Testing Vertical Relationships in the US Infant Formula Market: Implications for Government Costs and Welfare

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July 2025

Abstract

The US Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) provides free infant formula to low-income households, serving around 39% of US infants and accounting for over half of all domestically sold formula—making it a substantial government expenditure. To reduce government costs, WIC awards exclusive contracts to manufacturers offering the lowest net price in each state and collects rebates from the winning bidders via public auction, effectively creating government-sanctioned monopolies in the WIC market. The broader implications of this policy hinge on vertical relationships between manufacturers and retailers, which remain poorly understood. I identify the vertical relationship as best characterized by two-part tariffs, where retailers pay fixed fees to manufacturers and wholesale markups are zero. Counterfactual analyses show that, when pricing control shifts to manufacturers, average retail prices increase by 3.79%, producer surplus rises by 2.17%, and consumer surplus declines by 7.44%. I also observe heterogeneous price responses for WIC auction winners and losers. Notably, winners generally raise prices when granted retail pricing power. These findings underscore the importance of firm conduct in shaping program efficacy and market outcomes.

*I would like to thank Juan P. Sesmero, Meilin Ma, Diego S. Cardoso, Charlotte Ambrozek, Francisco Scott, and Joseph V. Balagtas for constructive comments and discussions. All remaining errors are my own. Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Keywords: vertical relationships, market structure, test of conduct, market performance, public nutrition assistance program, food policy

JEL Codes: L13, L22, C52

1 Introduction

As the third largest nutrition program in the United States, the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) offers free infant formula to low-income households and fully reimburses the retailers at the market prices.[1] In recent years, WIC serves an average of 6.6 million recipients per month and an estimated 39% of all infants (Jones and Toossi 2024). More than half of the domestically sold infant formula is distributed via WIC, which makes WIC a significant government expenditure (e.g., WIC costed $6.6 billion in fiscal year 2023). To reduce government costs, WIC employs a rebate system at the state level. Each state WIC agency calls for competitive bids from formula manufacturers and grants the bidder with the lowest net price (i.e., wholesale price minus rebates to the government) exclusive supply rights within the state. This bidder is referred to as the WIC auction winner. The winner's formula brands approved by WIC are referred to as WIC brands, while other brands produced by the same manufacturer are termed non-WIC brands. Due to this bidding system, WIC's unit cost for WIC brands equals the retail price minus rebates, rather than the full retail price.

However, the efficacy of the WIC rebate system in controlling costs and its impacts on welfare remains unclear, given the inherent tensions in its design. On the one hand, the system reduces costs by incentivizing manufacturers to offer competitive rebates to secure exclusive WIC contracts. On the other hand, it grants the winner monopoly power in the WIC market which can extend into the non-WIC market because of WIC's minimum stocking requirements and improved product placement (Oliveira, Frazão, and Smallwood 2011; Rojas and Wei 2019; Choi et al. 2020; Abito et al. 2022). When it comes to the price effect of WIC rebates, Rojas and Wei (2019) report increased retail prices for both WIC and non-WIC brands, while An et al. (2025) find no significant price effects on the winner's non-WIC brands. These results rely either on just reduced-form analysis or a pricing assumption without testing, which could result in limited policy implications.

1. No price discrimination is allowed between WIC and non-WIC consumers in any retail store.

The assumption may not be appropriate because the US infant formula supply chain exhibits an oligopoly-oligopsony structure, with high concentration in both the manufacturing and retailing stages. Three leading manufacturers, Abbott Nutrition, Mead Johnson, and Nestlé dominate the industry, occupying 95% of the entire market and holding all WIC contracts. The concentration in US food retail has been increasing, too (Sexton and Xia 2018; Ma et al. 2019; Hamilton, Liaukonyte, and Richards 2020; Dong, Balagtas, and Byrne 2023). In oligopoly-oligopsony markets, the vertical structure (namely, the relationship between manufacturers and retailers) of the industry, plays a pivotal role in determining not only equilibrium manufacturing and retail prices, but also, and more importantly in this context, in shaping the rebate system's impact on market and welfare outcomes (Bonnet and Dubois 2010; Gaudin 2018; Luco and Marshall 2020). Existing research on the infant formula market assumes that manufacturers directly control retail prices (Davis 2011; Abito et al. 2022; An et al. 2025), forgoing a more thorough examination of the possible vertical structures of the industry and how they mediate the effects of the rebate system on market outcomes.

I seek to fill this gap by performing conduct tests on the US infant formula market. I start with demand estimation using a random coefficients logit model. The analysis uses NielsenIQ Retail Scanner Data (2007–2018), defining markets as state-year-quarter combinations and products by brand, form (powder, ready-to-use, or concentrated), and base (milk or soy). This dataset is supplemented with NielsenIQ Consumer Panel data (2007-2018), which provides demographic and economic information on households (e.g., income and education). To address endogeneity, we use instrumental variables such as cost shifters (e.g., casein prices), "sums of characteristics" BLP instruments (Berry, Levinsohn, and Pakes 1995), and differentiation instruments (Gandhi and Houde 2020).

On the supply side, we consider vertical conduct models listed in Villas-Boas (2007), excluding the hybrid model due to the negligible market share of private labels (5%). Given the demand estimates, we compute markups and infer unobservable cost shocks. I adopt the

Rivers and Vuong (RV) framework (Rivers and Vuong 2002), refined by Duarte et al. (2024), to test the vertical conduct. This approach emphasizes model selection over model assessment under misspecification, identifying the most plausible supply-side model by minimizing the correlation between estimated cost shocks and instrumental variables, ensuring robust and reliable inference (Duarte et al. 2024).

The demand estimation results show that non-WIC consumers exhibit high price sensitivity, with an average own-price elasticity of -2.56 and a median of -2.43. The conduct test results suggest that the vertical relationship is best represented by a two-part tariff model, where retailers pay a fixed fee to manufacturers and wholesale margins are zero. In this setting, retailers set prices, earning an average markup of 44.8%.

To assess the implications of prevailing modeling assumptions in the literature, which assume manufacturers to set retail prices, we simulate market outcomes under a zero retail margin model and compare them against those under the data-supported model. Our analysis shows that, after the pricing power shifts from retailers to manufacturers, overall average retail prices and hence WIC cost increase by 3.80%, consumer surplus decreases by 7.44%, and producer surplus increases by 2.17%. I show further that WIC rebate auctions play a central role in determining the direction and magnitude of price changes at state-level markets. In general, WIC auction winners increase prices, while the responses from the loser manufacturers depend on the competitiveness in the market.

I am one of the first to empirically examine the vertical structure of the infant formula market and its costs and welfare implications for the third largest public nutrition programs in the U.S. The study is related to the growing work on quantifying vertical relationships and its impact in the food industry (Bonnet and Dubois 2010; Bonnet et al. 2013; Kim and Kim 2024; Michel, Paz y Miño, and Weiergraeber 2024; Duarte, Magnolfi, and Roncoroni 2025). Our result underscores the critical role of vertical relationships in evaluating policies in imperfectly competitive markets.

This paper adds to existing work (Oliveira and Prell 2004; Abito et al. 2022; Li 2024; An et al. 2025) that examines the welfare impact of the WIC rebate system by providing a key and novel perspective of empirically examining the vertical relationship between manufacturers and retailers. Our work shows that it is inadequate to draw policy implications just by focusing on one party of the industry without the knowledge of the vertical structure of the market as a whole. Our results help inform conceptual modeling efforts aimed at capturing the market structure of the infant formula industry. In particular, they provide empirical grounding that can help refine or challenge structural assumptions made in prior models (Davis 2011; Prell 2004; An et al. 2025).

It also speaks to related markets and public programs such as the Medicare program, where the government acts as a dominant buyer and relies on competitive auctions to reduce government costs. Cao, Yi, and Yu (2024) study the short-term welfare effect of quantity-based competitive bidding in China's drug procurement market. They find that the policy reduces government expenditure and increases consumer welfare. Their reduced-form analysis also suggests that the policy increases market concentration and hence, the authors raise concerns about the potential long-term impact on market structure and competition due to firm exit. Ding, Duggan, and Starc (2025) analyze the impact of the competitive bidding program of the US Medicare for durable medical equipment, focusing on government spending and consumer welfare. Their study reveals that the program massively reduces the cost of Medicare through lower prices. However, the supply constraints resulting from supplier exit disproportionately affect recipients with marginal clinical need. Despite this reduction in access, they report that savings from lower prices outweigh the welfare losses.

The paper proceeds as follows. Section 2 describes the institutional background: The WIC program and the mechanism of its rebate system, and stylized facts of the US infant formula market. Section 3 establishes the theoretical framework for the consumer demand and the supply side. Section 4 shows the data used for demand estimation and conduct testing, and details the identification strategy for demand estimation and the methodology of the RV test. Section 5 presents empirical results for demand and conduct testing. Section

6 compares the market outcomes derived from the baseline model and the counterfactual model. Section 7 concludes. Related supporting details are found in Appendix A.

2 Institutional Background

In this section, I first introduce the WIC program and the mechanism of its infant formula rebate system. Then, I move on to provide some stylized facts of the US infant formula market.

2.1 WIC Program and Its Rebate System

In 1972, the US Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) was established with the mission of providing vital supplemental food and nutrition resources to eligible pregnant, postpartum, and breastfeeding women, infants, and children. Over the years, WIC has grown into a major government program and the third-largest food and nutrition assistance program. In the fiscal year 2023, WIC's expenditures reached \$6.6 billion, covering an average of 6.6 million people per month, where children made up 55% of all participants, women comprised 22.6%, and infants constituted 22.4% (i.e., an estimated 39 % of all infants born in the United States). The average food costs per person per month was \$55.95, increased \$8 21 (17. 2%) in fiscal year 2022, which was the highest level since fiscal year 2013 (Jones and Toossi 2024).

WIC is a federal program administrated by the U.S. Department of Agriculture's Food and Nutrition Service (FNS) and operated by 89 WIC State agencies at the state level: the 50 geographic states, the District of Columbia, Puerto Rico, Guam, the Virgin Islands, American Samoa, Northern Marianas, and 33 Indian tribal organizations (ITO's) (U.S. Department of Agriculture 2013). State agencies receive grants that ensure WIC recipients access these benefits at no cost (U.S. Department of Agriculture 2022). Not being an entitlement program and given its size, the WIC program has implemented essential cost-

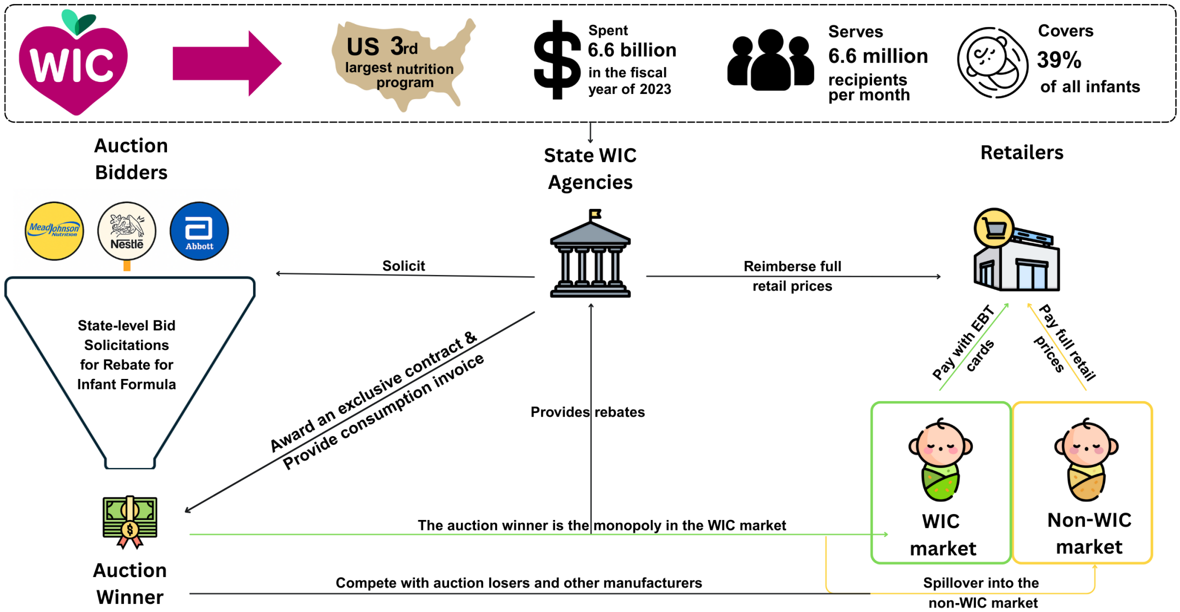

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Figure 1: Illustration of the WIC program and its rebate system

containment mechanisms to address its budgetary concerns. Since 1989, a cost-containment procedure for purchasing infant formula has been mandated for all WIC state agencies, except for states that operate home delivery or direct distribution food delivery systems, or Indian State agencies with fewer than 1,000 participants (Oliveira et al. 2001). The primary objective of this cost-containment system is to effectively reduce program expenses by securing rebates from manufacturers for each can of infant formula procured through WIC.

