Welfare Analysis of WIC Subsidy Program in the Infant Formula Market

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Abstract

The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) provides vouchers for specific foods to improve nutrition among at-risk beneficiaries. While effective, questions remain about optimizing the program to enhance social welfare. I estimates the demand for WIC in the infant formula market using a discrete choice model and Nielsen Consumer Panel Data, focusing on two key aspects: the effect of expanding the variety of WIC-eligible products and the impact of increasing participation among eligible households. I find that the current WIC program significantly benefits participants, with eligible households potentially doubling their consumer surplus upon joining. Furthermore, increasing the variety of WIC-eligible products could lead to a 17% rise in consumer surplus for current participants. This research underscores the critical value of WIC and provides an evaluation of various strategies to improve the program, enabling informed decision-making.

1 Introduction

In the wake of a national infant formula shortage precipitated by the closure of a major manufacturing plant in 2022, the vulnerabilities of the infant formula market were laid bare, revealing the critical need for a robust and responsive support system for families. The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) is a federal assistance program aimed at improving the nutrition and health of low-income families. It provides targeted support to households with pregnant women, breastfeeding mothers, and children under the age of 5 who are at nutritional risk. Eligibility for the WIC program is based on both income and household composition. Once enrolled, participants receive a monthly food allowance, which can be used to purchase designated nutritious foods, including formula to help meet their dietary needs.

The WIC program now stands at a crossroads, challenged by an unchanged framework that has scarcely evolved in addressing the dynamic needs of its beneficiaries or the market it operates within. This paper targets the heart of these challenges, proposing a twofold enhancement to the WIC program: revolutionizing its contracting style with infant formula manufacturers to ensure product variety and market stability, and expanding its reach to include more eligible households, thus amplifying its impact on social welfare. By navigating these two critical aspects, the research seeks to reimagine the WIC program as a more adaptable, inclusive, and effective support system for our future generations.

To achieve the objectives of this study, I utilize consumer purchasing panel data to gain insights into household behavior in the infant formula market. I use a discrete choice model to estimate demand, which allows for an analysis of consumer preferences and choices among various products. By utilizing this model, I am able to account for heterogeneity in consumer preferences and simulate different policy scenarios. I propose several improvements to the WIC program design, and consumer welfare is quantified by calculating the consumer surplus in dollar value under both baseline and counterfactual scenarios, comparing the effects of different program configurations on participants and non-participants. This approach provides a clear evaluation of how adjustments to the WIC program could influence overall welfare outcomes. The results indicate that increasing WIC product variety and mandating broader participation both lead to significant improvements in consumer welfare.

The rest of the paper is organized as follows: section 2 provides a brief background on the infant formula market and on going events. Section 3 reviews the existing theoretical and empirical studies regarding the WIC subsidy program, the infant formula market, and the structural methods of estimating demand. This section also highlights gaps in the literature and identifies the research questions that motivate my study. Section 4 describes the data sources and data cleaning process. Section 5 describe and implements the structural model for demand estimation. I also discusses the econometric methods used to address endogeneity and omitted variable bias. Section 7 conducts counterfactual analysis under different hypothetic scenarios using demand estimation results. Section 8 concludes by summarizing the main findings and contributions of the paper, discussing its limitations and suggesting avenues for future research.

2 Background

2.1 The WIC Program

The Women, Infants, and Children (WIC) program, established in 1974, stands as a pivotal federal assistance initiative aimed at safeguarding the health of low-income women, infants, and children up to age five who are at nutritional risk. Operated through state agencies, WIC provides nutritious foods, information on healthy eating, and referrals to health care to eligible participants. Benefits are tailored to supplement participants' diets with specific nutrients essential for growth and development, including infant formula, cereal, fruit, vegetable and various proteins. Over the years, WIC has undergone several revisions to enhance its impact, with a minor update in 2009 focusing on increasing allowances for fruits and vegetables, reflecting the latest nutritional science and dietary guidelines. Serving approximately 6.3 million participants each month, including almost half of all infants born in the United States, federal program costs for WIC totaled $5.7 billion in 2022.

