Equilibrium effects of minimum markup laws in grocery retailing markets

Daniel Herrera-Araujo and Jorge Florez*

This version: September 2024

Abstract

We examine the effects of minimum markup laws (MMLs) on downstream pricing, competition and welfare. Currently, half of the states of the U.S. have laws imposing minimum markups on merchandise because of exclusionary concerns. Using scanner data on supermarket sales in the U.S., we provide new evidence against the exclusionary view. We perform two exercises: a causal analysis of a temporary void of a state law in the U.S. in 2007, and a structural analysis of the equilibrium effects of setting a minimum markup provision on equilibrium retail prices and welfare. The main challenge to the estimation of demand of multiple products is the high-dimensional choice set. We propose a novel solution to this challenge and show with Monte Carlo simulations that it is effective in bias correction. Our estimates show that MMLs lead to higher average prices.

Keywords: Price floor, below-cost pricing, predation, multiproduct pricing, multiproduct demand, one-stop shopping, multistop shopping, shopping costs, complementarity, demand estimation.

JEL Codes: D12, L13, L81.

Acknowledgments: For helpful discussions, comments and suggestions we thank Daniel Chaves, Judy Chevalier, Olivier De Groote, Pierre Dubois, Margarita Gáfaro, Julien Monardo, Nathan Miller, Leonardo Morales, Andras Niedermayer, and Patrick Rey. We are grateful to seminar participants at Mines Paris, Université Paris-Dauphine, and CREST; and conference participants at the EARIE Annual Conference (2021), LACEA-LAMES Annual Conference (2021), Banco de la República Research Network Conference (2021), EEA-ESEM Annual Conference (2022), IIOC (2023), RIDGE-IO Workshop (2024), and BECCLE Conference (2024). Renzo Clavijo provided excellent research assistance.

Disclaimers: This paper uses the NielsenIQ datasets supplied by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The results in this paper are the researchers' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. The views expressed in this research are those of the authors and do not reflect the position of the Banco de la República or its board of directors. All errors and omissions remain the responsibility of the authors.

*Herrera-Araujo: Université Paris-Dauphine, LEDA (CGEMP), Place du Maréchal de Lattre de Tassigny, (e-mail: daniel.herrera@dauphine.psl.eu); Florez: Banco de la República and Universidad del Rosario, Bogotá, Colombia (e-mail: jhflorez@gmail.com).

1 Introduction

Large supermarket chains often set low prices on high demand products to draw consumers into the store and profit from their purchases of higher markup products. Evidence shows that for some competitive products prices can be set at or below cost (see Chevalier, Kashyap and Rossi (2003); Competition Commission (2008)). To prevent firms from setting too low prices, under claims that those are most likely exclusionary, half of the U.S. states and several countries worldwide impose price floors equal to estimated costs or require minimum positive markups on estimated costs. However, both anecdotal and economic evidence suggests that too low prices need not be exclusionary. In effect, the main features of predation, namely, a losses stage due to below-cost prices, exclusion of competitors and the subsequent recoup stage, are hardly observed in retailing markets (see, for example, Florez-Acosta and Herrera-Araujo (2020)). Recent theoretical literature provides formalization of alternative views of below-cost pricing and shows that such a practice may even be welfare enhancing (Chen and Rey, 2012, 2019; Johnson, 2017). These results rise new concerns about minimum markup laws; for instance, that a ban leads to higher equilibrium prices, and that it may prevent retailers from decreasing the price of some of their products below certain threshold during sales.

In this paper, we provide new evidence on the effects that price floors or minimum markups have on supermarket pricing, competition and consumer welfare, using scanner data on supermarket sales in the United States. To this end, we carry out two empirical exercises. First, we perform difference-in-differences analyses of a temporary void of the Wisconsin's *Unfair Sales Act*, a law that imposes a minimum markup on almost all products to prevent retailers from selling goods below-cost, between October 2007 and September 2010. Using sales data of milk and RTE cereals—which are products of high demand and often consumed together—in the U.S. between 2007 and 2010, we estimate the effect of the Wisconsin exogenous shock by comparing changes in prices between chains that were exposed to the shock (i.e., owning stores located in Wisconsin) and chains that were not exposed to it (our control group). We show that the law void causes both a decrease in average retail milk prices, and an increase in average RTE cereal prices. Consistent with recent theory findings, our case study suggests that laws imposing minimum markups lead to higher prices on popular products compared to free pricing states. Furthermore, our results empirically support recent theory predictions according to which supermarkets are willing to charge lower prices on some products to attract consumers into the stores, and compensate potential losses with high-markup products that exhibit strong complementarities with the former (see, for example, Chen and Rey (2019)).

In our second exercise, we estimate a structural model of demand and supply of multiple products. On the demand side, we build on Florez-Acosta and Herrera-Araujo (2020) and estimate a multiple-discrete choice model in the context of competition between supermarkets that offer the same product line to the same customers. Consumers can purchase bundles of products from up to three different supermarkets on each shopping occasion and incur shopping costs. On the supply side, we develop a model in which local supermarket chains compete in prices with national chains that set uniform prices in all of their locations; that is, stores that are owned by multi-state supermarket chains may not adjust their prices in response to the local market conditions but rather as a function of a chain-wide objective function (see, DellaVigna and Gentzkow (2019); Hitsch, Hortaçsu and Lin (2019); and Butters, Sacks and Seo (2022)).

Our general empirical strategy combines two main features. On the supply side, we model price competition between multiproduct retailers in a context in which retailers may or may not be free to set optimal prices (that may lie below cost). To do that, we restrict attention to chains that are only present in ban/non-ban states—to avoid the spill-over effects of the ban due to a chain's exposure to ban states. On the demand side, we model the choice of multiple products from multiple stores explicitly accounting for potential complementarities between *a priori* unrelated products and stores. We specify the utility of each product as a parametric function of observed and unobserved product and store characteristics. The total utility of a bundle of products is the sum over product-level utilities, a bundle level constant that rationalizes the bundle composition (i.e., product complementarity as in Gentzkow (2007)), and individual level shopping costs. In line with previous literature, we define *shopping costs* as all of the consumer's real or perceived costs of using a supplier (Klemperer, 1992; Chen and Rey, 2012, 2019; Florez-Acosta and Herrera-Araujo, 2020).

Our demand model explicitly rationalizes the heterogeneous shopping patterns that we observe in the data. That is, the fact that some consumers concentrate purchases on a single store (one-stop shoppers) while other consumers source multiple competing stores in the same shopping occasion (multistop shoppers). We achieve this by allowing shopping costs to vary across individuals and assuming that these costs increase with the number of supermarkets visited. On every shopping occasion, each consumer weighs up the extra benefits of dealing with an additional store against the extra costs involved. If the benefits exceed the costs, the individual will visit an additional supermarket. Otherwise, she will make all her purchases at a single location. Therefore, in the context of our model, shopping costs can also be interpreted as the degree of substitutabilty (for one-stop shoppers) or complementarity (for

multistop shoppers) between retail stores.

A common challenge to the estimation of demand for multiple products is the large size of the set of products and stores available to consumers. Previous literature has dealt with this shortcoming by following one of two approaches: by reducing the set of alternatives by arbitrarily selecting a subset of products (i.e., the "included products") and leaving both the remaining observed (i.e., the "excluded") and unobserved products as part of the outside good (e.g., Florez-Acosta and Herrera-Araujo (2020)). Or, on the other hand, by aggregating individual products up to the category levels (e.g., Thomassen et al. (2017)). Either approach may lead to bias in the demand estimates. In this article, we follow the former approach.

The source of the bias is as follows. When excluding an arbitrary number of observed products and stores, the resulting choice set (i.e., the set of all exclusive and exhaustive alternatives) will consist of all the possible combinations of included products and stores only (and, probably, the outside good). However, this rules out the fact that some included products can be jointly purchased with other excluded products that are observed in the data. Therefore, a choice set consisting exclusively of combinations of included products will not be exhaustive; as a consequence, the probability that a consumer chooses a given product will be underestimated. Specially, this bias may affect the estimates of both the product complementarity constants and the shopping costs, as long as the researcher is not fully accounting for the cross-product and cross-store complementarities.

We develop a novel approach to deal with this shortcoming in a tractable way. It allows us to focus on a reduced set of products and stores from the consumers' full choice set, and corrects the bias that arises from excluding observed products and stores. Our approach works as follows. We first notice that in a context of multiproduct demand, a specific product can be purchased alone or together with other included and, potentially, a set of excluded products. Consequently, the choice probability that we seek to estimate should account for this fact. We call this the *total* choice probability, which is a function of the utility of both included and excluded products. Next, rather than estimating the parameters of the latter, we exploit each consumer's observed full purchase history for an arbitrary number of periods before a given choice, compute proxies for the probabilities of choosing excluded products and treat them as observables. Specifically, we compute two empirical probabilities: the probability of choosing any set of excluded products conditional on choosing at least one included product, and the probability of choosing any set of excluded products alone. They nonparametrically account for the potential complementarities between included and excluded products and stores and, hence, correct the bias implied by the restrictions imposed

by the researcher on the choice set. Furthermore, the number of parameters to be estimated remains similar to that of a model that focuses on stand-alone choice probabilities.

We test our approach by performing Monte Carlo simulations. We consider a setting with three supermarkets each of which sells the same three products. We allow consumers to purchase any combination of products and stores or to opt for the no purchase option. Our simulation results show that the standard approach leads, in effect, to biased estimates; the coefficients related to the shopping costs have the greater bias. Once we introduce our proposed bias correction, Monte Carlo results show that we obtain unbiased estimates.

We estimate our supply and demand models using the NielsenIQ Consumer Panel on sales of three major supermarket chains in the state of Wisconsin using data from 2007 until 2011. We restrict attention to chains having stores in Wisconsin only to avoid any indirect effect of the ban in other states on prices. We focus on a set of nine goods, namely, canned soup, ready-to-eat breakfast cereals, coffee, carbonated soft-drinks, cookies, potato chips, eggs, milk and yogurt. We aggregate sales of all observed brands and brand varieties into a single composite product for each of our selected goods. The product line consists, hence, of 9 alternatives across three retailers, and the choice set consists of all of the combinations of products and stores plus and outside good.

Further, we use the NielsenIQ Consumer Panel to compute the empirical probabilities for our bias correction. We select a sample of 859 consumers and use their purchase history observed between 2007 and 2011. We estimate our demand model allowing for consumer considerations sets using Maximum Likelihood Estimation. With the demand estimates in hand, we back out product-level markups and marginal costs using our supply model. Finally, we simulate a counterfactual experiment in which a minimum markup law is implemented in Illinois, a state without a minimum markup law (i.e., a free pricing state).

Our results show that when supermarkets face a price floor, they increase the overall price level. An interpretation of this result in light of recent theoretical results (see Chen and Rey (2019)) is as follows: supermarkets usually have competitive products (potentially loss-leaders) and profitable products on which they have a comparative advantage; in a free pricing environment, this advantage allows them to charge high markups on the latter which they use to subsidize losses on competitive products; if a minimum markup is imposed, the markups of competitive products are required to comply leading firms to increase margins for profitable products. This finding gives support to the conclusion of the OECD (2008) report, arguing the minimum markup laws are likely to lead to higher prices and thus harm consumers.

This paper is structured as follows: the second section offers a review of the related literature. Next, we present an overview of our data and background concerning MMLs in the U.S. The fourth section presents our case study of the temporary void of the Wisconsin's *Minimum Markup Law*. The fifth section contains our structural analysis; we provide a detailed description of the model, the data, our bias correction and Monte Carlo simulations, our empirical strategy, estimation results and counterfactuals. Finally, the sixth section concludes.

2 Related literature

This paper relates to several strands of literature. First, a literature, mainly theoretical, that provides explanations for why multiproduct firms charge low prices on some products and high prices on other products (Holton, 1957; Hess and Gerstner, 1987; Gerstner and Hess, 1990; Lal and Matutes, 1994; Simester, 1995; Lazear, 1995; Verboven, 1999; Ellison, 2005; Gabaix and Laibson, 2006). Second, a strand of literature that studies the economic effects of below-cost pricing from a theoretical perspective, and finds that this practice is not predatory and may rather be welfare enhancing (Chen and Rey, 2012; Johnson, 2017; Chen and Rey, 2019).

This paper also relates to a literature that provides empirical evidence on the existence of loss-leader pricing on a number of retail markets such as the new car market (Verboven, 1999), the grocery retailing markets (Walters, 1988; Walters and MacKenzie, 1988; Chevalier, Kashyap and Rossi, 2003), and the internet commerce (Ellison and Ellison, 2009). Moreover, this paper relates to a literature that studies seasonal patterns of prices and price promotions in the U.S. retailing sector (Warner and Barsky, 1995; Johansen, 2000; Chevalier, Kashyap and Rossi, 2003; Chevalier and Kashyap, 2019; Gagnon and López-Salido, 2020) and a more recent literature that documents the existence of uniform pricing in the U.S. retailing chain sector (DellaVigna and Gentzkow, 2019; Hitsch, Hortaçsu and Lin, 2019), and the transmission of shocks (García-Lebergman, 2021).

Furthermore, this paper closely relates to a strand of literature investigating the effects of minimum markup laws on gasoline prices. Anderson and Johnson (1999) study weekly gasoline markets from 42 major cities of the U.S. between 1992 and 1993, and finds that average prices and retail margins were higher in cities in which below-cost pricing restrictions apply. By contrast, Anderson and Johnson (1999) and Peltier, Skidmore and Milne (2013) study gasoline markets on 50 states of the U.S. from 1983 to 2002 and find that MMLs

stimulate the entry of smaller competitors to regulated markets pushing average prices down compared to states without MMLs.

On the methodological dimension, this paper closely relates to the literature that estimates demand for bundles of products. Hendel (1999) develops a multiple-discrete choice model to explain how firms choose multiple alternative brands of personal computers. Further, Dubé (2004) applies Hendel's model to the case of carbonated soft drinks. Gentzkow (2007) develops a framework in which similar products can be either substitutes or complements. Wildenbeest (2011) sets out a search cost model in which consumers want to purchase a bundle of products in a single stop and care about the total price of the bundle. Thomassen et al. (2017), Florez-Acosta and Herrera-Araujo (2020) and Leung and Li (2021) develop demand models of multiproduct and multistore choice with shopping costs, which endogenously capture complementarities between categories/products and helps explain the composition of bundles.[1] Iaria and Wang (2020), Ershov et al. (2023), and Wang (2021) build on Gentzkow (2007) and develop frameworks to estimate demand for multiple products with complementarity, each of them focuses on particular challenges that emerge in this context.[2]

Finally, this paper relates to a strand of empirical literature that models consumer choice problems explicitly accounting for consumer frictions, such as, search (e.g. Hortaçsu and Syverson (2004); Hong and Shum (2006); Kim and Bronnenberg (2010); Wildenbeest (2011); De los Santos, Hortaçsu and Wildenbeest (2012); Moraga-Gonzalez, Sandor and Wildenbeest (2013); Koulayiev (2014); Honka (2014); Dubois and Perrone (2015)); switching (e.g., Shy (2002); Viard (2007); Honka (2014)); and shopping frictions (Brief (1967); Aguiar and Hurst (2007); Thomassen et al. (2017); Florez-Acosta and Herrera-Araujo (2020); Leung and Li (2021); Dolfen et al. (2022)).

