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Minimum Markup Laws and Multiproduct Pricing

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Abstract

This paper studies how minimum markup laws affect pricing in multiproduct retail markets. Exploiting the temporary suspension of Wisconsin's Unfair Sales Act, we show that removing price floors lowers milk prices but raises cereal prices, consistent with retailers reallocating markups across products. We estimate a structural model of multiproduct demand and supply, developing a bias correction for non-exhaustive choice sets. Counterfactuals show that minimum markups distort prices throughout the product assortment and reduce consumer surplus by 3.2%. We further show that the cross-subsidization mechanism underlying these pricing interactions is quantitatively important: eliminating cross-category pricing complementarities reduces total welfare by 44%.

Key words: Minimum markup laws, price floors, multiproduct pricing, demand complementarities, consumer welfare, retail competition.

JEL classification: D12, L13, L40, L51, L81, K21.

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Leyes de márgenes mínimos y fijación de precios en comercios multiproducto

Daniel Herrera-Araujo and Jorge Florez*

Resumen

Este artículo estudia cómo las leyes de márgenes mínimos afectan la fijación de precios en mercados minoristas multiproducto. Aprovechando la suspensión temporal de la *Ley de Ventas Injustas* del estado de Wisconsin en Estados Unidos, mostramos que la eliminación de los precios mínimos reduce los precios de la leche pero aumenta los de los cereales para el desayuno, lo cual es consistente con una reasignación de márgenes entre productos por parte de los supermercados. Estimamos un modelo estructural de demanda y oferta multiproducto en el que incorporamos una corrección del sesgo derivado de conjuntos de elección no exhaustivos, que es necesaria para recuperar estimaciones insesgadas de los costos de compra y las complementariedades entre productos. Experimentos contrafactuales revelan que los subsidios cruzados desempeñan un papel central en la competencia minorista: un margen mínimo del 5% reduce el excedente del consumidor en 3.2%, mientras que eliminarlos por completo disminuye el bienestar en 44%.

Palabras clave: Leyes de márgenes mínimos, precios mínimos, fijación de precios en empresas multiproducto, productos complementarios, bienestar del consumidor, competencia entre supermercados.

Clasificación JEL: D12, L13, L40, L51, L81, K21.

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Este artículo utiliza las bases de datos de NielsenIQ proporcionadas por el *Kilts Center for Marketing Data Center* de la Escuela de Negocios Chicago Booth de la Universidad de Chicago. Los resultados presentados son análisis propios de los investigadores, calculados (o derivados) en parte a partir de datos de Nielsen Consumer LLC y de las bases de datos de mercadeo provistas a través de las bases de datos de NielsenIQ del *Kilts Center for Marketing Data Center* de la Escuela de Negocios Chicago Booth de la Universidad de Chicago. Las conclusiones derivadas de los datos de NielsenIQ son responsabilidad de los investigadores y no reflejan las opiniones de NielsenIQ. NielsenIQ no es responsable de los resultados aquí presentados, no tuvo ningún papel en su elaboración, ni participó en su análisis o preparación.

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1 Introduction

In many multiproduct retail markets, firms set prices jointly across a broad assortment of products, using low prices on some items to attract consumers and recoup margins on others. This cross-subsidization mechanism is particularly prominent in supermarket retailing, where consumers purchase multiple goods in a single shopping trip and retailers compete over the value of the entire basket. Yet in these markets, regulation often constrains firms' ability to price aggressively. More than half of U.S. states enforce laws that prohibit below-cost pricing or mandate minimum markups, and similar policies are widespread internationally. By restricting retailers' ability to use some products as loss leaders, these minimum markup laws (MMLs) may distort pricing across the entire product assortment. As a result, regulating one price can affect all prices in a multiproduct system.

Understanding the effects of minimum markups in multiproduct retail markets is important given the scale and pricing practices of the supermarket industry. In the United States alone, this sector represents a market exceeding $1 trillion annually.[1] Supermarkets also account for the vast majority of food-at-home expenditures: in 2024, U.S. consumers spent 83% of their total food-at-home budget at supermarkets.[2] Loss-leader pricing is pervasive in multiproduct retail markets, particularly during periods of peak demand (e.g., Chevalier, Kashyap and Rossi, 2003).

Despite the prevalence of these pricing strategies and regulations, most economic research has focused on theoretical explanations of multiproduct pricing, where cross-subsidization arises endogenously (e.g., Bliss, 1988; Lal and Matutes, 1994; Chen and Rey, 2012; Johnson, 2017; Chen and Rey, 2019). Fewer papers study the effects of banning below-cost pricing, and those that do deliver ambiguous welfare predictions.[3] However, there is little empirical evidence on the effects of these regulations in retail markets. Existing work focuses on gasoline markets, where competition is effectively single-product (Anderson and Johnson, 1999; Peltier, Skidmore and Milne, 2013). No prior study has quantified the equilibrium effects of minimum markup laws in multiproduct retailing, where cross-product pricing and consumers' joint product–store choices—which shape demand linkages across goods and retailers—are

[1] According to Food Marketing Institute facts from 2024. See https://www.fmi.org/our-research/food-industry-facts . Last accessed: April 30, 2026.

[2] This includes grocery stores, warehouse clubs, and supercenters. Source: USDA Food Expenditure Series, see https://www.ers.usda.gov/data-products/food-expenditure-series . Last accessed: April 30, 2026.

[3] While Chen and Rey (2012) show that banning below-cost pricing can increase consumer surplus, Johnson (2017) argues that such a ban may harm consumers, and Chen and Rey (2019) show that it reduces consumer surplus, although total welfare effects depend on the distribution of shopping costs.

central. This paper fills that gap.

We examine the effects of minimum markup laws on supermarket pricing, competition, and welfare using scanner data from U.S. supermarket sales. Our empirical setting is Wisconsin, where a federal court ruling temporarily suspended the minimum markup provisions of the Unfair Sales Act, a state law enacted in 1939, between February 2009 and September 2010. We conduct two complementary empirical exercises.

Using a difference-in-differences design, we compare price changes between retail chains exposed to the policy (those operating in Wisconsin) and unexposed chains. Focusing on milk and ready-to-eat (RTE) cereals—two high-demand products frequently consumed together—we find that the suspension led to a significant decline in milk prices and a simultaneous increase in cereal prices. This pattern provides causal evidence that retailers reallocate markups across products when pricing constraints are relaxed: in the absence of minimum markup restrictions, retailers lower the price of one product to attract consumers while increasing margins on related goods.

To rationalize these patterns and quantify their implications, we estimate a structural model of multiproduct demand and supply. Our framework builds on Florez-Acosta and Herrera-Araujo (2020) by incorporating both product- and store-level interactions within a unified setting and allowing for a tractable correction to non-exhaustive choice sets. On the demand side, consumers choose baskets of products across stores, allowing for heterogeneous shopping behavior, including one-stop shoppers, who concentrate purchases in a single store, and multistop shoppers, who spread purchases across competing stores within the same shopping occasion. We capture cross-product interactions through a basket-level constant (as in Gentzkow, 2007), and allow retail stores to act as substitutes or complements through individual-specific shopping costs. Following the literature (Klemperer, 1992; Chen and Rey, 2012, 2019; Florez-Acosta and Herrera-Araujo, 2020), we interpret these as the real or perceived costs of using a retailer. These costs vary across individuals and increase with the number of stores visited, leading consumers to trade off the benefits of visiting an additional store against the associated costs. On the supply side, multiproduct retailers compete à la Nash-Bertrand, jointly setting prices across their assortments and internalizing cross-category demand linkages.

A central empirical challenge in this setting is the large choice set available to consumers.[4] Existing approaches address this challenge in one of two ways: by restricting attention to a subset of products and stores, which leads to a non-exhaustive choice set (e.g., Florez-Acosta

[4]According to the U.S. Food Industry Association, in 2024 a U.S. supermarket carried, on average, 31,795 different items.

and Herrera-Araujo, 2020; Ershov et al., 2025), or by aggregating products into broader categories while limiting the set of stores (e.g., Thomassen et al., 2017). Both approaches can bias demand estimates, as included products may be purchased jointly with excluded products and/or at excluded stores, but these possibilities are not captured in the estimated choice probabilities. As a result, the probability of selecting included products is systematically mismeasured, which in turn biases key parameters such as shopping costs and product complementarities.

We address this problem by developing a tractable correction that uses consumers' full purchase histories to construct empirical proxies for the likelihood of purchasing excluded products and/or visiting excluded stores. These proxies enter the choice probabilities of included products, allowing us to account for cross-product and cross-store interactions without explicitly modeling the full choice set. This approach recovers consistent estimates of demand parameters and improves the accuracy of counterfactual predictions, while maintaining a manageable number of parameters. Using Monte Carlo simulations, we show that the correction effectively removes the bias in demand estimates.

We estimate the model using both NielsenIQ Consumer Panel and Retail Scanner datasets from 2007 to 2011 (NielsenIQ, 2007-2011), focusing on Wisconsin. The sample covers the period before, during, and after the temporary suspension of the law. We analyze three major supermarket chains and 11 commonly purchased product categories. Within each category, we aggregate sales of all observed brands and varieties into a single composite product, yielding 11 products per retailer. The model is estimated by maximum likelihood, and the supply side is used to recover product-level markups and marginal costs.

We find that retailers systematically reallocate markups across products, offsetting low margins on some items with higher margins elsewhere in the basket. We document substantial heterogeneity across retailers in the set of low- and high-markup products, suggesting that the composition of the subsidized basket is itself a dimension of differentiation. We also find evidence of markup substitution across consumption complements such as milk and cereals.

We then use the model to evaluate the effects of minimum markup constraints. Imposing minimum markups distorts pricing across the entire product assortment: prices rise on directly affected goods and also increase on unconstrained products through equilibrium spillovers. In our setting, a 5% minimum markup raises average prices by up to 1% across retailers and reduces market shares by 2–7%. As a result, basket prices increase, aggregate demand falls, and consumer surplus declines (by 3.2%), while retailer profits increase, leading to a modest increase in total welfare. These results provide empirical support for recent theoretical work (Johnson, 2017; Chen and Rey, 2019) and policy discussions (OECD, 2005, 2007), and highlight that these effects operate through distortions in multiproduct pricing.

To quantify the equilibrium importance of cross-subsidization, we conduct a counterfactual exercise in which retailers no longer internalize cross-category pricing complementarities when setting prices. The results are stark: average prices increase by approximately 32%, market shares decline by 75–82%, and total welfare falls by 44%. Both consumers and retailers are worse off, with consumer surplus declining by 69% and profits by 30%. These findings show that cross-subsidization is not merely a redistributive pricing strategy, but a central feature of multiproduct retail markets that sustains demand and generates substantial gains from trade. Minimum markup laws, by constraining this mechanism, raise prices, reduce consumer welfare, and reallocate surplus toward retailers.

Our paper makes two main contributions. First, we provide the first empirical evidence on the equilibrium effects of minimum markup laws in multiproduct retailing, and document new evidence that cross-subsidization is a central feature of competition in grocery retailing. Second, we show that credibly estimating multiproduct demand in this setting requires addressing bias from non-exhaustive choice sets, and we develop a tractable correction that we show matters quantitatively for both estimation and counterfactual analysis.

This paper relates to several strands of the literature. First, it relates to previous studies on multiproduct pricing and loss-leader strategies. A large theoretical literature explains why firms set low prices on some products and high prices on others, emphasizing demand complementarities, consumer search, and strategic pricing across goods (e.g., Holton, 1957; Lal and Matutes, 1994; Ellison, 2005; Gabaix and Laibson, 2006). Empirically, prior work documents seasonal pricing patterns and intensive promotional activity during peak demand periods in retail markets (e.g., Warner and Barsky, 1995; Chevalier, Kashyap and Rossi, 2003; Chevalier and Kashyap, 2019; Gagnon and López-Salido, 2020; Butters, Sacks and Seo, 2025). We complement this literature by providing causal and structural evidence on cross-subsidization in supermarket pricing, highlighting a mechanism through which promotional discounts are recouped via higher margins on other products.

Our paper also relates to the literature on below-cost pricing and minimum markup laws. Existing work is primarily theoretical and shows that restricting below-cost pricing need not improve welfare (e.g., Chen and Rey, 2012, 2019; Johnson, 2017), while empirical evidence is largely confined to gasoline markets (e.g., Anderson and Johnson, 1999; Peltier, Skidmore and Milne, 2013). We extend this literature by providing empirical evidence on the welfare effects of minimum markup laws in a multiproduct retail setting with cross-product pricing.

Finally, our approach builds on a growing empirical literature on multiproduct demand and shopping behavior. Early contributions such as Hendel (1999) and Dubé (2004) model consumers' joint choices over multiple products, while Gentzkow (2007) introduces a framework that allows products to be either substitutes or complements. More recent work incorporates shopping behavior and store choice, showing how shopping costs generate complementarities across products and retailers (e.g., Thomassen et al., 2017; Florez-Acosta and Herrera-Araujo, 2020; Leung and Li, 2024). A related strand addresses empirical challenges that arise in these settings, including large choice sets and identification in the presence of complementarity (e.g., Ershov et al., 2025; Wang, 2024; Iaria and Wang, Forthcoming). We contribute to this literature by developing a tractable approach that accounts for both product and store interactions and corrects for bias arising from non-exhaustive choice sets, showing that this bias matters quantitatively for estimation and counterfactual analysis.

The remainder of the paper is organized as follows. Section 2 describes the data and institutional setting. Section 3 presents the reduced-form evidence. Section 4 develops the structural model and reports estimation and counterfactual results. Section 5 concludes.

2 Data and institutional setting

2.1 Overview of the data

This paper uses the NielsenIQ Consumer Panel and Retail Scanner datasets provided by the Kilts Center for Marketing at the University of Chicago Booth School of Business (NielsenIQ, 2007-2011). The Consumer Panel consists of household-level scanner data that record grocery purchases and demographic information for a representative sample of U.S. households. The Retail Scanner dataset contains store-level weekly data at the Universal Product Code (UPC) level, including retail prices, sales volumes, product characteristics, and store location (identified by the first three digits of the ZIP code). The two datasets can be linked using retailer identifiers and geographic information.

2.2 Minimum markup laws in the U.S.

Most U.S. states impose minimum markups (or, equivalently, price floors), either broadly across retail products or for specific categories. Many of these laws were enacted during the Great Depression to protect smaller businesses and consumers from potentially predatory (so-called unfair) practices by larger firms. In most regulated states—such as California, Wisconsin, and Massachusetts—the provisions apply to all merchandise, whereas in others, including Nevada, Missouri, and North Carolina, they apply only to specific grocery categories such as milk or dairy products. Figure 1 highlights the states that currently enforce minimum markup regulations covering a broad set of grocery products.

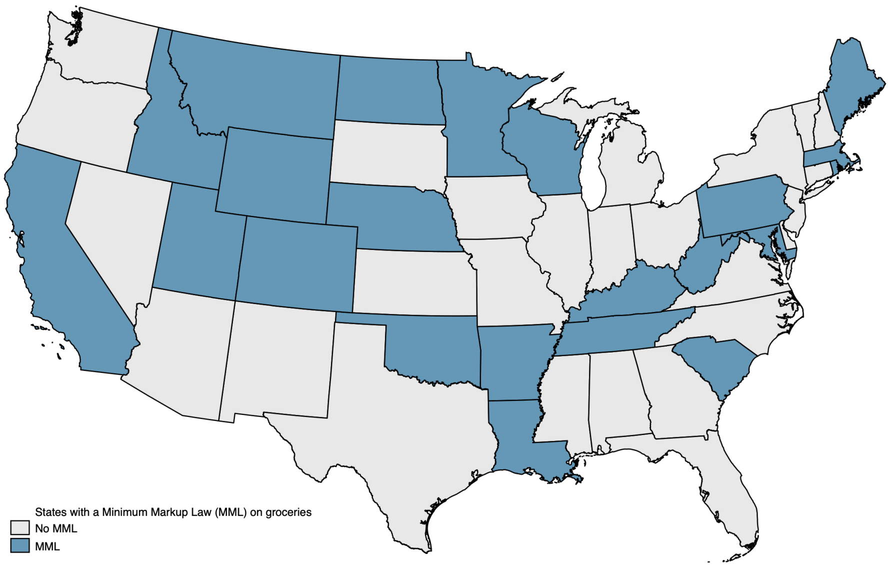


Figure 1: U.S. states with minimum markup laws covering grocery products

Notes: The figure highlights in blue the U.S. states that currently enforce laws imposing minimum markups on a broad set of grocery products. Some states impose similar restrictions only on specific grocery categories—such as milk or dairy products—or on non-grocery products, including gasoline, cigarettes, and alcoholic beverages. Because our analysis focuses on multiproduct grocery retailing, we display these partially regulated states in gray together with states that do not impose any minimum markup restrictions.
Source: Fleisher, Chris, "Loss-leaders: Predatory or practical?", American Economic Association, https://www.aeaweb.org/research/loss-leading-bans-retail-competition.

