0.024	0.052	0.065	0.035	0.041	0.048	0.062	0.184	0.134	0.064	0.062	0.043	0.073
KE Crispix	0.026	0.056	0.075	0.036	0.044	0.051	0.067	0.200	0.142	0.064	0.064	0.043	0.074
KE Rice Krispies	0.028	0.060	0.098	0.033	0.045	0.051	0.075	0.209	0.144	0.058	0.060	0.039	0.069
RAL Chex	0.023	0.050	0.063	0.034	0.041	0.046	0.058	0.176	0.128	0.061	0.059	0.041	0.070
RAL Wheat Chex	0.028	0.057	0.086	0.036	0.046	0.052	0.070	0.206	0.144	0.063	0.063	0.042	0.073
RAL Rice Chex	0.023	0.050	0.063	0.034	0.041	0.046	0.058	0.176	0.128	0.061	0.059	0.041	0.069
QU Quaker Oats	0.029	0.060	0.104	0.033	0.046	0.052	0.076	0.218	0.147	0.057	0.061	0.038	0.068
QU Capn Crunch	0.026	0.055	0.082	0.034	0.043	0.050	0.067	0.197	0.140	0.060	0.061	0.040	0.071
QU Life	0.029	0.060	0.103	0.034	0.046	0.052	0.077	0.216	0.146	0.058	0.062	0.038	0.069
Outside good (div.)	0.439	0.460	0.454	0.440	0.438	0.437	0.438	0.449	0.446	0.433	0.432	0.430	0.444