[1] Thomassen et al. (2017) focus on competition between specialized stores and supermarkets and develop a model of demand in which consumers make discrete-continuous choices over multiple *macro-categories* of groceries from up to two stores in each period conditional on their idiosyncratic shopping costs. Similarly, Leung and Li (2021) develop a model of demand for multiple categories of products (including both groceries and non-groceries) and stores and allow for continuous choice of quantity and shopping trip costs. Alternatively, Florez-Acosta and Herrera-Araujo (2020) focus on the role of shopping costs in predicting consumer substitution and shopping patterns in a context of competition between supermarkets of similar size and product range; in their setting, the number of stores visited by a consumer is endogenously determined by a stopping rule involving the extra utility and extra costs involved in visiting an additional store.

[2] Iaria and Wang (2020) and Wang (2021) address the problem of identification of demand models for multiple products when complementarity may emerge; the former provides conditions for identification and an MLE estimator when transaction level (individual) data is available; the latter focuses on aggregate (product-level) data and also provides conditions for identification of the demand parameters. Ershov et al. (2023) deals with large choice sets, which is a challenge that this literature commonly deals with, and propose an estimator based on aggregate data at the product category level but exploiting micro moments from transaction level data

3 Data and background

3.1 Overview of the data

This paper uses the NielsenIQ consumer panel and retail scanner data sets supplied by the Kilts Center for Marketing at the University of Chicago Booth School of Business. The consumer panel consists of home scanner data that records grocery purchases and household information of a representative sample of households from all states in the U.S. On the other hand, the retail data set is scanner data recorded by participating retail stores at the Universal Product Code (UPC) level in a weekly frequency, including retail prices, volume sales, product description, and store location (three first digits of zip code) of every UPC. The two data sets can be merged using both the retailer code and the zip codes.

3.2 Background: Minimum markup laws in the U.S.

Most states of the United States impose minimum markups (or, equivalently, price floors) either partially on a subset of retail products or fully on all kinds of retail products. Some of these state laws date back from the 1930s. Figure 1 shows the states of the U.S. that currently have laws imposing price floors on groceries. While in most regulated states, such as California, Wisconsin, Massachusetts and other 20 states, the restriction applies to all grocery products, in a few states, such as Nevada, Missouri and North Carolina, the ban applies only either to dairy or milk. Further, there are states imposing minimum markups on non-grocery products. Table 1 shows the products for which a minimum markup provision is in place in states in which a partial regulation applies. These are mainly cigarettes (banned in 11 states), and gasoline (banned in 6 states). Finally, only 10 states do not impose any restriction of this kind on the pricing of retail products; they include Illinois, Michigan, Texas, Arizona and other 6 states.

4 Preliminary evidence: Wisconsin case study

4.1 Background

Wisconsin is one of the states of the U.S. that prohibits selling goods bellow cost both upstream and downstream. The law that bans this practice, officially known as "Unfair Sales Act" but commonly referred to as the "Minimum Markup Law", has been in force for 83 years now. The prohibition covers all merchandise but establishes different cost thresholds

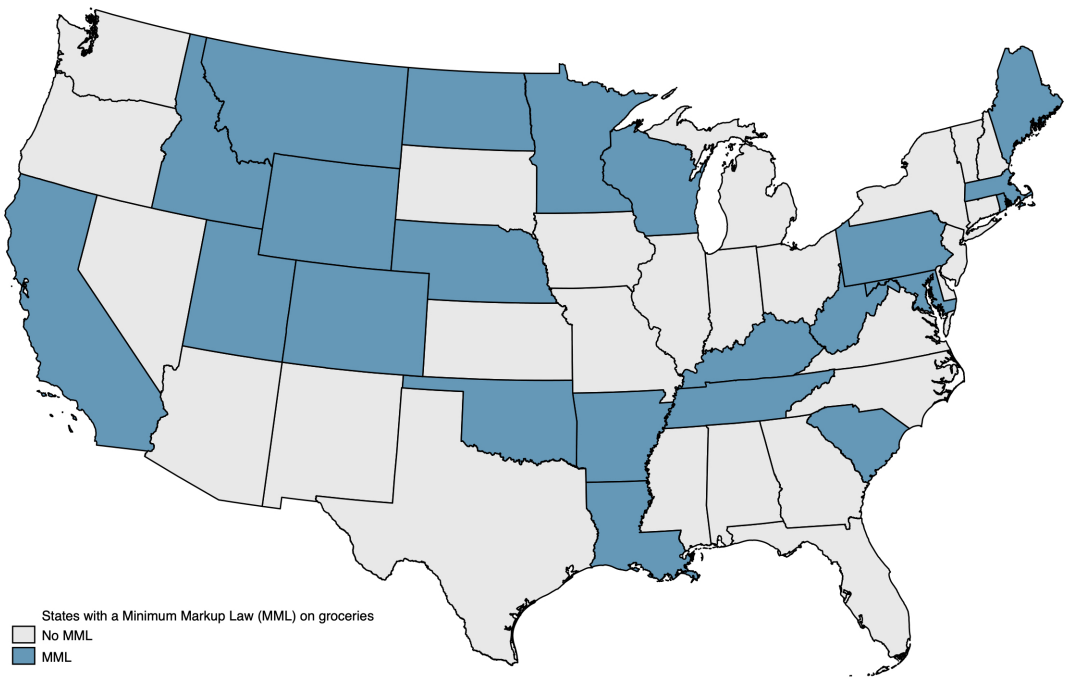


Figure 1: States of the United States of America requiring minimum markups

Notes: the figure shows in blue the States of the U.S. that currently have laws banning below-cost pricing on groceries. There are states that have partial bans on products other than groceries such as gasoline, cigarettes, or alcohol. Given that our focus is on grocery products, we consider those states as "non-ban" states; they appear in gray in the map.
Source: Fleisher, Chris, "Loss-leaders: predatory or practical?", American Economic Association, https://www.aeaweb.org/research/loss-leading-bans-retail-competition.

Table 1: Products included in sales-below-cost ban in states with partial restrictions

Included products	Number of states	States
Gasoline	6	Missouri, New York, North Carolina, Georgia, Alabama, Florida.
Cigarettes	11	Washington, Nevada, South Dakota, Iowa, Indianna, Ohio, New York, New Jersey, Delaware, Mississippi.
Milk	3	Nevada (dairy), Missouri, North Carolina.
Alcoholic beverages	2	Kansas, New Hampshire.

Source: Fleisher, Chris, "Loss-leaders: predatory or practical?", American Economic Association, https://www.aeaweb.org/research/loss-leading-bans-retail-competition.

for different groups of products. In effect, the cost threshold for all products except alcoholic beverages, tobacco and fuel, is defined as "invoice cost or replacement cost, whichever is lower, less all trade discounts, plus any excise taxes and any cost incurred for transportation

and any other charges not otherwise included in the invoice cost or replacement cost of the merchandise."[3] For alcohol and tobacco the cost threshold includes a minimum markup or "cost of doing business" which requires both manufacturers and retailers to sell their products at a minimum price equivalent to the corresponding cost plus 3% for manufacturers and 6% for retailers. Finally, for motor fuel, there are two ways of approximating the retailer cost: first, the invoice or replacement cost plus a 6% markup (so-called "cost of doing business"); or second, the average posted terminal price plus a 9.18% markup.[4] The retailer should take the greater of the two as its cost threshold. Further, the law requires refiners and wholesalers to add similar markups to their cost to set their tariffs. [5]

In the last two decades, there has been a debate about the pros and cons of the law as well as attempts to repeal it which has been reportedly supported by Wal-Mart (Badger Institute, 2016). Supporters, among which is the Wisconsin Petroleum Marketers and Convenience Store Association, claim that the law protects small and big local businesses against potential predatory practices from national chains, which ultimately favors consumers. On the other hand, opponents claim that the law is doing exactly the opposite: it is imposing an overprice onto consumers and crowding out demand from Wisconsin's stores and gas stations to neighboring states were below cost is not prohibited (Badger Institute, 2016).

The 2009 law suit and the temporary law void

Wisconsin's MML was temporarily void between February 2009 and September 2010, by a federal court. The decision was motivated by a court dispute between fuel retailers claiming that prices charged by one of them violated the Wisconsin's Statute. This court battle started in 2007, when the gasoline retailer Flying J Inc., allegedly engaged in selling gasoline at prices that were below the minimum retail price allowed by the law. Flying J submitted an answer in which it challenged the constitutionality of the law arguing that the minimum markup requirement for fuel distribution violated the Sherman Act. On October 12, 2007, Judge William Callahan concluded that the Wisconsin's Unfair Sales Act was, in effect, imposing a restraint of trade and, therefore, violated the Sherman Act.[6]

Despite Judge Callahan's decision, the Wisconsin's Department of Agriculture, Trade and

[3]See the Unfair Sales Act website at: https://datcp.wi.gov/Pages/Programs_Services/UnfairSalesAct.aspx, last accessed: December, 2022.

[4]The average posted terminal (or "rack") price is the average price posted by the terminal (i.e., fuel storage and distribution facility) which is closest, on straight line distance, to the gas station (See the Unfair Sales Act website). It has been considered a good measure of the true wholesale cost (Badger Institute, 2016).

[5]See the Unfair Sales Act website at https://datcp.wi.gov/Pages/Programs_Services/UnfairSalesAct.aspx,lastaccessed:December,2022..

[6]See Judge Callahan's Opinion on "Lotus Group Llc. v. Flying J Inc.", Case No. 07-C-0144.

Consumer Protection continued to require gasoline retailers to issue pricing reports under the MML "with the implicit threat of enforcement actions, civil penalties and other remedies to follow".[7] As a reaction, in January 2008 Flying J filed a lawsuit against the State of Wisconsin arguing that the minimum markup provisions required by the law were not linked to actual costs and, as a consequence, the law was softening competition, allowing inefficient retailers to make high profits, and affecting the competitiveness of companies on interstate commerce (Badger Institute, 2016). On February 11, 2009 Federal Judge Rudolph Randa concluded that the minimum markups on fuel were leading to collusive prices and, hence, the Unfair Sales Act imposed an illegal restraint of trade, violating the Sherman Act. Judge Randa, hence, ordered that, among other things, the Unfair Sales Act was unconstitutional and that the State should refrain from enforcing that law. The State decided not to appeal the decision and, hence, the law was void.

The Wisconsin Petroleum Marketers and Convenience Store Association, a key supporter, intervened before a U.S. Court of Appeals and on September 3, 2010 the Court overturned the federal judge ruling saying that there was no evidence of collusion or other conduct that violated the federal law. Wisconsin's minimum markup law has, therefore, been back in force ever since that date (Badger Institute, 2016).

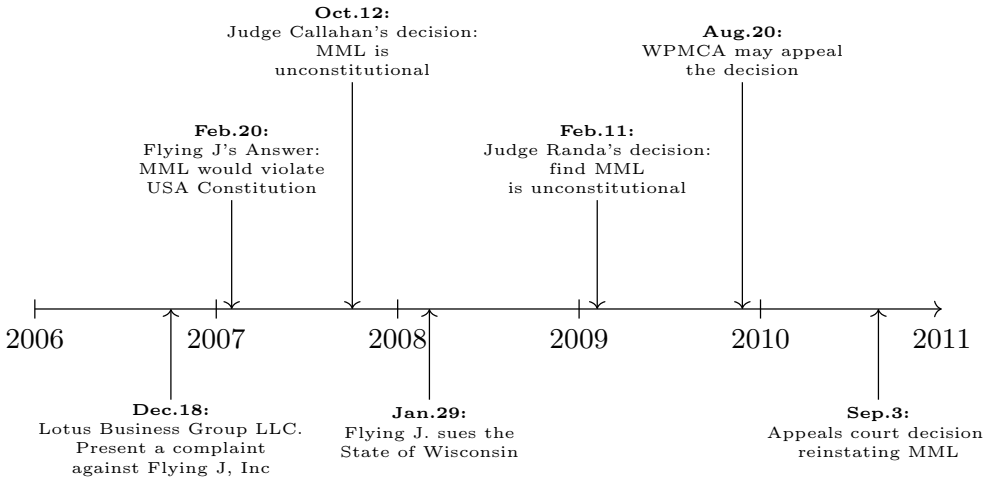


Figure 2: Timeline of the legal battle leading to Wisconsin's USA void

Notes: this figure shows a timeline with key facts in the legal battle that ended up with Judge Randa's order according to which Wisconsin's Unfair Sales Act (USA) was unconstitutional at least in the gasoline provisions (February 11, 2009).

[7]See Judge Randa's Opinion on "Flying J Inc. v. Van Hollen", Case No. 08-C-110.

4.2 Empirical strategy

We exploit this exogenous supply shock to identify the causal effect of the below-cost pricing laws on retail prices. Previous literature suggests that not all products may be equally affected by such a shock. For example, (Chevalier, Kashyap and Rossi, 2003) show that supermarkets considerably drop the price of specific products such as beer, soup, cheese, snack crackers and tuna during peak demand seasons to draw consumers into the stores. Further, (Chen and Rey, 2019) show that multiproduct firms price competitive (i.e., "weak") products below-cost and compensate their losses with a high price on other ("strong") products. That is, MMLs would shift optimal prices for certain products upwards, while for some others it would shift optimal prices downwards.

We examine the case of milk and ready-to-eat breakfast cereals. These products are well suited to perform our causal analysis as they are frequently purchased staples, and are often purchased and consumed together. To balance out our data set, we adopt a similar approach to Butters, Sacks and Seo (2022) and select chains and stores as follows: first, we define chains as combinations of two identifiers available in the data: parent company (the owner of one or multiple chains) and retailer (a specific chain); second, we keep chains that report at least 61.5% of weeks; third, we exclude from our sample the stores that are associated with multiple chains, which may be the result of changes in store ownership or mergers; next, we exclude stores with less than 17% of weeks reporting sales; last, we drop two chains that do not report any sales for several weeks around the event date. Further, we define products as UPC-version combinations and drop products with very few observations.

Table 2 presents summary statistics of our final samples by product. In the case of milk, it consists of 1495 products, and 13,293 stores in 88 chains. Of the total stores, 4% are owned by the 10 chains that were affected by the law void in Wisconsin, whereas the remaining stores are owned by 78 chains that were not exposed to the shock. The average price of a 8.4 oz serving of milk is 41 dollar cents. Note that the mean price per serving in exposed stores is 16% higher than in unexposed stores. Finally, the share of sales of the chains with stores in Wisconsin (i.e., exposed to the shock) is, on average, 26%. In the case of cereals, our sample consists of of 4182 products, and 15,255 stores in 91 chains. Of the total stores, about 5% are owned by the 15 chains that were affected by the law void in Wisconsin, whereas the remaining stores are owned by 91 chains that were not exposed to the shock. The average price of a 1.13 oz serving of RTE cereals is 27 dollar cents. Finally, the share of sales of the chains with stores in Wisconsin (i.e., exposed to the shock) is 31.4%, on average.