Some states also impose minimum markups on non-grocery products. Table 1 summarizes the categories subject to partial regulation, the most common of which are cigarettes (regulated in 10 states) and gasoline (regulated in 6 states). Only 10 states—including Illinois, Michigan, Texas, and Arizona—do not impose any minimum markup restrictions. This cross-state variation in pricing regulations provides a useful setting for identifying the causal effects of minimum markup laws on retail pricing.

Table 1: Minimum markup provisions in states with partial coverage

Included products	Number of states	States
Gasoline	6	Missouri, New York, North Carolina, Georgia, Alabama, Florida
Cigarettes	10	Washington, Nevada, South Dakota, Iowa, Indiana, Ohio, New York, New Jersey, Delaware, Mississippi
Alcoholic beverages	2	Kansas, New Hampshire
Milk	2	Missouri, North Carolina
Dairy	1	Nevada

Notes: This table reports U.S. states that impose minimum markup provisions on selected product categories rather than broadly across all retail merchandise. "Number of states" indicates the count of states in which a minimum markup applies to the corresponding product category. "Milk" refers to states where the provision applies narrowly to fluid milk, while "Dairy" refers to broader coverage of multiple dairy products.
Source: Fleisher, Chris, "Loss-leaders: predatory or practical?", American Economic Association, https://www.aeaweb.org/research/loss-leading-bans-retail-competition.

3 Preliminary evidence: Wisconsin case study

3.1 Background

Wisconsin is one of the U.S. states with a minimum markup law—officially known as the Unfair Sales Act—that imposes pricing restrictions on all merchandise at both the wholesale and retail levels. The law has been in force since 1939. To determine compliance, it defines cost thresholds that vary across product categories. For most goods (excluding alcoholic beverages, tobacco, and fuel), cost is defined as the invoice or replacement cost (whichever is lower), net of trade discounts, plus excise taxes, transportation costs, and other applicable charges.[5] For alcohol and tobacco, the law imposes explicit minimum markups—referred to as the "cost of doing business"—requiring manufacturers and retailers to price at least 3% and 6% above cost, respectively. For motor fuel, retailer cost is defined as the greater of (i) invoice or replacement cost plus a 6% markup, or (ii) the average posted terminal ("rack") price plus a 9.18% markup.[6] Similar markup provisions apply upstream to refiners and wholesalers.

Over the past two decades, the law has been the subject of sustained policy debate and

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

[6] The average posted terminal price is the price at the closest fuel distribution terminal and is commonly used as a proxy for wholesale costs (Badger Institute, 2016).

repeated attempts at repeal, reportedly supported by large national retailers such as Walmart (Badger Institute, 2016). Supporters—including the Wisconsin Petroleum Marketers and Convenience Store Association (WPMCA)—argue that the law protects smaller and local businesses from predatory pricing by large chains, ultimately benefiting consumers by preserving competition. Opponents, by contrast, contend that the law raises retail prices and distorts competition by limiting retailers' ability to offer discounts. They also argue that it may divert demand to neighboring states where below-cost pricing is not restricted (Badger Institute, 2016). These concerns have also been echoed at the federal level: in a 2003 comment to Congress, the Federal Trade Commission (FTC) noted that minimum markup laws can restrict price competition and lead to higher prices by preventing retailers from discounting selected products.[7] While these arguments are central to the policy debate, there is limited empirical evidence quantifying their equilibrium effects in multiproduct retail settings.

The 2009 lawsuit and temporary suspension of the law

Wisconsin's minimum markup law (MML) was temporarily suspended between February 2009 and September 2010 following a series of federal court rulings. The episode originated in a dispute among fuel retailers over alleged violations of the state's pricing provisions. In 2007, the gasoline retailer Flying J Inc. was accused of selling fuel below the minimum price permitted under the Unfair Sales Act. In its defense, Flying J 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 ruled in *Lotus Group LLC v. Flying J Inc.* that the Wisconsin Unfair Sales Act effectively imposed a restraint of trade and therefore conflicted with federal antitrust law.[8] Despite this ruling, the Wisconsin Department of Agriculture, Trade and Consumer Protection continued to enforce reporting requirements under the law, maintaining what was described as an implicit threat of penalties and enforcement actions.[9]

In response, Flying J filed a new lawsuit in January 2008 against the State of Wisconsin, arguing that the mandated markups were not tied to actual costs and instead softened competition, allowing inefficient firms to earn supra-competitive profits and distorting interstate

[7] See "FTC Staff: Wisconsin's Unfair Sales Act Likely Raises Gas Prices", https://www.ftc.gov/news-events/news/press-releases/2003/10/ftc-staff-wisconsins-unfair-sales-act-likely-raises-gas-prices. Last accessed: May 6, 2026.

[8] See Judge Callahan's Opinion in *Lotus Group LLC v. Flying J Inc.*, Case No. 07-C-0144.

[9] See Judge Randa's Opinion in *Flying J Inc. v. Van Hollen*, Case No. 08-C-110.

commerce (Badger Institute, 2016). On February 11, 2009, Federal Judge Rudolph Randa ruled in favor of Flying J, concluding that the markup provisions for motor fuel led to artificially high prices and constituted an unlawful restraint of trade under the Sherman Act. He declared the law unconstitutional and ordered the State to cease its enforcement. The State did not appeal this decision, and the law was effectively suspended.

The suspension lasted until September 3, 2010, when the U.S. Court of Appeals, following an appeal by the Wisconsin Petroleum Marketers and Convenience Store Association, overturned the district court's ruling. The appellate court found insufficient evidence that the law induced collusion or otherwise violated federal antitrust statutes. As a result, the Unfair Sales Act was reinstated and has remained in force since (Badger Institute, 2016).

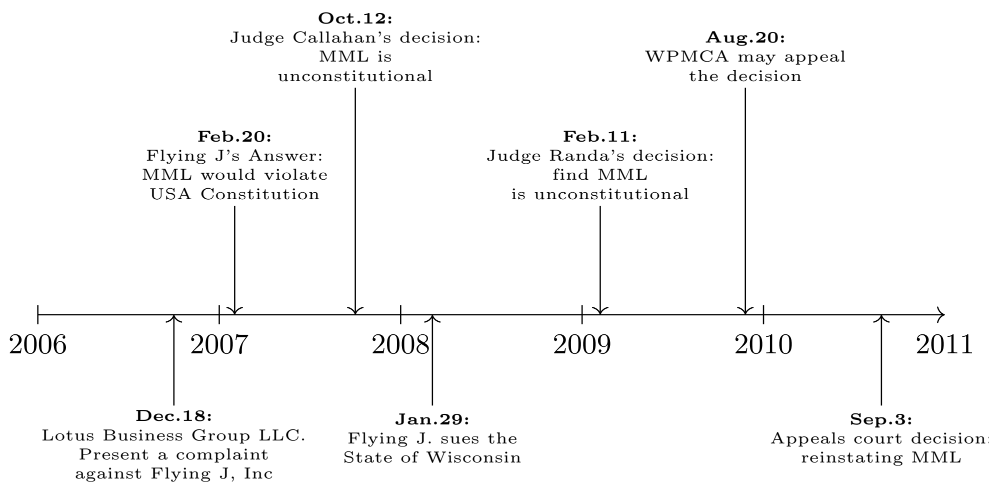


Figure 2: Timeline of legal rulings and suspension of Wisconsin's Unfair Sales Act

Notes: This figure summarizes key legal events leading to the temporary suspension of Wisconsin's Unfair Sales Act (MML). In February 2009, a federal district court ruled the law unconstitutional and prohibited its enforcement, initiating a suspension that lasted until September 2010, when the decision was overturned on appeal and the law was reinstated. The suspension period defines the policy variation exploited in the reduced-form analysis.
Source: Authors' construction based on court rulings.

3.2 Empirical strategy

We exploit the temporary suspension of Wisconsin's MML as an exogenous supply-side shock to identify its causal effect on retail prices. Previous work suggests that such shocks need not affect all products uniformly. For instance, Chevalier, Kashyap and Rossi (2003) document that supermarkets sharply reduce prices of selected items (e.g., beer, soup, cheese, snack crackers, and tuna) during peak demand periods to attract consumers. In a related vein, Chen and Rey (2019) show that multiproduct firms may price some goods below cost and recoup losses through higher margins on others. Consistent with these mechanisms, MMLs can induce a reallocation of markups across products, raising prices for some goods while lowering them for others.

To provide reduced-form evidence in a multiproduct setting, we focus on milk and ready-to-eat (RTE) breakfast cereals. These products are well suited for our analysis: they are staple goods, frequently purchased, and commonly consumed together, making them natural candidates for cross-product pricing strategies.

To construct a balanced sample, we follow an approach similar to Butters, Sacks and Seo (2022) and DellaVigna and Gentzkow (2019). We define retail chains as combinations of parent company and retailer identifiers. We retain chains that report sales in at least 60% of weeks and exclude stores associated with multiple chains (e.g., due to ownership changes or mergers). We further drop stores with sales reported in fewer than 17% of weeks and exclude two chains with missing observations around the policy change. Products are defined at the UPC-version level, and we remove items with very few observations.

Table 2 reports summary statistics for the final samples. The milk sample includes 1,495 products and 13,293 stores across 88 chains. Of these, 4% of stores belong to the 10 chains exposed to the Wisconsin policy, while the remaining stores belong to 78 unexposed chains. The average price of an 8.4 oz serving of milk is 41 cents, with prices in exposed stores about 16% higher on average. Exposed chains account for 26% of total sales. The cereals sample includes 4,182 products and 15,255 stores across 106 chains. Approximately 5% of stores belong to the 15 exposed chains, with the remainder in 91 unexposed chains. The average price of a 1.13 oz serving is 27 cents. Exposed chains account for 31.4% of total sales.

Our empirical strategy closely follows Butters, Sacks and Seo (2022). We compute weekly prices for each product j in store l as revenue divided by volume sold, denoted p_{jlt}. Given the size of the dataset, we reduce dimensionality in two steps. First, we construct residual prices $\widetilde{p}_{jlt}$ by removing product-store fixed effects $\overline{p}_{jl}$. Second, we aggregate these residuals to the chain-state-week level by averaging across all products and stores within a chain c in state s at time t, yielding $\widetilde{p}_{cst}$. This aggregation preserves identification, as treatment varies at the state level.

Figure 3 plots average residual prices for milk in exposed (Wisconsin) and unexposed stores. The two series evolve similarly prior to October 12, 2007, consistent with parallel trends. Following this date, modest differences emerge. After the suspension of the law on February 11, 2009, a clear divergence appears: prices in exposed stores decline more sharply

Table 2: Summary statistics: 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 reports summary statistics for milk and RTE cereal sales in the U.S. from 2007 to 2012. "Exposed" refers to chains with stores in Wisconsin (affected by the MML suspension), while "Unexposed" refers to chains operating exclusively outside Wisconsin. Prices are expressed in cents per serving. Chain-level weekly market shares are computed as a chain's total weekly sales divided by total sales across all chains in the sample. The final panel reports, for exposed chains, the share of total chain sales occurring in Wisconsin in the week of February 1-7, 2009.

relative to unexposed stores. This gap persists until late August 2009, after which it narrows and eventually disappears.[10] After the reinstatement of the law in September 2010, the two series again track each other closely.

[10] This timing coincides with the Court of Appeals granting standing to the Wisconsin Petroleum Marketers and Convenience Store Association in *Flying J Inc. v. WPMCA*, Case No. 09-1883.

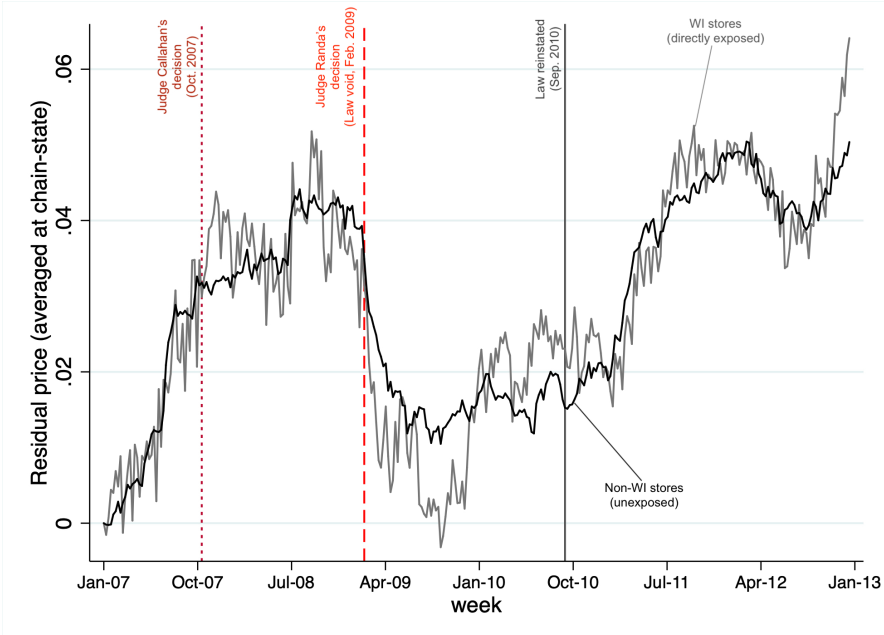


Figure 3: Average residual milk prices: exposed vs. unexposed stores

Notes: The figure plots average residual milk prices for stores in Wisconsin (exposed) and in other states (unexposed). Residual prices are constructed by removing product-store means and aggregating to the chain-state-week level. The dotted vertical line marks the pre-suspension ruling (October 12, 2007), the dashed line marks the suspension of the law (February 11, 2009), and the solid line marks reinstatement (September 3, 2010).

3.2.1 Event study

We examine the dynamic effects of the law suspension by comparing weekly price changes in exposed (treated) stores relative to unexposed (control) stores before and after the policy change.[11] We estimate 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 $Exposed_{cs}$ equals 1 for chain-state pairs directly affected by the suspension and 0 otherwise. The indicators $\mathbb{1}\{t - t^* = m\}$ index event time relative to the policy change at t^*. We include month fixed effects η_t and chain-state fixed effects ϕ_{cs}. The omitted category is $m = -1$, corresponding to the month prior to October 2007—the timing of Judge Callahan's initial ruling. The coefficients β_m^D therefore measure changes in prices in exposed stores relative to unexposed stores, normalized to this pre-event month.

[11]Because multistate supermarket chains may set uniform prices across locations (DellaVigna and Gentzkow, 2019), the control group includes stores located outside Wisconsin that belong to chains with no presence in Wisconsin.

We estimate equation (1) separately for milk and ready-to-eat (RTE) cereals. Figure 4 reports the estimated coefficients and 95% confidence intervals.[12] For milk, prices in exposed stores begin to decline shortly after the October 2007 ruling, with statistically significant effects emerging around the February 2009 suspension. This pattern is consistent with partial anticipation of the policy change, followed by a stronger response once the law is effectively suspended. This is consistent consistent with retailers lowering the price of a key traffic-driving product when pricing constraints are relaxed. For RTE cereals, we observe both increases and decreases in the post-event period, including a few precisely estimated effects. However, the estimates vary in sign, making it difficult to draw a clear conclusion from the event study alone. We therefore complement the event study with a difference-in-differences analysis to estimate average treatment effects.