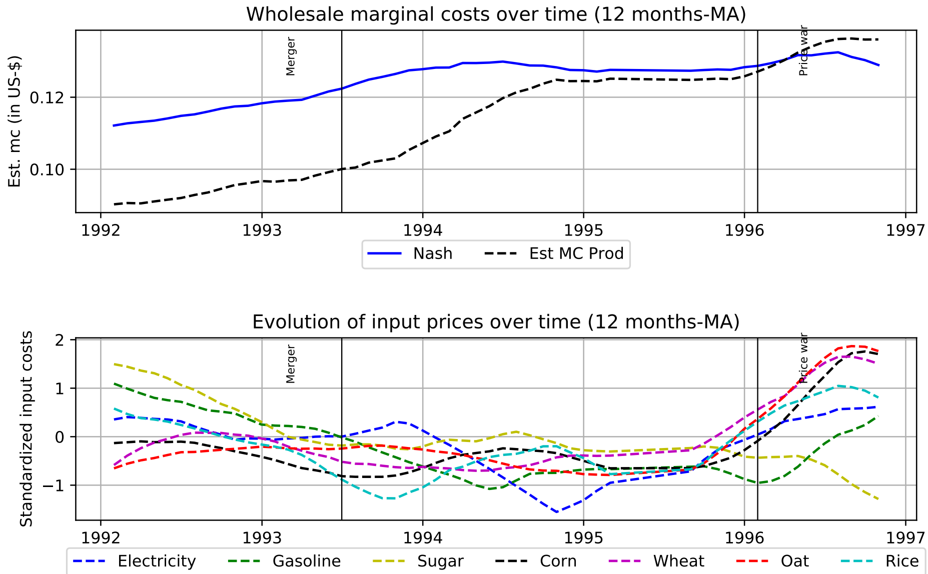
Notes: Cell entries i (indexing row), j (indexing column) give the percent change in market share of brand i associated with a one percent change in the price of j. Each entry represents the median of the elasticities across the 3712 markets. The last row displays the predicted diversion to the outside 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 15: 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	QU Li
NAB Shred Wheat	0.111	0.233	0.072	0.145	0.158	0.020	0.060	0.166	0.023	0.020	0.032	0.076	0.078	0.043
PO Raisin Bran	0.107	0.217	0.070	0.135	0.142	0.020	0.058	0.154	0.022	0.019	0.031	0.069	0.075	0.040
PO Grape Nuts	0.111	0.292	0.071	0.163	0.275	0.020	0.065	0.212	0.023	0.023	0.031	0.101	0.086	0.057
PO Honey Comb	0.098	0.183	0.065	0.116	0.101	0.018	0.051	0.128	0.020	0.017	0.029	0.058	0.065	0.033
GM RaisinNutBran	0.107	0.208	0.069	0.132	0.123	0.019	0.056	0.146	0.022	0.019	0.031	0.065	0.073	0.037
GM ApplCin Cheer	0.103	0.200	0.068	0.127	0.113	0.019	0.054	0.139	0.021	0.018	0.029	0.062	0.070	0.036
GM Wheaties	0.110	0.239	0.071	0.144	0.168	0.020	0.060	0.171	0.023	0.021	0.032	0.078	0.077	0.044
GM Cheerios	0.106	0.209	0.069	0.135	0.133	0.019	0.056	0.148	0.022	0.019	0.030	0.068	0.072	0.039
GM HonNut Cheer	0.105	0.204	0.068	0.132	0.123	0.019	0.055	0.144	0.021	0.018	0.030	0.065	0.071	0.037
GM Luck Charms	0.083	0.145	0.056	0.096	0.065	0.016	0.044	0.101	0.017	0.014	0.024	0.044	0.055	0.025
GM Tot CoFlakes	0.095	0.169	0.063	0.112	0.085	0.018	0.050	0.117	0.020	0.016	0.028	0.052	0.063	0.030
GM Trix	0.081	0.141	0.054	0.094	0.063	0.015	0.043	0.097	0.017	0.013	0.024	0.042	0.052	0.024
KE Froot Loops	0.093	0.170	0.061	0.110	0.088	0.017	0.048	0.117	0.019	0.016	0.027	0.054	0.062	0.030
KE Special K	-4.813	0.196	0.068	0.129	0.122	0.019	0.055	0.141	0.022	0.018	0.030	0.064	0.070	0.037
KE Frost Flakes	0.111	-4.369	0.071	0.156	0.225	0.020	0.063	0.199	0.023	0.022	0.032	0.091	0.083	0.051
KE Corn Pops	0.103	0.205	-4.666	0.128	0.120	0.019	0.056	0.143	0.021	0.018	0.030	0.064	0.070	0.037
KE Raisin Bran	0.111	0.250	0.070	-3.785	0.184	0.020	0.061	0.174	0.023	0.021	0.032	0.081	0.080	0.046
KE Corn Flakes	0.101	0.335	0.060	0.169	-4.052	0.017	0.064	0.262	0.020	0.024	0.028	0.125	0.081	0.069
KE Honey Smacks	0.103	0.195	0.067	0.125	0.111	-4.015	0.055	0.137	0.022	0.018	0.030	0.062	0.070	0.035
KE Crispix	0.109	0.220	0.071	0.138	0.141	0.020	-5.150	0.157	0.023	0.020	0.032	0.071	0.076	0.041
KE Rice Krispies	0.112	0.277	0.069	0.156	0.240	0.020	0.064	-5.119	0.023	0.023	0.032	0.095	0.082	0.052
RAL Chex	0.099	0.183	0.065	0.119	0.107	0.018	0.053	0.131	-4.557	0.018	0.030	0.060	0.067	0.034
RAL Wheat Chex	0.112	0.243	0.071	0.146	0.180	0.020	0.062	0.175	0.024	-4.401	0.033	0.080	0.079	0.046
RAL Rice Chex	0.100	0.183	0.065	0.118	0.108	0.018	0.053	0.132	0.022	0.018	-4.556	0.060	0.067	0.034
QU Quaker Oats	0.111	0.288	0.070	0.161	0.266	0.020	0.064	0.207	0.023	0.023	0.031	-4.105	0.084	0.054
QU Capn Crunch	0.106	0.232	0.068	0.141	0.160	0.019	0.059	0.160	0.022	0.020	0.030	0.077	-4.175	0.044
QU Life	0.112	0.286	0.071	0.163	0.258	0.020	0.065	0.210	0.023	0.023	0.032	0.098	0.085	-4.497
Outside good (div.)	0.432	0.512	0.444	0.453	0.463	0.440	0.437	0.445	0.426	0.434	0.426	0.451	0.508	0.447

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.

Figure 13: 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 two different models. The figures is based on the median over all brands 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.

Evolution of marginal cost estimates. 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 13 illustrates the evolution over time of the median marginal costs implied by two different models. Under the assumption of multiproduct Bertrand-Nash pricing (solid line), we obtain relatively stable marginal costs over time. The implied marginal costs from our conduct models exhibit a slightly different pattern (dashed line). In particular, they increase in the beginning of the post-merger period, and increase further during the price war period, while Bertrand-Nash pricing predicts relatively constant marginal costs during the price war period and even a slight decrease at the very end of our sample.