Figure 1 provides a visual representation of how the WIC program and its rebate system operates. In the WIC program, the state agency reimburses WIC retailers the complete retail price paid by the participant, as evidenced in the transaction-level data directly obtained by WIC agencies. WIC participants access infant formula products from retailers using Electronic Benefits Transfer (EBT) cards. Non-WIC consumers, instead, are required to pay the full retail prices for the same products.

While the state agency fully reimburses retailers, it receives partial compensation through rebates from manufacturers for each unit of product sold through the WIC program. To establish the rebates, WIC agencies conduct an auction involving infant formula manufacturers. This entails a single-source competitive sealed-bidding approach, where a WIC state agency selects the manufacturer with the most competitive total monthly net price for the infant formula contract. As a notable example, in the fiscal year 2021, state agencies received rebates for $1.6 billion (U.S. Department of Agriculture 2023).

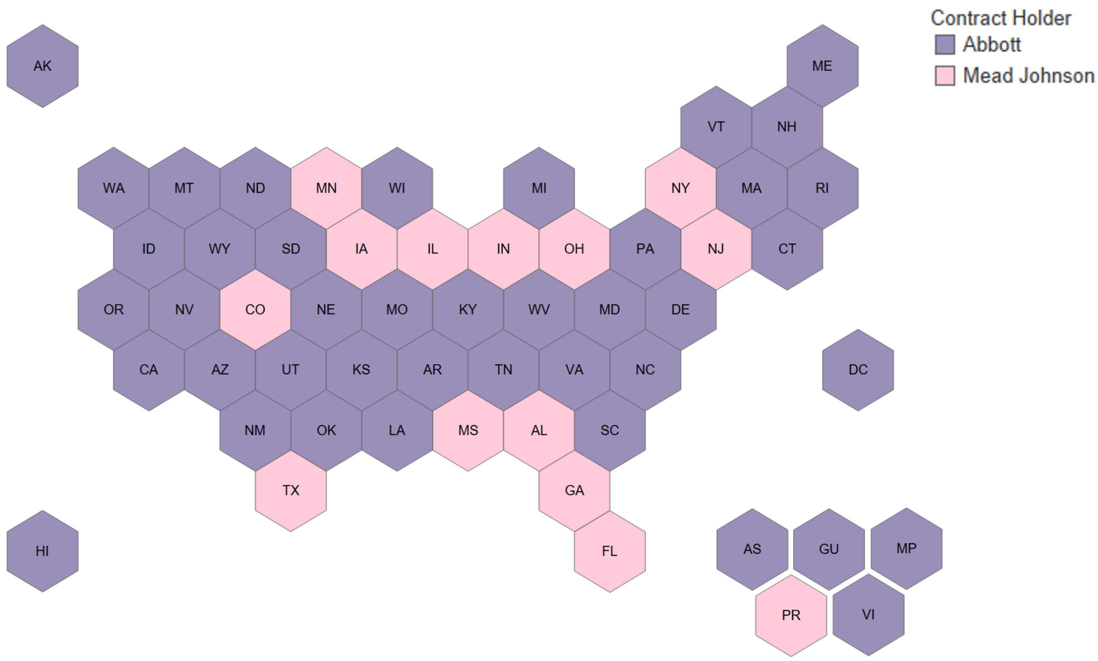
2.2 The US Infant Formula Industry

The US infant formula supply chain exhibits an oligopoly-oligopsony structure, with high concentration in both the manufacturing and retailing stages. Three leading manufacturers, Abbott Nutrition, Mead Johnson, and Nestlé dominate the industry, once even occupying 98% of the entire market and holding all WIC contracts (Oliveira, Frazão, and Smallwood 2011).[2] Figure 2 illustrates the distribution of the latest infant formula contract holders across states, with WIC contracts predominantly held by three major manufacturers to only two of them, indicating the infant formula market becomes even more concentrated in the WIC segment.

Mead Johnson and Abbott Nutrition jointly dominate the national infant formula market, commanding an impressive 80% of total sales in the US. Abbott Nutrition operates infant formula plants in Michigan, Ohio, and Arizona, while Mead Johnson's operations are based in Michigan and Indiana. An essential marketing strategy employed by these leading firms involves not only selling products directly to retailers but also targeting physicians and other professionals.

On the other hand, a later entrant to the US market and part of a Swiss parent company, Nestle, lacks pharmaceutical retailing channels (Betson 2009). Nestle operates a single plant in Wisconsin, but it acquired Gerber in 2007, resulting in a significant surge in the market share. While other minor players like Happy Family, Hain Celestial, Danone, and various private-label brands produced by Perrigo exist, their market presence remains much smaller in comparison.

2. At least until 2025, as in 2025, only Abbott and Mead Johnson are awarded WIC contracts



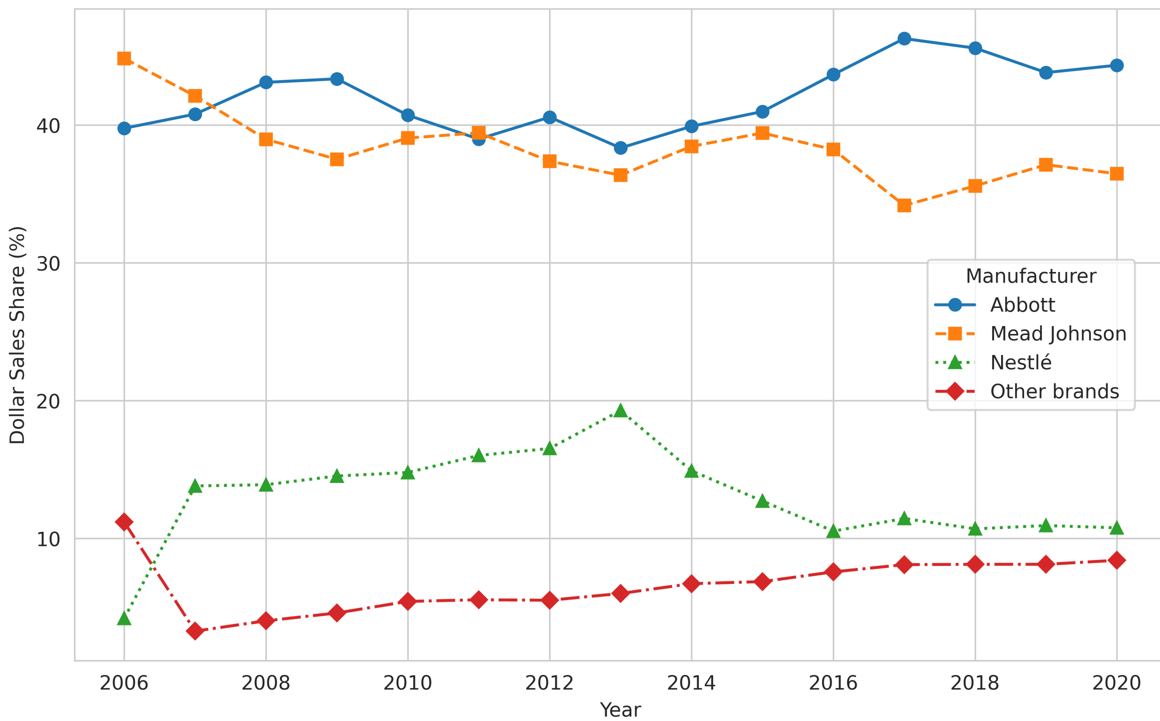
Source: https://www.fns.usda.gov/wic/requirements-infant-formula-contracts

Figure 2: Distribution of the auction winners as of 2025

Figure 3 presents the market share trends of leading infant formula manufacturers from 2006 to 2020 at the national level, highlighting the pronounced concentration of the market among the three leading manufacturers.

While the total market shares of the two main manufacturers may appear similar at the national level, significant asymmetries emerge when examining state-level data. At this level, markets tend to be dominated by the winners of the WIC rebate auction, leading to substantial variations. Figure 4 illustrates the annual sales shares of leading manufacturers from 2006 to 2020 in six states with the highest infant formula sales: California, Illinois, New York, Ohio, and Texas.

In these states, the market shares of manufacturers experience dramatic shifts as the WIC contract holder changes. For instance, in California, Abbott held a dominant 70% market share in 2006 when it was the WIC contract holder, while Mead Johnson only accounted for around 20% of the market sales. However, when Mead Johnson secured the WIC contract in 2007, its market share rapidly rose and reached 75% by 2008, while Abbott's share declined



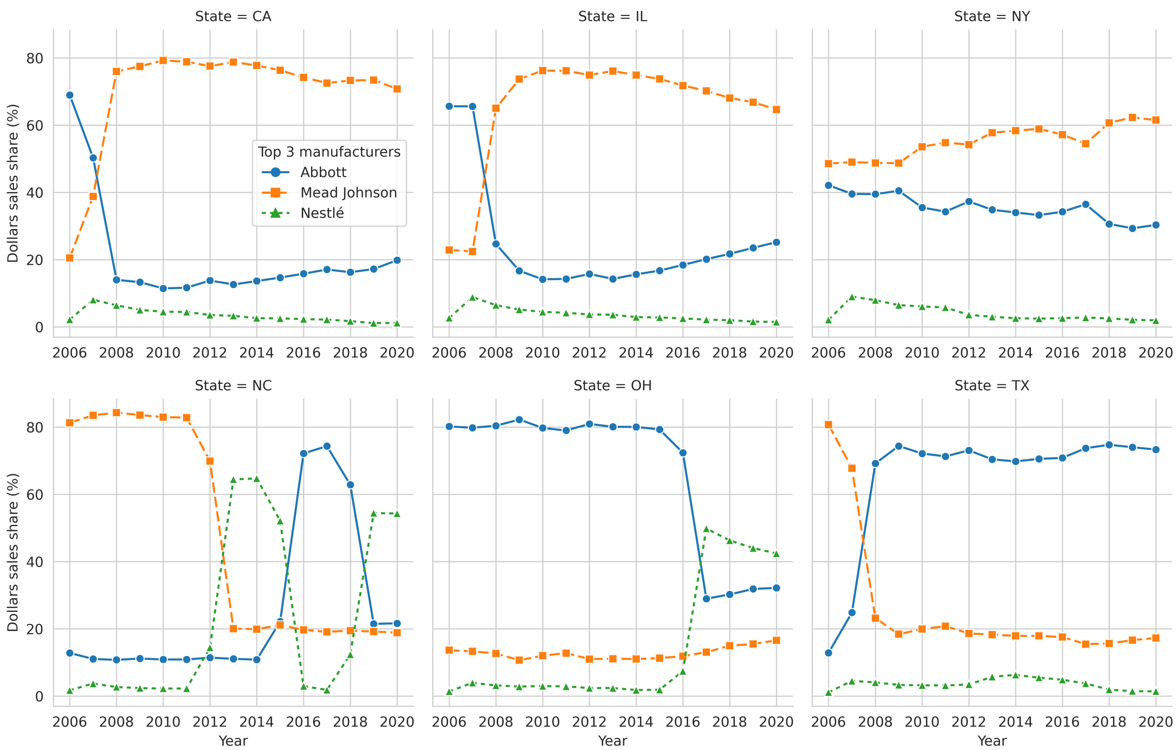
Source: Created by the author using NielsenIQ retailer scanner data.