Infant Formula Contracts

The dynamics between the WIC program and the infant formula market are fundamentally shaped by the competitive bidding process, wherein infant formula manufacturers competes for exclusive contracts to supply their products to WIC participants. States typically request manufacturers to resubmit bids every 3 to 6 years, ensuring competitive pricing remains a cornerstone of the program's cost-saving measures. The winning bidder is granted not only a contract but also guaranteed shelf space in retail outlets, a critical factor that often leads to increased sales and a larger market share. Abbott, Mead Johnson and Nestle are three manufacturer that are actively submitting bidding to participate in the WIC contract. This arrangement underscores the program's significant influence on the infant formula market, serving as a powerful incentive for manufacturers to offer substantial discounts to secure these lucrative contracts. Such discounts are pivotal in enabling WIC to extend its resources further. In 2022, infant formula rebates totaled about $1.5 billion. For participants, the use of WIC benefits to purchase infant formula is straightforward: upon enrollment, eligible families receive vouchers or electronic benefit transfer (EBT) cards that can be used to purchase specific types of infant formula, along with other nutritious foods, at participating retailers. The interaction between WIC and the infant formula industry thus plays a vital role in promoting public health objectives, influencing market dynamics, and ensuring the availability of nutritionally adequate products for both WIC beneficiaries and the broader consumer base.

2.2 The Infant Formula Market

Infant formula is a highly regulated product, designed to provide a balanced and nutrient-rich source of food for infants. The FDA has established specific requirements regarding the levels of protein, fat, carbohydrates, vitamins, and minerals that must be present in these products to ensure that they meet the nutritional needs of infants. As science and technology have progressed, manufacturers have also introduced additional nutrients and supplements to improve the variety and quality of their products. For instance, DHA and ARA, which are crucial for infant brain and eye development, were first added to infant formula in the late 1990s. The FDA approved their addition to infant formula in 2001, and since then, many formula brands have included these fatty acids in their products. In recent years, probiotics, prebiotics, and milk fat globule membrane have also been added to infant formula, providing additional health benefits for infants.

US consumers have a strong preference for domestically produced infant formula. The American Academy of Pediatrics (AAP) has advised against purchasing imported formulas online due to various reasons, such as inadequate regulation by the FDA, potential shipping and storage issues, labeling discrepancies, and delays in recall notices. The US infant formula market is considered to be mature and highly competitive, with a plethora of products available to consumers. Several large manufacturers, such as Abbott, Mead Johnson, Nestle, and Perrigo, dominate the market. The first three companies produce their own products, which are recognized as national brands. In contrast, Perrigo is the private label manufacturer of all store brand infant formula at retailers nationwide.

On average, it costs $400 to $800 for babies who are formula-fed exclusively for the 12-month period that they rely solely on formula. To alleviate the formula cost to households, the WIC assistance program provides supplemental nutrition to low-income pregnant women and children under five. The monthly supplemental package includes contracted infant formula products.

3 Literature Review

My research is closely related to three sets of literature: welfare effect of the WIC program; economics impact of WIC on the infant formula market; and the discrete choice model in market analysis.

The WIC program is well-known for the nutritional benefits it provides to families with young children. Jackson (2014)[9] utilized longitudinal surveys to examine the association between prenatal and early childhood exposure to WIC and cognitive abilities. The study found that WIC participation has significant cognitive and academic benefits. Another study on the welfare effects of the WIC program by Khan et al. (2017)[10] showed that households expand their cereal consumption volume after exposure to WIC, and the positive impacts on consumption and nutrition persist. Hamad et al. (2019)[7] studied the effect of a WIC policy change in 2009, which revised the WIC food package to increase allowances for whole grains, vegetables, fruits, and milk. However, they found that the improvement in dietary quality or nutrient intake for participating women was not significant during or after pregnancy.