Our empirical strategy follows Butters, Sacks and Seo (2022) closely. We compute weekly

Table 2: Summary statistics of the milk and RTE cereals samples

	Milk			RTE cereals		
Variable	Exposed	Unexposed	Total	Exposed	Unexposed	Total
Number of products	1213	1410	2623	2460	3817	4182
Serving size (oz)	——	——	8.4	——	——	1.13
Chains						
No. of chains	10	78	88	15	91	106
No. of multistate chains	8	54	62	13	61	74
No. of stores	557	13293	13850	739	14516	15255
Prices (dollar cents)						
Mean	42.46	36.48	41.13	27.30	27.15	27.21
10th percentile	22.84	19.56	21.46	15.28	15.11	15.18
Median	43.58	31.43	41.74	24.10	25.95	25.51
90th percentile	58.93	60.20	58.93	41.97	39.50	39.99
Share of weekly sales (chain level)						
Mean	2.56%	2.49%	2.53%	2.40%	2.40%	2.40%
10th percentile	0.09%	0.28%	0.09%	0.03%	0.06%	0.04%
Median	1.04%	2.37%	1.30%	1.57%	0.94%	1.20%
90th percentile	7.52%	5.21%	6.02%	7.16%	7.91%	7.18%
Share of sales in Wisconsin (within chain)						
Mean	26.33%	——	——	31.42%	——	——
10th percentile	0.56%	——	——	1.30%	——	——
Median	2.88%	——	——	5.28%	——	——
90th percentile	100%	——	——	100%	——	——

Notes: This table presents summary statistics of the sample composition of milk and RTE cereal sales data in the U.S. between 2007 and 2012. The column "Exposed" contains numbers for chains and stores located in Wisconsin; whereas the column "Unexposed" contains numbers for chains and stores located outside Wisconsin; that is, they were not exposed to the shock. The second to last panel of the table presents chain-level weekly market shares averaged across chains in the U.S.; shares are computed as the total sales of a chain in a week divided by the total sales of all of the supermarket chains in the sample that week. The bottom panel displays pre-event week market shares of stores located in Wisconsin relative to their chain total sales; shares are computed as the total sales of a chain's stores located in Wisconsin in the week of February 1st-7th, 2009, divided by the total sales of all that chain's stores in the U.S. that week.

average prices per product (j) and store (l), p_{jlt}, as weekly revenue over volume sales of that product in each store. We face a challenge given that our data set records a very large amount of transactions from all stores in the U.S. To reduce the computational burden of our empirical exercise, we proceed as follows: first, we compute residual prices $\widetilde{p}_{jlt}$ by

removing a product-store level average $\overline{p}_{jl}$ from the the observed price of product j; and, second, we aggregate residual prices at the chain-state-week level by taking the average of product-level prices across products and stores from the same chain (c) located in a given state (s) and at a given week. As a result, we obtain a chain-state-week level residual price $\widetilde{p}_{cst}$. This procedure greatly reduces the dimensionality of our data set and does not affect our identification strategy as the treatment vary at the state level.

Figure 3 plots average (across chains and states) residual prices of milk in stores located in Wisconsin, which were directly exposed to the shock, and stores located in states different from Wisconsin, which were not exposed to the shock. The two series show a similar evolution previous to October 12, 2007; this is suggestive of potential parallel trends. After this date, one can see some gaps between exposed and unexposed stores' prices; after the official law void on February 11, 2009, we can observe a clear gap between the two series: there is a steeper decrease in the average price of exposed stores relative to unexposed stores. Average milk prices in exposed stores appear to decrease until the end of August and after that it starts to increase; the gap disappears a few weeks after that date.[8] The behavior of average prices become similar again after the date the Court of Appeals ruled against the law void decision (in September 2010).

4.2.1 Event study

We look at weekly changes in a product's prices in Wisconsin-based stores relative to non-Wisconsin stores before and after the law void. our treated group consists of stores located in Wisconsin; following Butters, Sacks and Seo (2022), we refer to them as *directly exposed stores*. Alternatively, our control group consists of stores that are located in states different from Wisconsin and that are owned by chains that have no presence whatsoever in Wisconsin (*unexposed stores*). We estimate the effects of the law void using the following event study specification:

$$\tilde{p}_{cst} = Exposed_{cs} \times \sum_{m \neq -1} \beta_m^D \mathbb{1}\{t - t^* = m\} + \eta_t + \phi_{cs} + \varepsilon_{cst}, \tag{1}$$

where $Exposed_{cs}$ is a dummy that equals 1 if the store owned by chain c is directly exposed to the shock, and 0 otherwise. The indicators $\mathbb{1}\{t - t^* = m\}$ measure the time relative to

[8] The change in trends of prices coincides with a decision made by the Court of Appeals of the Seventh Circuit, which granted the Wisconsin Petroleum Marketers and Convenience Store Association a motion to intervene in the case through an appeal of judge Randa's decision (see "Flying J Inc. v. WPMCA", Case No. 09-1883).

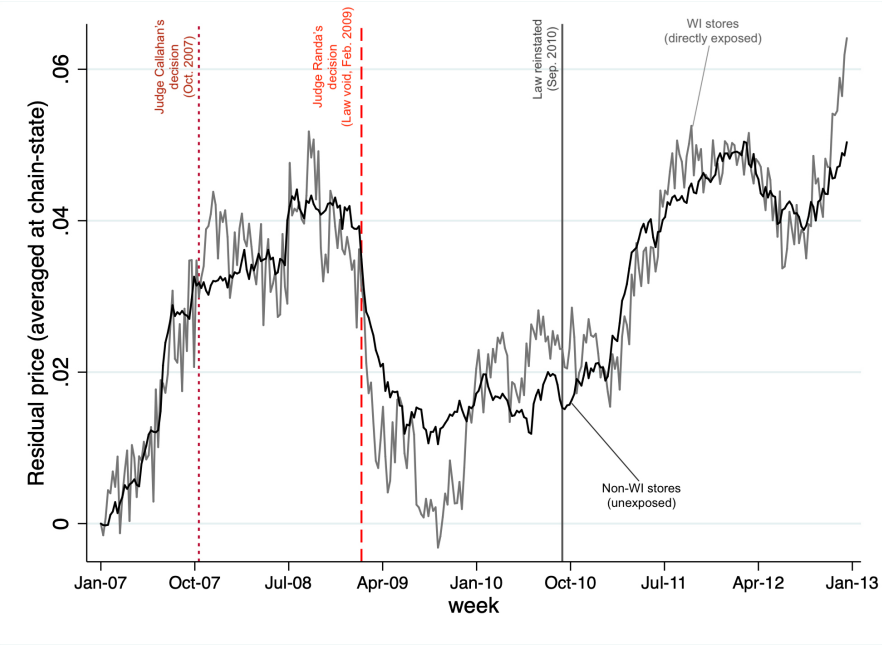


Figure 3: Average residual price of milk for directly exposed and unexposed stores

Notes: this figure shows the average residual price series for stores located in Wisconsin (WI), that were directly exposed to the shock, and for stores located in states other than Wisconsin and that were not exposed to the shock. The vertical dotted line marks the week in which Judge Callahan made the pre-void decision in a private lawsuit (October 12, 2007); the dashed vertical line indicates the week in which Judge Randa declared void the Wisconsin's Unfair Sales Act (February 11, 2009). The continuous vertical line marks the week in which a Court of Appeals reinstated the law (September 3, 2010).

the month in which the law void took place, t^*. Finally, η_t and ϕ_{cs} are, respectively, month and chain-state fixed effects. We omit from the regression the month prior to October, 2007, which is the month in which the first opinion about the unconstitutionality of the law was issued, $m = -1$, and interpret the estimated coefficients β_m^D as the change in prices in directly exposed stores compared to unexposed stores relative to one month prior to the event.

We perform separate event studies on milk and ready-to-eat (RTE) breakfast cereals using equation (1). Figure 4 shows the monthly estimates and their 95% confidence intervals for each product. In the case of milk, we find that prices in Wisconsin start decreasing two months after Judge Callahan's decision was issued but the decreases are only significant around the date in which judge Randa's decision was made public. This is consistent with the fact that the first decision did not imply a void of the law but firms started anticipating that the void would come in the future. In the case of RTE cereals, we estimate several increases and decreases; three of these are very precisely estimated: one decrease in month 15th after the event (one month before the second decision was made public), and two increases in months 16th (the month in which the second decision was made public) and

18th after the event. Our results on milk are consistent with theory and conventional wisdom on supermarket pricing: average milk prices significantly drop for several periods after the law void, suggesting that the price floor imposed by the law shifted optimal prices upwards. By contrast, the event study on RTE cereals shows both significant increases and decreases after the law void; while we can see more increases than decreases, it is difficult to draw an unambiguous conclusion as long as the magnitudes of the increases are smaller than the decreases. Therefore, below we use a difference-in-differences strategy to estimate the average effect of the law on both products.

4.2.2 Difference-in-differences model

To obtain the average effect across all post-shock months, we estimate difference-in-differences coefficients for our two products. Our post-event indicator, $post_t$, equals 1 from the month in which the first decision by Judge Callahan took place (October, 2007), and zero otherwise; we interact it with indicators for directly exposed stores (D_{cs}). Further, we restrict our post-event periods differently for each product based on the results of the corresponding event studies; we allow for 28 and 22 months after the event for milk and RTE cereals, respectively; that is, three months after the last significant effect is observed in each case. We use all unexposed stores (in ban and non-ban states) as controls. Formally, we estimate the following specification:

$$\tilde{p}_{cst} = \alpha + \beta^D D_{cs} \times post_t + \theta_t + \lambda_{cs} + \nu_{cst}, \tag{2}$$

where θ_t are month fixed effects and λ_{cs} are chain-state fixed-effects.

We test the robustness of our results by restricting our control group to the unexposed stores that are located in ban states only; this allows us to have a more precise definition of our control group based on a key pre-event characteristic.

Table 3 displays the results. Columns (1) and (2) use the full sample, while columns (3) and (4) restrict the control stores to those in ban states only. Our results are robust to the definition of the control group. Our preferred specifications (columns 1-2) show that removing the Wisconsin's MML implies a decrease in retail milk price by 0.51 cents, on average, per serving or 2.05 cents per liter of milk;[9]; and an increase in retail RTE cereal price of 0.09 cents per serving or 1.14 cents per 18 oz box of cereal.[10] Our results provide empirical support to recent theory predictions according to which supermarkets charge lower

[9] One serving of milk is 8.4 Oz and one liter contains 4 servings, approximately.

[10] One serving of RTE cereal is, on average, 1.13 oz, and a 18 oz box contains 15.9 servings, approximately

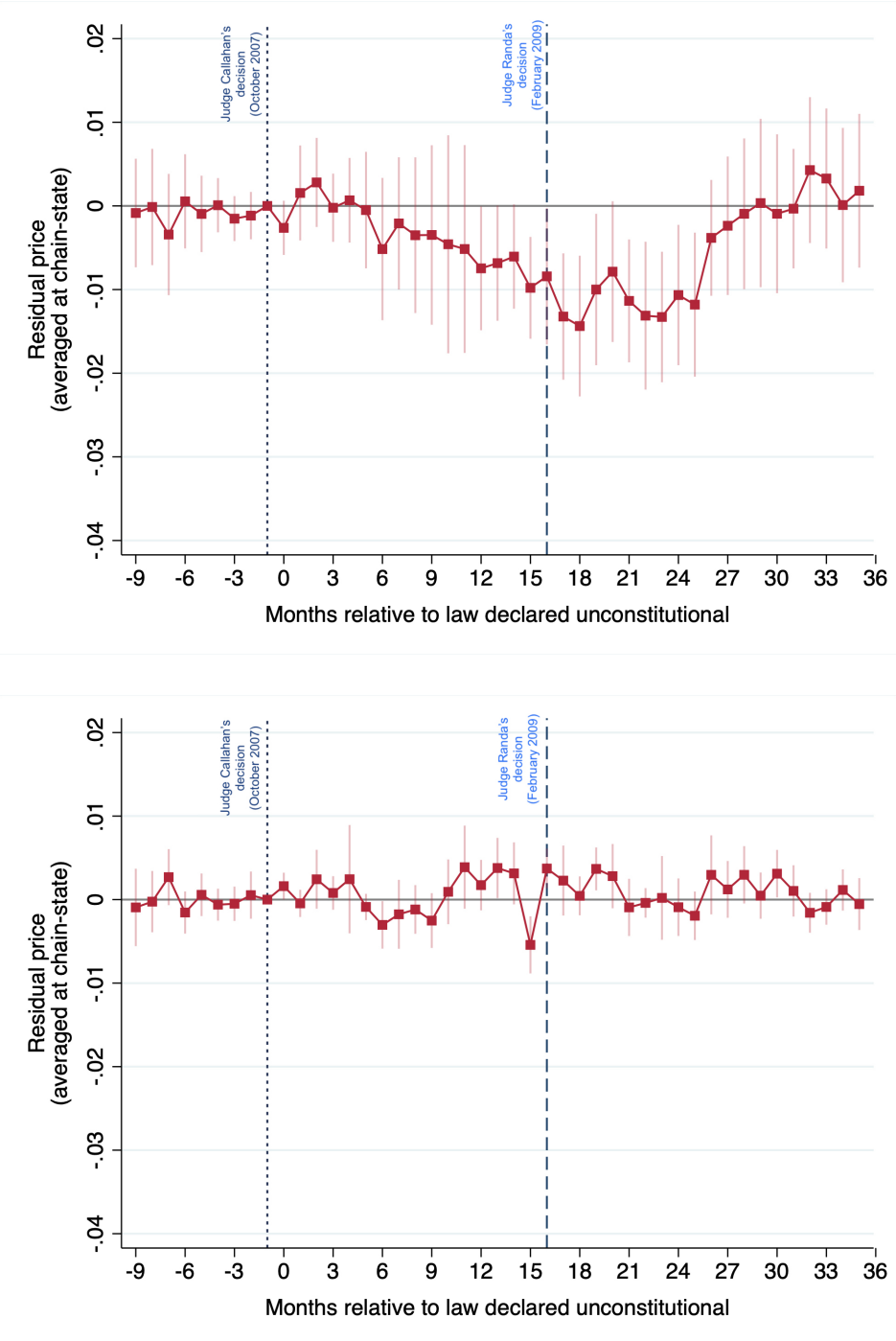


Figure 4: Effect of the law void on milk (top) and RTE cereal (bottom) prices of directly exposed stores

Notes: This figure shows estimated coefficients of equation (1) of residual prices of milk (top) and RTE cereals (bottom) at the chain-state-week level between 2007 and 2010. The estimates are for stores that were directly exposed to the law void because they are located in Wisconsin. Estimates capture the change in residual prices of each product for directly exposed stores with respect to unexposed stores in the 9 months before and 36 months after the first decision made by Judge Callahan in October 12, 2007, taking the month right before the event month (month "-1") as the reference. The dashed line marks the date, February 2009, in which Judge Randa declared the Wisconsin's Unfair Sales Act unconstitutional and voided it. The 95% confidence intervals are plotted for each data point.

prices on popular products to attract consumers into the stores, and compensate potential losses with high-markup products that exhibit strong complementarities with the former (see, for example, Chen and Rey (2019)).

Table 3: Difference-in-differences estimates of the effects of law void on prices

	Controls: All chains		Controls: chains in ban states	
Variable	Milk (1)	RTE Cereals (2)	Milk (3)	RTE Cereals (4)
Directly exposed × post	-0.0051*	0.0009**	-0.0046*	0.0009**
	(0.0026)	(0.0003)	(0.0025)	(0.0004)
No. Observations	49,531	44,554	29,292	26,834
No. Chains	88	95	64	69
R-squared	0.60	0.06	0.61	0.06

Notes: This table displays the results of difference-in-differences regressions with chain-state-week prices as the dependent variable. All regressions show estimates with the post indicator defined from month 10. Regressions (1) and (2) use the full sample, while regressions (4) and (5) restrict the control stores to those in ban states only. All regressions include a constant, and chain-state and month fixed-effects. Standard errors clustered at the chain level are given in parentheses. Significance levels: *=10%, **=5%, ***=1%.

5 A structural analysis of the effects of minimum markup laws

5.1 The model

Our demand model is based on Florez-Acosta and Herrera-Araujo (2020). In each choice occasion, consumers can purchase bundles of products from either one or multiple stores, conditional on their idiosyncratic shopping costs.