Figure 3: Sales Market Share Trends of Leading Infant Formula Manufacturers in the U.S. from 2006 to 2020

to 15%. Similar patterns were observed in Illinois, where Mead Johnson won the WIC contract in 2008, leading to notable changes in market shares.

The highly concentrated nature of the infant formula market in the United States can be attributed, in part, to the strict regulations imposed by the Food and Drug Administration (FDA), which translates to a substantial entry barrier. These regulations ensure rigorous compliance and supervision across various aspects of the industry. For instance, infant formula manufacturing and distribution must adhere to the requirements outlined in the Federal Food, Drug, and Cosmetic Act (hereafter, the Act). The Act sets minimum standards for nutrient content, quantity, and quality of infant formula, and mandates specific practices such as labeling, reporting, and recalling procedures (U.S. Food and Drug Administration 2022).

Additionally, the production of infant formula involves combining a diverse range of



Source: Created by the author using Nielsen scanner data.

Figure 4: Sales Market Share Trends of Three Manufacturers in Six States from 2006 to 2020

inputs, which are typically sourced through a complex, global network of companies. This intricate supply chain can present challenges and high fixed costs for potential entrants, making it harder for new players to establish themselves in the market.

3 Theoretical Framework

In this section, I start describing the random coefficients logit model used to estimate the demand from non-WIC consumers. Follwing this, I detail the six supply models used for the test of conduct.

3.1 Demand Model

I apply the general framework of the random coefficients logit model of Berry, Levinsohn, and Pakes (1995). A market t is defined as a state-month combination. The indirect utility function of consumer i from purchasing product j in market t is given by the following equation.

$$\begin{gathered} V_{ijt} = -\alpha_i p_{jt} + \mathbf{x_{jt}}\beta_i + \xi_{jt} + \epsilon_{ijt} \\ i = 1, ..., I_t, \quad j = 1, ..., J_t, \quad t = 1, ..., T \end{gathered} \tag{1}$$

where p_{jt} is the price of product j in market t, $\mathbf{x_{jt}}$ is a K-dimensional (row) vector of observed product characteristics. ξ_{jt} represents unobserved attributes of product j in market t, and ϵ_{ijt} denotes a mean-zero error term.

Coefficients α_i and β_i vary across consumers. In particular, β_i is a K-dimensional (column) vector coefficient that captures consumer i's taste for product characteristics and α_i reflects individual consumer's price sensitivity. Assume α_i and β_i are independent and

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \Pi \mathbf{D_i} + \sum v_i, \quad v_i \sim N(0, I_{K+1}) \tag{2}$$

where α and β are the mean taste which is the average value of α_i and β_i, $\mathbf{D_i}$ denotes a $d \times 1$ vector of consumer demographics, Π is a $(K+1) \times d$ matrix of coefficients that measure the heterogeneity in taste characteristics vary with demographics. v_i follows a normal distribution and $\sum$ is a $(K+1) \times (K+1)$ scaling matrix that. For simplicity, D_i and v_i are assumed to be independent.

Let $\theta = (\theta_1, \theta_2)$ represents all parameters. $\theta_1 = (\alpha, \beta)$, and $\theta_2 = (\Pi, \sum)$, then the indirect utility can be expressed as

$$\begin{aligned} V_{ijt} &= [-p_{jt}, x_{jt}] \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} + \xi_{jt} + \epsilon_{ijt} \\ &= (-p_{jt}\alpha + x_{jt}\beta + \xi_{jt}) + [-p_{jt}, x_{jt}](\Pi\mathbf{D_i} + \sum v_i) + \epsilon_{ijt} \\ &= \delta_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, D_i, v_i; \theta_2) + \epsilon_{ijt} \end{aligned} \tag{3}$$

Assume that the indirect utility from purchasing the outside product $j = 0$ in market t is normalized as

$$V_{i0t} = \epsilon_{i0t} \tag{4}$$

Assume ϵ_{ijt} and ϵ_{i0t} are i.i.d. with the type I extreme value distribution, then the market share of product j in market t is

$$s_{jt}(\mathbf{x_t}, \mathbf{p_t}, \delta_t; \theta_2) = \int \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k \in J_t} exp(\delta_{kt} + \mu_{ikt})} f(\mu_{it} \mid \theta_2) d\mu_{it} \tag{5}$$

where $\mathbf{x_t}, \mathbf{p_t}$ denote the collection of x_{jt} and p_{jt} across product j within a market t, and $\delta_t = (\delta_{1t}, ..., \delta_{J_t,t})'$

3.2 Supply Model

3.2.1 Linear Pricing Model

In this model, manufacturers set their wholesale prices first, and then retailers set retail prices. Assume N_r Nash-Bertrand multi-product-oligopolist retailers compete in the downstream retail market and suppose there are N_w Nash-Bertrand multi-product-oligopolist manufacturers competing in the upstream wholesale market. Each retailer r's profit in market t is

$$\pi_t^r = \sum_{j \in J_{rt}} [p_{jt} - p_{jt}^w - c_{jt}^r] M_t s_{jt}(p, x, \xi; \theta) \tag{6}$$

where J_{rt} is the set of infant formula products sold by retailer r in market t, p_{jt}^w is the wholesale price the retailer pays for product j to manufacturer w, c_{jt}^r is the retailer's marginal cost of product j, and $s_{jt}(p, x, \xi; \theta)$ is the market share of product j.

Assume there is a pure-strategy Nash equilibrium, and the first-order conditions are derived as

$$s_{jt} + \sum_{k \in J_{rt}} [p_{kt} - p_{kt}^w - c_{kt}^r] \frac{\partial s_{kt}}{\partial p_{jt}} = 0 \qquad \forall j \in J_{rt}, \quad \text{for} \quad r = 1, ..., N_r \tag{7}$$

Define Ω_t^r as the retailer's ownership matrix in which element $\Omega_t^r(i, j) = 1$ if both products i and j are sold by the same retailer r and $\Omega_t^r(i, j) = 0$ otherwise. Define $D_t^r = \frac{\partial s_{jt}}{\partial p_{it}}$, which represents the jacobian matrix of market share with respect to retail price. Then downstream markup can be expressed as

$$\Delta_t^{\text{downstream}} = p_t - p_t^w - c_t^r = -(\Omega_t^r \odot D_t^r)^{-1} s_t(p) \tag{8}$$

where $\odot$ is the element-by-element Hadamard product. This unique equilibrium gives an implicit function of wholesale prices as equation (8) shows.

In the upstream, the manufacturer's profit is given by

$$\pi_t^w = \sum_{j \in J_{wt}} [p_{jt}^w - c_{jt}^w] s_{jt}(p(p^w)) \tag{9}$$

where J_{wt} is the set of infant formula sold by manufacturer w in market t, and c_{jt}^w is the marginal cost for producing product j. Similarly, the first-order conditions are

$$s_{jt} + \sum_{k \in J_{wt}} [p_{kt}^w - c_{kt}^w] \frac{\partial s_{kt}}{\partial p_{jt}^w} = 0 \qquad \forall j \in J_{wt}, \quad \text{for} \quad w = 1, ..., N_w \tag{10}$$

Similarly, define $\Omega_t^w(j,k)$ as the manufacturer's ownership matrix in which element $\Omega_t^w(j,k) = 1$ if both products j and k are sold by the same manufacturer w and $\Omega_t^w(j,k) = 0$ otherwise. Define $D_t^w = \frac{\partial s_{jt}}{\partial p_{kt}^w}$, which represents the jacobian matrix of market share with respect to wholesale price. Then, upstream markups can be expressed as

$$\Delta_t^{\text{upstream}} = p_t^w - c_t^w = -(\Omega_t^w \odot D_t^w)^{-1} s_t(p) \tag{11}$$

3.2.2 Zero Wholesale Margin Model

In this model, manufacturers remove wholesale margins by setting wholesale prices equal to their marginal costs, that is, $\Delta_t^{\text{upstream}} = p_t^w - c_t^w = 0$. Retailers maximize their profit by choosing retail prices given manufacturers' decisions. The implied downstream markups for the retailers are given by

$$\Delta_t^{\text{downstream}} = p_t - p_t^w - c_t^r = p_t - c_t^w - c_t^r = -(\Omega_t^r \odot D_t^r)^{-1} s_t(p) \tag{12}$$

Manufacturers capture the monopoly rents by charging retailers a fixed fee, F.

3.2.3 Zero Retail Margin Model

In this model, retailers maximize their profits by setting zero retail margins for all products, that is, $\Delta_t^{\text{downstream}} = p_{jt} - p_{jt}^w - c_{jt}^r = 0 \ \forall j$, and receiving a fixed fee F from manufacturers. The implied upstream markups are given by

$$\Delta_t^{\text{upstream}} = p_t^w - c_t^w = p_t - c_t^r - c_t^w = -(\Omega_t^w \odot D_t^r)^{-1} s_t(p) \tag{13}$$

3.2.4 Wholesale Collusion Model

Under this assumption, manufacturers collude and act as a representative decision-maker and choose the wholesale price to maximize the sum of profits from all manufacturers. So Ω_t^w is a matrix with every entry equal to one. Define this ownership matrix as Ω_1. Therefore, the upstream markup is given by

$$\Delta_t^{\text{upstream}} = p_t^w - c_t^w = -(\Omega_1 \odot D_t^w)^{-1} s_t(p) \tag{14}$$

The downstream markup is given by

$$\Delta_t^{\text{downstream}} = p_t - p_t^w - c_t^r = -(\Omega_t^r \odot D_t^r)^{-1} s_t(p) \tag{15}$$

3.2.5 Retailer Collusion Model

In this model, collusion happens at the retail level. So Ω_t^r is a matrix with every entry equal to one, equivalently, $\Omega_t^r = \Omega_1$. Therefore, the upstream markup is given by

$$\Delta_t^{\text{upstream}} = p_t^w - c_t^w = -(\Omega_t^w \odot D_t^w)^{-1} s_t(p) \tag{16}$$

The downstream markup is given by

$$\Delta_t^{\text{downstream}} = p_t - p_t^w - c_t^r = -(\Omega_1 \odot D_t^r)^{-1} s_t(p) \tag{17}$$

3.2.6 The Horizontally and Vertically Integrated Model

The major difference between this model and the zero wholesale margin model is that retailers collude to maximize total profit. The implied markup is given by

$$\Delta_t = \Delta_t^{\text{downstream}} = p_t - c_t^w - c_t^r = -(\Omega_1 \odot D_t^r)^{-1} s_t(p) \tag{18}$$

4 Empirical Strategy

In this section, I describe the data used to construct the sample for demand estimation and conduct testing. What follows is my identification and estimation strategies for the demand estimation, and the framework for the test of conduct.