This section of the literature review investigates the economic impact of the WIC program on the infant formula market, specifically focusing on how it influences formula pricing, competition among manufacturers, and overall market dynamics. Davis (2012)[5] estimated a high price-cost markup and found that this markup is more likely due to profit-maximizing strategies set by manufacturers rather than the WIC program itself. Interestingly, being a WIC contract brand brings additional benefits such as increased prominence in stores, which boosts sales to non-participants. Similarly, Oliveira et al. (2011)[12] observed that changes in WIC contracts affect the market shares of different brands, though they did not identify a clear pattern in relative pricing changes. A more recent study by Choi et al. (2020)[3] corroborated these findings, noting that WIC contracts impact manufacturers' volume sales and market share. They reported that sales of a former WIC brand decrease while those of a new WIC brand increase, yet the total market volume remains unchanged. This body of research highlights the nuanced effects of WIC policies on market behaviors and economic outcomes within the infant formula industry. The research conducted by by Abito et al. (2022)[16] emphasizes the significant spillover effects of the WIC program on both WIC-eligible and non-WIC households. Specifically, the study finds substantial spillover effects on market shares among non-WIC households, even though retail prices experience minimal changes.

A number of studies discuss the accessibility challenges of the WIC program. Woelferl et al. (2004)[17] studied WIC participants in New York State and identified a set of 11 barriers affecting more than 20% of participants. One of the most frequently cited barriers was the excessive waiting time. Structural barriers such as transportation or work conflicts may prevent participation. Moreover, immigrants face significant linguistic barriers in navigating the system and accessing services. Liu and Liu (2016)[4] used a population-based survey to explore how demographic, social support, and structural barriers affect WIC participation. They found that participation patterns vary by ethnic groups, but in general, mothers with unplanned pregnancies, fewer social supports, and more structural barriers were less likely to participate in WIC.

This section explores the methodological tools used to analyze the market. Most often, discrete choice models is used to dissect the complex interactions between consumer preferences and firm supplies. A number of work examine policy effects by estimating demand using a multinomial logit or mixed logit model and calculate the consumer surplus as compensation variation in the counterfactual scenario: Small & Rosen (1981)[14], Trajtenberg (1989)[15], Nevo (2000)[11], Zhao, et, al. (2008)[18]. Most research employing discrete choice models has addressed the endogeneity issue in demand estimation by using instrumental variables, following the approach pioneered by Hausman (1996)[8]. My study builds upon this foundation by not only utilizing instrumental variables but also incorporating the control function concept as outlined by Petrin & Train (2010)[13], thereby extending the analytical capabilities of this model in the context of WIC policy effects.

My study presents a novel application of discrete choice models to estimate consumer demand within the infant formula market. By focusing on this specific market, I study the dynamics that influence consumer behavior and how these can inform the design of more effective and inclusive subsidy programs. This research tailored demand and supply models to the nuanced needs of subsidy program design. Through a comprehensive analysis, I contribute to the literature by providing a richer understanding of consumer demand dynamics in the infant formula market and lay a foundation for policymakers to craft programs that promote societal well-being.

4 Data

4.1 Data Description

My empirical analysis relies on NielsenIQ marketing data. First, I use longitudinal household purchase panel data in 2019 from Nielsen's Consumer Panel Dataset. This consumer panel data provides demographic and geographic variables of the 40,000-60,000 active panelists that are crucial to my study. Specifically, it includes key variables indicates household's current WIC participating status, household income, size and present of children under 6. In addition, it contains detailed purchase trip information on price and quantities for purchased products at the universal product code (UPC) level, including value of coupons that were applied to the purchase. I leverage the detailed demographic information at the household level to estimate the heterogenous preferences for infant formula product in the sample.

I kept households that ever made a baby formula purchase in year 2019 in my sample. Only powdered form baby formula products are included, I and grouped similar products as a single alternative by their brand, type and sizes. I kept alternatives that has been purchased at least twice in the sample period as the set of available alternatives. Lastly, I standardized price as per ounce powder price.

I also use point-of-sale data on powder baby formula products sold in retail stores in the U.S. in 2019 from Nielsen's Retail Scanner Dataset to construct the product choice set. This dataset includes quantities sold and consumer expenditures at the weekly-store-UPC level. For my empirical analysis, I average the price of products by county and add it to the household's choice set if there was a record of sale of this product in the county where the household resides in, and in the same week that the household made a baby formula purchase.

For my key explanatory variable, price, it is important to note that the scanner data tends to have higher price for the same product than the consumer panel data. This may be due to household's selective purchasing behaviors. I use linear prediction to adjust price of available choice alternatives to reconcile systematic discrepancies in prices between these datasets, and use this as my endogenous price variable. Lastly, I set price to 0 for WIC eligible products to WIC participants to reflect the fact that they get voucher for WIC contracted products in their states.