5.1.1 Consumer choice model

There are I consumers in the market indexed by $i = 1, \ldots, I$ with idiosyncratic valuations of K grocery products indexed by $k = 1, \ldots, K$. Suppose that there are three store chains in

the market indexed by $r \in \{A, B, C\}$ that supply the same products to all consumers.[11] We observe consumers making choices of products and stores on many time periods, indexed by $t = 1, \ldots, T$. Customer i purchasing product k from store r in period t derives a net utility of $\overline{v}_{ikrt}$, which is a function of the price of the product and other characteristics.[12]

Consumers have unit demand for each product class and can purchase one, two or three products in the same period. Let $\mathcal{B}$ be the set of all exclusive and exhaustive bundles. Consumers may purchase bundles with multiple products from a single store (*one-stop shopping*) or from multiple stores (*multistop shopping*). To understand the composition of the bundle purchased by consumer i, we allow for two factors: first, following Gentzkow (2007), a factor that captures the potential incremental utility of purchasing two or more (possibly *a priori* unrelated) products together, Γ; and second, a factor that captures consumer costs of shopping and, hence, determines the number of different stores that consumer i can visit in the same shopping occasion; that is, this factor captures potential complementarities between competing stores. Therefore, in our model a multistop shopper has sufficiently small shopping costs, otherwise she will optimally make her purchases from a single store.

We focus on the fixed component of the total shopping costs that may account for the consumer's taste for shopping. From now on, we will refer to this fixed cost as "shopping costs" and denote it as s_i. Transport costs, which are an important component of the total cost of shopping, are accounted for by including the distance to stores as an additive term to the utility function of a bundle of products (see below). Accordingly, shopping costs are assumed to be independent of store characteristics (e.g., size, facilities, location) and time invariant. Furthermore, we assume that s_i is randomly drawn from a continuous distribution function $G(\cdot)$ and positive density $g(\cdot)$ everywhere. Finally, we assume that consumers are well informed regarding prices and product characteristics. Therefore, consumers do not need to engage in a costly search to gather information about prices and product quality.

Consumer i is supposed to exhibit optimal shopping behavior. This implies that she makes an optimal choice involving two elements: whether to be a one- or multistop shopper, and which stores to visit for each of the products she wants to buy. Roughly speaking, the choice set of consumer i will be restricted by the number of stores she can visit given her shopping costs, so that her choice will consist of selecting the mix of products and stores that maximize

[11] Assuming that all consumers have access to the same product range may appear unreasonable. However, this helps us to reduce dimensionality issues in the estimation of the model. An extension of the model would be to relax this assumption and allow for heterogeneous choice sets.

[12] For now, we do not specify a functional form for the product-level utility, as it is not necessary for setting out the model. We will assume a parametric specification at the empirical implementation stage in Section 5.2.

the overall value of the desired bundle. In line with this, a three-stop shopper who can visit all stores and wants the three products will select the best product–store combination from the alternatives existing in the market within each category. A two-stop shopper will select the mix of two stores maximizing the utility of the desired bundle from all possible product–store combinations. Her final bundle will consist of the best of the two alternatives in each product category. Finally, a one-stop shopper will choose the store offering the largest overall value for the whole bundle of products.

Formally, let D_{ir} denote the distance traveled by consumer i from her household location to store r's location, for all $r \in \{A, B, C\}$, and τ denote a parameter that captures the consumer's valuation of the physical and perceived costs of traveling that distance. We define the utility net of transport costs of a shopper who is able to visit only one of the three stores in the market as follows:[13]

$$v^1_{ibt} = \max\left\{\sum_{k\in b_A} \overline{v}_{ikAt} + \Gamma_{b_A} - \tau D_{iA}, \sum_{k\in b_B} \overline{v}_{ikBt} + \Gamma_{b_B} - \tau D_{iB}, \sum_{k\in b_C} \overline{v}_{ikCt} + \Gamma_{b_C} - \tau D_{iC}\right\}. \tag{3}$$

Similarly, the net utility of a two-stop shopper is given by:

$$\begin{aligned} v^2_{ibt} = \max\Bigg\{ & \sum_{k\in b_{AB}} \max\{\overline{v}_{ikAt}, \overline{v}_{ikBt}\} + \Gamma_{b_{AB}} - \tau(D_{iA} + D_{iB}) \,, \\ & \sum_{k\in b_{AC}} \max\{\overline{v}_{ikAt}, \overline{v}_{ikCt}\} + \Gamma_{b_{AC}} - \tau(D_{iA} + D_{iC}), \\ & \sum_{k\in b_{BC}} \max\{\overline{v}_{ikBt}, \overline{v}_{ikCt}\} + \Gamma_{b_{BC}} - \tau(D_{iB} + D_{iC})\Bigg\}. \end{aligned} \tag{4}$$

Finally, the net utility of a consumer who is able to visit all of the stores is given by:

$$v^3_{ibt} = \sum_{k\in ABC} \max\left\{\overline{v}_{ikAt}, \overline{v}_{ikBt}, \overline{v}_{ikCt}\right\} + \Gamma_{b_{ABC}} - \sum_{r\in\{A,B,C\}} \tau D_{ir}. \tag{5}$$

Note that the expressions in (3), (4), and (5) are particular cases of a more general utility function, in which—conditional on shopping costs—an n-stop shopper selects the subset of stores that maximizes the overall utility of her desired bundle. For a one-stop shopper, these subsets are singletons, for a two-stop shopper they contain two elements, and for a three-stop

[13] Note that the utilities below depend on the vector of all prices of products sold by the three stores in the market, which we denote by $\mathbf{p}_t$. However, we omit this for the sake of simplicity in the presentation of the model.

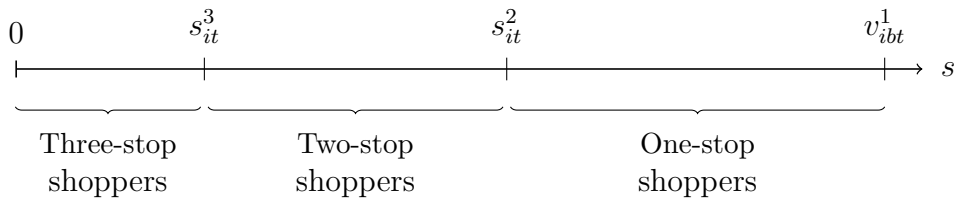
shopper each subset of stores contains precisely the number of stores in the market, which is why she does not need to maximize over subsets of supermarkets.[14]

To determine the number of stops to be made, consumer i weighs the extra utility of undertaking n-stop shopping with the extra costs involved, taking into account the fact that the total cost of shopping increases with the number of stores visited. Let $\delta_{it}^2 \equiv v_{ibt}^2 - v_{ibt}^1$ and $\delta_{it}^3 \equiv v_{ibt}^3 - v_{ibt}^2$ be the incremental utilities that consumer i derives from visiting, respectively, two stores rather than one and three stores rather than two.[15] Florez-Acosta and Herrera-Araujo (2020) show that consumer i will choose the mix of stores that maximizes her utility conditional on the extra shopping cost being at most the extra utility obtained from visiting additional stores. Therefore, the highest possible shopping costs for any consumer able to undertake multistop shopping at either two or three stores, respectively, in equilibrium are given by the following critical cutoff points:

$$\begin{aligned} s_{it}^2 &= \delta_{it}^2, && \text{for two-stop shopping, and} \\ s_{it}^3 &= \delta_{it}^3, && \text{for three-stop shopping.} \end{aligned} \tag{6}$$

Note that these cutoff points depend on the period of purchase, t. The derived cutoffs for the distribution of shopping costs in (6) indicate that for given shopping costs, consumers only care about the marginal utility of visiting an additional store in making their final decision on how many stores to visit. Moreover, one-, two- and three-stop shopping patterns arise in equilibrium and will be defined over the entire support of $G(\cdot)$ (see Figure 5).

Figure 5: One-, two-, and three-stop shopping



[14] A general expression of the utility and choices of an n-stop shopper is derived by Florez-Acosta and Herrera-Araujo (2020).

[15] For the sake of simplicity, we drop the bundle subscripts from the utilities. Note that under the assumption that each consumer looks to purchase a bundle with all K products, in the context of our model all bundles are sets of K goods with different compositions of stores where those goods were purchased from.

5.1.2 Aggregate demand

Let $\mathcal{B}_2, \mathcal{B}_3 \in \mathcal{B}$ be subsets of bundles involving two- and three-stop shopping, respectively. The aggregate demand for product k supplied by store r is given by:

$$\begin{aligned} q_{krt}\left(\mathbf{p}_t\right) = & \left[G(v_{ibt}^1(\mathbf{p}_t)) - G\left(s_{it}^2\left(\mathbf{p}_t\right)\right)\right] P_{irt}^1(\cdot) \\ & + \left[G\left(s_{it}^2\left(\mathbf{p}_t\right)\right) - G\left(s_{it}^3\left(\mathbf{p}_t\right)\right)\right] \prod_{\{b \in \mathcal{B}_2 \,|\, kr \in b\}} P_{irt}^2(\cdot) \\ & + G\left(s_{it}^3\left(\mathbf{p}_t\right)\right) \prod_{\{b \in \mathcal{B}_3 \,|\, kr \in b\}} P_{irt}^3(\cdot), \end{aligned} \tag{7}$$

where $\mathbf{p}_t$ is the $(K * 3) \times 1$ vector of prices of the products sold by the three stores in the market, P_{irt}^1 is the probability that a one-stop shopper decides to shop at store r, P_{irt}^2 is the probability that a two-stop shopper chooses store r as one of the two stores that she will visit, and P_{irt}^3 is the probability that a three-stop shopper decides to select bundle b including product kr. All of these probabilities are known by shoppers, and are functions of observable characteristics and parameters. However, for the sake of simplicity we do not specify this dependence at this stage. We defer these details to the empirical section below.

The own- and cross-price elasticities of demand are given by the standard formula $\eta_{krht} = \frac{\partial q_{krt}}{\partial p_{jht}} \frac{p_{jht}}{q_{krt}}$ for all $j \in \{1, \ldots, K\}$, $h \in \{A, B, C\}$. It is important to note that a price change may affect not only the market shares per type of shopper but also the shopping cost cutoff values given that they depend on utilities. As a consequence, the distribution of shoppers between one-, two-, and three-stop shopping groups changes. In fact, an increase in product k's price at store r reduces the indirect utility of consumer i visiting store r. Therefore, she may consider making fewer stops and purchasing a substitute for this product from a rival store, say h, as the gain in utility from visiting an additional store may not be sufficient to offset the extra shopping cost.

5.1.3 Supply

Suppose that there are M local markets, indexed by $m = \{1, \ldots, M\}$.[16] In each local market there are $l = 1, \ldots, L_m$ retail chains that set the same prices for all of their stores located in local market m.[17] Further, assume that there are $n = 1, \ldots, N$ retail chains that are

[16] In the context of our paper, local markets can be thought of as geographic regions where certain regulations apply equally for all retailers within the region; e.g., states.

[17] This assumption is consistent with the findings of Hitsch, Hortaçsu and Lin (2019) who document that prices and promotions are similar across stores that belong to the same chain and may be quite different across stores from different chain in each local market.

present in all local markets and set product-level uniform prices for all their stores across local markets (we will refer to these retailers as "National retailers"). That is, national firms set the same price for each local market.[18] We assume that all chains sell similar product lines that are *ex ante* homogeneous and consider that the supermarket supplying a given product is a source of differentiation. That is, each chain sells the same $k = 1, \ldots, K$ products. Given that product lines are *ex post* differentiated (i.e., sold by different retail chains), there are $J_m = K * (L_m + N)$ products in each local market m.

Let $\mathcal{L}_l$ and $\mathcal{L}_n$ denote the product lines of a local retailer l and a national retailer n, respectively. We assume that retail chains face a product-level marginal cost, c_j, that is the same for all stores that belong to the chain, and a store-level fixed cost per product, C_{jh}, where h denotes store.[19] Let $s_{j(m)}$ be the market share of product j in local market m. In the case of national chains, let s_j denote the national market share of product j, and it is computed as the weighted sum of the market share of that product in each local market m;[20] that is:

$$s_j(\mathbf{p}) = \sum_{m=1}^{M} \omega_m s_{j(m)}(\mathbf{p}), \quad \text{for } j \in \mathcal{L}_n. \tag{8}$$

where $\omega_m = \mathcal{M}_m/\mathcal{M}$ for all $m = 1, \ldots, M$, is a measure of the size of local market m, denoted $\mathcal{M}_m$, relative to the national potential market, $\mathcal{M}$; $\mathbf{p}$ is the $J \times 1$ vector of prices. Further, for mathematical purposes, suppose that the J products are ordered such that we can use a partition of the price vector in two subvectors, namely, the vector of all local prices set by local retailers in all local markets $\mathbf{p}_L$ and the vector of all national prices set by all of the national retailers $\mathbf{p}_N$; that is, $\mathbf{p} = [\mathbf{p}_L, \mathbf{p}_N]'$.

The problem of a local firm. A local firm l from market m has profits given by:

$$\pi_{l(m)} = \sum_{j \in \mathcal{L}_l} \left[(p_{j(m)} - c_{j(m)}) \mathcal{M}_m s_{j(m)}(\mathbf{p}) \right] - \sum_h C_h. \tag{9}$$

Assuming the existence of a pure-strategy Nash equilibrium in retail prices, the price of

[18] This assumption is consistent with DellaVigna and Gentzkow (2019) who find strong evidence according to which most retail chains use uniform pricing across its stores even if they are located in different geographic regions.

[19] This assumption is consistent with evidence and previous literature. Stroebel and Vavra (2019) find that a chain's costs vary very little across geographic regions. DellaVigna and Gentzkow (2019) use this evidence and assume a chain-level marginal cost per product for their model of optimal pricing and find similar evidence from their data.