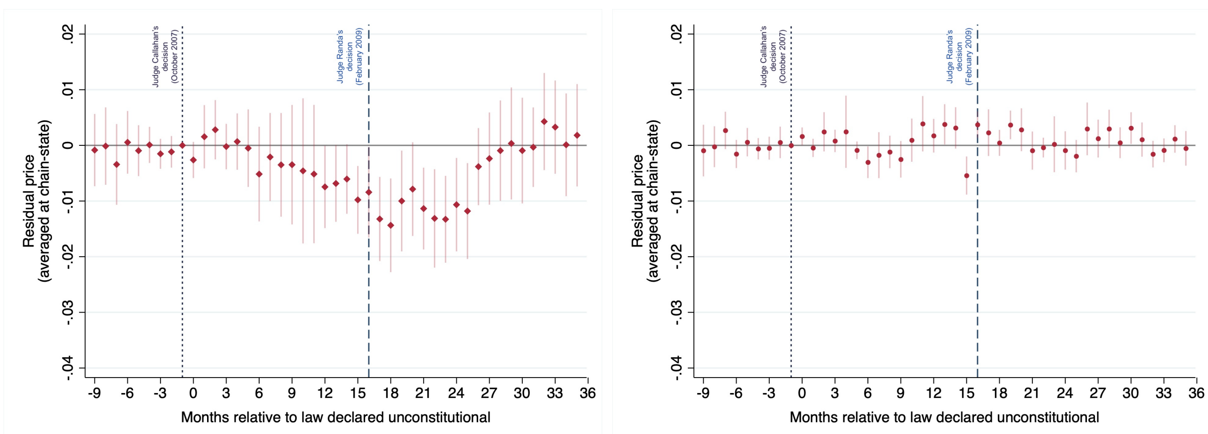


Figure 4: Event study: effects of the law suspension on milk (left) and RTE cereal (right) prices

Notes: The figure plots estimates of equation (1) for residual prices of milk (left) and RTE cereals (right) at the chain-state-week level. Coefficients measure price changes in exposed stores (Wisconsin) relative to unexposed stores, normalized to the month prior to October 2007 ($m = -1$). The sample covers 9 months before and 36 months after the October 2007 ruling. The dashed vertical line indicates February 2009, when the law was effectively suspended. Bars denote 95% confidence intervals.

3.2.2 Difference-in-differences analysis

To quantify the average effect across post-shock periods, we estimate difference-in-differences specifications for both products. The post-event indicator, $post_t$, equals one from October 2007 onward—the month of Judge Callahan's initial ruling—and zero otherwise. We interact this indicator with a dummy for exposed stores, D_{cs}.

[12] As a robustness test, we conduct the same event-study analysis using only states with a minimum markup law as the control group. Appendix Figure A.1 reports the results, which show that the estimated effects are essentially unchanged.

We define the post-event window based on the event study evidence and include the 26 months beginning in October 2007. Our baseline control group consists of unexposed stores in all U.S. states outside Wisconsin, including states without minimum markup laws. Formally, we estimate:

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

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

As a robustness check, we restrict the control group to unexposed stores located only in states with minimum markup laws, thereby comparing treated stores to observationally more similar markets.

Table 3 reports the results. Columns (1) and (2) use the full sample, while columns (3) and (4) restrict the control group to MML states. The estimates are stable across specifications. In our preferred specification (columns 1-2), the suspension of Wisconsin's MML is associated with a decrease in milk prices of 0.53 cents per serving (2.12 cents per liter) and an increase in RTE cereal prices of 0.06 cents per serving (0.95 cents per 18 Oz box).[13]

Taken together, these results provide evidence of markup reallocation across products in response to the relaxation of pricing constraints. The decline in milk prices combined with the increase in cereal prices suggests that retailers adjust margins within the product basket, lowering prices on some items while increasing them on others. This pattern is consistent with multiproduct pricing models in which firms internalize cross-product demand linkages and optimally reallocate markups across goods.

4 Structural analysis

In this section, we develop a structural model of multiproduct demand and retail competition. We first present a consumer choice framework in which households purchase multiple products from up to three stores within a shopping occasion. The model allows for both product- and store-level interactions, implying that products and stores may act as substitutes or complements, and accommodates heterogeneous shopping behavior, including one-stop and multistop shopping. We then describe the empirical implementation of the model, including the econometric specification and estimation strategy. Finally, we present the estimation results and counterfactual exercises.

[13]One serving of milk is 8.4 oz and one liter contains approximately four servings. One serving of RTE cereal is 1.13 oz, and an 18 oz box contains approximately 15.9 servings.

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

	Controls: All chains		Controls: chains in MML states	
	Milk	RTE Cereals	Milk	RTE Cereals
Variable	(1)	(2)	(3)	(4)
Exposed × post	-0.0053**	0.0006*	-0.0048*	0.0006*
	(0.0026)	(0.0003)	(0.0025)	(0.0003)
No. Observations	41,126	43,380	21,537	22,646
No. Chains	88	95	64	69
R-squared	0.56	0.05	0.54	0.05

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 (October 2007). Regressions (1) and (2) use the full sample, while regressions (3) and (4) restrict the control stores to those in states with a MML 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%.

4.1 Theoretical framework

4.1.1 Consumer choice model

Our demand model builds on Florez-Acosta and Herrera-Araujo (2020). Consider a market with I consumers indexed by $i = 1, \ldots, I$ and three store chains indexed by $r \in \{A, B, C\}$, each supplying the same set of K product categories indexed by $k = 1, \ldots, K$. At each period $t = 1, \ldots, T$, consumers choose baskets of products across stores. Consumers may purchase multiple products from up to three stores, subject to visiting each store at most once per period and purchasing at most one unit from each product category. The utility that consumer i derives from purchasing product k from store r in period t is denoted by $\overline{v}_{ikrt}$, which depends on prices and other product and store characteristics.

Let $\mathcal{B}$ denote the set of all feasible product–store combinations, where each element $b \in \mathcal{B}$ represents a basket. Consumers may purchase baskets containing products from a single store (*one-stop shopping*) or from multiple stores (*multistop shopping*). To rationalize basket composition, we incorporate two additional components into utility. First, following Gentzkow (2007), we include a basket-level term, Γ, that captures the incremental utility from purchasing multiple products jointly. Second, consumers face shopping costs, s_i, which capture the real or perceived costs associated with visiting an additional store and therefore govern the number of stores visited within a shopping occasion.[14]

We assume that shopping costs are independent of store characteristics and time invariant. They are continuously distributed according to cumulative distribution function $G(\cdot)$ with positive density $g(\cdot)$ over the entire support. Finally, consumers are assumed to be fully informed about prices and product characteristics, so that shopping decisions do not involve costly search.

Each period, consumer i chooses both the set of products to purchase and the stores from which to purchase them in order to maximize the utility generated by the basket. We first characterize basket choice conditional on shopping costs and then determine equilibrium shopping patterns.

Conditional on shopping costs, a one-stop shopper selects the single store that provides the highest utility from the entire basket of products. The utility of a one-stop shopper is:

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

Similarly, a two-stop shopper will select the mix of two stores maximizing the utility of the desired basket from all possible product–store combinations. Her final basket will consist of the best two alternatives in each product category. The utility of a two-stop shopper is given by:

$$\begin{aligned} v_{ibt}^{2} = \max\Bigg\{ & \sum_{k\in b_{AB}} \max\{\overline{v}_{ikAt}, \overline{v}_{ikBt}\} + \Gamma_{b_{AB}}, \\ & \sum_{k\in b_{AC}} \max\{\overline{v}_{ikAt}, \overline{v}_{ikCt}\} + \Gamma_{b_{AC}}, \\ & \sum_{k\in b_{BC}} \max\{\overline{v}_{ikBt}, \overline{v}_{ikCt}\} + \Gamma_{b_{BC}} \Bigg\}. \end{aligned} \tag{4}$$

Finally, a three-stop shopper who wishes to purchase K products will select the best product–store combination from the alternatives existing in the market within each category.

[14]Shopping costs may include transportation costs as well as perceived or opportunity costs associated with shopping activities. We focus on the fixed component of these costs and refer to it simply as "shopping costs."

The utility of a consumer who is able to visit all of the stores is given by:[15]

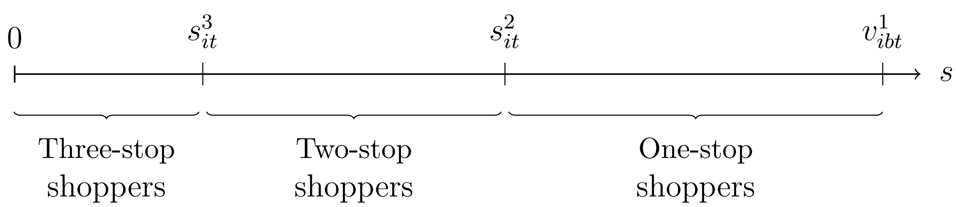
$$v_{ibt}^{3} = \sum_{k \in ABC} \max \left\{ \overline{v}_{ikAt}, \overline{v}_{ikBt}, \overline{v}_{ikCt} \right\} + \Gamma_{b_{ABC}}. \tag{5}$$

To determine the number of stores to visit, consumer i compares the additional utility generated by visiting an extra store with the associated shopping cost. Let $\delta_{it}^{2} \equiv v_{ibt}^{2} - v_{ibt}^{1}$ and $\delta_{it}^{3} \equiv v_{ibt}^{3} - v_{ibt}^{2}$ denote the incremental utility from visiting, respectively, two rather than one store and three rather than two stores.[16] As shown by Florez-Acosta and Herrera-Araujo (2020), consumer i chooses the number of stores that maximizes utility conditional on the additional shopping cost being no greater than the corresponding utility gain from visiting another store. The resulting cutoff values are:

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

Note that these cutoff points depend on the period of purchase, t. These cutoff values imply that consumers choose the number of stores to visit based on the marginal utility generated by an additional shopping trip relative to its cost. As a result, one-, two-, and three-stop shopping patterns emerge endogenously in equilibrium (see Figure 5).

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



Aggregate demand

Let $\mathcal{B}_2$ and $\mathcal{B}_3$ denote the subsets of baskets involving, respectively, two-stop and three-stop shopping. Aggregate demand for product k sold by store r is obtained by aggregating across

[15] Equations (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 utility of her desired basket. For a one-stop shopper, the feasible subsets are singletons; for a two-stop shopper, they contain two stores; and for a three-stop shopper, the feasible subset coincides with the full set of stores in the market, so no maximization over subsets is required. A general formulation of the utility maximization problem for an n-stop shopper is derived in Florez-Acosta and Herrera-Araujo (2020).

[16] For simplicity, we omit basket subscripts from the utility notation.

shopper types and over the distribution of shopping costs:

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

where $\mathbf{p}_t$ is the $(3K) \times 1$ vector of prices of the products sold by the three stores in the market, P^1_{irt} is the probability that a one-stop shopper decides to shop at store r, P^2_{irt} is the probability that a two-stop shopper chooses store r as one of the two stores that she will visit, and P^3_{irt} is the probability that a three-stop shopper decides to select basket b including product kr. All of these probabilities are known to 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 $\eta_{krmt} = \frac{\partial q_{krt}}{\partial p_{lmt}} \frac{p_{lmt}}{q_{krt}}$ for all $l \in \{1, \ldots, K\}$, $m \in \{A, B, C\}$. 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 m, as the gain in utility from visiting an additional store may not be sufficient to offset the extra shopping cost.

4.1.2 Supply

Assume that all supermarkets supply the same set of K products. Because retailer identity enters consumer utility, the same product sold by different retailers constitutes a differentiated product. Let $\mathcal{A}_r$ denote the set of products sold by retailer r. Retailer r's profits are given by:

$$\Pi_{rt} = \sum_{k \in \mathcal{A}_r} (p_{krt} - mc_{krt}) M_t q_{krt}(\mathbf{p}_t),$$

where M_t denotes the market size in period t, and q_{krt} is retailer r's market share of product k, as defined in equation (7).

We assume that supermarkets compete in prices. Under the assumption that a pure-strategy Nash–Bertrand equilibrium exists, the price p_{krt} of product k sold by retailer r

satisfies the following first-order condition:

$$q_{krt}(\mathbf{p}_t) + \sum_{l \in \mathcal{A}_r} (p_{lrt} - mc_{lrt}) \frac{\partial q_{lrt}(\mathbf{p}_t)}{\partial p_{krt}} = 0.$$

Let $J = 3K$ denote the total number of retailer–product combinations in the market. The first-order conditions generate a system of J equations that jointly determines equilibrium price-cost margins across all products. Let $\mathbf{S}_t$ denote the $J \times J$ matrix of demand derivatives, with element

$$S_t(h,j) = -\frac{\partial q_{jt}(\mathbf{p}_t)}{\partial p_{ht}}, \qquad h,j = 1,\ldots,J.$$

Let $\mathbf{\Omega}_t$ denote a $J \times J$ matrix, whose (h,j) element is $\Omega_t(h,j) = \omega_{hj} S_t(h,j)$, where ω_{hj} is an indicator equal to one if product-retailer combinations h and j are sold by the same retailer and zero otherwise. The system of first-order conditions can then be written in matrix form as:

$$\mathbf{q}_t - \mathbf{\Omega}_t(\mathbf{p}_t - \mathbf{mc}_t) = \mathbf{0}. \tag{8}$$

where $\mathbf{q}_t$, $\mathbf{p}_t$, and $\mathbf{mc}_t$ are J-dimensional vectors of market shares, prices, and marginal costs, respectively. Solving for price-cost margins yields:

$$\mathbf{p}_t - \mathbf{mc}_t = \mathbf{\Omega}_t^{-1}\mathbf{q}_t. \tag{9}$$

4.2 Empirical specification

4.2.1 Product-level demand

We empirically specify product-level utility as a function of observed and unobserved product-store characteristics and time fixed effects. We allow the price coefficient to vary across households as a function of observed and unobserved household characteristics. Let the utility of consumer i from purchasing product k from store r at time t be:

$$\overline{v}_{ikrt} = -\alpha_i p_{krt} + \mathbf{x}_{kr}\boldsymbol{\beta} + \xi_{kr} + \phi_t, \tag{10}$$

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.

4.2.2 Basket-level demand

Consistent with our theoretical framework, we specify the utility that a n-stop shopper ($n \in \{1, 2, 3\}$) derives from purchasing basket $b \in \mathcal{B}$ as:

$$\begin{aligned} u_{ibt} &= \sum_{kr \in b} \overline{v}_{ikrt} + \Gamma_b - s_i n_b + \varepsilon_{ibt}, \\ &= v_{ibt} - s_i n_b + \varepsilon_{ibt}, \end{aligned} \tag{11}$$

where v_{ibt} is the overall utility of basket b defined by equations (3) through (5) above; n_b is the number of stores visited to purchase basket b; s_i is the individual shopping cost; and ε_{ibt} is an idiosyncratic basket-level shock to utility. Consumer unobserved heterogeneity also enters the model through the shopping cost term, s_i.