4.1 Data

I use two sources of data. First, NielsenIQ Retail Scanner (RMS) data (2007-2018) are used to construct the product data sample. RMS provides product-store-week level data of infant formula prices, quantity sold, geographic markets, retail formats and product information. Detailed product information, including universal product code (UPC), brand description, and product attributes (e.g., product form, size, organic, product base), allows a flexible demand estimation method.

I define markets as state-year-quarter combinations and products by brand, form (powder, ready-to-use, or concentrated), and base (milk or soy). To keep the sample size manageable for demand estimation, I retain major states (spanning at least five years), retailers (observed for more than one year), the top three manufacturers (Abbott, Mead Johnson, and Nestlé), and products in the RMS sample, as detailed in Appendix A.

Product characteristics include lactose tolerance, prebiotics, and size. Prebiotics and lactose tolerance attributes take values of 1 or 0. Sizes are categorized in fluid ounces as small (up to 32 fluid ounces), middle (32 to 100 fluid ounces), and large (over 100 fluid ounces). Market size is defined as the potential infant formula purchase volume from the estimated total number of non-WIC consumers in a state in a quarter (see Appendix A for details).

The final trimmed sample consists of 103,852 observations across 46 states. In total, there are 1,983 state-year-quarter markets. The sample includes 103 retailers (defined by retailer code), 3 manufacturers, and 2,795 products. Table 1 shows summary statistics for the estimation sample.

Table 1: Summary Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Price ($ per fl oz)	0.20	0.04	0.07	0.17	0.19	0.21	0.65
Shares	0.007	0.010	0.001	0.002	0.003	0.007	0.085
Outside Share	0.496	0.155	0.087	0.390	0.499	0.622	0.854
Size, medium	0.56	0.50	0.00	0.00	1.00	1.00	1.00
Size, large	0.29	0.45	0.00	0.00	0.00	1.00	1.00
Lactose tolerance, 1 if yes	0.36	0.48	0.00	0.00	0.00	1.00	1.00
Prebiotics, 1 if yes	0.35	0.48	0.00	0.00	0.00	1.00	1.00

Note: Share is the product-level volume share within state-year-quarter. "Size, medium" is the indicator for products of size between 32 and 100 fluid ounces, and "Size, large" is the indicator for products of size larger than 100 fluid ounces.

Second, NielsenIQ Consumer Panel Dataset (HMS) is used to add demographic information, including household income and education level (college and above). HMS data helps estimate the consumer heterogeneity (Π and Σ parameters) and also is used to construct micro moments. To prepare the agent data, I draw 300 households for each market and record the standardized household income and education level of the head of the household. I consider a household to be "college-educated or above" if either the male or female head of household is labeled as "Graduated College or above" in the HMS data.

Input prices for important dairy ingredients, including whey protein concentrate, lactose, and casein, are collected from the Agricultural Marketing Service (AMS) of the U.S. Department of Agriculture (USDA). Diesel prices are collected from the U.S. Energy Information Administration. Transportation cost is measured as the multiplication of the distance between the nearest plant to a state and the diesel price. I use the distance from a state capital to a manufacturer's plant to determine the nearest plant. Plant information is collected from each manufacturer's official website.

4.2 Demand Estimation

4.2.1 Identification

The demand model is identified by assuming that the demand shocks ξ_{jt} are uncorrelated with a set of excluded demand-side instruments z_{jt}, as prices and market shares are assumed endogenous. Three commonly used sets of instruments are used. The first set consists of cost shifters, defined as interactions between input prices (including whey protein concentrate, lactose, and casein) and both transportation costs and product size. Transportation cost is measured as the distance to the nearest manufacturing plant multiplied by the national diesel price. The second set includes interactions between the local differentiation instruments and market-level household demographics (Gandhi and Houde 2020). Finally, the third set includes the interaction between predicted prices and the mean of market-level household income.

To improve the identification of the random coefficients, following Petrin (2002) and Conlon and Gortmaker (2025), I leverage two micro-moments: the conditional expectation of income given a purchase of inside product j ($E[\text{income}_i|1\{j > 0\}]$) and the conditional expectation of household-head education given a purchase of Prebiotics formula product j ($E[\text{education}_i|1\{\text{Prebiotics} = 1\}]$).

4.2.2 Estimation

Following Conlon and Gortmaker (2025), I estimate demand with micro moments. The GMM problem for the standard BLP estimation is

$$\min_{\theta} q_D(\theta) = g_D(\theta)' W g_D(\theta), \tag{19}$$

$$g_D = \frac{1}{N} \sum_{jt} \xi_{jt} z_{jt}, \tag{20}$$

$$\xi_{jt} = \delta_{jt} - x_{jt}\beta + \alpha p_{jt}, \tag{21}$$

$$\mathcal{S}_{|\sqcup} = s_{jt}(\delta_t; \theta_2) = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_{k \in J_t} \exp(\delta_{kt} + \mu_{ikt})} f(\mu_{it} \mid \theta_2) d\mu_{it} \tag{22}$$

where $q(\theta)$ is the GMM objective, W is a $M_D \times M_D$ weighting matrix, $g_D(\theta)$ is a $M_D \times 1$ vector of demand moments, and $\mathcal{S}_{|\sqcup}$ is observed market shares. With additional micro moments, $g_M(\theta)$, there is a total of $M = M_D + M_M$ moments:

$$G(\theta) = \begin{bmatrix} g_D(\theta) \\ g_M(\theta) \end{bmatrix} \tag{23}$$

Extend the standard GMM problem in 19 with the above M_M micro moments, the GMM estimator for estimating a BLP model with micro moments is given by:

$$\begin{aligned} \min_{\theta} Q(\theta) &= G(\theta)' \bar{W} G(\theta), \\ G(\theta) &= \begin{bmatrix} g_D(\theta) \\ g_M(\theta) \end{bmatrix}, \\ \mathcal{S}_{|\sqcup} = s_{jt}(\delta_t; \theta_2) &= \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_{k \in J_t} \exp(\delta_{kt} + \mu_{ikt})} f(\mu_{it} \mid \theta_2) d\mu_{it} \end{aligned} \tag{24}$$

where $\bar{W}$ is the new weighting matrix. I rely on the package *PyBLP* to implement the estimation method (Conlon and Gortmaker 2020).

4.3 Test for Conduct

4.3.1 Testing Environment

Following Duarte et al. (2024) I define the demand system for market t as $\boldsymbol{s_t}(\boldsymbol{p_t}, \boldsymbol{x_t}, \boldsymbol{\xi_T}; \boldsymbol{\theta_0})$, where $\boldsymbol{p_t}$ is the vector of prices for all products, $\boldsymbol{x_t}$ is the vector of observed product characteristics for all products, $\boldsymbol{\xi_t}$ is the vector of unobserved product characteristics for all products, and $\boldsymbol{\theta_0}$ is the true vector of demand parameters. The market equilibrium in market t then is given by

$$\boldsymbol{p_t} = \Delta_{0t} + mc_{0t} \tag{25}$$

where $\Delta_{0t} = \Delta_0(\boldsymbol{s_t}, \boldsymbol{p_t}; \boldsymbol{\theta_0})$ is the true vector of the sum of downstream markups $\Delta_{0t}^{\text{downstream}}$ and upstream markups $\Delta_{0t}^{\text{upstream}}$, and mc_{0t} is the true vector of marginal costs. Assume $mc_{0jt} = \tilde{c}_{0jt}(q_{jt}, w_{jt}, \omega_{jt}) = \bar{c}(q_{jt}, w_{jt}) + \omega_{0jt}$, where $\bar{c}_j(q_{jt}, w_{jt})$ is the unknown cost function of quantity and observed cost shifters, and ω_{0jt} is the unobserved cost shifter. Assume $\bar{c}_j(q_{jt}, w_{jt})$ is constant in q_{jt} and $E[\bar{c}(w_{jt})\omega_{0jt}] = 0$.

The product data used to estimate demand is also used to test firm conduct models. For a given demand system, a firm's marginal cost under a specified model of supply is recovered by using the first-order conditions that arise from profit-maximizing behavior. Following the same notation in section 3.1, for each product-market pair, we observe prices vector $\boldsymbol{p_{jt}}$, market shares $\boldsymbol{s_{jt}}$, demand shifters such as product characteristics vector $\boldsymbol{x_{jt}}$, and cost shifters $\boldsymbol{w_{jt}}$.

Denote $\hat{\theta}$ as the estimated demand parameter, and then estimated markups under each specified model of conduct m can be obtained as $\hat{\Delta}_{mt} = \hat{\Delta}_m(\boldsymbol{s_t}, \boldsymbol{p_t}; \hat{\boldsymbol{\theta}})$. The estimated demand parameter $\hat{\theta}$ converges in probability to the true parameter θ_0 in large samples, so I treat the implied markups calculated using $\hat{\theta}$ as data for firm conduct tests. (estimation adjustment needed?)

Following the notation in Duarte et al. (2024), I use i for a generic observation, replacing the original jt index and suppress the i index when referring to stacked vectors or matrices.

Consider a simple case with two conduct models: m_1 and m_2. As the true markup Δ_0 is usually not observed by researchers, valid instruments are required to estimate model-implied markups Δ_{1i} and Δ_{2i}. Two important assumptions are needed:

Assumption 1. $E[\mathbf{z}_i\omega_{0i}] = 0$, where $\mathbf{z}_i$ is a vector of demand-side excluded instruments.

Assumption 2. (i) $\{\Delta_{0i}, \Delta_{1i}, \Delta_{2i}, \mathbf{z}_i, \mathbf{w}_i, \omega_{0i}\}_{i=1}^n$ are jointly iid; (ii) $E[(\Delta_{1i}-\Delta_{2i})^2]$ is positive and $E[(\mathbf{z}_i'\mathbf{w}_i)(\mathbf{z}_i'\mathbf{w}_i)']$ is positive definite; (iii) the entries of $\Delta_{0i}, \Delta_{1i}, \Delta_{2i}, \mathbf{z}_i, \mathbf{w}_i$, and ω_{0i} have finite fourth moments.

Assumption 4.3.1 requires that the instruments are exogenous for testing and uncorrelated with the unobserved cost shifters for the true model. Assumption 2 assumes data are independent and identically distributed across markets, rules out cases where the two models give identical markups or where instruments are collinear with cost shifters, and assumes a regularity condition ensuring valid asymptotics as sample size grows.

4.3.2 Models of Conduct

As described in section 3.2, six models of conduct from Villas-Boas (2007) are considered, as shown in Table 2.