[20] This is consistent with recent literature according to which prices are not so responsive to local demand shocks (see, in particular, DellaVigna and Gentzkow (2019) and Butters, Sacks and Seo (2022)). In this case, the size of the response of national prices to local demand shocks depends on the relative importance of a local market for the firm.

product j sold by local firm l in market m satisfies the first order condition:

$$s_{j(m)}(\mathbf{p}) + \sum_{g \in \mathcal{L}_l} \left[(p_{g(m)} - c_{g(m)}) \frac{\partial s_{g(m)}(\mathbf{p})}{\partial p_j} \right] = 0. \tag{10}$$

There is one equation for each of the products sold by local retailers. Writing this system of equations in matrix notation allows to solve for the vector of price-cost markups of all local retailers. Let $\mathbf{S}_L$ be the square matrix containing the local retailers' market share responses to changes in retail prices, with entry $S_L(j,g) = -\frac{\partial s_{g(m)}}{\partial p_{j(m)}} * d_{jg}$ for $j, g \in \{1, \ldots, J\}$, with d_{jg} being a dummy variable taking on 1 if the products j and g are in retailer l's product line and zero otherwise. Therefore, the system of first-order conditions for local retailers can be written in matrix form as:

$$\mathbf{s}_L(\mathbf{p}) - \mathbf{S}_L(\mathbf{p}_L - \mathbf{c}_L) = \mathbf{0}, \tag{11}$$

where $\mathbf{s}_L(\cdot)$ and $\mathbf{c}_L$ are the vectors of market shares and marginal costs, respectively, of all local retailers. Solving for the markups yields:

$$\mathbf{p}_L - \mathbf{c}_L = \mathbf{S}_L^{-1}\mathbf{s}_L(\mathbf{p}). \tag{12}$$

The problem of a national firm. A national firm n has total profits given by:

$$\pi_n = \sum_{j \in \mathcal{L}_n} [(p_j - c_j)\mathcal{M} s_j(\mathbf{p})] - \sum_h C_h. \tag{13}$$

Plugging (8) into (13) yields:

$$\pi_n = \sum_{j \in \mathcal{L}_n} \left[(p_j - c_j)\mathcal{M} \sum_m \omega_m s_{j(m)}(\mathbf{p}) \right] - \sum_h C_h. \tag{14}$$

Assuming the existence of a pure-strategy Nash equilibrium in retail prices, the price of product j sold by national firm n in all local markets satisfies the first order condition:

$$\sum_m \omega_m s_{j(m)}(\mathbf{p}) + \sum_{g \in \mathcal{L}_n} \left[(p_g - c_g) \sum_m \omega_m \frac{\partial s_{g(m)}(\mathbf{p})}{\partial p_j} \right] = 0. \tag{15}$$

In this case, there is also one equation for each of the products sold by national retailers. Let $\mathbf{S}_N$ be the square matrix containing the national retailers' market share responses to changes in retail prices weighted by the relative size of the corresponding local market, with entry $S_N(j,g) = \left(-\sum_m \omega_m \frac{\partial s_{g(m)}}{\partial p_j} \right) * d_{jg}$ for $j, g \in \{1, \ldots, J\}$, with d_{jg} being a dummy

variable taking on 1 if the products j and g are in retailer n's product line and zero otherwise. Therefore, the system of first-order conditions for national retailers can be written in matrix form as:

$$\mathbf{s}_N(\mathbf{p}) - \mathbf{S}_N(\mathbf{p}_N - \mathbf{c}_N) = \mathbf{0}, \tag{16}$$

where $\mathbf{s}_N(\cdot)$ is the vector of national market shares and $\mathbf{c}_N$ is the vector of marginal costs of all national retailers. Solving for the markups yields:

$$\mathbf{p}_N - \mathbf{c}_N = \mathbf{S}_N^{-1}\mathbf{s}_N(\mathbf{p}). \tag{17}$$

5.2 Empirical implementation

5.2.1 Product-level demand

We empirically specify the product-level utility as a function of observed and unobserved product and store characteristics, and time fixed effects. We allow consumer heterogeneity to enter the model through the price coefficient, which is a function of observed and unobserved household characteristics. Formally, let the utility of consumer i from purchasing product k from store r at time t be given by:

$$\overline{v}_{ikrt} = -\alpha_i p_{krt} + \mathbf{x}_{kr}\boldsymbol{\beta} + \xi_{kr} + \phi_t, \tag{18}$$

where p_{krt} is the price of product k at store r, $\mathbf{x}_{kr}$ is a vector of observed product-store characteristics, ξ_{kr} captures the mean valuation of unobserved product-store characteristics, which we capture by including product-store dummy variables, and ϕ_t are time fixed-effects. Finally, α_i is an individual-specific coefficient that captures the marginal utility of price and $\boldsymbol{\beta}$ is a vector of parameters common to all households.

5.2.2 Bundle-level demand

In line with our modeling framework, we empirically define the utility that a n-stop shopper ($n \in \{1, 2, 3\}$) derives from purchasing a bundle $b \in \mathcal{B}$ as:

$$\begin{aligned} u_{ibt} &= \sum_{kr \in b} (\overline{v}_{ikrt} - \tau D_{ir}) + \Gamma_b - s_i n_b + \varepsilon_{ibt}, \\ &= v_{ibt} - s_i n_b + \varepsilon_{ibt}, \end{aligned} \tag{19}$$

where v_{ibt} is the overall utility of bundle b net of transport costs defined by equations (3) through (5) above; n_b is the number of stores visited to purchase bundle b; s_i is the individual

shopping cost; and ε_{ibt} is an idiosyncratic bundle-level shock to utility. We allow consumer unobserved heterogeneity to enter the model through the price sensitivity parameter, α_i, and shopping cost, s_i.

Note that equations (18) and (19) fully specify the preferences of one- and multistop shoppers for both inside products and stores, and shopping patterns (one- and multistop shopping). Furthermore, these equations account for both the vertical and horizontal dimensions of consumers' valuations of products; the vertical component is captured by product-store characteristics, while the horizontal component is captured by distance to stores and shopping costs. We complete the specification of our demand model with the outside good. We normalize the observed utility of the "no purchase option" to zero, so that its utility is a function of an individual random shock to utility, $u_{iOt} = \varepsilon_{iOt}$.

A consumer who wishes to buy a bundle b at time t faces a choice set $\mathcal{B}$ of mutually exclusive and exhaustive alternatives consisting of combinations of products and stores. The bundle she chooses is such that she obtains the highest possible utility net of shopping costs. This is, for all $b' \in \mathcal{B}$, consumer i chooses bundle b at time t if:

$$u_{ibt} > u_{ib't}, \ \forall\, b' \neq b.$$

Let $\boldsymbol{\theta} = (\boldsymbol{\alpha}', \boldsymbol{\beta}', \mathbf{s}', \tau, \boldsymbol{\Gamma}')'$ be a vector containing the parameters to be estimated, where $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_I)'$ and $\mathbf{s} = (s_1, \ldots, s_I)'$ denote the vector of individual preference parameters. We follow Dubois, O'Connell and Griffith (2020) and use the large T dimension of our panel to recover estimates of individual specific parameters $(\boldsymbol{\alpha}, \mathbf{s})$, while the large I dimension of our panel allows us to identify nonparametrically the joint probability distribution function $f(\alpha_i, s_i)$ using the empirical probability distribution function of estimated $(\boldsymbol{\alpha}, \mathbf{s})$. Further, $\boldsymbol{\Gamma} = (\Gamma_1, \ldots, \Gamma_B)'$ denotes the vector of complementarity effects of all bundles in $\mathcal{B}$.

We assume that the random shocks to utility, ε_{ibt}, are distributed i.i.d. Type I Extreme Value. Integrating over ε_{ibt} yields the closed-form choice probability of purchasing exactly bundle b—i.e., under the assumption of not buying any other product along with—those in b, at time t, as a function of the characteristics of products and supermarkets:

$$P_{ibt}(\mathbf{X}, \mathbf{p}_t; \boldsymbol{\theta}) = \frac{\exp(v_{ibt} - s_i n_b)}{1 + \sum_{b' \in \mathcal{B}} \exp(v_{ib't} - s_i n_{b'})}, \tag{20}$$

where $\mathbf{X}$ is the matrix of characteristics of all inside products and stores, $\mathbf{p}_t$ is the vector of prices of all products and n_b and $n_{b'}$ correspond to the number of supermarkets visited to purchase bundles b and b', respectively.

5.2.3 Total purchase probability

A typical consumer purchases many different products from more than one store per month. Estimating a demand model with the full product range supplied by supermarkets entails a dimensionality problem.To keep the problem involving multiproduct and multistore choices tractable, we as researchers need to impose some restrictions on the consumers' choice set used for demand estimation.

Let l denote the list of products and stores which the researchers restrict their focus on. Let $\mathcal{B}_l$ denote the set of bundles consisting exclusively of both listed products and listed stores. Further, let $\mathcal{B}_{nl}$ be the set of bundles including exclusively both non-listed products and non-listed stores; its complement set, $\mathcal{B}_{nl}^c$, contains both the set $\mathcal{B}_l$, and the set of all bundles consisting of combinations of listed and non-listed product-stores, which is equivalent to the cartesian product of listed and non-listed subsets, $\mathcal{B}_l \times \mathcal{B}_{nl}$. Therefore, the exhaustive set of bundles available to consumers is given by $\mathcal{B} = \mathcal{B}_l \cup \mathcal{B}_{nl} \cup \mathcal{B}_l \times \mathcal{B}_{nl}$.

Consider a bundle b^* that contains some listed products purchased from listed stores; that is, $b^* \in \mathcal{B}_l$. The probability that a consumer purchases a bundle containing b^* is given by the sum over the choice probabilities of all bundles containing b^*, which yields:

$$\begin{aligned} Q_{ib^*t}(\boldsymbol{X}, \mathbf{p}; \boldsymbol{\theta}) &= P_{ib^*t} + \sum_{h \in b^* \times \mathcal{B}_{nl}} P_{iht} \\ &= \frac{\exp(v_{ib^*t} - n_{b^*} s_i) + \sum_{h \in b^* \times \mathcal{B}_{nl}} \exp(v_{iht} - n_h s_i)}{1 + \sum_{b' \in \mathcal{B}} \exp(v_{ib't} - n_{b'} s_i)}, \end{aligned} \tag{21}$$

where $n_b \, (b \in \{b^*, h, b'\})$ is the number of stops needed to purchase the products in bundle b.

In Appendix B we show that this probability can be re-written as a modified Logit probability of purchasing bundles in the researchers' list subset, $\mathcal{B}_l$, including two terms that account for the consumer's observed full purchase history up to period t. That is:

$$Q_{ib^*t}(\boldsymbol{X}, \mathbf{p}; \boldsymbol{\theta}) = \frac{\exp(v_{ib^*t} - n_{b^*} s_i - ln(\Delta_{1it}) + ln(\Delta_{2it|b^*}))}{1 + \sum_{g \in \mathcal{B}_l} \exp(v_{igt} - n_g s_i - ln(\Delta_{1it}) + ln(\Delta_{2it|g}))}, \tag{22}$$

with:

$$\Delta_{1it} = 1 + \sum_{b' \in \mathcal{B}_{nl}} \exp(v_{ib't} - n_{b'} s_i), \tag{23}$$

and

$$\Delta_{2it|b^*} = 1 + \sum_{h \in \mathcal{B}_{nl}} \exp(v_{iht} - n_{h|b^*} s_i). \tag{24}$$

where $n_{h|b^*}$ denotes the number of additional stops made to purchase the non-listed products conditional on purchasing b^*. Notice that the first term is the denominator of a Logit probability of purchasing a bundle that includes non-listed products only; and the second term is f a Logit probability of purchasing a bundle of non-listed products only, conditional on having purchased b^* on the same shopping occasion.

5.3 Proposed solution

Individual full purchase history. We assume that consumer choice sets are potentially heterogeneous across individuals but stable over the choice occasions. For each consumer in our data, we assume that their choice set consists of their full purchase history (FPH) (Crawford, Griffith and Iaria, 2020). That is, we single out consumers that never purchase particular products over the time series dimension of our data as having zero probability of purchasing those products (Dubois, O'Connell and Griffith, 2020). Accordingly, let each individual's FPH-based choice set be denoted by $\mathcal{B}_i$ and the subset of bundles based on the researchers' list (non-listed products) be denoted by $\mathcal{B}_{li}$ ($\mathcal{B}_{nli}$). The choice probability of bundle b^* equals the sum over the choice probabilities over all bundles containing b^*, which yields:

$$Q_{ib^*t}(\boldsymbol{X}, \mathbf{p}; \boldsymbol{\theta}) = \frac{\exp(v_{ib^*t} - n_{b^*} s_i - ln(\Delta_{1it}) + ln(\Delta_{2it|b^*}))}{1 + \sum_{g \in \mathcal{B}_{li}} \exp(v_{igt} - n_g s_i - ln(\Delta_{1it}) + ln(\Delta_{2it|g}))}, \tag{25}$$

where Δ_{1it} and $\Delta_{2it|b^*}$ are defined over $\mathcal{B}_{nli}$.

Estimation. To estimate the parameters of our model, we use the data set described in Section 3. Given that we allow random coefficients for price and shopping costs, our choice probabilities do not have a closed-form solution. Thus, we use simulated methods to estimate them. In our data, we observe consumers choosing a bundle of products (which may be the outside option) at each period t during a number of T periods. Let H index the set of all possible sequences of choices our data takes; that is, all bundle sequences at all choice occasions during our period of observation. The probability of observing consumer i making

a sequence of choices $h \in H$ is given by:

$$\mathcal{P}_{ih}(\mathbf{X}, \mathbf{p}; \boldsymbol{\theta}) = \prod_{t=1}^{T} Q_{ib^*t}(\mathbf{X}, \mathbf{p}_t; \boldsymbol{\theta}). \tag{26}$$

Let $\mathbf{h}$ be the vector of observed choices of each consumer, a natural way to estimate $\boldsymbol{\theta}$ would be to maximize the log-likelihood function:

$$\mathcal{L}(\mathbf{X}, \mathbf{h}; \boldsymbol{\theta}) = \sum_{i} \ln \mathcal{P}_{ih}(\mathbf{X}, \mathbf{p}; \boldsymbol{\theta}). \tag{27}$$

Adjusting by the researcher's choice set. Let P_{iot} denote individual i's probability of no purchase at week t, and P_{ib^*t} denote the probability that only the goods within bundle b^* are purchased by individual i. We can re-write Δ_{1it} as

$$\Delta_{1it} = 1 + \sum_{b' \in \mathcal{B}_{nli}} \exp(v_{ib't} - n_{b'} s_i) = \frac{Q_{iot}}{P_{iot}},$$

and, Δ_{2ib^*t} as

$$\Delta_{2it|b^*} = 1 + \sum_{h \in \mathcal{B}_{nli}} \exp(v_{iht} - n_{h|b^*} s_i) = \frac{Q_{ib^*t}}{P_{ib^*t}}.$$

Given that it is not possible to observe Δ_{1it} in each period t, we approximate Δ_{1it} using the ratio of each individual's average probabilities of Q_{iot} and P_{iot} over the periods where we do not observe the choice of any inside goods; this yields $\overline{\Delta}_{1i} = \overline{Q}_{io}/\overline{P}_{io}$. Further, we approximate the second term using the ratio between each individual's observed probabilities of purchasing any of the bundles that contain listed products and stores averaged over the periods where we observe those choices, $\overline{Q}_{ib^*}$, with the observed probability of purchasing any of the bundles consisting exclusively of listed products averaged over the periods where we observe those choices $\overline{P}_{ib^*}$ yielding $\overline{\Delta}_{2b^*i} = \overline{Q}_{ib^*}/\overline{P}_{ib^*}$.

5.4 Monte Carlo results

5.4.1 The full choice set

Our demand model allows shoppers to make a series of multiple-discrete choices regarding products and supermarkets from a set of mutually exclusive and exhaustive alternatives. We consider a simple setting containing three product classes, three stores and a no purchase option. Consumer choices follow model described in section 5.1. Assuming that households

can purchase at most one unit per product class, per period, restricts the full choice set to 64 bundles. We base our results on 78 simulated consumers.

5.4.2 The restricted choice set

We consider two scenarios including three product classes and two stores in the researchers' list. In the first scenario, we consider all potential combinations generated by the listed products and stores. This means that each consumer's choice set includes 26 bundles, corresponding to all possible combinations of the three products and two stores, consistent with our model, as well as an outside good. The outside good represents all bundles that do not include any of the listed products, as well as the no-purchase option. In the second scenario, consumers' consideration sets are constructed based on their observed purchase combinations using the full purchase history.

To demonstrate that our correction performs well even when the researcher's product selection is arbitrarily small, and to assist in the identification of all product-store preferences in a single estimation, we construct nine singleton bundle choice sets (i.e., bundles containing at most one product class). These choice sets include an outside option that captures all other bundles not containing the listed product, as well as the no-purchase option.

We set the number of shopping occasions to 208 ($= 4 \times 52$), which is consistent with the number of periods that we use from the NielsenIQ Consumer Panel data.