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 13. It is important to note that input prices are not a perfect proxy for economic marginal costs. However, especially for the price war period, we find that the predictions from our estimated conduct pattern are more consistent with input price data than the ones from a Bertrand-Nash model: In the price war period, there is a sharp increase in input prices shortly before and during the price

Table 16: Summary of Marginal Cost and Margin Estimates

	Small model Pre-merger	Small model Post-merger	Small model Price War	Large model Pre-merger	Large model Post-merger	Large model Price War	Nash
MC prod	0.0957	0.1252	0.1391	0.0947	0.1233	0.1390	0.1251
Total MU	0.5167	0.4021	0.3344	0.5240	0.4007	0.3340	0.3947
Manuf MU	0.4141	0.1879	0.0448	0.4148	0.1869	0.0484	0.2147

Notes: The table summarizes estimates for manufacturer marginal costs, total markups (assuming a retailer marginal cost of zero), and wholesale markups. The numbers are medians over all brands and months separately for the pre-merger, post-merger, and price-war period. The last column displays the statistics assuming multiproduct Bertrand-Nash pricing over the whole sample.

war.[45] Overall, this patterns is more difficult to reconcile with the marginal costs predicted by Bertrand-Nash pricing. We believe that these results provide further support for our conduct models.

Table 17: Time-Brand Specific Wholesale Price-Cost-Margins

	Small model Pre-merger	Small model Post-merger	Small model Price War	Large model Pre-merger	Large model Post-merger	Large model Price War	Nash
NAB Shred Whe	0.3459	0.1805	0.0717	0.3715	0.1571	0.0722	0.1657
PO Raisin Bra	0.4621	0.2874	0.1330	0.4905	0.2565	0.1325	0.2575
PO Grape Nuts	0.4563	0.1804	0.1020	0.4853	0.1368	0.1021	0.2035
PO Honey Comb	0.3453	0.2171	0.0672	0.3649	0.1886	0.0677	0.1978
GM RaisinNutB	0.4334	0.2573	0.1052	0.4336	0.2773	0.1070	0.2611
GM ApplCin Ch	0.4270	0.2415	0.0953	0.4283	0.2581	0.0971	0.2541
GM Wheaties	0.4170	0.1997	0.0660	0.4173	0.2226	0.0679	0.2125
GM Cheerios	0.3836	0.1868	0.0417	0.3839	0.2059	0.0400	0.1962
GM HonNut Che	0.4172	0.2245	0.0521	0.4173	0.2510	0.0498	0.2350
GM Luck Charm	0.4709	0.3073	0.1745	0.4712	0.3270	0.1779	0.3314
GM Tot CoFlak	0.3500	0.1743	0.0731	0.3500	0.1974	0.0751	0.2191
GM Trix	0.4167	0.2471	0.1178	0.4168	0.2732	0.1212	0.2704
KE Froot Loop	0.4115	0.2737	−0.0886	0.4120	0.2855	−0.0917	0.2752
KE Special K	0.3455	0.1954	0.0293	0.3462	0.2117	0.0297	0.2093
KE Frost Flak	0.4223	0.1293	−0.0163	0.4242	0.1443	−0.0193	0.2198
KE Corn Pops	0.3625	0.1854	−0.0067	0.3640	0.2024	−0.0040	0.2109
KE Raisin Bra	0.4876	0.2605	−0.0413	0.4900	0.2787	−0.0415	0.2825
KE Corn Flake	0.5071	0.1299	−0.1082	0.5087	0.1175	−0.1108	0.2374
KE Honey Smac	0.4256	0.2504	−0.0200	0.4265	0.2609	−0.0181	0.2569
KE Crispix	0.3589	0.1742	0.0108	0.3598	0.1885	0.0143	0.1988
KE Rice Krisp	0.3799	0.1405	−0.0281	0.3818	0.1479	−0.0270	0.1812
RAL Chex	0.3316	0.1996	0.0764	0.3540	0.1770	0.0791	0.1860
RAL Wheat Che	0.4122	0.1960	0.0718	0.4379	0.1526	0.0734	0.1837
RAL Rice Chex	0.3323	0.2032	0.1134	0.3549	0.1823	0.1150	0.1897
QU Quaker Oat	0.4588	0.1704	−0.0207	0.4868	0.1424	−0.0175	0.2073
QU Life	0.3771	0.1662	−0.2004	0.4020	0.1176	−0.1978	0.1710
QU Capn Crunc	0.4053	0.1617	0.0089	0.4301	0.1399	0.0097	0.1843

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

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

Conduct estimates: Hypothesis testing. In the following, we present resuls from a series of statistical hypotheses tests (t-statistics) for the equality of the conduct parameters over time and across firms for both our small and our large conduct model. Table 18 summarizes the associated results.

The first two rows display the results of testing $H_0 : \lambda_t = 0$, which is equivalent to static Bertrand-Nash pricing. While we reject the null hypothesis for the pre-merger period and the price war period, we cannot reject Betrand-Nash pricing in the post-merger for our small model with a homogeneous conduct parameter and in the large model for the four smaller firms. For the large firms, we find that pricing is more cooperative than Bertrand-Nash in the post-merger period.