4.2 Summary Statistics

Table 1 presents descriptive statistics for the household sample, grouped by WIC eligibility. The income distribution for the non-WIC population is statistically higher than that for the WIC population. However, the distribution of years of education is not significantly different between these two groups. On average, WIC households made more shopping trips, consistent with the fact that WIC allowances renew each month. Due to the limited monthly allowance, WIC-eligible households are less likely to stockpile infant formula.

Table 2 provides detailed information on per-ounce retail prices, manufacturers, types, and sizes of the products. Hypoallergenic formulas are more expensive due to their specialized design. Store brands generally have significantly lower prices because their lower production costs are a result of reduced spending on advertising.

Figure 1 illustrates the number of counties having different percentage of total sales from WIC brand products. Less than 1% of counties only had WIC brand products sold, while the majority of counties have between 20% to 80% of their sales from WIC brands. This suggests that stores do not intentionally prioritize stocking more WIC brand products.

To analyze consumer purchasing behavior, I employ a measure similar to the Herfindahl-Hirschman index, where the index is calculated as $\sum_j^J share_j^2$, with $share_j$ representing the fraction of brand j in a household's consumption. Figure 2 shows that over 80% of households have a brand composition percentage equal to 1, indicating strong brand loyalty among households.

5 Structural Model

5.1 Demand

To address the research question, this study adopts a random-coefficient (or mixed logit) model of consumer demand within the differentiated product market. Consumers in the same geographic market and time face the same choice set of powdered infant formula product. Household i's utility at time t from purchasing product j is given by

$$U_{ijt} = \alpha_i \mathbf{p}_{ijt} + \beta \mathbf{x}_{ijt} + \epsilon_{ijt} \tag{1}$$

Different from the simple Logit model, α_i are random coefficients that vary over individuals in the population, and p_{ijt} is the retail price of product j faced by consumer i at time t. β are fixed coefficients on $\mathbf{x}_{ijt}$. ϵ_{ijt} is a random term that follows a type I extreme value distribution. The parameters of the mixed logit model is estimated by maximum simulated likelihood. The probability that consumer i chooses alternative j at time t, conditional on the random parameter α_i is

$$P_{ijt}(\alpha) = \frac{e^{\alpha_i \mathbf{p}_{ijt} + \beta \mathbf{x}_{ijt}}}{\sum_j e^{\alpha_i \mathbf{p}_{ijt} + \beta \mathbf{x}_{ijt}}} \tag{2}$$

By integrating over the mixing distribution $f(\alpha)$, the unconditional choice probability P_{ijt} can be evaluated.

$$P_{ijt} = \int P_{ijt}(\alpha) f(\alpha) d\alpha \tag{3}$$

The random coefficient (or mixed logit) model offers a significant advantage over the simple logit model by accommodating heterogeneity in consumer preferences, which is a better representation of real-world decision-making processes. While the simple logit model assumes that all individuals respond to changes in explanatory variables in a uniform manner, the random coefficient model allows for individual-specific preference variations.

5.2 Estimation Procedure

Estimation of the model involves first estimating demand and using these demand parameters, along with the supply model to recover marginal costs. The demand parameters are estimated using maximum simulated likelihood method.

Maximum Simulated Likelihood Estimator

The maximum simulated likelihood estimator is the set of parameters that maximizes the simulated log-likelihood

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \ln \check{L}(\theta \mid \mathbf{y}, \mathbf{X}) \tag{4}$$

where

$$\ln \check{L}(\theta \mid \mathbf{y}, \mathbf{X}) = \sum_{n=1}^{N} \ln \check{f}(y_n \mid \mathbf{x}_n, \theta) \tag{5}$$

is the log of the simulated likelihood and $\check{f}(y_n \mid \mathbf{x}_n, \theta)$ is a simulated density function. For discrete choice applications, the log of simulated likelihood is a function of simulated choice probabilities

$$\ln \check{L}(\theta \mid \mathbf{y}, \mathbf{X}) = \sum_{n=1}^{N} \sum_{i=1}^{J} y_{ni} \ln \check{P}_{ni}(\mathbf{x}_n, \theta) \tag{6}$$

which gives first-order conditions equivalent to

$$\sum_{n=1}^{N} \sum_{i=1}^{J} y_{ni} \frac{\partial \ln \check{P}_{ni}(\mathbf{x}_n, \widehat{\theta})}{\partial \theta} = \mathbf{0}. \tag{7}$$