5.4.3 Parameter values

The first column of Table 4 reports the parameter values underlying the true preferences. The product-store preferences are all positive, ranging between 0.5 and 3. The preference complementarities across pairs of products are all equal to 0.25, with the preference complementarities for the purchase of all three goods normalized to 0. We assume that price and the number of stores visited (stops) have mean disutilities (across consumers) of 3 each. We allow for random coefficients on price and the number of stops for each individual, assuming that both are independently drawn from normal distributions with zero mean and a standard deviation of 2. Furthermore, we assume that individual draws are independent across consumers. Finally, once an individual's realization is drawn, it remains constant across periods.

5.4.4 Simulation results

Table 4 reports estimates of the model parameters using 25 Monte Carlo simulations for both scenarios described above. The column labeled "True model" provides the true values of the parameters in our data-generating process; the columns labeled "Standard" display estimation results using the standard discrete choice method commonly employed in empirical IO; and the column labeled "Corrected" shows estimation results with our proposed bias correction, which utilizes the empirical probabilities of purchasing excluded products. Panel A reports results from our first scenario, where the choice sets include products 1, 2, and 3 from store 1, and products 1, 2, and 3 from store 2, allowing for all combinations consistent with our model. It also includes singleton bundle choice sets for each of the nine products. Panel B reports the results from our second scenario, which includes only the combinations observed in the simulated consumers' full purchase history.[21,22]

Simulation results show that both the mean price coefficient and its standard deviation are consistently estimated using both the standard method and our proposed approach. However, while both methods accurately estimate the mean and standard deviation for price, our method provides a significantly better estimation of the shopping cost. As a result, nearly all the true values fall within the confidence intervals when using our method, in contrast to the standard method.

Finally, our method outperforms the standard one in estimating both product-store-specific constants and product complementarities. Overall, our Monte Carlo experiments suggest that our method effectively corrects the biases resulting from the exclusion of products and stores from the estimating choice set.

5.5 Empirical estimation and results

5.5.1 Home Scanner Data

To estimate our structural model, we use the NielsenIQ home scanner data, collected by households using a hand-held device (i.e., scanner or mobile) after each shopping trip to scan each individual product purchased, including information of the product's UPC, date

[21] This serves two purposes: (1) to better identify the product-store constants included in the researchers' list in the first choice set, and (2) to identify the product-store constants for the products excluded from the first choice set.

[22] Our method works even when only the singleton bundle choice sets are included. However, relying on singleton bundle choice sets do not allow for the separate identification of the product-specific constants from the consumers' shopping costs. The inclusion of a choice set that allows for combinations of products across stores is key for separately identifying both coefficients.

Table 4: Estimation results based on simulated data

		Panel A		Panel B	
	True model	Standard	Adjusted	Standard	Adjusted
Price disutility					
Mean	3	3.09	3.06	3.17	3.14
		[2.71, 3.54]	[2.68, 3.49]	[2.87, 3.61]	[2.84, 3.58]
Standard deviation	2	1.85	1.87	1.88	1.89
		[1.59, 2.20]	[1.61, 2.22]	[1.64, 2.20]	[1.65, 2.28]
Shopping costs					
Mean	3	1.61	2.95	1.53	2.90
		[1.45, 1.75]	[2.75, 3,12]	[1.43, 1.74]	[2.72, 3,17]
Standard deviation	1	0.62	1.02	0.57	0.99
		[0.48, 0.81]	[0.82, 1.24]	[0.46, 0.75]	[0.86, 1.18]
Mean preferences					
Product 1 - store 1	3	2.30	2.91	2.20	2.85
		[2.22 , 2.35]	[2.83 , 3.00]	[2.07 , 2.28]	[2.72 , 2.95]
Product 2 - store 1	2	1.75	1.87	1.68	1.85
		[1.70, 1.81]	[1.76, 2.01]	[1.61, 1.78]	[1.76, 2.00]
Product 3 - store 1	1	0.79	1.00	0.80	1.00
		[0.73, 0.87]	[0.86, 1.12]	[0.75, 0.88]	[0.86, 1.12]
Product 1 - store 2	1	0.17	0.94	0.21	0.98
		[0.07, 0.28]	[0.82, 1.03]	[0.10, 0.30]	[0.88, 1.10]
Product 2 - store 2	0.5	-0.07	0.49	0.02	0.57
		[-0.17, 0.03]	[0.35, 0.58]	[-0.02, 0.11]	[0.44, 0.71]
Product 3 - store 2	2	0.89	1.87	0.83	1.82
		[0.76, 1.08]	[1.78, 2.01]	[0.70, 0.98]	[1.70, 1.92]
Product 1 - store 3	1	-0.52	0.92	-0.59	0.86
		[-0.72, -0.30]	[0.77, 1.11]	[-0.77, -0.43]	[0.66, 1.06]
Product 2 - store 3	1	-0.30	0.90	-0.39	0.90
		[-0.51, -0.12]	[0.67, 1.12]	[-0.55, -0.23]	[0.67, 1.12]
Product 3 - store 3	0.5	-0.60	0.61	-0.69	0.57
		[-0.77, -0.37]	[0.37, 0.80]	[-0.86, -0.47]	[0.42, 0.77]
Product complementarity					
Product 1 & Product 2	0.25	-0.02	0.29	0.02	0.31
		[-0.09, 0.05]	[0.15, 0.42]	[-0.03, 0.089]	[0.17, 0.43]
Product 1 & Product 3	0.25	0.10	0.22	0.08	0.21
		[0.05, 0.19]	[0.12, 0.38]	[0.02, 0.14]	[0.12, 0.28]
Product 2 & Product 3	0.25	-0.24	0.24	-0.22	0.24
		[-0.35, -0.13]	[0.15, 0.35]	[-0.33, -0.11]	[0.15, 0.32]

Notes: This table presents estimation results based on simulated data from 78 consumers over 208 choice occasions, with 25 simulations. The full choice set includes 64 baskets. The column labeled "True model" provides the true values of the parameters in our data-generating process; the columns labeled "Standard" display estimation results using the standard discrete choice method commonly employed in empirical IO; and the columns labeled "Corrected" show estimation results with our proposed bias correction, which utilizes the empirical probabilities of purchasing excluded products. Panel A reports results from a scenario in which the choice sets exclude products 1, 2, and 3 from store 3. It also includes a stack of nine choice sets, each containing only a single product. All choice sets in Panel A are constructed based on the full 64 baskets. Panel B is identical to Panel A in all respects, except that the choice sets are based solely on the full purchase history from simulated households. The 99% confidence intervals are given in square brackets.

of purchase and store location. For trips to stores that NielsenIQ is in partnership with, the average price of the UPC for that store-week is used, otherwise households enter the

price paid from their receipt. Households also record if products were purchased while on a discount (i.e., "on sale", coupon).[23] We focus on data from the states of Winsoncsin and Illinois, separately, from 2007 to 2011. As opposed to the state of Winsconsin, the state of Illinois allows for free pricing. To approximate the individual's full purchase history, we restrict our attention to consumers reporting purchases over 5 years, yielding +800 consumers for each state.

5.5.2 Shopping period

We define a shopping occasion as a week in which a household records grocery purchases. During this period, a household that concentrates its purchases at a single supermarket chain can either make one visit to a store in the chain, make several visits to the same store or can visit several stores in the same chain. Regardless, we define this household as a one-stop shopper as long as it is observed to deal only with a single supermarket chain during the week. Conversely, when we see the household purchasing products from stores in competing chains during the week, we define it as a multi-stop shopper.

5.5.3 Products, stores and prices

We focus on a reduced set of nine product categories that represent the most frequently purchased products. Consumer expenditure on these nine product categories corresponds to 17% of all grocery product expenditures in our sample. Our selection of products is based on several criteria that make our empirical exercise consistent with our structural model. First, they are frequently purchased by U.S. households (typically consumed every day), and are not stored for long periods, so stockpiling is not a first order concern. Second, these categories are not close substitutes, which ensures that we can observe sufficient variation in shopping patterns, as consumers may tend to concentrate their purchases from the same category in a particular store but may wish to diversify purchases from other categories across stores.

Concerning stores, we restrict our attention to three supermarket chains. Further, we focus on local (state-wsie) chains; that is, chains that do not have stores in multiple states. Our selected chains are widely present in each state and account for nearly 25% of groceries sales made by store chains in the corresponding state in 2010. The remaining chains observed in our data are included in the outside option along with the no purchase of the included goods option. Thus, we have nine *ex-ante* homogeneous products that are available at three

[23] The home and store level scanner dataset sets can be linked. Both datasets use the same codes to identify retailers, product modules, product brands as well as barcodes.

Table 5: Characteristics of the selected categories

Product	Weekly amount[a]	Prices[b] ($)	Share[c] (%)
Soup	61	5.1	1.5
RTE cereals	37	6.4	2.4
Coffee	34	7.8	1.5
Carbonated Soft drinks	319	10.9	2.7
Cookies	25	4.2	1.6
Potato Chips	17	3.9	1.4
Eggs	19	2.2	0.9
Milk	184	4.6	3.1
Yogurt	46	4.5	1.5

Notes: [a]The weekly amount is measured in ounces, except for eggs which is measured in units. We use the average weekly amount for each year, but report only that of 2010. [b]Average weekly expenditure per product category. [c]The share on total expenditures in 2010. Source: NielsenIQ database 2010. Authors' calculations.

supermarket chains. This is consistent with our modeling framework of oligopolistic competition with differentiated product lines, where customers that value variety can visit multiple stores in the same shopping period.

As we do not observe prices but total expenditure and total quantity purchased for each product and store sourced by each household, our price variable is created in the following way: (1) compute the sum of expenditures, net of coupons, per product-supermarket pair per week at the store level; (2) divide the total expenditure over total quantity per store-week to obtain a common unit price; (3) If no price information is available after (2), take average unit prices of the product-retailer pair across stores at the zip-code level for the same week. If no price information is available after (3), take average unit prices at the DMA-code level for the same week.

A limitation of the consumer panel is the unavailability of prices for product categories not purchased, but potentially considered, by consumers at the moment of purchase. Using a similar algorithm as for the consumer panel, we exploit the retailer scanner dataset to compute prices for product categories available, but not purchased. A further limitation is the fact that we do not observe the exact location of any household, nor the exact location of stores in the retailer dataset. We only observe locations at the zip-code level. Therefore, we match the price-retailer combinations from the closest zip-code to the households zip-code every week.

5.6 Identification

We observe sufficient cross-sectional and time series variation in terms of the choices of products and stores that allow us to identify the mean utility parameters. We are able to separately identify the price coefficient from the mean utility thanks to the observed variation in the price of the same product-retailer combination. The predicted probabilities vary as a result of this variation in prices, which generates sufficient moments for identification.

Mean shopping costs are identified from the observed week-to-week variation in the number of different supermarkets visited by each consumer; for example, a household undertaking one-stop shopping one week can be observed undertaking multi-stop shopping the following week. Week-to-week variation is necessary but not sufficient for identification, as variation in terms of the set of products purchased from each store is also needed to enable the separation of shopping costs from mean product–store utility parameters. Week-to-week variation in visited chains and purchased products also allows to identify the complementarity coefficient across product categories.

A concern in the identification of demand models is the potential endogeneity of prices. There are two sources for this endogeneity commonly discussed in the literature. On the one hand, firms often react to changes in consumers' valuations for (unobserved) product characteristics by changing prices, which is the reason why prices may be correlated with the error term of the model. On the other hand, the observed variation in prices of the same product across markets may be due to market specific demand shocks that are not independent of price. We try to exploit the panel structure of our data to control for unobservables by including brand and chain fixed effects. However, given that these controls may not fully account for all the exogenous variation in prices, we estimate our demand model by applying a control function approach for price. In a first stage, we regress the price of each brand on a variation of Hausman instruments (Hausman (1997)) introduced by DellaVigna and Gentzkow (2019), which we compute as the prices of the same product-chain combination in other DMAs, excluding the DMA in which the price to be instrumented was observed.

5.6.1 Estimation results

We report estimates of the utility parameters and shopping costs according to two specifications and two estimation methods in Table 6. The first two columns, from left-to-right, report results derived from the standard demand estimation method, while the last two columns report coefficients using our proposed method with bias correction. Columns (1) and (3) do not account for product-category complementarities, while Columns (2) and (4) do.

Results are as expected: demands are downward sloping; the estimates of the mean coefficient of the number of supermarkets visited in a week are negative, indicating that shopping implies a transaction cost for the average consumer.[24] As specifications (2) and (4) allow for complementarity across product categories, including across stores, the coefficient on the number of visited stores decreases significantly. In addition, the coefficient on prices remains statistically unchanged across all four specifications.

Our bias correction yields a coefficient for the number of visited stores that is higher by a factor of two. The product attributes remained unchanged between models that do not allow for product category complementarities, while increase by a factor close to two from model (2) to model (4). Our preferred specification to compute the shopping costs is displayed in column (3). We back out the average shopping cost per visited supermarket by translating the mean coefficient of the number of visited stores into dollars, dividing it by the mean price coefficient. The average shopping cost from our preferred specification is 43 dollars per store visited.

Next, we report the averages of the estimated own- and cross-price elasticities for retailer 1 in Table 7. Own-price elasticities are negative and most are larger than -1. Cross-price elasticities intra-store are negative for all products. We interpret this as complementarity between categories in the same chain. Further, almost all cross-price elasticities are positive for the same product across stores. When the price of a product rises in a given supermarket chain, the demand for products from different categories within that supermarket decreases, whereas the demand for products in competing stores increases.

With the demand estimates in hand, we back-out product-retailer level markups for each week, akin to allowing retailers to maximize prices each week. We present backed-out markups in dollars, averaged across supermarkets, for four example weeks of 2010 in Wisconsin in Table 8. In this time window, margins are positive for most products and negative for coffee and cookies, which is consistent with previous literature on supermarket pricing behavior, setting low margins on certain competitive products and compensating the loss with positive margins on other products.

To have a detailed view of the time-series dynamics of our estimated markups, we present markup series for milk, RTE cereal, cookies and coffee from January 2007 through December 2011 in Figure 6. We observe that milk and RTE cereal markups are consistently positive, while coffee markups are consistently negative throughout the period, although we can see some positive deviations from the historical negative average; alternatively, the markups for

[24] We present the coefficients of mean price and mean number of visits in absolute values.