Rows 3 and 4 show the results of testing $H_0 : \lambda_t = 1$, which implies perfectly collusive pricing. We reject this hypothesis in all periods for the small model, and for the large model during the post-merger and the price war period for all firms. During the pre-merger period, the large model indicates that the pricing behavior of the smaller firms is consistent with perfect price coordination.

Rows 5 to 8 test the equality of different pairs of conduct parameters. For the small model (row 5) we reject clearly that the conduct parameters in any two periods are equal. The corresponding results for the large model (rows 6 and 7) are similar. However, we cannot reject the hypothesis that the conduct parameters for Kellogg's and General Mills are equal before and after the merger, see column 1 in row 6.

Finally, row 8 tests whether the conduct parameters of our large model are statistically different across firm groups within a given time period. We can reject the equality of the conduct parameters for the small and large firms during the post-merger period at the 10%-level. In the pre-merger period, however, the conduct parameters are not statistically different across firm groups.

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, changes in markups cannot only be explained by the *unilateral effects* of the merger but also by a changes in industry conduct in the post-merger period (*coordinated effects*).

Table 18: Conduct Estimates: Hypothesis Tests

Model	$\lambda_{Pre} = 0$	$\lambda_{Post} = 0$	$\lambda_{Pw} = 0$
Small	5.45***	1.35	-3.30***
Large	3.73*** 3.51***	2.44** -0.33	-2.94***
	$\lambda_{Pre} = 1$	$\lambda_{Post} = 1$	$\lambda_{Pw} = 1$
Small	-3.04***	-6.21***	-5.62***
Large	-2.17** -1.37	-2.82*** -5.49***	-5.08***
	$\lambda_{Pre} = \lambda_{Post}$	$\lambda_{Post} = \lambda_{PW}$	$\lambda_{Pre} = \lambda_{PW}$
Small	7.09***	3.97***	4.88***
	$\lambda_{Pre}^{KE,GM} = \lambda_{Post}^{KE,GM}$	$\lambda_{Post}^{KE,GM} = \lambda_{PW}^{KE,GM}$	$\lambda_{Pre}^{KE,GM} = \lambda_{PW}^{KE,GM}$
Large	1.55	4.22***	4.32***
	$\lambda_{Pre}^{Rest} = \lambda_{Post}^{Rest}$	$\lambda_{Post}^{Rest} = \lambda_{PW}^{Rest}$	$\lambda_{Pre}^{Rest} = \lambda_{PW}^{Rest}$
Large	5.99***	2.79***	4.29***
	$\lambda_{Pre}^{KE,GM} = \lambda_{Pre}^{Rest}$		$\lambda_{Post}^{KE,GM} = \lambda_{Post}^{Rest}$
Large	0.31		1.88*

*Notes: This table summarizes the t-statistics associated with the hypothesis tests described above. Standard errors account for two-step estimation. *, **, *** denote significance of the test statistic at the 10%, 5%, and 1%-level, respectively.*

Nevo (2001) measures market power in the RTE cereal industry. His sample contains data from 65 U.S. cities covering a period from 1988 to 1992. Time-wise, this partially overlaps with our pre-merger period. Our demand estimates differ somewhat from his estimates for several, but related, reasons. Nevo (2001, 2000b) uses a much richer data set covering many U.S. regions and several retailers. In contrast, we have to rely on data from only one retailer and one geographic market. The richer data structure allows him to estimate substantially more random coefficients and demographic interactions than what we are able to do with our data. The advantage of our data is that we can rely on wholesale price data, which allows us to directly model manufacturer pricing instead of relying only on retail price data.

The limitations of our data force us to use a less general random coefficient specification. For example, we only incorporate four income-interactions and group all the inside goods into one nest instead of estimating a random coefficient on the constant to capture the substitution patterns between the inside products and the outside good. In addition, Nevo uses Hausman (1996)-style instruments based on prices from other regions, and a slightly different product set.[46] If one believes that our demand model overestimates demand elasticities, our conduct estimates would provide an upper bound on the conduct parameter, but the qualitative trend of industry conduct becoming more competitive over time should still be robust. We believe that the advantages of conducting our analysis using wholesale price data outweigh the drawbacks of using a more restrictive demand specification. Replicating our empirical approach using a more comprehensive data set, such as the ones from IRI used by Nevo or Nielsen as used by Backus *et al.* (2021) is a promising avenue for future research on this topic.

To select among different forms of industry conduct, Nevo (2001) compares the recovered marginal cost for different pre-specified conduct specifications 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 to 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 around 50 percent.[47]

[46] We include all products used by Nevo, and we additionally include products from the manufacturer Ralston.

[47] Assuming multiproduct Nash pricing, we find an implied gross margin for the pre-merger period of approximately 40 percent, which is only slightly lower than Nevo's (2001).