Table 2: Models Estimated

Models	Retailers	Manufacturers	Vertical Interaction
1. Zero wholesale margin model	Bertrand	Perfect competition	No
2. Zero retail margin model	Perfect competition	Bertrand	No
3. Linear pricing model	Bertrand	Bertrand	No
4. Wholesale collusion model	Bertrand	Collusion	No
5. Retail collusion model	Collusion	Bertrand	No
6. The integration model	Collusion	Perfect competition	Yes

4.3.3 Model Falsification and Instruments

As discussed in section 4.3.1, implied markups Δ_m from different models allow us to distinguish firm conduct. Since we cannot observe true markups, we rely on a set of exogenous instruments to falsify a model. The analog of of assumption 1 is $E[z_i(p_i - \Delta_{mi})] = 0$, where

$p_i - \Delta_{mi}$ is the residualized marginal revenue under model m. Under assumption 1, we have $E[z_i p_i] = E[z_i \Delta_{oi}]$. Therefore, to test a model is to compare $E[z_i \Delta_{oi}]$ and $E[z_i \Delta_{mi}]$.

Thus, under assumptions 1 and 2, we falsify a model m if the following is not true:

$$E[(\Delta^z_{0i} - \Delta^z_{mi})^2] = 0 \tag{26}$$

where Δ^z_{mi} is the predicted markups with instruments z for model m. Equation 26 is the mean squared error (MSE) in predicted markups.

Following Gandhi and Nevo (2021), Backus, Conlon, and Sinkinson (2021), and Duarte et al. (2024), I consider four common sets of exogenous instruments: (1) the number of own and rival products in a market (NumProd IV), (2) the differentiation instruments (Diff), (3) the average transportation costs of rival firms' products (Cost), and (4) the interaction between mean household income with prices and the interaction between mean household education level with prebiotics (Demo). The NumProd and Diff instruments consider the variations from observed product characteristics of own and other products, and the number of other firms and products. The Cost and Demo instruments leverage the variations from rival cost shifters and market-level demographics.

4.3.4 The Rivers-Vuong Test (RV) and Hypotheses Formulation

To infer conduct with a finite sample using condition 26, we rely on hypotheses and valid instruments. The RV test is a model selection approach used to test non-nested model hypotheses (Rivers and Vuong 2002), and is proven to be robust under model misspecification (Duarte et al. 2024). Consider the case of only two candidate models. The null hypothesis of the RV test is that two competing models of firm conduct $m = 1, 2$ have the same lack-of-fit:

$$H_0 : Q_1 = Q_2, \tag{27}$$

where Q_m is a population measure for lack of fit in conduct model m. Alternative hypotheses are:

$$H_1 : Q_1 < Q_2 \quad \text{and} \quad H_2 : Q_2 < Q_1 \tag{28}$$

where hypothesis 1 states that model 1 has a better fit than model 2, while hypothesis 2 states the opposite.

According to Duarte et al. (2024), the lack of fit Q_m measurement is defined with a GMM objective function:

$$Q_m = g_m' W g_m \tag{29}$$

where $g_m = E[z_i(p_i - \Delta_{mi})]$ and $W = E[z_i z_i']^{-1}$. The difference $p_i - \Delta_{mi}$ represents the residual marginal revenue under model m, where p_i is the price and Δ_{mi} is the markup implied by model m.

Then the sample statistic of Q_m is

$$\hat{Q}_m = \hat{g}_m' \hat{W} \hat{g}_m \tag{30}$$

where $\hat{g}m = \frac{1}{n}\hat{z}_i(\hat{p}_i - \hat{\Delta}_{mi})]$ and $\hat{W} = n(z_i z_i')^{-1}$.

The RV test statistic that compares the relative fitness of two competing models is:

$$T^{RV} = \frac{\sqrt{n}(\hat{Q}_1 - \hat{Q}_2)}{\hat{\sigma}_{RV}} \tag{31}$$

where $\hat{\sigma}_{RV}$ is the estimated asymptotic variance of the measure of fit. Specifically,

$$\hat{\sigma}^2_{RV} = 4[\hat{g}_1' \hat{W}^{1/2} \hat{V}^{RV}_{11} \hat{W}^{1/2} \hat{g}_1 + \hat{g}_2' \hat{W}^{1/2} \hat{V}^{RV}_{22} \hat{W}^{1/2} \hat{g}_2 - 2\hat{g}_1' \hat{W}^{1/2} \hat{V}^{RV}_{12} \hat{W}^{1/2} \hat{g}_2 \tag{32}$$

where $\hat{V}^{RV}_{\ell k}$ is an estimator of the covariance between $\sqrt{n}\hat{W}^{1/2}\hat{g}_\ell$ and $\sqrt{n}\hat{W}^{1/2}\hat{g}_k$, and

$$\hat{V}^{RV}_{\ell k} = n^{-1} \sum_{i=1}^{n} \hat{\psi}_{\ell i} \hat{\psi}_{ki}' \tag{33}$$

where

$$\hat{\psi}_{mi} = \hat{W}^{1/2}\left(\hat{z}_i(\hat{p}_i - \hat{\Delta}_{mi}) - \hat{g}_m\right) - \frac{1}{2}\hat{W}^{3/4}\left(\hat{z}_i\hat{z}_i' - \hat{W}^{-1}\right)\hat{W}^{3/4}\hat{g}_m.$$

The test statistic T^{RV} follows a standard normal distribution under the null hypothesis if $\sigma^2_{RV} > 0$ and we reject the null if $|T^{RV}| > Z_{1-\frac{\alpha}{2}}$, where $Z_{1-\frac{\alpha}{2}}$ is the critical value at the significance level of α. If $\sigma^2_{RV} = 0$, the RV test is degenerate.

Duarte et al. (2024) prove that the RV test can be expressed in terms of the falsification condition in 26, and it only rejects the model whose predicted markups deviate more from the true markups. I use the pyRVtest package offered by Duarte et al. (2024) to implement the testing methods outlined in section 4.3.

5 Results

The sections below present findings from demand estimation results and conduct testing results.

5.1 Demand Estimation Result

Table 3 presents the estimated results from the demand model. Comparing the Logit-OLS and Logit-2SLS specifications, the findings support the relevance of the instrumental variables, as the price coefficient becomes more negative, shifting from -1.969 to -6.456 when price instruments are included. Incorporating consumer heterogeneity further strengthens this effect, with the price coefficient decreasing to -13.150. However, the interaction terms income × price and education × prebiotics are statistically insignificant, suggesting limited variation in preferences across consumers in this sample.

Table 3: Demand Estimates

	(1) Logit-OLS		(2) Logit-2SLS		(3) BLP	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Prices	-1.969	(0.294)	-6.456	(2.280)	-13.150	(3.511)
Lactose tolerance	-0.141	(0.030)	-0.010	(0.076)	0.2118	(0.096)
Prebiotics	0.150	(0.032)	0.118	(0.031)	-0.011	(0.352)
Size, medium	0.593	(0.045)	0.445	(0.080)	0.209	(0.114)
Size, large	0.528	(0.046)	0.365	(0.081)	0.115	(0.112)
Income $\times$ price					0.414	(1.048)
Education $\times$ prebiotics					0.122	(0.757)
No. observations	103,852		103,852		103,852	
State FEs	Yes		Yes		Yes	
Manufacturer FEs	Yes		Yes		Yes	
Retailer FEs	Yes		Yes		Yes	
Year FEs	Yes		Yes		Yes	
Quarter FEs	Yes		Yes		Yes	
Own price elasticity-mean	-0.383		-1.256		-2.559	
Own price elasticity-median	-0.363		-1.190		-2.425	
Diversion outside option-mean	0.631		0.630		0.630	
Diversion outside option-median	0.636		0.636		0.636	

5.2 Testing Conduct

Table 4 presents the pairwise Rivers-Vuong (RV) test results. Panel A shows results using the NumProd instruments. Negative values of the RV test statistic suggest support for the row model, and a value less than -1.96 rejects the null of equal fit in favor of the row model at the 95% significance level. The test statistics are strongly negative for all comparisons involving model 1, indicating that the zero wholesale margin model consistently outperforms the alternatives.

The corresponding pair-wise F-statistics are calculated to provide evidence on the quality of inferences made based on the RV statistics, as weak instruments cause invalid inferences. Critical values for size and power are constructed. By comparing the F statistics to these thresholds, I can determine whether the instruments are weak for size or for power. When the number of instruments is small, a lack of power is the major concern (Duarte et al. 2024). Since there are only two instruments for panel A, size distortion is not a concern. All F-statistics in Panel A exceed the critical threshold required for achieving 0.95 maximal power across all model pairs. This indicates that the NumProd instruments are strong in terms of power. In Panel A, the MCS p-value contains only model 1 corresponding to the zero wholesale model; the other models have MCS p-values below the selected 0.05 level.

Panels B through D report results using alternative instrument sets (Diff, Cost, and Demo). In each of these, all models remain in the MCS. The pair-wise F-statistics in Panels B and D suggest that the failure to reject models is due to the Demo and Diff instruments having low power, though they are strong for size. Similarly, the Cost instrument in Panel C is weak for power even at a level of 0.5, and for some pairs of models, this instrument is also weak for size.

Table 5 presents summary statistics for the estimated price-cost margins (PCMs) under the six models. Each row corresponds to a specific model and shows the distribution of total vertical margins. Except the zero wholesale margin model and the integration model, the remaining four models exhibit a substantial proportion of PCMs greater than one, implying negative implied marginal costs for those products. Only the zero wholesale margin model and the integration model yield less than 6% of marginal cost estimates below zero. These two models share the same upstream market structure; however, retailers compete à la Bertrand in the downstream in Model 1, while they collude in Model 6.

Table 4: RV Test Results

	T^{RV}					F-statistics					MCS p-val.
Models	1	2	3	4	5	1	2	3	4	5	
Panel A: NumProd IVs ($d_z = 2$)											
m1. Zero wholesale margin	-3.925	-3.938	-5.314	-4.207	-4.864	$100.1^{\dagger}$	$80.2^{\dagger}$	$23.1^{\dagger}$	$11.1^{\dagger}$	$30.0^{\dagger}$	1.00
m2. Zero retail margin		3.439	-3.311	-4.242	2.158		$98.7^{\dagger}$	$191.3^{\dagger}$	$6.1^{\dagger}$	$163.3^{\dagger}$	0.00
m3. Linear pricing			-4.148	-4.230	-3.311			$164.8^{\dagger}$	$6.2^{\dagger}$	$132.0^{\dagger}$	0.00
m4. Wholesale collusion				-3.549	5.039				$78.8^{\dagger}$	$75.8^{\dagger}$	0.00
m5. Retail collusion					3.891					$56.2^{\dagger}$	0.00
m6. The integration model											0.00
Panel B: Demo IVs ($d_z = 2$)											
m1. Zero wholesale margin	-1.354	-1.355	-1.211	-1.321	-1.326	1.4	1.5	2.2	0.4	2.9	1.00
m2. Zero retail margin		1.081	1.115	-1.309	1.155		2.0	2.6	0.2	2.2	0.435
m3. Linear pricing			1.093	-1.309	1.128			2.7	0.2	2.3	0.464
m4. Wholesale collusion				-1.291	0.254				0.8	2.2	0.226
m5. Retail collusion					1.293					0.6	0.303
m6. The integration model											0.421
Panel C: Cost IVs ($d_z = 1$)											
m1. Zero wholesale margin	0.171	0.048	0.410	-0.728	0.978	1.3	1.8	$1.5^{\ddagger}$	$0.6^{\ddagger}$	$1.3^{\ddagger}$	0.739
m2. Zero retail margin		-0.930	0.288	-0.824	0.292		1.4	0.2	$0.4^{\ddagger}$	0.4	0.953
m3. Linear pricing			0.430	-0.817	0.392			0.4	$0.2^{\ddagger}$	0.6	0.713
m4. Wholesale collusion				-0.794	0.074				0.8	1.2	0.941
m5. Retail collusion					0.777					0.9	0.710
m6. The integration model											1.00
Panel D: Diff IVs ($d_z = 10$)											
m1. Zero wholesale margin	-1.088	-1.060	-0.529	-1.067	-0.568	1.1	1.2	0.7	0.3	1.4	1.00
m2. Zero retail margin		1.037	1.094	-1.058	1.095		1.5	1.8	0.1	1.5	0.647
m3. Linear pricing			1.073	-1.063	1.069			1.8	0.1	1.5	0.637
m4. Wholesale collusion				-1.067	-0.013				0.5	0.6	0.597
m5. Retail collusion					1.067					0.4	0.622
m6. The integration model											0.820

Aggregating Evidence: $\boldsymbol{M^* = \{0\}}$

Step 0: $M^*_{z0} = \{0\}$, $M^*_{z1} = \{1, 2, 3, 4, 5, 6\}$, $M^*_{z2} = \{1, 2, 3, 4, 5, 6\}$, $M^*_{z3} = \{1, 2, 3, 4, 5, 6\}$.