Table 6: Demand estimates based on observed data

	Standard		Our solution	
	(1)	(2)	(3)	(4)
Price disutility				
Mean	0.17	0.15	0.17	0.15
Standard deviation	0.02	0.02	0.02	0.01
Number of visited stores				
Mean	3.23	0.36	7.43	0.64
Standard deviation	0.24	0.42	0.72	0.35
Product attributes				
Soup	0.41	-2.75	0.41	-6.07
	[0.23, 0.59]	[-3.00, -2.48]	[0.23, 0.59]	[-6.55, -5.57]
RTE Cereals	0.69	-2.55	0.69	-5.96
	[0.47, 0.90]	[-2.85, -2.24]	[0.48, 0.90]	[-6.47, -5.44]
Coffee	0.987	-2.55	1.00	-5.89
	[0.65, 1.31]	[-2.97, -2.13]	[0.67, 1.33]	[-6.45, -5.31]
Soft drinks	0.838	-2.29	0.84	-5.65
	[0.63, 1.04]	[-2.58, -2.00]	[0.63, 1.04]	[-6.16, _5.13]
Cookies	0.376	-2.94	0.38	-6.30
	[0.18, 0.56]	[-3.22, -2.65]	[0.18, 0.56]	[-6.80, -5.79]
Potato Chips	0.458	-2.66	0.45	-6.01
	[0.29, 0.61]	[-2.92, -2.39]	[0.29, 0.61]	[-6.49, -5.52]
Eggs	-0.147	-3.39	-0.16	-6.76
	[-0.27, -0.01]	[-3.64, -3.14]	[-0.28, -0.02]	[-7.24, -6.28]
Milk	0.672	-2.18	0.67	-5.60
	[0.49, 0.85]	[-2.43, -1.92]	[0.48, 0.85]	[-6.08, -5.12]
Yogurt	0.634	-2.39	0.63	-5.74
	[0.44, 0.82]	[-2.67, -2.11]	[0.44, 0.82]	[-6.25, -5.21]
Product complementarity - FE	No	Yes	No	Yes

Notes: This table presents estimation results of the price and shopping patterns parameters, and the estimated product-store constants for selected products (Retailer 1's products). To allow for consumer heterogeneity, we create a set of bins using household size, income and marital status. We then allow the price and number of visits coefficients to be interacted with demographic fixed effects. We report the mean of the price (number of visited stores) coefficients across bins, and its standard deviation. Consumer purchase history between 2007 and 2013 from 859 individuals in Wisconsin is used to generate individual level choice sets and bias corrections. "Standard" refers to the standard demand estimation method; "Our solution" refers to our proposed method with bias correction. The 95% confidence intervals are given in square brackets.

Table 7: Mean own- and cross-price elasticities

		Soup	Cereal	Coffee	S. Drinks	Cookies	P. Chips	Eggs	Milk	Yogurt
Retailer 1	Soup	**-1.48**	-0.32	-1.21	-0.32	-0.29	-0.21	-0.17	-0.2	-0.29
	RTE Cereal	-0.34	**-1.67**	-1.45	-0.4	-0.45	-0.27	-0.22	-0.28	-0.38
	Coffee	-0.18	-0.2	**-4.63**	-0.17	-0.15	-0.14	-0.1	-0.11	-0.15
	Soft drinks	-0.34	-0.41	-1.24	**-1.72**	-0.4	-0.36	-0.19	-0.21	-0.27
	Cookies	-0.32	-0.49	-1.18	-0.43	**-1.37**	-0.33	-0.19	-0.22	-0.28
	Potato Chips	-0.35	-0.43	-1.65	-0.55	-0.48	**-1.14**	-0.21	-0.25	-0.3
	Eggs	-0.33	-0.4	-1.31	-0.34	-0.32	-0.24	**-0.77**	-0.26	-0.3
	Milk	-0.45	-0.61	-1.67	-0.44	-0.44	-0.34	-0.3	**-1.14**	-0.47
	Yogurt	-0.46	-0.56	-1.6	-0.4	-0.38	-0.29	-0.25	-0.33	**-1.3**
Retailer 2	Soup	0.03	-0.1	-0.11	0.02	0.01	0	-0.01	-0.04	-0.05
	RTE Cereal	0.23	0.04	0.44	0.13	-0.09	-0.07	-0.06	-0.01	0
	Coffee	-0.05	0	0.46	0.03	-0.02	-0.05	0	0	-0.06
	Soft drinks	0.03	0	-0.27	0.16	0.01	0	0.04	-0.05	-0.01
	Cookies	-0.02	-0.1	0.43	0.04	0.06	0.18	0.07	-0.01	-0.03
	Potato Chips	0	-0.25	0.33	-0.05	-0.05	0	0.02	-0.03	0.03
	Eggs	0	-0.04	-0.12	-0.04	-0.01	-0.02	0.06	0	0
	Milk	-0.11	-0.2	0.73	0	0.07	-0.09	0	0.18	0.11
	Yogurt	-0.15	-0.01	-0.24	-0.03	-0.04	-0.07	0.03	0	0.07
Retailer 3	Soup	0.06	0.01	-0.21	-0.03	0	0.01	0	0	0
	RTE Cereal	0.02	0.18	-0.27	0.02	-0.03	0.01	-0.02	0.05	0.01
	Coffee	0.01	-0.03	0.43	-0.08	0	0	-0.01	0.02	0
	Soft drinks	-0.01	0.03	-0.1	0.13	-0.02	0	0	0.02	0.01
	Cookies	0	0.01	0.02	-0.02	0.05	-0.02	0	0.02	0.02
	Potato Chips	-0.03	-0.04	-0.21	-0.07	0	0.11	-0.02	0.01	0.01
	Eggs	-0.03	0.03	-0.31	-0.04	-0.02	-0.02	0.07	0	0
	Milk	-0.02	0	-0.09	0.02	0	0.02	0	0.2	0.01
	Yogurt	-0.03	0.03	-0.36	-0.04	-0.02	-0.01	-0.01	0.01	0.14

Notes: Table reports mean own and cross-price elasticities for retailer 1 over the 52 weeks in 2010. Each entry i, j, where i indexes rows and j columns, gives the percentage change of demand for product category i with respect to a percentage change in price of j. Own-price elasticities are highlighted in bold characters. Zeros indicate that there are not consumers purchasing the (i, j) product combination in our sample.

Table 8: Retail markups in Winsconsin (in $)

	Average markups per weekly amount			
Weeks #	17	18	19	20
Soup	0.342	0.323	0.321	0.333
RTE Cereal	0.280	0.226	0.215	0.232
Coffee	-0.127	-0.117	-0.142	-0.154
Soft M	0.426	0.376	0.393	0.418
Cookies	-0.002	-0.010	-0.017	-0.017
Potato Chips	0.311	0.320	0.267	0.273
Eggs	0.419	0.459	0.485	0.519
Milk	1.365	1.379	1.391	1.366
Yogurt	0.442	0.453	0.460	0.466

Notes: This table presents implied markups per weekly amount of each product, averaged across supermarkets, for weeks 17 through 20 in 2010 in Wisconsin.

cookies are positive for several weeks in the first part of our period and shift to negative from the first week of 2009 (week 105). A common pattern in the series of all products is that there are three breaks in the series (this is not so clear for RTE cereals). These are partly explained by the way we estimate our preferences. Preferences used to back-out the margins are not allowed to change within a year, but are allowed to change across years. Alternatively, estimating the preferences on a more narrow time-window will probably smooth out the breaks; however the qualitative result will remain the same.

A striking feature of these breaks is that they coincide with court decisions on the Wisconsin's MML Margins. To see this, we plot estimated markups of milk in Wisconsin in Figure 7 with vertical lines marking the three key decisions issued by different courts. The figure shows that markups are very stable for several weeks before a break takes place. They are, on average, 2.43 dollars per weekly amount purchased in 2007. Then, an abrupt drop takes place in the first week of 2008 and markups remain stable during this year around 1.69 dollars per weekly amount; this implies a decrease on average margins of 30% between 2007 and 2008. Further, in the first week of 2009 markups drop again and remain stable for 104 weeks around 1.29 dollars per weekly amount; this implies a further decrease on average margins of 24% with respect to 2008. Finally, markups suddenly increase in the first week of 2011 and remain stable during that year around 2.06 dollars per weekly amount; this implies an increase on average markups of 59% relative to 2009-2010 markups. As the graph shows, the first drop happens a few weeks after the first decision on the unconstitutionaly of

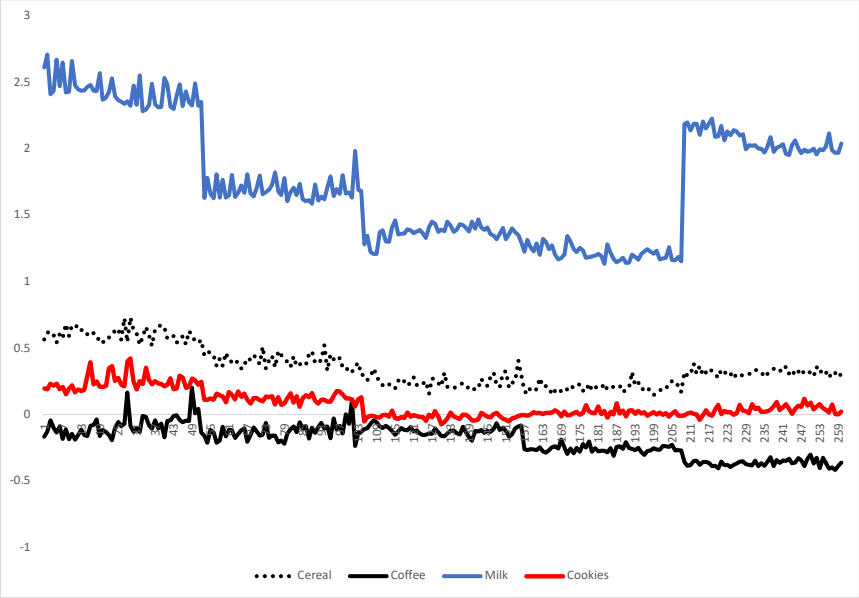


Figure 6: Estimated retail markups for milk, cereal and coffee in Wisconsin, January 2007-December 2011.

Notes: This figure shows estimated time series of margins in dollars for milk, cereals, coffee and cookies from 2007 until 2011, averaged across the three retailers considered in our sample.

the Wisconsin's MML was made; the second break happens a few weeks before the second decision was made, which is consistent with the anticipation that we captured in our reduced form estimates; last, the third break happens a few weeks after a court reinstated the law on September 2010.

5.7 Counterfactuals

With the demand estimates in hand, we simulate a counterfactual policy consisting of introducing a MML in a setting of free pricing. For this reason, we focus our attention to the State of Illinois where no MML is in force. As for Wisconsin, we estimate the preferences for consumers in the state of Illinois, restricting to the same set of product categories and chains. The chains of Illinois respect the same geographical criteria, namely, no stores located outside Illinois, and thus differ from the chains in Wisconsin. Introducing a MML means that supermarket chains in Illinois are no longer in a free pricing context as long as the MML imposes a price floor for each product. Formally, under the counterfactual scenario chains maximize profits subject to the constraint that prices should be above marginal cost.

Table 9 reports our counterfactual results where simulated MML prevents retailers from

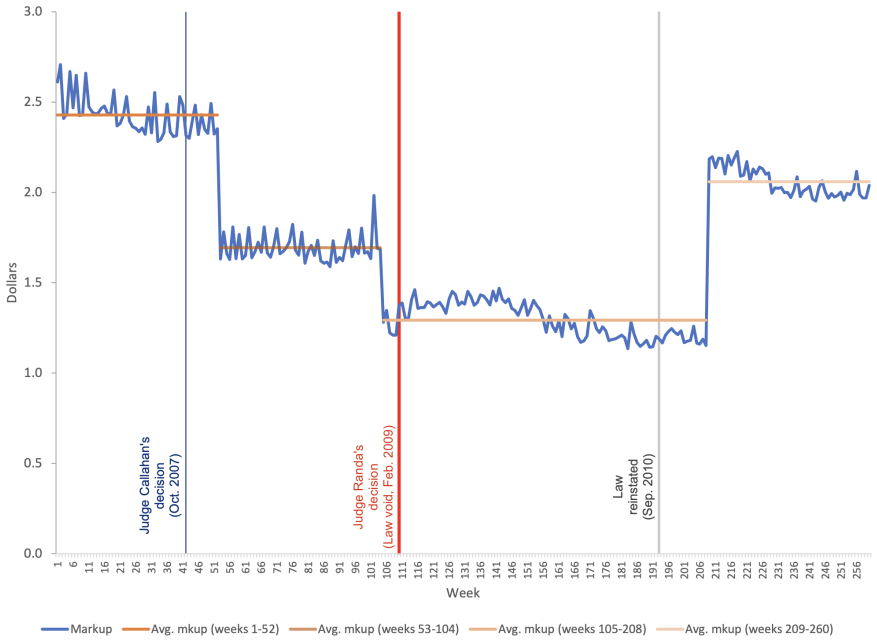


Figure 7: Estimated retail margins for milk in Wisconsin, January 2007-December 2011.

Notes: This figure shows estimated time series of margins for milk in dollars from 2007 until 2011, averaged across the three retailers considered in our sample.

setting negative markups. This table displays estimated margins in the baseline scenario (first four columns) and changes in the margins after introducing a MML with respect to the baseline (last four columns). Consistent with the cross subsidies hypothesis, the price of all products increase. The average margins for coffee increase by 100%, for weeks 18 to 20, reaching a level of zero. In week 17, MML lead to higher than zero margins for coffee. The margins for all other products consistently increase, with the highest increases coming often from Cookies, Yogurt and Eggs.

As prices uniformly increase for all retailers, the effect on welfare on consumers is likely to be negative. Consumers deciding to be one-stop shoppers are charged higher prices for all products within one store, and multi-stop shopper, which usually visit multiple stores seeking lower prices, are also charged uniformly higher prices.

6 Conclusions

In this study, we present novel insights into the impact of price floors on supermarket pricing, competition, and consumer welfare, using scanner data from U.S. supermarket sales. Our

Table 9: Changes in markups when minimum markups are imposed in a free pricing environment (four weeks of 2010)

	Baseline Average markups (in $)				Counterfactual Change with respect to baseline			
Week #	17	18	19	20	17	18	19	20
Soup	0.745	0.650	0.642	0.722	1.44%	1.15%	1.25%	1.34%
Cereal	0.657	0.733	0.675	0.595	0.81%	0.51%	1.40%	1.53%
Coffee	-0.506	-0.841	-0.789	-0.580	123.05%	100.00%	100.00%	100.00%
Soft drinks	0.837	0.907	0.896	0.919	1.13%	0.83%	0.92%	1.08%
Cookies	0.567	0.594	0.578	0.532	2.68%	1.82%	1.77%	2.27%
Potato Chips	0.739	0.702	0.712	0.642	0.67%	0.33%	0.83%	1.32%
Eggs	0.438	0.533	0.436	0.449	1.85%	0.35%	1.56%	2.49%
Milk	1.854	1.830	1.848	1.824	0.16%	0.14%	0.21%	0.35%
Yogurt	0.602	0.593	0.618	0.710	1.92%	1.54%	1.78%	1.51%

Notes: This table displays estimated margins in the baseline scenario (first four columns) and changes in the margins after introducing a minimum markup law with respect to the baseline (last four columns). The simulated minimum markup law prevents retailers to have negative margins. We simulate new equilibrium margins with the MML restriction in Illinois, which is originally a "free pricing" State, for four weeks of 2010.

analysis comprises two empirical exercises. Firstly, we conduct difference-in-differences analyses concerning the temporary absence of Wisconsin's *Unfair Sales Act*—legislation imposing a minimum markup on nearly all products to prevent the sale of goods below cost—during the period from October 2007 through September 2010. We focus on high demand, often complementary products in the U.S. between 2007 and 2010, namely, milk and ready-to-eat cereals, we gauge the impact of the Wisconsin exogenous shock by contrasting price changes between chains exposed to the shock (i.e., owning stores in Wisconsin) and those not exposed (our control group). Our findings reveal a significant decrease in milk average retail prices in Wisconsin in response to the law void, and an increase in ready-to-eat cereal prices, on average. This is consistent with recent theory predictions according to which supermarkets charge lower prices on popular products to attract consumers into the stores, and compensate potential losses with high-markup products that exhibit strong complementarities with the former (see, for example, Chen and Rey (2019)).