The steps for simulation-based estimation involves first, draw K random coefficients for each of N different decision makers for each of R different simulation draws. Second, find the set of paramters that maximizes the objective function. Starting from the initial parameter θ^0, simulate choice probabilities given by equation (3). Use these simulated choice probabilities to calculate simulated log-likelihood and iterate to a better set of parameters until it converges.

5.3 Identification Challenges and Strategies

As unobserved demand shock affect both price and demand, I must address the endogenous issue when estimating equation (1).

Instrument Construction

In the market dynamics, price not only influences but is also influenced by the demand. Coupled with potential omitted variables, the demand estimation result could be biased. Therefore, I constructed instrumental variables to address the price endogeneity when estimating demand parameters.

Following Hausman (1996), I use the prices of the products from other markets as input cost instrumental variable for price. I use price of the product in other counties in the same state at the same time as my price instrument, and filled in missing values with price of the product at the same time in other states which are contracted with the same formula manufacturer. It's worth noting that I use scanner data to construct Hausman IV for alternative choices, and I replace the instrument using Hausman IV constructed using consumer panel data for purchased products. My set of instruments is valid because it shares the common cost shock of producing certain brand and type of formula, and it is not correlated with the market-specific demand shocks of the product.

Control Function

As noted by Foster (1997), the well-known two stage least square method of incorporating instrumental variables in estimation cannot be simply extended to non-linear models such as logistic regression. To correct for the inconsistent estimation caused by endogeneity, I adopt the Control Function approach by (Petrin & Train 2010).

It should be noted that, without correcting for endogeneity, aggregate demand is estimated to be upward-sloping, suggesting that omitted variables are positively correlated with demand. The control function approach tends to derive a proxy variable that isolated part of the error term that is correlated with the dependent variable. To do so, first assume a general utility function form

$$U_{ij} = V(y_{ij}, x_i, \beta_i) + \epsilon_{ij} \tag{8}$$

Then decompose the error term into the part that can be explained by a general function of μ_{ij} and the residual

$$\epsilon_{ij} = F(\mu_{ij}, \lambda) + \hat{\epsilon}_{ij} \tag{9}$$

For the mixed logit model, the control function takes a more general parametric functional form as

$$F(\mu_{ij}, \lambda) = \lambda\mu_{ij} + \sigma\eta_{ij} \tag{10}$$

Where η_{ij} is i.i.d standard normal. If we break the error term in the utility function into two parts by whether it is correlated with y_{ij} and replace the correlated error term with the control function, then

$$\begin{align} U_{ij} &= V(y_{ij}, x_i, \beta_i) + \epsilon^1_{ij} + \hat{\epsilon}_{ij} \tag{11} \\ &= V(y_{ij}, x_i, \beta_i) + \lambda\mu_{ij} + \sigma\eta_{ij} + \hat{\epsilon}_{ij} \tag{12} \end{align}$$

The model is estimated in two steps. The endogenous variable is regressed on observed choice characteristics and instruments. The residual as represented as the μ_{ij} of this regression are retains as the control function. Second, the choice model is estimated with the control function entering as an extra variable.

5.4 Estimation Equation

First, the control function μ_{ij} can be obtained by estimating equation (13), where X_{ij} is a vector of product attributes: brand, type, size, and WIC program eligibility.

Z_{ij} denotes price instruments.

$$P_{ij} = \beta X_{ij} + \gamma Z_{ij} + \mu_{ij} \tag{13}$$

Then I estimate equation (14) for the logit model.

$$\begin{aligned} ln\Big(\frac{Y}{1-Y}\Big) = \beta_0 + \beta_1\mu_{ij} + \beta_2\text{wicproduct}_{ij} + \alpha_1\text{price}_{ijt} \\ + \lambda_i + \gamma_j + \theta_s + \zeta_t + \epsilon_{ijt} \end{aligned} \tag{14}$$

Where *wicproduct* is a dummy variable that equals to 1 if product j is WIC eligible in the state where consumer i resides. λ_i, γ_j, θ_s, and ζ_t are the fixed effects of household i, product j, state s, and week t.