Equations (10) and (11) jointly determine preferences over products, stores, and shopping patterns (one-stop versus multistop shopping). The specification captures both vertical and horizontal dimensions of consumer preferences. The vertical dimension is governed by product-store characteristics, while the horizontal dimension arises through shopping costs and idiosyncratic basket-level utility shocks. 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 basket b at time t faces a choice set $\mathcal{B}$ of mutually exclusive and exhaustive alternatives consisting of combinations of products and stores. The basket she chooses is such that she obtains the highest possible utility net of shopping costs. That is, for all $b' \in \mathcal{B}$, consumer i chooses basket b at time t if:

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

Let $\boldsymbol{\theta} = (\boldsymbol{\alpha}', \boldsymbol{\beta}', \mathbf{s}', \boldsymbol{\Gamma}')'$ be a vector containing the parameters to be estimated, where $\boldsymbol{\alpha}'$ and $\mathbf{s}'$ denote the vector of individual preference parameters. We allow for consumer heterogeneity through a discrete distribution over eight household types defined by household size, income, and marital status (see Section 4.4.1); within each type, we restrict the coefficients on price and store visits to be constant across households. Further, $\boldsymbol{\Gamma} = (\Gamma_1, \ldots, \Gamma_B)'$ denotes the vector of complementarity effects of all baskets 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 basket b and no additional products, at time t as a function of the characteristics of products and supermarkets:

$$P_{ibt}(\mathbf{X}, \mathbf{p}_t; \boldsymbol{\theta}) = \frac{\exp(v_{ibt} - s_i n_b)}{1 + \sum_{b' \in \mathcal{B}} \exp(v_{ib't} - s_i n_{b'})}, \tag{12}$$

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 baskets b and b', respectively.

Estimating the model in equation (12) would result in biased coefficients. The bias arises because restricting the consumer choice set implies treating excluded products and stores as unobserved alternatives. As a result, purchases involving excluded products or excluded stores are incorrectly absorbed into the outside option. This is problematic because consumers often purchase included products jointly with excluded products and/or from excluded stores. Consequently, the model understates the probability of purchasing included baskets, leading to biased estimates of demand parameters such as shopping costs and product complementarities.

4.2.3 Proposed solution: Total purchase probability and bias correction

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 multiproduct, multistore choice problem tractable, we as researchers need to impose some restrictions on the consumers' choice set used for demand estimation.

Let $\mathcal{B}_{inc}$ denote the set of baskets composed exclusively of included products and included stores. Let $\mathcal{B}_{exc}$ denote the set of baskets composed exclusively of excluded products and excluded stores. Finally, baskets combining included and excluded products/stores belong to the set $\mathcal{B}_{inc} \times \mathcal{B}_{exc}$. The exhaustive set of baskets available to consumers is therefore given by:

$$\mathcal{B} = \mathcal{B}_{inc} \cup \mathcal{B}_{exc} \cup (\mathcal{B}_{inc} \times \mathcal{B}_{exc}).$$

Consider a basket $b^* \in \mathcal{B}_{inc}$. The probability that a consumer i purchases a basket containing b^* equals the sum of the probabilities of all baskets that contain b^*, which yields:

$$\begin{aligned} Q_{ib^*t}(\boldsymbol{X}, \mathbf{p}; \boldsymbol{\theta}) &= P_{ib^*t} + \sum_{h \in b^* \times \mathcal{B}_{exc}} P_{iht} \\ &= \frac{\exp(v_{ib^*t} - n_{b^*} s_i) + \sum_{h \in b^* \times \mathcal{B}_{exc}} \exp(v_{iht} - n_h s_i)}{1 + \sum_{b' \in \mathcal{B}} \exp(v_{ib't} - n_{b'} s_i)}, \end{aligned} \tag{13}$$

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

Appendix B shows that this probability can be rewritten as a modified Logit probability over the researcher's included choice set, augmented by two correction terms that account for purchases involving excluded products and stores. That is:

$$Q_{ib^*t}(\boldsymbol{X}, \mathbf{p}; \boldsymbol{\theta}) = \frac{\exp(v_{ib^*t} - n_{b^*}s_i - ln(\Delta_{1it}) + ln(\Delta_{2it|b^*}))}{1 + \sum_{g \in \mathcal{B}_{inc}} \exp(v_{igt} - n_g s_i - ln(\Delta_{1it}) + ln(\Delta_{2it|g}))}, \tag{14}$$

with:

$$\Delta_{1it} = 1 + \sum_{b' \in \mathcal{B}_{exc}} \exp(v_{ib't} - n_{b'} s_i), \quad \text{and} \quad \Delta_{2it|b^*} = 1 + \sum_{h \in \mathcal{B}_{exc}} \exp(v_{iht} - n_{h|b^*} s_i). \tag{15}$$

where $n_{h|b^*}$ denotes the number of additional stops made to purchase the excluded products conditional on purchasing b^*. The first term has the same functional form as the denominator of a Logit probability of purchasing a basket composed exclusively of excluded products and stores, while the second term has the functional form of the denominator of a Logit probability of purchasing baskets containing excluded products conditional on purchasing b^* on the same shopping occasion.

Proposed correction. We assume that individual choice sets are heterogeneous across consumers but stable over time. Following Crawford, Griffith and Iaria (2020), we approximate each consumer's feasible choice set using her full purchase history (FPH). Under this approach, products never purchased by a consumer are treated as having zero choice probability for that individual (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 baskets considered by the researcher be denoted by $\mathcal{B}_{inc,i}$. Thus, the subset of excluded products and stores is represented by ($\mathcal{B}_{exc,i}$). The probability of purchasing basket b^* is obtained by summing the probabilities of all baskets containing b^* and is given by equation (14) with Δ_{1it} and $\Delta_{2it|b^*}$ defined over $\mathcal{B}_{exc,i}$.

Let P_{i0t} denote the probability that individual i purchases none of the included products in week t, and let Q_{i0t} denote the probability that individual i purchases none of the included products but purchases at least one excluded product. Let P_{ib^*t} denote the probability that individual i purchases basket b^* and no excluded products. We can then rewrite Δ_{1it} as

$$\Delta_{1it} = 1 + \sum_{b' \in \mathcal{B}_{exc,i}} \exp(v_{ib't} - n_{b'} s_i) = \frac{Q_{i0t}}{P_{i0t}},$$

Similarly, Δ_{2ib^*t} can be written as

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

Because Δ_{1it} is not directly observed in each period t, we approximate it using the ratio of each individual's average probabilities of Q_{i0t} and P_{i0t} computed over the periods in which no included products are observed. Specifically, we define

$$\overline{\Delta}_{1i} = \frac{\overline{Q}_{i0}}{\overline{P}_{i0}}.$$

We approximate the second term analogously. For each basket b^*, we compute the ratio of the individual's average probability of purchasing any basket that contains the included products and stores in b^*, denoted $\overline{Q}_{ib^*}$, to the individual's average probability of purchasing basket b^* with no excluded products, denoted $\overline{P}_{ib^*}$. Both averages are computed over the periods in which the corresponding choices are observed. This yields

$$\overline{\Delta}_{2i|b^*} = \frac{\overline{Q}_{ib^*}}{\overline{P}_{ib^*}}.$$

Consistent with the theoretical derivation in equation (14), we fix the coefficients on $\ln(\overline{\Delta}_{1i})$ and $\ln(\overline{\Delta}_{2i|b^*})$ at their population values of -1 and 1, respectively.

4.3 Monte Carlo simulations

We conduct Monte Carlo simulations to evaluate the performance of our model and the proposed bias correction relative to a standard discrete choice model.

4.3.1 Design

We simulate the choices of 78 consumers, each of whom purchases baskets of products from one or multiple stores.

Choice set. We consider a setting with three product categories and three stores, and analyze two scenarios. In the first scenario, consumers face a choice set consisting of all possible combinations of the included products and stores—potentially including the outside good—which results in 64 possible baskets overall. To separately identify the product-specific constants from shopping costs, we construct 9 singleton baskets (i.e., baskets containing at most one product). The outside good represents all baskets that include excluded products and stores, as well as the no-purchase option.

In the second scenario, we construct consumer-specific choice sets based on the purchase histories observed in our data. We set the number of shopping occasions to 208 (i.e., 52 weeks per year over 4 years), consistent with the time-series dimension of our data.

Parameter values. We assign positive values to the dummies capturing product–store preferences, ranging from 0.5 to 3. The coefficients associated with the dummies capturing complementarities between pairs of products are all set equal to 0.25, while the complementarity associated with the joint purchase of all three products is normalized to zero. We set both the price coefficient and the disutility associated with the number of store visits equal to 3. To incorporate consumer heterogeneity, we allow individual-specific tastes for these two variables and assume they are independently and identically distributed Normal random variables with zero mean, and standard deviations equal to 2 and 1, respectively.

4.3.2 Monte Carlo results

Table C.1 in the Appendix reports parameter estimates from 25 simulations for both scenarios described above. The results indicate that both the mean price coefficient and its standard deviation are consistently estimated under the standard method and our proposed approach. However, our method yields substantially more accurate estimates of the shopping disutility coefficients. Consequently, nearly all confidence intervals obtained under our method contain the true parameter values, unlike those produced by the standard approach.

Figure 6 plots the density of the shopping disutility coefficients—that is, the coefficients associated with the number of store visits—for the true parameters and for the estimates obtained under both methods. The figure shows that our model, together with the proposed bias correction, closely recovers the distribution of shopping preferences. By contrast, the standard method markedly understates these preferences, resulting in biased estimates of both the mean and the standard deviation of the distribution.

Finally, our method also outperforms the standard approach in estimating both product–store specific constants and product complementarities. Overall, the Monte Carlo experiments indicate that our method largely corrects the biases arising from excluding products and stores from the estimated choice set.

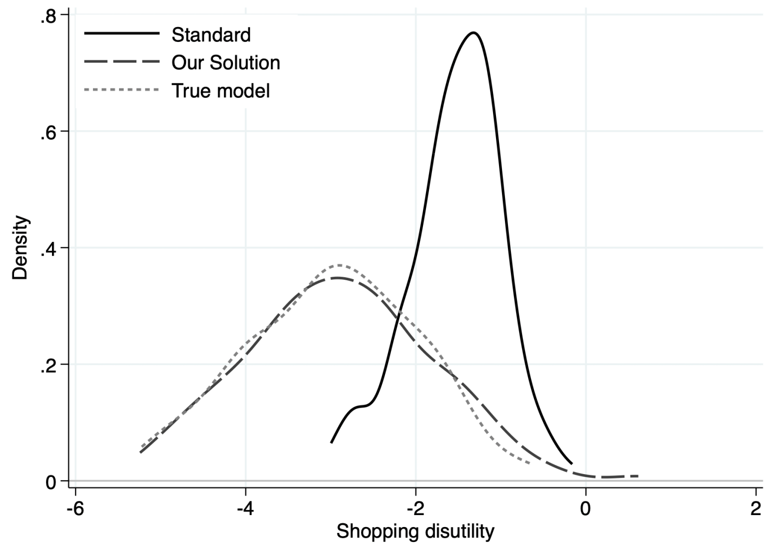


Figure 6: Density of true and estimated shopping disutility coefficients under the standard and proposed methods

Notes: This figure plots the density of the shopping disutility coefficients for the true parameters and for the estimates obtained using the standard and proposed methods. The proposed method more accurately recovers the distribution of shopping preferences.

4.4 Empirical application and results

4.4.1 Data

To estimate our structural model, we use the NielsenIQ Consumer Panel data, which records household purchases using hand-held scanners or mobile device after each shopping trip (NielsenIQ, 2007-2011). For each purchased item, the data include the product UPC, purchase date, and store location. For trips to retailers partnered with NielsenIQ, prices correspond to the average UPC-level price at the store-week level; otherwise, households manually enter the price paid using information from their receipts. Households also report whether purchases were made under promotional conditions (e.g., sales or coupons).[17]

We estimate the model using Wisconsin as our case study over the period January 2007—nine months before the first judicial ruling that signaled the eventual suspension of the minimum markup law—through December 2011, slightly more than one year after the law was reinstated.

[17] The household- and store-level scanner datasets can be linked because both use the same identifiers for retailers, product modules, brands, and UPCs.

Shopping period. We define a shopping occasion as a week in which a household records grocery purchases. During a given week, a household that concentrates purchases within a single supermarket chain may make one visit to a store in the chain, multiple visits to the same store, or visits to several stores belonging to the same chain. Regardless of the number of visits or store locations, we classify the household as a one-stop shopper as long as purchases are observed only within a single supermarket chain during the week. Conversely, if purchases are made from stores belonging to competing chains, we classify the household as a multi-stop shopper.

Products, stores, and prices. We focus on 11 product categories selected according to several criteria. First, these products are frequently purchased and commonly consumed by U.S. households on a daily basis. Second, they are generally not stored for long periods, making stockpiling less of a concern. Third, the categories are not mutually exclusive, and many are commonly purchased together, either within the same store or across multiple stores during a given week. Table 4 summarizes average weekly purchases for the selected categories. On average, consumers allocate 22% of their weekly grocery expenditures to these 11 categories, with milk, low-calorie drinks, and ready-to-eat (RTE) breakfast cereals accounting for the largest expenditure shares.

Table 4: Summary of Weekly Purchases for the Selected Categories

Product	Quantity (Ounces)	Price (dollars)	Expenditure Share (%)
Canned soup	56	4.9	1.5
RTE cereals	41	7.3	2.9
Coffee	30	8.6	1.4
Carbonated soft drinks	307	10.9	2.6
Cookies	25	4.4	1.2
Potato chips	17	3.9	1.3
Eggs	18	2.0	0.9
Milk	186	4.7	3.5
Yogurt	47	4.7	1.7
Low-calorie drinks	363	11.5	3.0
Bread	36	3.7	2.1

Notes: This table reports the average quantity purchased, expenditure, and expenditure share for the selected product categories in our consumer panel between 2007 and 2011. Averages are computed at the weekly level across transactions, households, and years. Quantities are measured in ounces for all products except eggs, which are measured in units. Expenditure shares are calculated as the ratio of weekly spending on a given category to total weekly grocery spending.

Source: NielsenIQ database. Authors' calculations.

On the retail side, we restrict attention to three supermarket chains. In addition, we focus on regional chains that operate exclusively within Wisconsin. These chains have broad geographic coverage within the state and account for nearly 25% of grocery sales across all supermarket chains in Wisconsin in 2010. All remaining retailers in the data are incorporated into the outside option together with the option of not purchasing any of the included product categories. Consequently, consumers choose among baskets containing up to 11 products purchased across multiple supermarket chains, consistent with our framework of oligopolistic competition with differentiated retail assortments, where consumers with a preference for variety may shop at multiple stores within a given week.

Because the household panel does not directly report prices but rather expenditures and quantities purchased for each product-store combination, we construct prices as follows. First, we aggregate expenditures net of coupons and quantities at the product-supermarket-week level within stores. Second, we divide total expenditures by total quantities to obtain a common unit price for each store-week observation. Third, when no price is available after this step, we impute prices using the average unit price for the corresponding product-retailer pair across stores within the same zip code and week. If prices remain unavailable, we progressively expand the geographic aggregation, using averages at the three-digit zip code by week, DMA by week, and three-digit zip code by month levels. Remaining missing observations are imputed using the national weekly mean price for the corresponding product-retailer pair.

To ensure comparability across retailers and product categories, we compute demeaned prices by removing the within-year UPC-store mean price. As in the reduced-form analysis, this transformation removes persistent price-level differences across categories and retailers. We then scale the demeaned price by the average weekly quantity purchased within each product category (reported in the "Quantity" column of Table 4), converting prices into weekly demeaned expenditure equivalents. Demeaned prices are used to estimate consumer preferences, while non-demeaned prices are used to compute demand elasticities. To recover marginal costs from the supply-side first-order conditions, we use the market-week average observed price.

A limitation of the consumer panel is that prices are only observed for products actually purchased, not for products that were available but not chosen. To address this issue, we use the retailer scanner dataset to recover prices for non-purchased categories, following the same steps described above.[18]

[18] In the retailer scanner data, the posted price field records the total price associated with a promotional bundle rather than the unit price. For example, a "2 for \$5" promotion is recorded as a price of \$5 with a price multiplier (`prmult`) equal to 2. We therefore divide the posted price by `prmult` to recover the transaction-level

Another limitation is that neither household nor store locations are observed precisely; both are available only at the zip-code level. We address this issue by matching households to retailer prices using the geographically closest zip code available in each week.

Household demographics. To approximate complete purchase histories, we restrict the sample to households observed in at least three of the six years covered by the NielsenIQ panel (2007–2012), which spans both the regulated and unregulated periods. This restriction yields a sample of 1,443 Wisconsin households. We classify households according to three demographic dimensions: household size, income, and marital status. Household size and income are each split at the median into two groups (smaller/larger and low/high, respectively), while marital status is categorized as either single or married/partnered. This classification generates eight household types. Table 5 reports the number and share of households in each group.