Step 1: No conflicting evidence.

Step 2: Smallest MCS is $\boldsymbol{M^* = \{0\}}$, supported by strong instruments.

The first five columns report pair-wise T^{RV} statistics for all pairs of models in the respective row and column. Negative values of the test statistic suggest a better fit of the row model. The second five columns show all the pair-wise F-statistics. † indicates F-statistic above critical value for a best-case power of 0.95. ‡ means the F-statistics are below the critical values for a worst-case size of 0.075. All other F-statistics are above the critical value for a worst-case size of 0.075. The last column reports MCS p-values for the row model. MCS p-values below 0.05 indicate rejection of a row model.

Table 5: Summary Statistics of Price-Cost Margins

Model	Mean	S.D.	Min	Max	Percentage > 1
1. Zero wholesale margin model	0.448	0.088	0.131	1.469	0.01
2. Zero retail margin model	0.931	0.185	0.255	2.499	31.14
3. Linear pricing model	0.964	0.189	0.272	2.784	40.27
4. Wholesale collusion model	1.168	0.278	0.333	4.457	73.99
5. Retail collusion model	1.276	0.367	0.319	4.673	81.52
6. The integration model	0.668	0.187	0.176	2.440	5.37

Price-cost margins are computed as $PCM = \widehat{\Delta}_m/p$, where $\widehat{\Delta}_m$ is the estimated markup under model m and p is the retail price. The last column shows the percentage of observations with PCM greater than 1.

6 Counterfactual Analyses

The conduct test indicates that the U.S. infant formula industry is best captured by the zero wholesale margin model. I then evaluate the impact of firm conduct on market outcomes. Specifically, I simulate equilibrium prices and shares under alternative vertical conduct models that are rejected in section 5.2. The baseline model is the data-supported zero wholesale margin model. Here, I present the analysis of a counterfactual scenario in which manufacturers set retail prices directly, corresponding to a zero retail margin model, which is a commonly implicit assumption in current literature.

Under the counterfactual scenario in which manufacturers set retail prices, I find that average prices and producer surplus increase relative to the baseline model. This upward shift in prices reflects the ability of manufacturers to recapture downstream markups and exert greater control over final retail prices. As a consequence, non-WIC consumer surplus declines, since higher prices reduce utility for out-of-pocket buyers, who are not shielded by WIC benefits. While this pattern holds across the national market, firm-level and regional price responses vary significantly depending on WIC contract status and local competitive dynamics.

Both the baseline and counterfactual models are variants of two-part tariff contracts that eliminate double marginalization, either at the retail stage (the counterfactual model) or at the manufacturer stage (the baseline model). Theoretically, the switch in pricing control as well as ownership can affect market outcomes depending on the intensity of competition at each stage. In the baseline model, where pricing is delegated to retailers, the market structure is relatively fragmented: the full sample contains 103 unique retailers, and the average number of retailers per market exceeds 10. Under Bertrand competition among these retailers, price-setting incentives are constrained by aggressive inter-brand competition at the retail level.

Table 6: Counterfactual Analysis: Impact of firm conduct

	m1	m2	Changes in percentage
Panel A: Average prices comparison			
Overall	0.196	0.203	3.794
Abbott	0.198	0.207	4.433
Mead Johnson	0.202	0.211	4.032
Nestlé	0.171	0.173	0.738
Panel B: Surplus comparison			
Consumer surplus	66.528	61.579	-7.439
Producer surplus	59.865	61.164	2.170
Abbott	27.323	27.881	2.042
Mead Johnson	23.367	24.015	2.776
Nestlé	9.175	9.268	1.008

Consumer surplus is normalized and reported in utils. Producer surplus is population-normalized gross profits.

By contrast, when pricing control shifts to manufacturers in the counterfactual model, market concentration increases substantially. There are only three major manufacturers — Abbott, Mead Johnson, and Nestlé—and their competition could be notably less intense than competition among retailers. Historical positioning and market incumbency further shape their strategic behavior. Abbott and Mead Johnson, both U.S.-based and long-established in the domestic formula market, appear to exploit their advantageous positions under manufacturer pricing by raising prices to a greater extent than Nestlé. This structural asymmetry helps explain the overall rise in prices and producer surplus observed in the counterfactual simulations. While two-part tariff integration mitigates double marginalization in both cases, the distribution of pricing power across a more or less competitive tier of the supply chain alters the direction of price effects.

To explore how the mechanism plays out in specific regional contexts, we examine three representative states—Louisiana (LA), California (CA), and Massachusetts (MA)—over the 2007 to 2018 period. In each case, we track firm-specific pricing changes under the baseline model and the counterfactual one. These comparisons reveal that WIC auction winners often—but not always—raise prices more substantially under manufacturer pricing, while non-WIC firms may respond by lowering prices to remain competitive.

In Louisiana, from 2007 to 2012, Nestlé and Mead Johnson jointly held the WIC contract. From 2013 to 2017, Mead Johnson held the contract exclusively, followed by Abbott becoming the new WIC contract winner in 2018. Mead Johnson consistently increased prices relative to the baseline, whereas Nestlé, despite holding the contract in some years, reduced prices across the period. This suggests that factors beyond contract status—such as brand strength, demand responsiveness, or distribution—may shape pricing responses to conduct changes. Figure 5 describes this pattern.

In California, where Mead Johnson held the WIC contract continuously from 2007 to 2018, we observe a consistent increase in prices for Mead Johnson under manufacturer pricing conduct. Abbott raised prices only in 2007, but reduced them in every subsequent year. Nestlé would lower its prices for all years. These patterns shown in Figure 6 are consistent with a scenario in which the WIC winner leverages exclusive shelf access and upstream control to raise prices, while non-WIC firms adjust downward to maintain their presence in the market.

The case of Massachusetts highlights how conduct effects evolve alongside changes in WIC contract allocations, as Figure 7 illustrates. From 2006 to 2011, Nestlé was the WIC winner and raised prices substantially under the counterfactual model, while Abbott consistently reduced its prices. Between 2012 and 2016, Mead Johnson held the contract. Abbott was the new WIC action winner between 2016 and 2018. During this period, Abbott increased

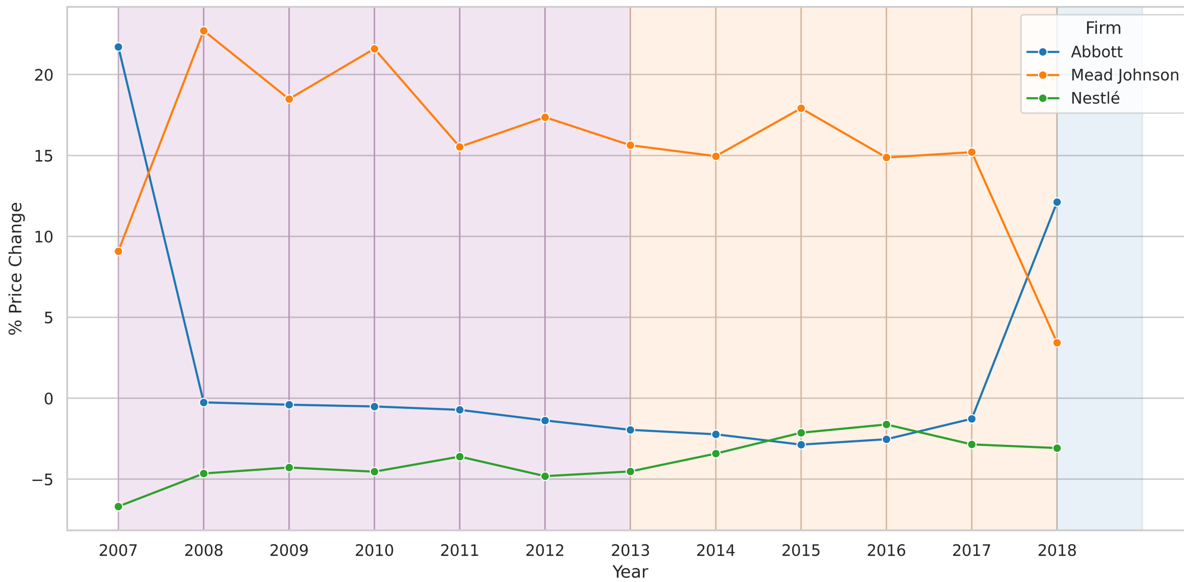


Figure 5: Yearly % Change in Average Prices by Firm in LA

Note: The shaded vertical bars indicate the years during which a manufacturer held the WIC contract in LA. The purple region (2007–2013) represents a period when both Nestlé and Mead Johnson were WIC contract holders. The orange region corresponds to the years when Mead Johnson was the sole WIC auction winner. The blue region marks 2018, when Abbott held the WIC contract. While this figure does not include a green shaded region, in other figures a green bar would indicate years when Nestlé was the sole WIC winner. This interpretation also applies to Figures 6 and 7.