In our second exercise, we estimate a structural model of demand and supply of multiple products. Our general empirical strategy combines two main features. On the supply side, we model price competition between multiproduct retailers in a context in which retailers may or may not be free to set optimal prices (that may lie below cost). On the demand side, we

model the choice of multiple products from multiple stores explicitly accounting for potential complementarities between *a priori* unrelated products and stores. A common challenge to the estimation of demand for multiple products is the large size of the set of products and stores available to consumers. We develop a novel approach to deal with this shortcoming in a tractable way. It allows us to focus on a reduced set of products and stores from the consumers' full choice set, and corrects the bias that arises from excluding observed products and stores.

We estimate our demand model allowing for consumer considerations sets using Maximum Likelihood Estimation, exploiting with our bias correction. With the demand estimates in hand, we back out product-level markups and marginal costs using our supply model. Finally, we simulate a counterfactual experiment in which a minimum markup law is implemented in Illinois, a state where no such laws are in effect. Our results show that when supermarkets face a price floor, they increase the overall price level. Our finding gives support to the conclusion of the OECD (2007) report, arguing the minimum markup laws are likely to lead to higher prices and thus harm consumers.

References

Aguiar, Mark, and Erik Hurst. 2007. "Life-cycle prices and production." *The American Economic Review*, 97(5): 1553–1559.

Anderson, Rod, and Ronald Johnson. 1999. "Antitrust and Sales-Below-Cost Laws: The Case of Retail Gasoline." *Review of Industrial Organization*, 14.

Badger Institute. 2016. "Real-world impacts of Wisconsin's Minimum Markup Law." https://www.badgerinstitute.org/real-world-impacts-of-wisconsins-minimum-markup-law/ (last accessed December, 2022).

Brief, Richard. 1967. "Measuring Shopping Costs." *Journal of Industrial Economics*, 15(3): 237–241.

Butters, Andrew, Daniel Sacks, and Boyoung Seo. 2022. "How do national firms respond to local cost shocks?" *American Economic Review*, 112(5): 1737–1772.

Chen, Zhijun, and Patrick Rey. 2012. "Loss leading as an exploitative practice." *The American Economic Review*, 102(7): 3462–3482.

Chen, Zhijun, and Patrick Rey. 2019. "Competitive Cross-Subsidization." *RAND Journal of Economics*, 50(3): 645–665.

Chevalier, Judith, and Anil Kashyap. 2019. "Best Prices: Price Discrimination and Consumer Substitution." *American Economic Journal: Economic Policy*, 11(1): 126–159.

Chevalier, Judith, Anil Kashyap, and Peter Rossi. 2003. "Why don't prices rise during periods of peak demand? Evidence from scanner data." *American Economic Review*, 93(1): 15–37.

Competition Commission. 2008. "The Supply of Groceries in the UK Market Investigation." http://webarchive.nationalarchives.gov.uk/20140402141250/http://www.competition-commission.org.uk/our-work/directory-of-all-inquiries/groceries-market-investigation-and-remittal/final-report-and-appendices-glossary-inquiry (accessed May 7, 2016).

Crawford, Gregory, Rachel Griffith, and Alessandro Iaria. 2020. "A survey of preference estimation with unobserved choice set heterogeneity." *Journal of Econometrics*, 4–43.

DellaVigna, Stefano, and Matthew Gentzkow. 2019. "Uniform pricing in U.S. retail chains." *Quarterly Journal of Economics*, 134: 2011–2084.

De los Santos, Babur, Ali Hortaçsu, and Matthijs Wildenbeest. 2012. "Testing models of consumer search using data on web browsing and purchasing behavior." *The American Economic Review*, 102(6): 2955–2980.

Dolfen, Stefano, Liran Einav, Peter Klenow, Benjamin Klopack, Jonathan Levin, Larry Levin, and Wayne Best. 2022. "Assessing The Gains from E-Commerce." *American Economic Journal: Macroeconomics*, Forthcoming.

Dubé, Jean-Pierre. 2004. "Multiple discreteness and product differentiation: demand for carbonated soft drinks." *Marketing Science*, 23(1): 66–81.

Dubois, Pierre, and Helena Perrone. 2015. "Price Dispersion and informational frictions: Evidence from supermarket purchases."

Dubois, Pierre, Martin O'Connell, and Rachel Griffith. 2020. "How well targeted are soda taxes?" *American Economic Review*, 110.

Ellison, Glenn. 2005. "A model of add-on pricing." *Quarterly Journal of Economics*, 120(2): 585–637.

Ellison, Glenn, and Sara Fisher Ellison. 2009. "Search, obfuscation, and price elasticities on the internet." *Econometrica*, 77(2): 427–452.

Ershov, Daniel, Jean-William Laliberté, Mathieu Marcoux, and Scott Orr. 2023. "Estimating complementarity with large choice sets: an application to mergers." *Unpublished manuscript*.

Florez-Acosta, Jorge, and Daniel Herrera-Araujo. 2020. "Multiproduct retailing and consumer shopping behavior: The role of shopping costs." *International Journal of Industrial Organization*, 68.

Gabaix, Xavier, and David Laibson. 2006. "Shrouded attributes, consumer myopia and information supression in competitive markets." *Quarterly Journal of Economics*, 121(2): 505–540.

Gagnon, Etienne, and David López-Salido. 2020. "Samll price responses to large demand shocks." *Journal of the European Economic Association*, 18(2): 792–828.

García-Lebergman, Ezequiel. 2021. "Multi-establishment Firms, Pricing and the Propagation of Local Shocks: Evidence from US Retail." *Unpublished manuscript*.

Gentzkow, Matthew. 2007. "Valuing new goods in a model with complementarity: online newspapers." *The American Economic Review*, 97(3): 713–744.

Gerstner, Eitan, and James Hess. 1990. "Can bait and switch benefit consumers?" *Marketing Science*, 9.

Hausman, Jerry. 1997. "Valuation of new goods under under perfect and imperfect competition." In *The Economics of New Goods*. , ed. R. Gordon and T. Bersnahan, Chapter 5, 207–248. University of Chicago Press.

Hendel, Igal. 1999. "Estimating multiple-discrete choice models: an application to computerization returns." *The Review of Economic Studies*, , (66): 423–446.

Hess, James, and Eitan Gerstner. 1987. "Loss leader pricing and rain check policy." *Marketing Science*, 6(4): 358–374.

Hitsch, Günter, Ali Hortaçsu, and Xiliang Lin. 2019. "Prices and Promotions in U.S. Retail Markets: Evidence from Big Data." *NBER Working Paper No. 26306*, 91p.

Holton, Richard. 1957. "Price discrimination at retail: the supermarket case." *Journal of Industrial Economics*, 6(1): 13–32.

Hong, Han, and Matthew Shum. 2006. "Using price distributions to estimate search costs." *RAND Journal of Economics*, 37(2): 257–275.

Honka, Elizabeth. 2014. "Quantifying search and switching costs in the U.S. auto insurance industry." *RAND Journal of Economics*, 45(4): 847–884.

Hortaçsu, Ali, and Chad Syverson. 2004. "Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 Index Funds." *The Quarterly Journal of Economics*, 119(2): 403–456.

Iaria, Alessandro, and Ao Wang. 2020. "Identification and estimation of demand for bundles." *Unpublished manuscript*.

Johansen, Bjorn. 2000. "Demand, Information, and competition: Why do food prices fall at seasonal demand peaks?" *Journal of Industrial Economics*, 48(1): 27–45.

Johnson, Justin. 2017. "Unplanned purchases and retail competition." *American Economic Review*, 107(3): 931–965.

Kim, Jun, Paulo Albuquerque, and Bart Bronnenberg. 2010. "Online demand under limited consumer search." *Marketing Science*, 29(6): 1001–1023.

Klemperer, Paul. 1992. "Equilibrium product lines: competing head-to-head may be less competitive." *The American Economic Review*, 82(4): 740–755.

Koulayiev, Sergei. 2014. "Search for differentiated products: identification and estimation." *RAND Journal of Economics*, 45(3): 553–575.

Lal, Rajiv, and Carmen Matutes. 1994. "Retail pricing and advertising strategies." *Journal of Business*, 67(3): 345–370.

Lazear, Edward. 1995. "Bait and switch." *Journal of Political Economy*, 103(4): 813–830.

Leung, Justin, and Zhonglin Li. 2021. "Big-box store expansion and consumer welfare." *Working Paper*, 67 p.

Moraga-Gonzalez, Jose Luis, Zsolt Sandor, and Matthijs Wildenbeest. 2013. "Semi-Nonparametric estimation of consumer search costs." *Journal of Applied Econometrics*, 28(7): 1205–1223.

OECD. 2008. "Monopsony and buyer power." *Policy Roundtables*, 328.

Peltier, James, Mark Skidmore, and George Milne. 2013. "Assessing the Impact of Gasoline Sales-Below-Cost Laws on Retail Price and Market Structure: Implications for Consumer Welfare." *Journal of Public Policy and Marketing*, 32(2): 239–254.

Shy, Oz. 2002. "A quick-and-easy method for estimating switching costs." *International Journal of Industrial Organization*, , (20): 71–87.

Simester, Duncan. 1995. "Signalling price image using advertised prices." *Marketing Science*, 14.

Stroebel, Johannes, and Joseph Vavra. 2019. "House prices, local demand, and retail prices." *Journal of Political Economy*, 127(3): 1391–1436.

Thomassen, Oyind, Howard Smith, Stephan Seiler, and Pasquale Schiraldi. 2017. "Multi-Category Competition and Market Power: A model of Supermarket Pricing." *American Economic Review*, 107(8): 2308–2351.

Verboven, Frank. 1999. "Product line rivalry and market segmentation–with an application to automobile optional engine pricing." *The Journal of Industrial Economics*, 47(4): 339–425.

Viard, Brian. 2007. "Do switching costs make markets more or less competitive? The case of 800-number portability." *RAND Journal of Economics*, 38(1): 146–163.

Walters, Rockney. 1988. "Retail promotions and retail store performance: a test of some key hypotheses." *Journal of Retailing*, 64.

Walters, Rockney, and Scott MacKenzie. 1988. "A Structural Equations Analysis of the Impact of Price Promotions on Store Performance." *Journal of Marketing Research*, 25(1): 51–63.

Wang, Ao. 2021. "A BLP Demand Model of Product-Level Market Shares with Complementarity." *Unpublished manuscript.*

Warner, Elizabeth, and Robert Barsky. 1995. "The timing and magnitude of retail stores markdowns: evidence weekends and holidays." *Quarterly Journal of Economics*, 110(2): 321–352.

Wildenbeest, Matthijs. 2011. "An empirical model of search with vertically differentiated products." *RAND Journal of Economics*, 42(4): 729–757.

Appendix

A Reduced-form robustness check

In the following, we use ban states as the control group rather than both ban and non-ban states. Figure (A.1) plots the estimation results of the event studies of milk and RTE cereal prices. The effect of the decision is essentially the same with either unexposed ban and non-ban states in the control group (see Figure 4) or with only unexposed ban states in the control group. Therefore, our results are robust to the composition of the control group.

B Derivation of the total purchase probability

[To be completed]

C Robustness of the structural model

[To be completed]

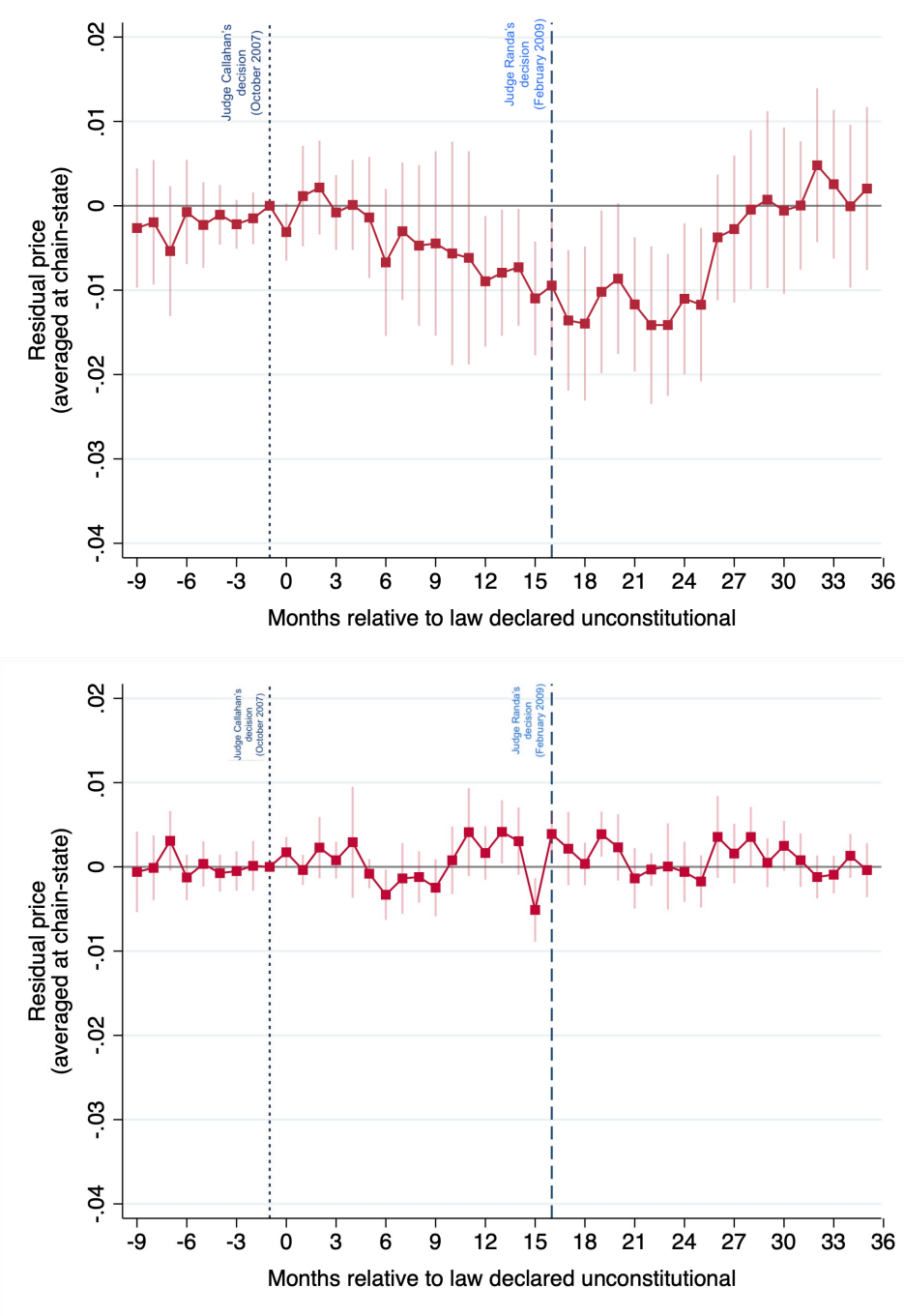


Figure A.1: Effect of the law void on milk (top) and RTE cereal (bottom) prices of directly exposed stores using ban states as the control group

Notes: This figure shows estimated coefficients of equation (1) of residual prices of milk (top) and RTE cereals (bottom) at the chain-state-week level between 2007 and 2010. The estimates are for stores that were directly exposed to the law void because they are located in Wisconsin. Estimates capture the change in residual prices of each product for directly exposed stores with respect to unexposed stores located in ban states other than Wisconsin, in the 9 months before and 36 months after the first decision made by Judge Callahan in October 12, 2007, taking the month right before the event month (month "-1") as the reference. The dashed line marks the date, February 2009, in which Judge Randa declared the Wisconsin's Unfair Sales Act unconstitutional and voided it. The 95% confidence intervals are plotted for each data point.