Table 5: Household Types

Size	Income	Marital Status	No. Households	Percent Share
Smaller	Low	Single	208	14.4%
		Married/Partnered	354	24.5%
	High	Single	264	18.3%
		Married/Partnered	96	6.7%
Larger	Low	Single	130	9.0%
		Married/Partnered	39	2.7%
	High	Single	327	22.7%
		Married/Partnered	25	1.7%
Total			1443	100%

Notes: The table reports the composition of the sample by household size, income, and marital status. Household size and income are split at the median into two groups (smaller/larger and low/high).
Source: NielsenIQ database. Authors' calculations.

In estimating the demand model, we allow the coefficients on prices and store visits to vary across household types, implying that price sensitivity and shopping-trip preferences are homogeneous within each demographic group.[19]

unit price before aggregating expenditures and computing per-ounce prices. This adjustment is unnecessary in the consumer panel, where the recorded expenditure already reflects the transaction-level unit price.

[19]This specification is motivated by the fact that households rarely purchase a single product when visiting

4.4.2 Identification and estimation

Identification of the demand parameters relies on rich cross-sectional and intertemporal variation in household shopping behavior, product choices, and store visitation patterns. The mean utility parameters are identified from observed differences in product-store purchase frequencies across households, retailers, and time. The price coefficient is separately identified from mean utility through within-product-retailer variation in prices over time. Intuitively, conditional on product-store fixed effects, changes in the price of a given product-retailer combination shift purchase probabilities in a manner that identifies households' price sensitivity.

Shopping costs are identified from within-household variation in shopping patterns across weeks. In particular, households frequently alternate between one-stop and multi-stop shopping behavior over time. This variation is informative about the utility cost of visiting additional stores. Identification additionally requires variation in the composition of purchased baskets across shopping trips. Conditional on store choice, changes in the allocation of products across retailers help disentangle shopping costs from product-store mean utilities. Moreover, week-to-week variation in the joint purchase of products across stores identifies the complementarity parameters governing basket composition.

A central identification concern in demand estimation is the potential endogeneity of prices that stems from two sources. First, retailers may adjust prices in response to unobserved product characteristics or local demand conditions valued by consumers. Second, market-level demand shocks may simultaneously affect equilibrium prices and purchase decisions. We exploit the panel structure of the data to absorb persistent unobserved heterogeneity through product and retailer fixed effects. Nevertheless, residual price endogeneity may remain if retailers respond to time-varying local demand shocks.

To address this concern, we adopt a control-function approach for prices. In a first stage, we regress prices on a set of Hausman-style instruments following DellaVigna and Gentzkow (2019). Specifically, for each product-retailer combination, we use prices observed in other DMAs excluding the DMA in which the focal price is observed. These instruments exploit common cost variation across geographic markets while remaining plausibly orthogonal to local demand shocks. The resulting residuals are then incorporated into the demand specification to control for endogenous price variation.

An additional identification issue arises from multiproduct pricing by retailers. Because

a supermarket, making it difficult to separately identify household-level preferences for product characteristics in a basket-demand setting.

supermarkets jointly determine prices across a broad set of categories, restricting the analysis to a narrow subset of products could bias inferred markups if excluded categories materially affect retailers' pricing incentives. We mitigate this concern by focusing on 11 product categories that are frequently purchased, commonly purchased together, and characterized by strong consumption complementarities. Products outside this set are purchased substantially less frequently and are therefore less likely to exert a first-order influence on pricing incentives within the included categories.

We estimate the demand system separately by year, exploiting both cross-sectional heterogeneity and within-household variation over time. This approach allows price sensitivities and shopping-cost parameters to vary flexibly across household types and years, thereby accommodating changes in consumer behavior over time. In addition, we estimate year-specific product-store fixed effects and complementarity parameters, which capture time-varying demand conditions and shifts in basket composition patterns.

Formally, in each week t, consumer i chooses a basket of products, potentially including the outside option. Let H denote the set of all feasible sequences of basket choices over the year, and let $h = (b_1, \ldots, b_T)' \in H$ denote a particular sequence, where b_t is the basket chosen in week t. The probability that consumer i chooses sequence h is:

$$\mathcal{P}_{ih}(\mathbf{X}, \mathbf{p}; \boldsymbol{\theta}) = \prod_{t=1}^{T} Q_{ib_t t}(\mathbf{X}, \mathbf{p}_t; \boldsymbol{\theta}). \tag{16}$$

Let h_i denote the sequence of choices observed for consumer i, and let $\mathbf{h}$ denote the $N \times 1$ vector of observed choice sequences for all consumers in the sample. The parameter vector $\boldsymbol{\theta}$ is estimated by maximizing the log-likelihood function:

$$\mathcal{L}(\mathbf{X}, \mathbf{h}; \boldsymbol{\theta}) = \sum_{i} \ln \mathcal{P}_{ih_i}(\mathbf{X}, \mathbf{p}; \boldsymbol{\theta}). \tag{17}$$

4.4.3 Estimation results

Table 6 reports the means and standard errors of estimated distributions of the coefficients on price and number of stores visited by year in our sample period. Results are as expected: demand is 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. While the price coefficients are similar across years, the coefficients of the shopping patterns range between 0.35 and 0.58 in absolute value, indicating that shopping costs vary with time, on average.

We recover the average shopping cost per visited supermarket by converting the mean coefficient on the number of store visits into dollar terms, dividing it by the mean price coefficient. This yields an average shopping cost of $2.30 per store visited. Table 6 presents both means and standard deviations of retrieved shopping costs and the across-year means. Our average estimate corresponds to 3.45% of weekly expenditure and is comparable to those reported in related case studies: Thomassen et al. (2017) estimate an average cost of 5.42% of weekly expenditure per store visit, while Florez-Acosta and Herrera-Araujo (2020) report 2.87%.

Table 6: Demand estimates based on observed data

	Price ($/basket)		No. of visited stores		Shopping cost ($/trip)	
Year	Mean	SE	Mean	SE	Mean	SE
2007	-0.1493	0.0024	-0.3469	0.0089	2.32	0.0177
2008	-0.2047	0.0038	-0.5149	0.0067	2.52	0.0139
2009	-0.2206	0.0062	-0.4827	0.0060	2.19	0.0091
2010	-0.2490	0.0063	-0.3806	0.0061	1.53	0.0053
2011	-0.1795	0.0037	-0.5794	0.0081	3.23	0.0052
Average	-0.2006	0.0021	-0.4609	0.0032	2.30	0.0051

Notes: The table reports cross-group averages of demand estimates and corresponding standard errors for the price coefficient, the store-visits coefficient, and the implied shopping cost. Shopping costs are calculated by expressing the store-visits coefficient in dollar units relative to the price coefficient. Standard errors are obtained using a parametric bootstrap.

Table 7 reports averages of retailer-specific median own- and cross-price elasticities, distinguishing between within-retailer elasticities (top panel) and cross-retailer elasticities (bottom panel). As expected, average own-price elasticities are negative for all product categories and smaller than -1 for all products except eggs, which exhibit inelastic demand on average. Within-retailer cross-price elasticities are negative for all product pairs, with average values ranging from -0.222 to -1.253. We interpret this pattern as evidence of complementarity between product categories within the same chain. Intuitively, because a large share of consumers are one-stop shoppers, an increase in the price of one product may induce them to switch retailers for their entire basket rather than substitute toward other products within the same store. As a result, products sold by the same retailer behave as complements, while competing supermarkets behave as substitutes from the consumer's perspective. This finding is consistent with previous studies estimating multiproduct demand models using supermarket data (see, for example, Thomassen et al., 2017; Florez-Acosta and Herrera-Araujo, 2020).

Average cross-retailer elasticities are predominantly positive, ranging from -0.059 to 0.309 in the averaged matrix. This indicates that retailers are substitutes at the store level, consistent with the high proportion of one-stop shoppers in our sample. At a more granular product-retailer level, however, a non-negligible share of product pairs exhibits negative cross-retailer elasticities. This pattern reflects the substitution behavior of multistop shoppers, who face lower shopping costs and can spread purchases across retailers, thereby generating complementarities across competing stores.

Table 7: Average median own- and cross-price elasticities across retailers

Product	Soup	Cereal	Coffee	S.Dr.	Cookies	Chips	Eggs	Milk	Yogurt	L.C.Dr.	Bread
					Within-retailer						
Canned Soup	**-2.323**	-1.039	-0.940	-0.645	-0.667	-0.617	-0.252	-0.539	-0.585	-0.903	-0.630
RTE Cereal	-0.811	**-3.435**	-0.782	-0.654	-0.703	-0.549	-0.237	-0.655	-0.739	-0.981	-0.637
Coffee	-0.869	-0.936	**-4.178**	-0.702	-0.668	-0.570	-0.267	-0.522	-0.605	-0.886	-0.608
Soft Drinks	-0.818	-1.084	-0.924	**-3.714**	-0.770	-0.693	-0.225	-0.571	-0.534	-1.253	-0.672
Cookies	-0.855	-1.151	-0.913	-0.792	**-2.156**	-0.718	-0.226	-0.598	-0.642	-1.067	-0.749
Potato Chips	-0.820	-0.943	-0.807	-0.755	-0.750	**-2.157**	-0.222	-0.511	-0.522	-1.082	-0.602
Eggs	-0.780	-0.959	-0.914	-0.563	-0.560	-0.520	**-0.788**	-0.666	-0.584	-0.869	-0.660
Milk	-0.677	-1.047	-0.721	-0.566	-0.577	-0.482	-0.261	**-1.592**	-0.574	-0.712	-0.655
Yogurt	-0.730	-1.200	-0.801	-0.534	-0.619	-0.502	-0.235	-0.586	**-2.075**	-0.839	-0.582
Low Cal. Drinks	-0.786	-1.091	-0.806	-0.838	-0.710	-0.643	-0.238	-0.489	-0.566	**-4.219**	-0.635
Bread	-0.683	-0.905	-0.705	-0.579	-0.647	-0.481	-0.230	-0.573	-0.501	-0.815	**-1.411**
					Cross-retailer						
Canned Soup	0.170	0.052	-0.102	0.045	0.041	0.019	0.017	0.037	0.046	0.067	0.080
RTE Cereal	0.032	0.257	0.046	0.030	0.005	0.039	0.027	0.054	0.060	0.029	0.053
Coffee	-0.024	0.089	0.196	0.024	-0.024	0.043	0.009	0.069	0.093	0.028	0.057
Soft Drinks	0.097	0.035	-0.002	0.249	-0.004	0.002	0.005	0.038	0.045	0.001	0.037
Cookies	0.058	0.066	0.004	0.034	0.147	0.003	0.016	0.038	0.022	0.113	0.056
Potato Chips	-0.000	0.055	0.029	0.014	-0.059	0.124	0.007	0.039	0.027	0.050	0.040
Eggs	0.064	0.127	-0.012	0.046	0.029	0.025	0.063	0.084	0.059	0.037	0.072
Milk	0.068	0.102	0.062	0.035	0.028	0.044	0.032	0.156	0.059	0.054	0.068
Yogurt	0.091	0.103	0.167	0.052	0.021	0.020	0.019	0.062	0.153	0.058	0.087
Low Cal. Drinks	0.114	0.063	-0.005	0.050	0.048	0.048	0.016	0.050	0.061	0.309	0.092
Bread	0.094	0.103	0.029	0.044	0.040	0.032	0.026	0.059	0.069	0.093	0.144

Notes: This table reports averages of retailer-specific median own- and cross-price elasticities, computed from the retailer-level elasticity matrices. The within-retailer panel averages the three within-retailer submatrices, while the cross-retailer panel averages the six cross-retailer submatrices. Each entry (i, j) gives the average percentage change in the market share of product i with respect to a one percent change in the price of product j. Own-price elasticities in the within-retailer panel are highlighted in bold.

Our own-price elasticity estimates are broadly comparable with those reported in the literature, which has mainly focused on single-product demand models. Table 8 summarizes the comparison for the products covered both in our analysis and in previous studies using U.S. retail data. The values in the column "Our Estimate" are averages of the product-retailer-specific median own-price elasticities reported on the main diagonal of the top panel of Table 7. Chevalier, Kashyap and Rossi (2003) report estimates of -1.98 for canned soup and −3.60 for cookies. Nevo (2001) reports median brand-level elasticities for RTE cereals ranging from −2.28 to −4.25, with an average across reported medians of −3.02. Nakamura and Zerom (2010) report a median own-price elasticity of −3.46 for coffee. Dubé (2004) estimate an average elasticity of −2.74 for carbonated soft drinks, with estimates ranging from −2.11 to −3.59 across products. Ershov et al. (2025) reports an average own-price elasticity of −2.13 for potato chips, and Döpper et al. (2025) reports an average own-price elasticity of −3.12 for yogurt. Overall, our estimates fall within a comparable range across the seven products.[20]

Table 8: Comparison of Own-Price Elasticity Estimates

Product	Our Estimate	Literature Estimate	Source
Canned Soup	−2.32	−1.98	Chevalier, Kashyap and Rossi (2003)
RTE Cereal	−3.44	−3.02	Nevo (2001)
Coffee	−4.18	−3.46	Nakamura and Zerom (2010)
Soft Drinks	−3.71	−2.74	Dubé (2004)
Cookies	−2.16	−3.60	Chevalier, Kashyap and Rossi (2003)
Potato Chips	−2.16	−2.13	Ershov et al. (2025)
Yogurt	−2.08	−3.12	Döpper et al. (2025)

Notes: This table compares our own-price elasticity estimates with estimates available in the literature using U.S. retail or scanner data. The column "Our Estimate" reports averages across retailers of the product-retailer-specific median own-price elasticities reported in Table 7. For Nevo (2001), the reported figure is the average of brand-level median elasticities, which range from −2.28 to −4.25. For Dubé (2004), the reported figure is the average own-price elasticity, with a range of −2.11 to −3.59 across products.

We use the demand estimates and the supply model to recover markups at the product-retailer-week level during the period in which the minimum markup provisions of the Unfair Sales Act were suspended (March 2009–August 2010), which we refer to as the *free-pricing* period. Figure 7 presents the implied price-cost markups for each product, expressed as a percentage of price and averaged across retailers and weeks. The vertical bars report the range across retailer-specific average markups over the same period. Appendix Figure D.1 reports weekly product-level markup series averaged across retailers, together with the weekly minimum-to-maximum range across retailers.

The figure shows that retailers charged positive average markups on all products during the free-pricing period, although there is substantial heterogeneity across categories. Bread

[20] For cookies and yogurt, our estimates of −2.16 and −2.08, respectively, are smaller in absolute value than the corresponding benchmarks of −3.60 and −3.12. These differences may reflect differences in product market definitions, model specification, or sample periods across studies.

and eggs exhibit the highest average markups, at approximately 29.7% and 28.6%, respectively. Milk markups are also relatively high and stable across retailers, averaging about 20.2%. Soup, potato chips, and yogurt display intermediate markups, ranging from 10.5% to 13.2%. Soft drinks, cookies, coffee, cereal, and low-calorie drinks exhibit the lowest average markups, ranging from 3.6% to 5.8%.

Our estimates also reveal substantial heterogeneity in markups across retailers for several products. For instance, average markups for bread range from 18.1% to 44.5%, while those for RTE cereal range from 2.5% to 10.7%. Carbonated soft drinks are especially relevant for the counterfactual analysis below. Although their overall average markup is positive, retailer-specific weekly markups are very small for some retailers, ranging from approximately -1% to 10.7%. Appendix Figure D.1 shows that the lower end of the weekly cross-retailer markup range falls below zero during several weeks of the free-pricing period. Thus, while negative markups are not a generalized pattern across retailers, soft drinks are the only category for which we estimate below-cost pricing in some retailer-week observations. This pattern is consistent with the conventional view of loss-leader pricing, whereby retailers may sell selected products at or below cost to attract consumers into the store. This case motivates our first counterfactual experiment, which imposes a zero minimum markup constraint, consistent with a restriction against below-cost pricing, as in Wisconsin.