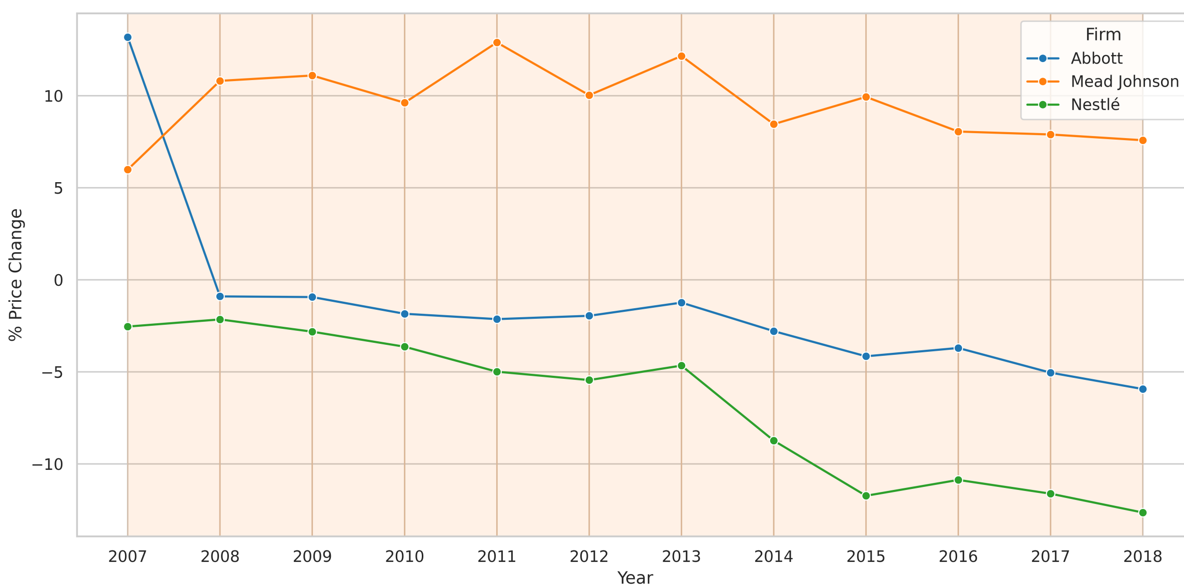


Figure 6: Yearly % Change in Average Prices by Firm in CA

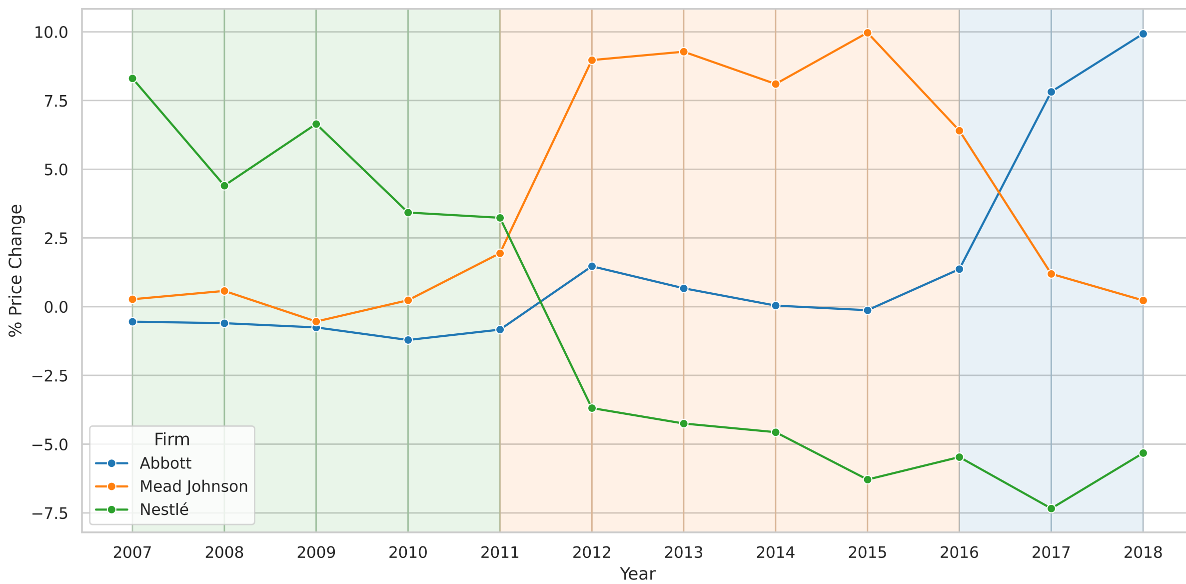


Figure 7: Yearly % Change in Average Prices by Firm in MA

prices.

Taken together, these results emphasize that, while the shift from retailer to manufacturer pricing increases average prices and firm profits, its effects are heterogeneous across firms and markets. The identity of the WIC contract holder plays a central role in determining the direction and magnitude of price changes, yet firm-specific strategies and local market conditions introduce additional complexity. Mead Johnson stands out as the only firm that uniformly increased prices across all observed state-year markets, while Nestlé and Abbott display more variable responses depending on their contract status and competitive environment.

It is important to note, however, that the Nielsen dataset used in this analysis includes only a subset of retail channels, specifically, food and mass merchandise stores, and does not cover some important (e.g, Walmart) and growing retail formats such as dollar stores (e.g., Dollar General which have expanded significantly in recent years and increasingly serve price-sensitive consumers). As such, the level of retail competition in the broader market is likely more intense than what is captured by our sample. This suggests that the price-disciplining effect of retailer pricing under the baseline model may be understated, and the observed price increases and welfare losses under manufacturer pricing should be interpreted as lower-bound estimates of the true effects.

7 Conclusions

To understand the policy implications for market outcomes and government costs under the U.S. WIC program and its rebate system, we highlight the importance of identifying vertical relationships in the infant formula industry—a critical yet previously overlooked component in the existing literature. I empirically test six firm conduct models in the context of the U.S. infant formula market following the method developed by Duarte et al. (2024). To perform the test, we first estimate a random coefficients logit demand. The average own price elasticity is around -2.56, which is consistent with earlier estimates in An et al. (2025). With demand estimation results, we then calculate the markups implied by each conduct and evaluate their fit using the RV test. I find that only the two-part tariffs model, where retailers set retail prices and manufacturers charge wholesale prices equal to marginal costs, is supported by the data. This result challenges a key assumption in prior work (e.g., Prell (2004), Betson (2009), and An et al. (2025)) that manufacturers set retail prices.

I use counterfactual simulations to quantitatively evaluate the impact of firm conduct on market outcomes. I find infant formula manufacturers' conduct influences retail prices and hence government costs: when pricing authority shifts from retailers to manufacturers (i.e., violating the data-supported model), retail prices rise by 3.79% on average. This reflects stronger pricing incentives on the manufacturer side under direct retail pricing. The reallocation of pricing power also causes a 2.17% gain in producer surplus but a 7.44% drop in consumer surplus, underscoring how vertical structure affects welfare distribution. Importantly, price responses vary across manufacturers: WIC rebate auction winners raise prices more aggressively under manufacturer pricing control. This behavior likely reflects winners' increased bargaining power and product placement advantages after winning the auction, as well as their incentive to recoup losses from aggressive bidding. Manufacturers even bid below cost to secure WIC contracts. These findings emphasize the important role of firm conduct in shaping market efficiency and the effectiveness of WIC's rebate programs.

Policy-wise, our results suggest that delegating pricing control to manufacturers tends to undermine WIC's cost containment objective, even if rebates remain in place. Consequently, policy evaluations must consider not only the mechanism of the program, but also the nature of firm conduct.

A key limitation of our approach is the assumption of homogeneous conduct across firms within each model. However, in practice, conduct may vary by WIC auction results and a firm's market dominance. For example, WIC auction winners may behave differently from losers, particularly given differences in slotting access and strategic interactions with retailers. Testing-based methods like ours cannot capture such firm-level heterogeneity. Future work could address this by adopting estimation-based frameworks that allow firm-specific conduct parameters, potentially offering a more nuanced view of strategic behaviors in this special context.

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A Data for Demand Estimation

sectionAppendix A In this appendix, I discuss all of the decisions I make when constructing the sample that I use for demand estimation in 4.2.

Products, Non-WIC Demand, and Standardization of Unit

In the NielsenIQ Retail Scanner dataset, I define a product as a combination of brand, form, and base. Since I am estimating demand from non-WIC consumers for the top three manufacturers' brands, and Nielsen does not distinguish between WIC and non-WIC purchases, I need to estimate non-WIC sales for WIC brands. To do this, I follow the method from An et al. (2023), which uses a non-WIC ratio.

Before calculating non-WIC demand, I first define WIC brands using bidding data from the Food and Nutrition Service (FNS) from 2006 to 2020. This dataset includes information on winning manufacturers, brands for each form, and contract start and end times for each state. I merge this bidding data with the Nielsen dataset to generate a dummy variable for WIC products, marking products as WIC brands if the brand descriptions match. I then apply the non-WIC ratio to estimate the volume purchased by non-WIC consumers for these WIC products.

$$\text{non-WIC sales} = \left\{1 - \frac{(1 - \text{WIC breastfeeding rate}) \times \#\text{ of WIC infants}}{(1 - \text{overall breastfeeding rate}) \times \#\text{ of all infants}}\right\} \times \text{total sales} \tag{34}$$

The numerator in parentheses represents the number of formula-fed WIC infants, while the denominator represents the total number of formula-fed infants. Starting in 2010, WIC annual data from FNS directly provides this information. For years prior to 2010, I calculate it using the WIC breastfeeding rate and the total number of infant participants.

Annual breastfeeding rates by state are obtained from DNPAO Data of the CDC, where breastfeeding is defined as "Breastfed at 12 months", which includes breastfeeding to any extent, with or without complementary liquids or solids. The total number of infants per quarter by state is calculated using monthly birth data from CDC WONDER. The distribution and summary statistics for these calculations are presented in Figure 8.

To standardize the different forms of formula in the Nielsen dataset to the same unit, I convert all the measurements (including powder and concentrate) to fluid ounces. The ready-to-use formula is already in fluid ounces. For powder, I convert the quantity from ounces to grams (using 28.35 grams per ounce) and then calculate the number of scoops, assuming each scoop weighs 8.7 grams and reconstitutes to 2 fluid ounces. For concentrate, I simply double the quantity, as concentrate doubles in volume when mixed with water.

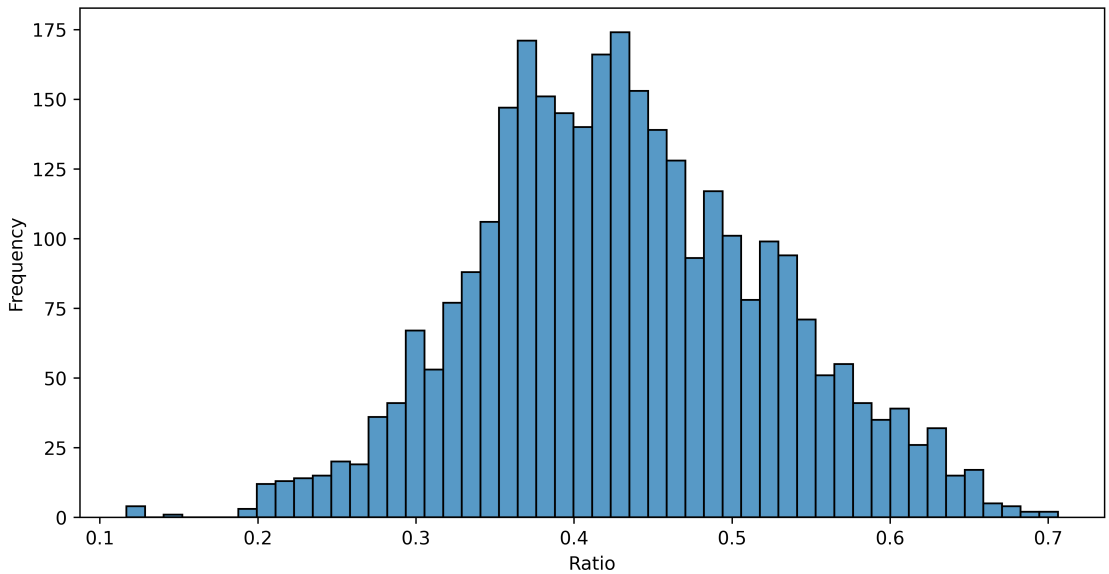

Figure 8: Distribution of non-WIC Demand Ratios

Markets and Market Sizes

I define a market as a state, year, and quarter combination. To quantify market size, I construct two measures, denoted as $\mathcal{M}_t^1$ and $\mathcal{M}_t^2$, which differ in the scope of potential formula consumptions. Market size 1 ($\mathcal{M}_t^1$) represents the estimated total volume of formula consumed by non-WIC formula-fed infants in a given market. This measure reflects the consumption of infants who rely exclusively on purchased formula and is used to calculate the scale-up ratio. The set of outside options remains restricted to other formula brands, including private labels. Market size 2 ($\mathcal{M}_t^2$) extends the scope by including all non-WIC infants, regardless of breastfeeding status. Unlike $\mathcal{M}_t^1$, which captures actual formula consumption, $\mathcal{M}_t^2$ accounts for the full potential demand, including infants who may be breastfed.