Our model predicts that cross-product pricing externalities explain why retailers make joint pricing decisions across products, even when those products are unrelated in consumption. Empirically, joint pricing decisions may respond to two distinct forces: the composition of the basket that the average consumer frequently purchases, which we refer to as a *bundle* effect, and complementarity in consumption, which we refer to as a *consumption* effect. We use our implied markups to test both predictions.

We first examine the *bundle* effect by testing whether, at the aggregate level, products with persistently low markups are compensated by higher markups on the remaining products in our set, given that these goods are often purchased together by consumers in our data. To do so, we compute demeaned markups for all products as the residuals from retailer-specific regressions of implied markups on product, week, and year fixed effects; this removes level differences across products and retailers and facilitates comparisons of markup dynamics within and across retailers. We then aggregate demeaned markups into two subsets. The low-markup subset consists of products whose markups are frequently close to, or below, a 5% benchmark.[21] The high-markup subset comprises the remaining products.

[21] Operationally, we classify as low-markup products those with markups at or below 5% in at least 55% of product–retailer observations during the free-pricing period. We also include a small number of product–

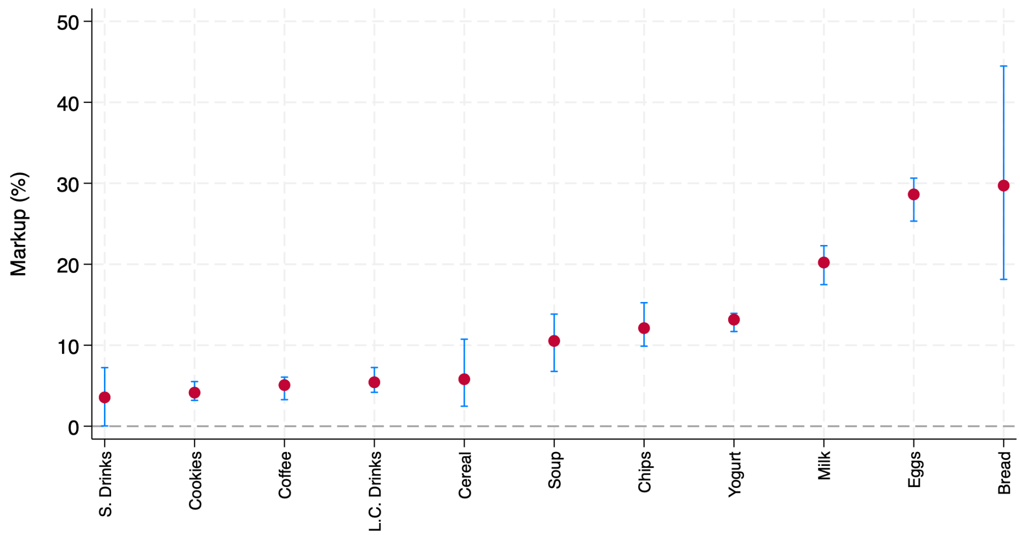


Figure 7: Average implied retail markups and cross-retailer dispersion in Wisconsin during the free pricing period (March 2009–August 2010)

Notes: This figure shows average implied product-level markups across retailers and weeks during the free pricing period (March 2009–August 2010). Dots denote product-level averages across retailer-week observations, and vertical bars indicate the range across retailer-specific average markups over the same period. Markups are computed as the price-cost margin over price, $(p - c)/p$.

The low-markup group includes products such as cookies, RTE cereal, coffee, carbonated soft drinks, and low-calorie drinks, several of which are commonly purchased and likely to enter consumers' regular shopping baskets. This pattern is consistent with the conventional view that retailers use frequently purchased staple products to attract consumers (see, for example, Chevalier, Kashyap and Rossi, 2003; Johnson, 2017; Holler and Rickert, 2022). We also find that the composition of the low-markup basket differs across retailers, suggesting an additional dimension of differentiation: retailers may attract one-stop shoppers not only through the overall price of the basket, but also through the particular products they choose to price aggressively. To the extent that consumers differ in the combinations of products they seek to purchase, this heterogeneity in low-markup baskets may soften competition relative to a setting in which all retailers subsidize the same products.

Figure 8 presents the results in two panels. The left panel shows a scatter plot of weekly demeaned markups averaged across product-retailer observations within the low- and high-markup groups. It reveals a clear negative relationship: weeks in which markups on low-

retailer cases whose markups are concentrated just above 5%, with most observations remaining below 6%.

markup products are lower are also weeks in which markups on high-markup products are higher, and vice versa. This pattern provides evidence that retailers systematically reallocate markups across products that are frequently purchased together. Consistent with the theoretical predictions of Chen and Rey (2012, 2019) and the evidence documented by Florez-Acosta and Herrera-Araujo (2020), low-markup products help retailers attract one-stop shoppers, who care about the overall value of their shopping basket, while higher markups on the remaining products allow retailers to extract rents from multistop shoppers, who have strong preferences for specific products at particular retailers and are therefore willing to pay a price premium even when those products are available at lower prices elsewhere.

The right panel shows the dynamics of average demeaned markups for the two groups over time. The negative co-movement between the groups is visible throughout the sample period, providing further evidence that basket-level cross-subsidization is not an isolated episode but rather a persistent feature of retailers' pricing strategies during the free-pricing period.

The dynamics also reveal a notable trend shift around the end of 2009, consistent with our structural model results capturing a pricing response to the legal battle surrounding the Unfair Sales Act. During the first part of the free-pricing period, the average markup of the low-markup subset was consistently below both the overall average and the average markup of the high-markup group. By the end of 2009, however, the average markup of low-markup products rises above its mean and remains elevated until the end of the free-pricing period, while the average markup of high-markup products exhibits a slight decline and the gap between the two groups narrows. This reversal coincides with the Court of Appeals granting the Wisconsin Petroleum Marketers and Convenience Store Association (WPMCA) standing to appeal the ruling that had struck down the Unfair Sales Act, and suggests that retailers may have anticipated its eventual reinstatement by gradually reducing cross-subsidization in advance.

We next examine whether our results provide evidence of joint pricing across products, and in particular whether such decisions are reflected in cross-subsidization patterns across product pairs. To do so, we regress the demeaned markup of a given product on the demeaned markup of another product sold by the same supermarket, and repeat this exercise for all ordered product pairs. Figure 9 reports the resulting pairwise regression coefficients, averaged across retailers. Positive coefficients indicate that markups for two products tend to move together, while negative coefficients indicate that higher markups on one product are associated with lower markups on the other. The heatmap reveals substantial heterogeneity across product pairs. Product pairs that are natural complements in consumption—such as

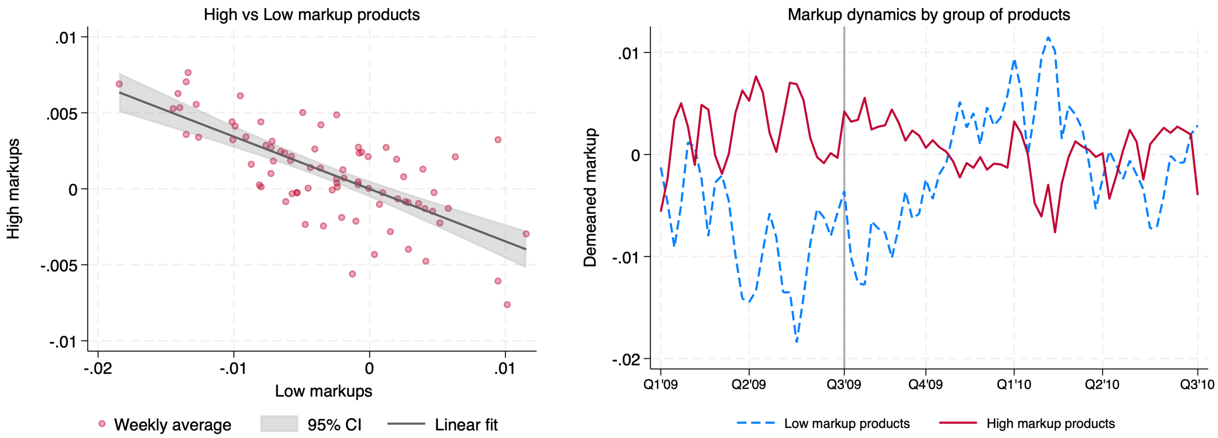


Figure 8: Average retail markups by product group in Wisconsin during the free-pricing period (March 2009-August 2010)

Notes: The figure displays demeaned implied retail markups for products grouped according to their average markup levels. Low-markup products are defined as product-retailer pairs with markups at or below 5% in at least 55% of weeks during the free-pricing period. Demeaned markups are obtained by residualizing product-retailer-week markups on product, retailer, week, and year fixed effects. Markups are computed as the price-cost margin over price, $(p - c)/p$. The left panel plots weekly average demeaned markups across product-retailer observations within each group, along with a linear fit and 95% confidence interval. The right panel displays weekly demeaned markups averaged across product-retailer observations within each group. The vertical gray line marks the last week of August 2009, when the Court of Appeals granted WPMCA standing to appeal the ruling that had struck down Wisconsin's Unfair Sales Act.

cereal and milk, or eggs and coffee—exhibit negative markup relationships on average. This pattern is consistent with cross-subsidization driven by the consumption effect.

Not all pairs with negatively correlated markups are direct consumption complements, however. Some pairs—such as eggs and canned soup—are not typically consumed together but are often purchased as part of the same shopping basket. We interpret these patterns as further evidence of the bundle effect: retailers adjust markups across products that enter the same basket even when they are not jointly consumed. Taken together, these results suggest that joint pricing decisions are shaped by both consumption complementarities and complementarities in purchase.

A particularly striking pattern in the heatmap concerns milk and eggs. Although these products do not exhibit negative average markups during the free-pricing period, their markups are negatively correlated with the markups of many other products in our set. These patterns are consistent with the conventional wisdom that staple products serve as traffic-generating goods in grocery retailing. They also suggest that cross-subsidization operates not only through below-cost pricing, but also through the strategic compression of markups on key products that remain priced above cost.

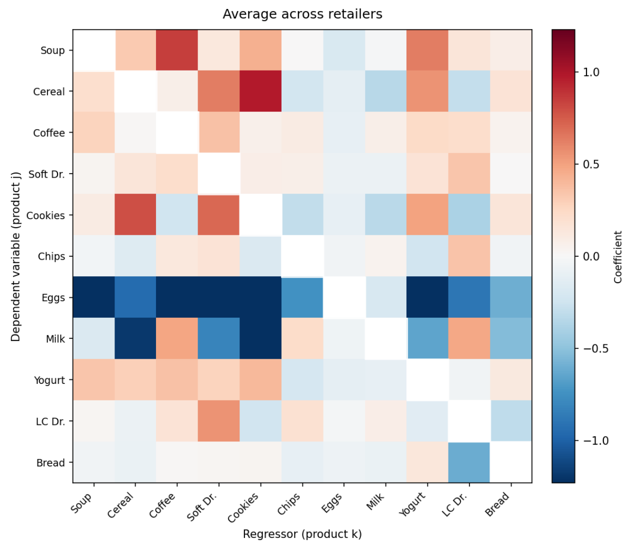


Figure 9: Average pairwise markup regression coefficients across retailers

Notes: The figure displays a heatmap of average pairwise regression coefficients across retailers. For each retailer, each cell (j, k) is obtained from a regression of the demeaned markup of product j (row) on the demeaned markup of product k (column). The figure reports the average coefficient across retailers for each product pair. Demeaned markups are obtained by residualizing implied product-level markups on product, week, and year fixed effects using retailer-specific regressions. Markups are computed as the price-cost margin over price, $(p - c)/p$. Blue cells indicate negative coefficients and red cells indicate positive coefficients. Diagonal cells are left blank because a product is not regressed on itself.

To illustrate these markup patterns in detail, Figure 10 plots weekly-level demeaned markups for two selected product pairs, averaged across retailers. The left panel shows the negative markup relationship between cereal and milk, while the right panel shows the positive markup relationship between cereal and cookies. Appendix Figure D.2 provides four additional examples.

4.5 Counterfactual experiments

We conduct counterfactual experiments in which we simulate the imposition of alternative minimum markup provisions within a free-pricing environment. To implement this, we focus on Wisconsin during the free-pricing period, when no minimum markup law was in force, and impose two constraints in turn. First, we simulate a zero minimum markup requirement, under which no product can be priced below its marginal cost; this corresponds to grocery retailing under Wisconsin's Unfair Sales Act. Second, we simulate a 5% minimum markup requirement, motivated by the fact that some U.S. states impose strictly positive minimum

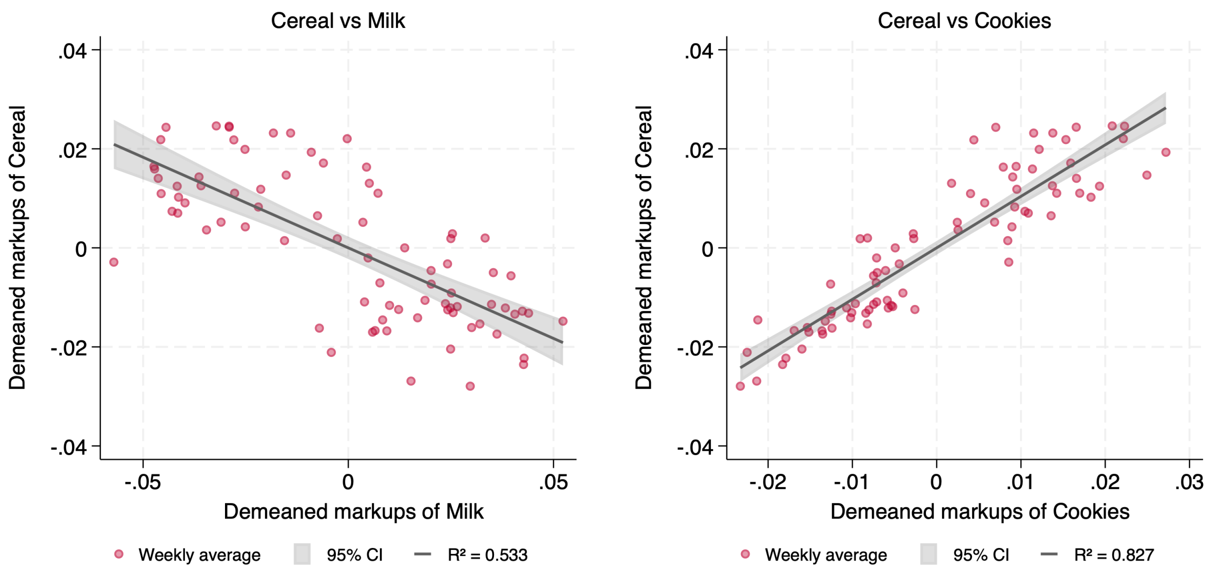


Figure 10: Average retail markups by selected product pairs in Wisconsin during the free-pricing period (March 2009–August 2010)

Notes: The figure displays weekly demeaned retail markups for two selected product pairs, averaged across retailers. Each panel includes a linear fit and 95% confidence interval. Demeaned markups are obtained by residualizing product-retailer-week implied markups on product, week, and year fixed effects using retailer-specific regressions. Markups are computed as the price-cost margin over price, $(p - c)/p$.

markups;[22] in these counterfactuals, multiproduct retailers internalize cross-category pricing externalities arising from joint profit maximization across their product assortment, which may give rise to cross-subsidization across products.

Additionally, to assess the extent to which product-level prices are shaped by cross-category pricing externalities, we simulate a counterfactual equilibrium in which all cross-category terms in retailers' first-order conditions are set to zero. Under this scenario, retailers set prices independently across products, effectively behaving as a collection of single-product retailers. This exercise complements the minimum markup analysis by quantifying the role of cross-subsidization in multiproduct retailing. All counterfactuals are evaluated over the first ten weeks of 2010, and the results reported below compare each scenario to the observed equilibrium over the same period. All price, share, and welfare figures are reported as weekly

[22] California's Unfair Practices Act imposes a default minimum markup standard of 6% on all products. See https://calawyers.org/publications/antitrust-unfair-competition-law/competition-spring-2017-vol-26-no-1-below-cost-pricing-recent-defense-friendly-decisions/. Last accessed: April 23, 2026. Wisconsin's Unfair Sales Act also imposes positive minimum markups that can reach up to 9.18% in product markets such as alcohol, tobacco, and gasoline.

averages over this period.

4.5.1 Effects of minimum markup regulations

A. Zero minimum markups

Table 9 reports the effects of imposing a zero minimum markup constraint, which prohibits retailers from pricing below cost. Under the free-pricing equilibrium, this constraint binds only for soft drinks—the sole product exhibiting negative markups for some retailer-week observations (see Appendix Figure D.1). Consistent with this pattern, the largest average price response is concentrated in soft drinks: their price increases by 0.403%, leading to a 1.315% decline in market share. The remaining products experience negligible average price changes, while their market shares decline only modestly. The bottom panel reinforces this point: binding products exhibit substantially larger responses than non-binding products, whose average price response is essentially zero.

The dispersion columns show that these average effects mask meaningful heterogeneity across retailers. This is expected because the constraint binds only for a subset of retailer-product observations. Retailers for which the constraint is binding must raise the price of the affected product, whereas unconstrained retailers face only indirect competitive effects. The comparatively large standard deviation for soft drinks captures this asymmetry. At the same time, the effects on non-binding products remain small on average, suggesting that the competitive spillovers generated by the zero-markup constraint are limited when only one product category is directly affected. Overall, this counterfactual shows that a minimum markup regulation that rules out below-cost pricing can generate spillovers beyond the directly constrained product through basket-level demand substitution, but that these effects are quantitatively small when the constraint binds narrowly.

B. Positive minimum markups

We now consider a more restrictive scenario, a 5% minimum markup, which binds on a broader set of products across all three retailers, allowing us to examine the equilibrium consequences of a regulation that constrains cross-subsidization more extensively.

Table 10 reports percentage changes in prices and market shares under the 5% minimum markup counterfactual relative to the free-pricing equilibrium. Because retailers internalize cross-category pricing externalities, the minimum markup constraint affects prices throughout the assortment, not only for products on which the constraint binds directly. Average prices increase most for products that were priced relatively aggressively in the free-pricing equilibrium. For example, prices increase by 2.76% for soft drinks, 1.99% for low-calorie

Table 9: Counterfactual Effects of a Nonnegative Markup Constraint

	%Δ Price		%Δ Share	
Product	Average	SD	Average	SD
Canned Soup	0.000	0.001	-0.099	0.199
RTE Cereal	-0.007	0.010	-0.086	0.185
Coffee	-0.004	0.007	-0.076	0.150
Soft Drinks	0.403	0.698	-1.315	2.325
Cookies	0.021	0.034	-0.183	0.341
Potato Chips	-0.007	0.011	-0.151	0.290
Eggs	0.018	0.031	-0.114	0.216
Milk	-0.012	0.018	-0.107	0.209
Yogurt	0.006	0.009	-0.100	0.196
Low Calorie Drinks	0.007	0.011	-0.289	0.526
Bread	-0.015	0.024	-0.116	0.227
Average Binding	0.403	0.698	-1.315	2.325
Average Non-binding	0.001	0.001	-0.132	0.254
Average all products	0.037	0.065	-0.240	0.442

Notes: This table reports percentage changes in prices (%Δ Price) and market shares (%Δ Share) between the free-pricing equilibrium and the counterfactual equilibrium in which retailers are constrained to set nonnegative markups. Percentage changes are computed using mean values over the first ten weeks of 2010. The standard deviation columns report the dispersion of retailer-specific average responses across retailers for each product. The bottom rows report simple averages across binding products (those for which the constraint binds for at least one retailer), non-binding products, and all products, respectively.

drinks, 1.17% for coffee, and 0.98% for cookies. Average prices rise for nearly all products, with the exception of bread, which experiences a modest price decline. These results are consistent with the mechanism predicted by Chen and Rey (2019): when retailers are prevented from using selected products as low-markup traffic generators, prices may rise not only for directly constrained products but also for non-binding products, allowing retailers to extract more surplus from multistop shoppers. Thus, minimum markup constraints can increase prices across the broader basket and affect all consumers.

Changes in average market shares reveal a pattern that goes beyond standard product-level demand responses. Market shares decline for all products, with the largest losses concentrated among baseline low-markup products, such as soft drinks and low-calorie drinks. The decline is substantially larger for binding products, whose market shares fall by 9.09% on average, than for non-binding products, whose market shares fall by 2.44%. The relatively large share declines among non-binding products, despite their small price changes, reflect the response of one-stop shoppers, who choose baskets rather than isolated products. When the prices of key low-markup products increase, some one-stop shoppers either switch retailers for the entire basket or opt for the outside good, reducing demand for other products in the affected retailer's assortment as well.

Table 10: Counterfactual Effects of a 5% Minimum Markup Constraint

	%Δ Price		%Δ Share	
Product	Average	SD	Average	SD
Canned Soup	0.13	0.21	-2.57	0.75
RTE Cereal	0.55	0.64	-4.13	1.51
Coffee	1.17	1.30	-6.62	5.38
Soft Drinks	2.76	3.35	-10.75	10.84
Cookies	0.98	0.72	-4.31	1.62
Potato Chips	0.01	0.11	-2.88	1.65
Eggs	0.24	0.07	-2.51	1.21
Milk	0.00	0.10	-2.38	1.06
Yogurt	0.12	0.12	-2.40	1.10
Low Calorie Drinks	1.99	1.76	-9.76	8.18
Bread	-0.14	0.18	-2.23	1.27
Average Binding	2.12	1.50	-9.09	5.67
Average Non-binding	0.06	0.07	-2.44	1.15
Average all products	0.71	0.34	-4.59	2.44

Notes: This table reports percentage changes in prices (%Δ Price) and market shares (%Δ Share) between the free-pricing equilibrium and the counterfactual equilibrium in which a 5% minimum markup constraint is imposed. Percentage changes are computed using mean values over the first ten weeks of 2010. The standard deviation columns report the dispersion of retailer-specific average responses across retailers for each product. The bottom rows report simple averages across binding products (those for which the constraint binds for at least one retailer), non-binding products, and all products, respectively.

C. Welfare Analysis

We analyze the effects of minimum markup laws on consumer surplus, producer surplus, and total welfare. Following Small and Rosen (1981), we measure consumer surplus in dollar terms under both the baseline (free-pricing) and counterfactual (minimum markup) scenarios, and compute the difference between the two. Let $\mathbf{p}_0$ and $\mathbf{p}_1$ denote the vectors of baseline and counterfactual prices, respectively. The expected change in consumer surplus is given by:

$$\Delta CS = \int \frac{1}{\alpha_i} \left[CS_i(\mathbf{p}_1) - CS_i(\mathbf{p}_0) \right] dP(d_i) \tag{18}$$

where CS_i is individual-level consumer surplus given by the log of the denominator in equation (14), $P(\cdot)$ is the cumulative distribution function of consumer demographics, and d_i

denotes consumer i's demographic group.

The minimum markup constraint affects prices through two channels: a direct effect on products for which the minimum markup constraint is binding, and an indirect effect on the remaining products, which adjust in equilibrium as retailers reoptimize their pricing strategies across the full assortment. To isolate the contribution of each channel, we partition the price vector as $\mathbf{p} = (\mathbf{p}^b, \mathbf{p}^{nb})'$, where $\mathbf{p}^b$ and $\mathbf{p}^{nb}$ denote prices of *binding* and *non-binding* products, respectively. The expected change in consumer surplus can then be decomposed as:

$$\Delta CS = \int \frac{1}{\alpha_i} \Bigg\{ \underbrace{\Big[CS_i(\mathbf{p}_1^b, \mathbf{p}_0^{nb}) - CS_i(\mathbf{p}_0^b, \mathbf{p}_0^{nb}) \Big]}_{\text{Direct effect}} + \underbrace{\Big[CS_i(\mathbf{p}_1^b, \mathbf{p}_1^{nb}) - CS_i(\mathbf{p}_1^b, \mathbf{p}_0^{nb}) \Big]}_{\text{Indirect effect}} \Bigg\} dP(d_i) \tag{19}$$

Finally, we compute the aggregate change in consumer surplus by scaling the individual expected values in equation (19) by the market size, which we approximate by the population of Wisconsin aged 17 to 84 in 2010 (U.S. Census Bureau, 2012). This reflects the assumption that the reachable market for the basket of products we consider consists of individuals who are both potential consumers of the products and autonomous decision makers.

Table 11 reports the welfare effects of imposing minimum markup constraints, expressed in thousands of dollars and decomposed into direct and indirect effects. The direct effect captures welfare changes for products whose baseline markups fall below the regulatory threshold and are therefore directly constrained, while the indirect effect captures changes arising from equilibrium repricing of the remaining products.

Under the zero minimum markup provision (Counterfactual 1), which binds only on soft drinks, the total welfare gain is modest at \$7.82 thousand per week. The direct effect accounts for the bulk of this gain (\$20.60 thousand), driven by an increase in profits of \$26.43 thousand from the mechanical elimination of the negative markup on soft drinks, partially offset by a consumer surplus loss of \$5.83 thousand. By contrast, the indirect effect reduces welfare by \$12.78 thousand. Although it generates a small increase in consumer surplus (\$0.42 thousand), reflecting optimal price reductions for non-binding products, it lowers profits by \$13.20 thousand as equilibrium repricing compresses margins on those products. As a result, the overall welfare gain arises entirely from the direct effect on the constrained product, while indirect equilibrium adjustments partially offset these gains.

Under the 5% minimum markup provision (Counterfactual 2), the effects are substantially larger. Total welfare increases by \$37.36 thousand per week, equivalent to a 0.37% increase relative to the free-pricing equilibrium, again driven by a profit gain (\$152.68 thousand) that more than offsets the consumer surplus loss (\$115.32 thousand). The direct effect is positive (\$201.91 thousand), as the constraint forces binding products away from their aggressively low markups and toward levels that substantially increase retailer margins (\$317.52 thousand), partially offset by a direct consumer surplus loss of \$115.61 thousand. The indirect effect is again welfare-reducing (−\$164.55 thousand): profits on non-binding products decline by \$164.84 thousand as retailers adjust their pricing across the assortment, while the indirect contribution to consumer surplus remains negligible (\$0.29 thousand). Across both counterfactuals, a consistent pattern emerges: minimum markup provisions benefit retailers at the expense of consumers, with the direct effect on constrained products generating the welfare gains and the indirect equilibrium adjustments partially offsetting them. This finding that consumers are made worse off by minimum markup regulations is consistent with the theoretical predictions of Johnson (2017) and Chen and Rey (2019).

Table 11: Welfare effects of minimum markup constraints (in thousand U.S. dollars)

	Consumer Surplus	Profit	Total Welfare
Counterfactual 1: Zero minimum markup			
Direct effect	−5.83	26.43	20.60
Indirect effect	0.42	−13.20	−12.78
Total change	−5.41	13.23	7.82
% change	−0.15	0.21	0.08
Counterfactual 2: 5% minimum markup			
Direct effect	−115.61	317.52	201.91
Indirect effect	0.29	−164.84	−164.55
Total change	−115.32	152.68	37.36
% change	−3.18	2.39	0.37

Notes: This table reports changes in consumer surplus, retailer profits, and total welfare between the free-pricing equilibrium and each counterfactual scenario. The direct effect captures changes attributable to products for which the constraint is binding; the indirect effect captures changes on non-binding products arising from equilibrium repricing through the internalization of cross-category externalities. The "% change" rows report percentage changes relative to the free-pricing equilibrium level. All values are weekly averages over the first ten weeks of 2010.

4.5.2 Quantifying the welfare value of cross-subsidization

Our previous counterfactual experiments show that minimum markup regulations affect not only directly constrained products, but also the pricing of the broader assortment through equilibrium repricing. These spillovers arise from cross-subsidization—the mechanism through which retailers internalize cross-product demand linkages when setting prices jointly across categories. To quantify the equilibrium contribution of cross-subsidization in multiproduct retail markets, we conduct a third counterfactual exercise in which we remove cross-category terms from retailers' first-order conditions, so that each retailer effectively sets prices independently across products.

Table 12 reports average price and share changes by product relative to the baseline equilibrium. The results confirm that the effects of eliminating cross-category pricing are substantial. Prices increase by approximately 32% on average, while market shares decline by 79%. The magnitude of these effects underscores the central role that cross-subsidization plays in sustaining multiproduct pricing equilibria. Notably, some of the largest price increases are observed for products with high markups in the unconstrained equilibrium—such as eggs (77.5%), milk (35.4%), and bread (32.7%)—suggesting that joint pricing not only allows retailers to price some products aggressively, but also keeps prices lower on high-markup products than they would be under independent product pricing. Meanwhile, low-markup products such as cookies, coffee, and low-calorie drinks—which are among the primary beneficiaries of cross-subsidization—also experience substantial price increases (17.8–37.9%). The dramatic share declines (72.5–82.8%) highlight the importance of overall basket value for consumers, reinforcing retailers' incentives to price some staple products aggressively. Overall, these results illustrate how cross-category pricing fundamentally shapes competitive interactions in multiproduct retail markets.

Using the consumer surplus measure described by equation (18), Table 13 reports the welfare effects of eliminating cross-category pricing. Total welfare declines by \$4,441 thousand per week—a 44.39% reduction relative to the free-pricing equilibrium. While consumer surplus accounts for the largest share of this decline (−\$2,501 thousand, or 69.02%), retailer profits also decline substantially, by \$1,940 thousand (30.40%), reflecting the collapse in demand induced by the large price increases. The fact that both consumers and retailers are worse off under this scenario underscores that cross-subsidization is not merely a competitive strategy that redistributes surplus across market participants; rather, it is a welfare-enhancing feature of multiproduct retail markets that generates substantial gains for both sides. More broadly, these results highlight the social value embedded in cross-category pricing: by al-

Table 12: Counterfactual Effects of Removing Cross-Category Pricing

	%Δ Price		%Δ Share	
Product	Avg.	SD	Avg.	SD
Canned Soup	29.42	3.37	-77.64	0.50
RTE Cereal	19.83	5.10	-79.44	3.21
Coffee	17.82	2.02	-79.96	3.73
Soft Drinks	23.45	4.11	-81.94	6.63
Cookies	37.92	1.18	-82.86	3.08
Potato Chips	31.83	3.68	-79.54	2.80
Eggs	77.53	2.36	-80.74	3.52
Milk	35.42	2.58	-77.25	3.42
Yogurt	30.85	0.80	-77.77	3.25
Low Cal. Drinks	18.07	3.50	-79.37	7.70
Bread	32.70	11.53	-72.50	9.39
Avgerage all products	32.26	0.31	-79.00	3.53

Notes: This table reports percentage changes in prices (%Δ Price) and market shares (%Δ Share) between the multiproduct free-pricing equilibrium and the counterfactual equilibrium in which cross-category pricing terms are removed from retailers' first-order conditions, so that each retailer effectively behaves as a single-product price setter for each of its products. Percentage changes are computed using mean values over the first ten weeks of 2010. The standard deviation columns report the dispersion of retailer-specific average responses across retailers for each product.

lowing retailers to price some products aggressively in order to attract consumers into the store, cross-subsidization sustains a pricing equilibrium that benefits consumers through lower prices on a subset of products while allowing retailers to recover margins elsewhere in the assortment.