To estimate the potential consumption per infant, I use WIC's maximum monthly allowance for fully formula-fed infants. Table 7 presents the upper limit of monthly formula issuance by age and physical form.

First, I calculate the simple average volume for each formula form based on its national volume share. To account for the dominance of each form, I assign weights by multiplying the average volume of each form by its respective national volume share. The sum of these weighted volumes is then multiplied by the number of non-WIC formula-fed infants or the total number of non-WIC infants. Finally, I multiply the result by 3 to convert the estimate from a monthly to a quarterly value.

$$\begin{aligned}\text{market size 1} = &(842 \times \text{national volume share of powder}\\ &+ 783 \times \text{national volume share of concentrate}\\ &+ 796 \times \text{national volume share of RTU})\\ &\times \text{total number of non-WIC formula-fed infants} \times 3\end{aligned} \tag{35}$$

$$\begin{aligned}\text{market size 2} = &(842 \times \text{national volume share of powder}\\ &+ 783 \times \text{national volume share of concentrate}\\ &+ 796 \times \text{national volume share of RTU})\\ &\times \text{total number of non-WIC infants} \times 3\end{aligned} \tag{36}$$

The number of non-WIC formula-fed infants in a given market is calculated as:

$$\text{Non-WIC formula-fed infants} = \text{Total formula-fed infants} - \text{WIC formula-fed infants} \tag{37}$$

where total formula-fed infants is the estimated number of all infants who consume formula, calculated as:

$$\text{Total formula-fed infants} = (1 - \text{overall breastfeeding rate}) \times \text{Total infants} \tag{38}$$

WIC formula-fed infants represent the estimated number of formula-fed infants within the WIC program. The calculation depends on the available data from FNS. For 2006-2009, it is estimated as:

$$\text{WIC formula-fed infants} = (1 - \text{WIC breastfeeding rate}) \times \text{Total WIC infant participants} \tag{39}$$

For 2010-2020, it is directly obtained from the number of fully formula-fed infants in the WIC program. The WIC breastfeeding rate is estimated by:

$$\text{WIC breastfeeding rate} = \frac{\text{Number of breastfeeding women}}{\text{Total WIC women participants}} \tag{40}$$

$$\text{Total non-WIC infants} = \text{Total infants} - \text{Total WIC infant participants} \tag{41}$$

Since the Nielsen Retail Scanner data accounts for only around 20% of U.S. retail sales, I apply a scale-up ratio to adjust the market shares to better reflect the actual market.

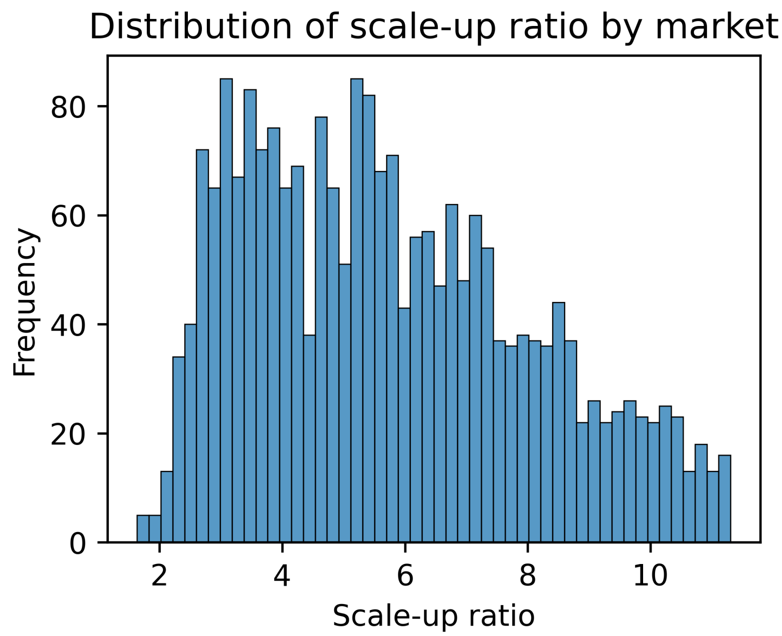

Figure 9: Distribution of scale-up ratios by market

Assuming the Nielsen sample is perfectly randomized, I calculate a common scale-up ratio for all products within a market. This ratio is obtained by dividing the estimated market size by the total non-WIC volume sales of all products in the untrimmed Nielsen sample (untrimmed Nielsen volume sales), which includes products from all manufacturers. The final market share is then calculated using this adjusted value.

$$\text{scale-up ratio} = \frac{\text{market size 1}}{\text{untrimmed Nielsen volume sales}} \tag{42}$$

$$\begin{aligned} \text{scaled-up market share} &= \frac{\text{product volume}}{\text{market size 2}} \times \text{scale-up ratio} \\ &= \frac{\text{product volume}}{\text{market size 2}} \times \frac{\text{market size 1}}{\text{untrimmed Nielsen volume sales}} \end{aligned} \tag{43}$$

Table 7: WIC Maximum Monthly Allowance of Infant Formula for Fully Formula-Fed Infants in Fluid Ounce

	Reconstituted Powder	Reconstituted Liquid Concentrate	RTU
0-3 months	870	823	832
4-5 months	960	896	913
6-11 months	696	630	643
Average	842	783	796

Sample Trimming

The process includes seven steps. (1) I focus on food and mass merchandiser (NielsenIQ channel codes are F and M), which together account for 99% of weekly UPC-store-level transactions. I focus on the period 2007 to 2019 to avoid potential disruptions caused by the COVID-19 pandemic and the implementation of the EBT card. Since Nestlé entered the U.S. formula market through its acquisition of Gerber in 2007, the year 2006 is excluded. (2) I drop markets with extremely large scale-up ratios by removing the top 10% of the sample (above a threshold of 11.38). I also drop markets where the ratio of market size 2 to market size 1 is less than 1, since market size 2 should theoretically be greater than market size 1. (3) I remove the upper and lower 1% of the price distribution for each form to exclude extreme price values. (4) I exclude products with market shares smaller than 10^{-3}. (5) I remove states observed for less than 4 years, and then remove the upper and lower 1% outliers of market shares based on the remaining data. (6) I exclude retailers observed for only one year. (7) Year 2019 is not included due to the lack of input price data from the 2018 quarter four onward. Figure 10 shows the distribution of market shares of inside products across markets in the final sample. Figure 11 presents the distribution of total market shares of inside products by market in the final sample. Figure **??** shows the distribution of total market shares of outside products by market in the final sample.

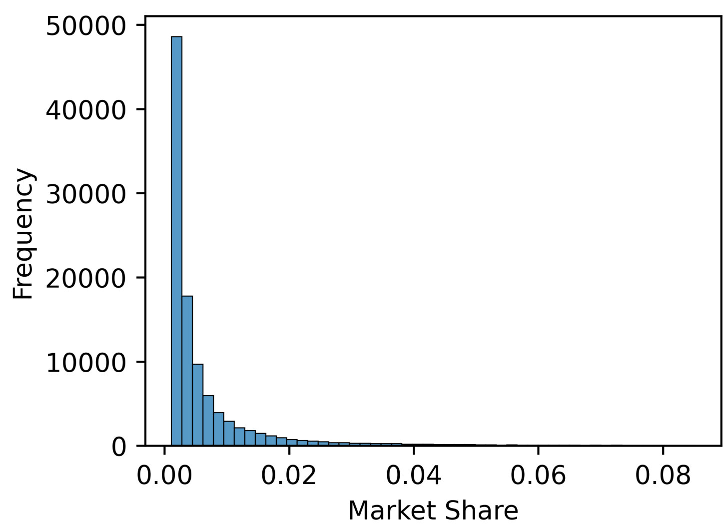

Figure 10: Distribution of market shares of inside products across markets in the final sample

Additional summary statistics Table 8 presents summary statistics on the product offerings and market presence of the three major infant formula manufacturers in the sample. Abbott has the broadest product portfolio with 1,214 products, followed by Mead Johnson with 1,055 and Nestlé with 526. All three firms are observed across the same 46 states and

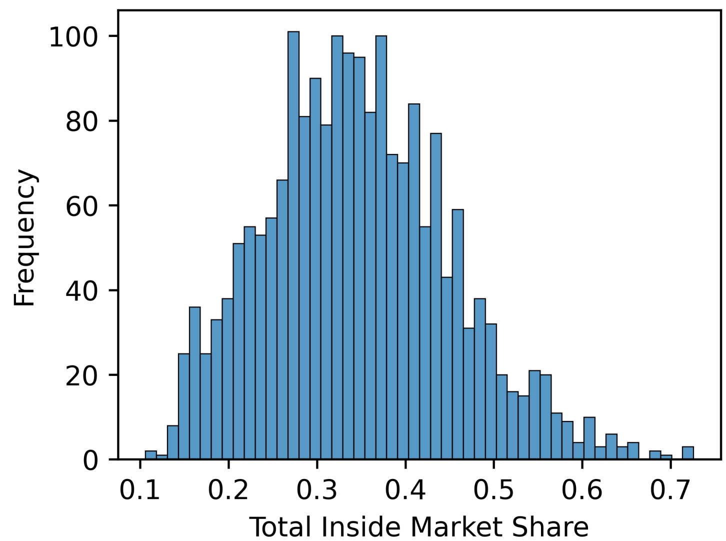

Figure 11: Distribution of total market shares of inside products by market in the final sample

12 years, with varying coverage across retailers. Abbott and Mead Johnson are sold in 102 retailers each, while Nestlé appears in 78. In terms of product attributes, Abbott offers a higher share of prebiotic (53%) and lactose-tolerant (49%) products compared to the others. Nestlé offers no prebiotic products in the sample and has the lowest lactose-tolerant share (19%). Average prices per fluid ounce are similar across firms, ranging from $0.17 (Nestlé) to $0.20 (Mead Johnson). Finally, the average volume share—defined as the mean total inside market share per manufacturer across all markets—is highest for Abbott (15.82%), followed by Mead Johnson (13.63%) and Nestlé (5.25%).

Table 8: Additional Summary Statistics on Manufacturers and Their Products

Statistic	Abbott Nutrition	Mead Johnson	Nestlé
#Products	1214	1055	526
#States	46	46	46
#Years	12	12	12
#Retailers	102	102	78
Prebiotics fraction	0.53	0.28	0.00
Lactose fraction	0.49	0.27	0.19
Average prices ($/fl oz)	0.18	0.20	0.17
Average volume share	0.1582	0.1363	0.0525

The row with # sign report the total number of products/states/years/retailers that a manufacturer is observed in the sample. Prebiotics fraction is the fraction of prebiotics products for a given manufacturer. Lactose fraction is the fraction of lactose-tolerant products for a given manufacturer. Volume share is the average total inside volume share for a manufacturer. Average prices are the simple average of its products' prices for a manufacturer. "Size, medium" is the indicator for products of size between 32 and 100 fluid ounces, and "Size, large" is the indicator for products of size larger than 100 fluid ounces. Average volume share represents the mean of total volume share per manufacturer across all markets.