Table 13: Welfare effects of suppressing cross-subsidization (in thousand U.S. dollars)

	Consumer Surplus	Profit	Total Welfare
Total change	−2,501	−1,940	−4,441
% change	−69.02	−30.40	−44.39

Notes: This table reports changes in consumer surplus, retailer profits, and total welfare between the multiproduct free-pricing equilibrium and the counterfactual scenario in which cross-category terms are removed from retailers' first-order conditions, so that each retailer effectively behaves as a single-product price setter. The "% change" row reports percentage changes relative to the free-pricing equilibrium level. All values are weekly averages over the first ten weeks of 2010.

5 Conclusions

This paper studies how minimum markup laws affect equilibrium pricing and welfare in multiproduct retail markets. Exploiting the temporary suspension of Wisconsin's Unfair Sales Act, we show that removing price floors lowers the prices of some goods while raising others, consistent with retailers reallocating markups across products. To understand the mechanisms behind these patterns, we develop and estimate a structural model of multiproduct demand and supply that accounts for product and store interactions and corrects for bias arising from non-exhaustive choice sets.

Our results show that the effects of price regulation depend critically on multiproduct pricing. By constraining retailers' ability to use some products as loss leaders, minimum markup laws distort pricing throughout the product assortment: prices increase not only for directly affected goods but also for unconstrained products through equilibrium spillovers. In our setting, a 5% minimum markup raises average prices and reduces market shares, leading to a decline in consumer surplus, while increasing retailer profits.

More broadly, we show that cross-subsidization is a central feature of supermarket competition. A counterfactual exercise that removes cross-category pricing complementarities from retailers' pricing decisions increases prices by approximately 32%, reduces market shares by 75–82%, and lowers total welfare by 44%. These results indicate that cross-subsidization is not merely redistributive, but a central mechanism through which multiproduct retailers generate gains from trade by increasing overall demand.

These findings have implications for the design of retail price regulation. Policies that target pricing at the product level can generate unintended equilibrium effects when firms compete over baskets of goods. Accounting for these interactions is therefore essential for evaluating the incidence and welfare consequences of such regulations.

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Appendix

A Reduced-form robustness check

In the following, we use states with a Minimum Markup Law (MML) as the control group rather than both all 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 all unexposed states in the control group (see Figure 4) or only unexposed ban states in the control group. Therefore, our results are robust to the composition of the control group.

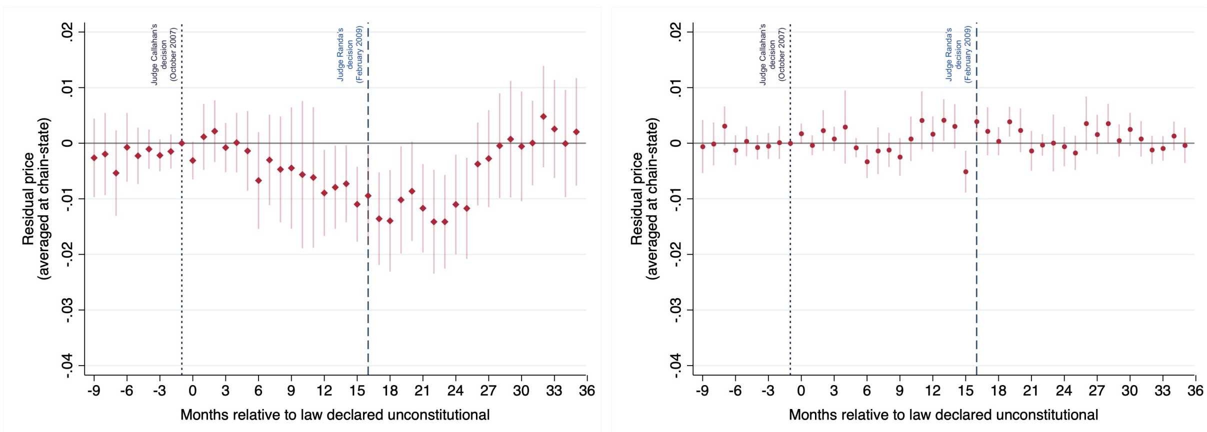


Figure A.1: Effects of the law suspension on milk (left) and RTE cereal (right) prices of directly exposed stores using ban states as the control group

Notes: This figure shows estimated coefficients of equation (1) of residual prices of milk (left) and RTE cereals (right) at the chain-state-week level between 2007 and 2010. The estimates are for stores that were directly exposed to the law suspension 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 suspended it. The 95% confidence intervals are plotted for each data point.

B Derivation of the total purchase probability

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

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

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

Notice that the second term in the numerator can be rewritten in terms of the numerator of the marginal Logit probability of equation (12):

$$\sum_{h \in b^* \times \mathcal{B}_{exc}} \exp(v_{iht} - n_h s_i) = \sum_{h \in \mathcal{B}_{exc}} \exp(v_{ib^*t} - n_{b^*} s_i) \exp(v_{iht} - n_{h|b^*} s_i), \tag{B.2}$$

where $n_{h|b^*}$ denotes the number of additional stops made to purchase the non-listed products conditional on purchasing b^*. Therefore, we can factor the numerator by the common factor, resulting in:

$$Q_{ib^*t}(\cdot) = \frac{\exp(v_{ib^*t} - n_{b^*} s_i) \left[1 + \sum_{h \in \mathcal{B}_{exc}} \exp(v_{iht} - n_{h|b^*} s_i)\right]}{1 + \sum_{b' \in \mathcal{B}} \exp(v_{ib't} - n_{b'} s_i)}. \tag{B.3}$$

Let us define the following quantity that includes the terms in square brackets of the numerator in (B.3):

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

which is the denominator of a Logit probability of purchasing a basket of non-listed products only, conditional on having purchased b^* on the same shopping occasion. Plugging this into (B.3) yields:

$$Q_{ib^*t}(\cdot) = \frac{\exp(v_{ib^*t} - n_{b^*} s_i) \Delta_{2it|b^*}}{1 + \sum_{b' \in \mathcal{B}} \exp(v_{ib't} - n_{b'} s_i)}. \tag{B.4}$$

Concerning the denominator of (B.4), we can decompose the second term in three sums, each with respect to a subset of baskets:

$$Q_{ib^*t}(\cdot) = \frac{\exp(v_{ib^*t} - n_{b^*} s_i) \Delta_{2it|b^*}}{1 + \sum_{b' \in \mathcal{B}_{exc}} \exp(v_{ib't} - n_{b'} s_i) + \sum_{b \in \mathcal{B}_{inc}} \exp(v_{ibt} - n_b s_i) + \sum_{g \in \mathcal{B}_{inc} \times \mathcal{B}_{exc}} \exp(v_{igt} - n_g s_i)}. \tag{B.5}$$

Let us define the following quantity that includes the first two terms of the denominator in (B.5):

$$\Delta_{1it} = 1 + \sum_{b' \in \mathcal{B}_{exc}} \exp(v_{ib't} - n_{b'} s_i), \tag{B.6}$$

which is the denominator of a Logit marginal probability of purchasing a basket that includes non-listed products only. Furthermore, the last term in the denominator of equation (B.5) can further be decomposed into sums over baskets in $\mathcal{B}_{inc}$ and baskets in $\mathcal{B}_{exc}$:

$$\sum_{g \in \mathcal{B}_{inc} \times \mathcal{B}_{exc}} \exp(v_{igt} - n_g s_i) = \sum_{b \in \mathcal{B}_{inc}} \exp(v_{ibt} - n_b s_i) \sum_{g' \in \mathcal{B}_{exc}} \exp(v_{ig't} - n_{g'|b} s_i).$$

Plugging this into the denominator and factorizing the relevant terms yields:

$$Q_{ib^*t}(\cdot) = \frac{\exp(v_{ib^*t} - n_{b^*} s_i)\Delta_{2it|b^*}}{\Delta_{1it} + \sum_{b \in \mathcal{B}_{inc}} \exp(v_{ibt} - n_b s_i) \underbrace{\left[1 + \sum_{g' \in \mathcal{B}_{exc}} \exp(v_{ig't} - n_{g'|b} s_i)\right]}_{\Delta_{2it|b}}}. \tag{B.7}$$

Factoring Δ_{1it} out of the denominator results in:

$$Q_{ib^*t}(\cdot) = \frac{\exp(v_{ib^*t} - n_{b^*} s_i)(\Delta_{2it|b^*}/\Delta_{1it})}{1 + \sum_{b \in \mathcal{B}_{inc}} \exp(v_{ibt} - n_b s_i)(\Delta_{2it|b}/\Delta_{1it})}. \tag{B.8}$$

Finally, we can express the probability in Logit form by introducing the log-transformed Δs into the exponential functions:

$$Q_{ib^*t}(\cdot) = \frac{\exp(v_{ib^*t} - n_{b^*} s_i - \log \Delta_{1it} + \log \Delta_{2it|b^*})}{1 + \sum_{b \in \mathcal{B}_{inc}} \exp(v_{ibt} - n_b s_i - \log \Delta_{1it} + \log \Delta_{2it|b})}. \tag{B.9}$$

C Monte Carlo results

Table C.1 reports estimates of the model parameters based on 25 Monte Carlo simulations for each scenario. The column labeled "True model" presents the true parameter values from the data-generating process; the columns labeled "Standard" report estimates obtained using the standard discrete choice method; and the column labeled "Corrected" shows estimation results from our proposed bias-correction approach. Panel A presents results for the first scenario, and Panel B reports results for the second scenario, which includes only the combinations observed in the simulated consumers' full purchase history.

Table C.1: Estimation results based on simulated data

	True model	Panel A Standard	Panel A Corrected	Panel B Standard	Panel B Corrected
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]
No. of stops					
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 reports estimation results based on simulated data from 78 consumers over 208 choice occasions, with 25 simulations. The full choice set comprises 64 baskets. The column "True model" shows the true parameter values from the data-generating process; the columns "Standard" report estimates obtained using the standard discrete choice method; and the columns "Corrected" report estimates obtained using our proposed bias correction. Panel A reports results from a scenario in which the choice sets exclude products 1, 2, and 3 from store 3, and additionally includes 11 single-product baskets. Panel B shows results with choice sets constructed based on observed product-store combinations. Values in square brackets are the 99% confidence intervals.

D Implied markups

D.1 Evolution of markups over time

To provide a detailed view of markup dynamics during the free-pricing period, Figure D.1 reports weekly product-level markup series averaged across retailers, together with the weekly minimum-to-maximum range across retailers.

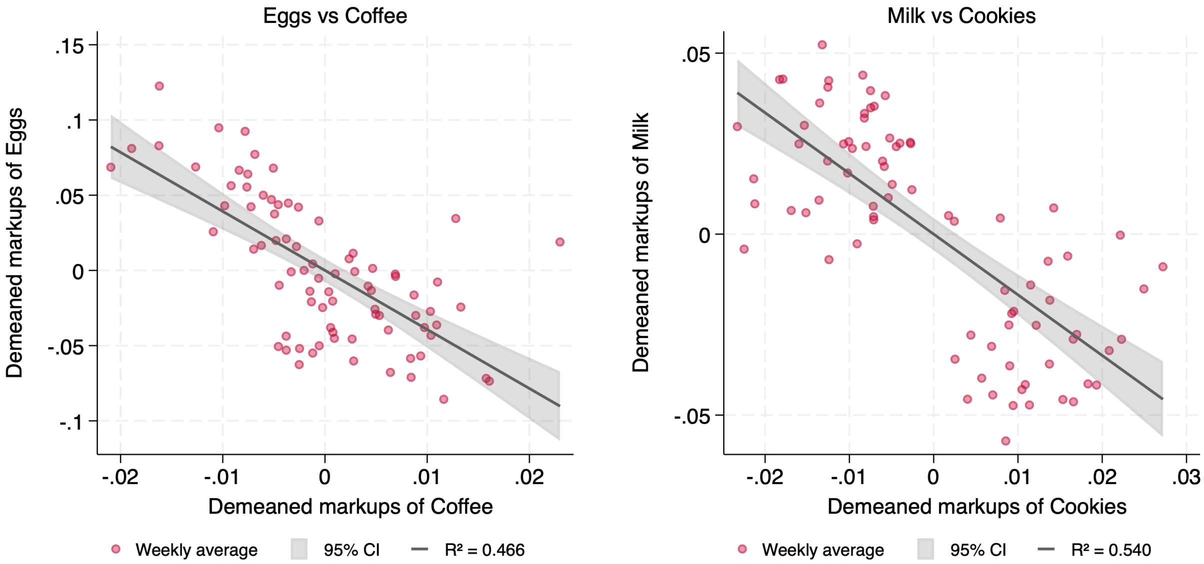
D.2 Pairwise scatter plots for selected products

Figure D.2 provides more examples of pairwise markup correlations for selected pairs. The top panel shows pairs with negative markup relationships, including eggs and coffee, and milk and cookies, which are often complements in consumption. The bottom panel shows pairs with positive markup relationships—soup and yogurt, which are usually not related in consumption, and carbonated soft drinks and low calorie soft drinks, which are substitutes in consumption.

Figure D.1: Weekly average retail markups and cross-retailer dispersion during the free-pricing period, March 2009–August 2010

Notes: The figure displays weekly product-level retail markups during the free-pricing period (March 2009–August 2010). Each panel corresponds to a different product. Solid lines denote average markups across retailers in each week, and shaded areas indicate the minimum-to-maximum range across retailer-specific markups in that week. Implied markups are computed as the price-cost margin over price, $(p-c)/p$.

Negative markup relationships



Positive markup relationships

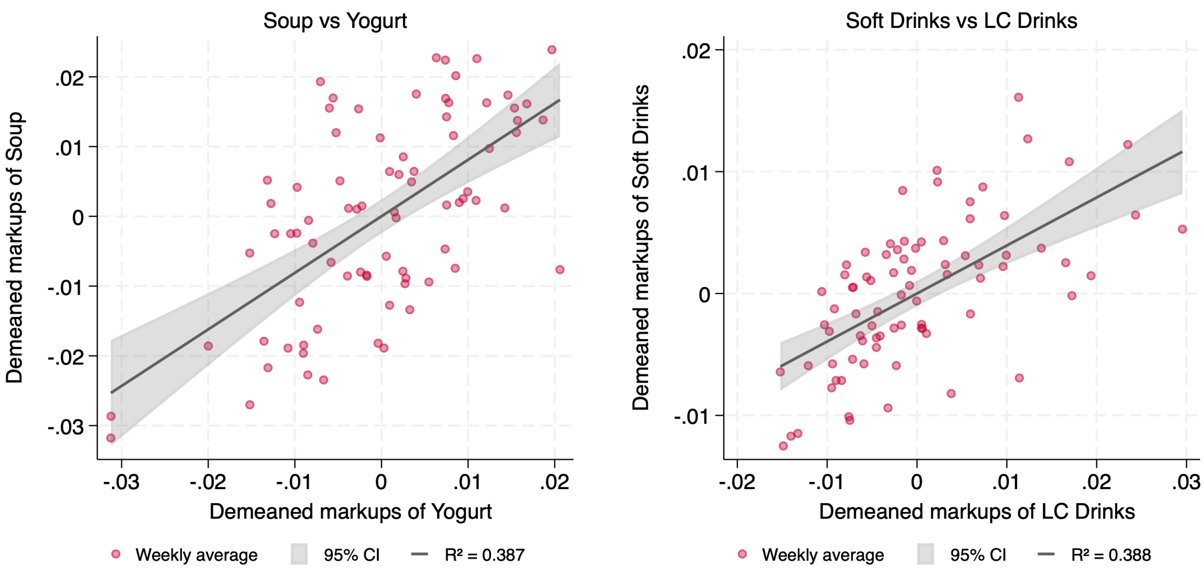


Figure D.2: Retail Markups by selected product pairs in Wisconsin during the free-pricing period (March 2009–August 2010)

Notes: The figure displays weekly demeaned retail markups for four selected product pairs, averaged across retailers. The top row shows pairs exhibiting a negative markup relationship, while the bottom row shows pairs exhibiting a positive markup relationship. Each panel includes a linear fit and 95% confidence interval. Demeaned markups are obtained by residualizing product-retailer-week implied markups on product, week, and year fixed effects using retailer-specific regressions. Markups are computed as the price-cost margin over price, $(p - c)/p$.