I estimate equation (15) for the mixed logit model, which replaces the fixed coefficient α_1 with the random coefficient α_i for each individual. I specified the distribution of this random parameter using both normal and lognormal distributions.

$$\begin{aligned} ln\Big(\frac{Y}{1-Y}\Big) = \beta_0 + \beta_1\mu_{ij} + \beta_2\text{wicproduct} + \alpha_i\text{price}_{ijt} \\ + \lambda_i + \gamma_j + \theta_s + \zeta_t + \epsilon_{ijt} \end{aligned} \tag{15}$$

The random coefficient on α_i offers a significant advantage over the simple logit model by accommodating heterogeneity in consumer preferences. In particular, the mixed logit model allows for unobserved preference variation through random coefficients, which yields correlations in utility over time for the same decision maker. α_i allows for individual-specific preference variations, capturing the idea that different consumers may value the attributes of alternatives differently. As a result, the random coefficient model can more accurately predict choices across a diverse population. Moreover, this approach enhances the model's flexibility, allowing it to approximate any random utility model and to capture more complex substitution patterns among alternatives.

6 Estimation Results

I apply the control function method to estimate my baseline logit model, which includes county, week, and product fixed effect. The estimation results are presented in table 3. The first column is the simple logit with control function applied. The control function residuals enter significantly and with the expected positive sign, indicates that price of a product is higher than can be explained by observed attributes. The price coefficient is -2.3, which implies that quantity decrease by 2.7% for a 1% increase in price on average for all products. The baseline estimation result indicates an overall elastic demand for the infant formula product. The WIC product dummy variable has a positive coefficient indicates that consumers do prefer the product when it is the product contracted with the WIC program in the consumer's state.

When incorporating the variation in price sensitivity across the population and assuming a normal distribution for the price coefficient, the estimates yield a mean price coefficient of -3.0 with a standard deviation of 2.47, as shown in column 3. This distribution implies that approximately 10% of the estimated demand coefficients are positive. To ensure consistency with the expected disutility of price, a lognormal distribution assumption for the price coefficient is preferred. Since the lognormal distribution is strictly positive, I reverse the sign of the relevant variables, resulting in a strictly negative estimated price coefficient. As shown in column 3, the price coefficient has a mean of -1.31 with a standard deviation of 0.84. When converted to the corresponding normal distribution, the price coefficient has a mean of approximately -5.3, indicating an average own-price elasticity of 6.65 among the products in my sample. The results suggest significant heterogeneity in individual price sensitivity, as evidenced by the significant coefficient on the lognormal standard deviation parameter.

The results from both the logit and mixed logit models consistently indicate that demand in the market is elastic, meaning that consumers are highly responsive to price changes. The negative coefficient on price is as expected because consumers generally have dis-utility towards price. And it is align with other empirical study of demands in various industries: Trajtenberg (1989) [15], Berry et al. (1995) [1], Brownstone & Train (1998) [2], Nevo (2000),and Goolsbee & Petrin (2004) [6].

The multinomial logit model only give a weak forecasts because of its restrictive assumption of Independence of Irrelevant Alternatives. In contrast, the mixed logit model leverages the rich panel dataset that tracks consumer purchases over time, capturing variations in prices for the same product at different points in time. The random coefficient on price is identified by how some individuals consistently prefer cheaper products while others do not. And the distribution of the random coefficient is estimated by how choices shift when prices change, and how the price sensitivity various across the population. The mixed logit result suggests that when individual preferences are considered, demand appears to be more elastic. The more negative coefficient in the mixed logit model arises because it captures variation in consumer preferences more accurately, reflecting the fact that some consumers may be more price-sensitive than others, leading to a higher overall elasticity.

After establishing the primary results, it is crucial to assess their robustness by evaluating the validity of the instruments used and testing the sensitivity of the results to different methods of instrument construction. Specifically, I compare two approaches: μ_1 is the residual from a price regression using the average price of the same product in the same week in other counties within the state (IV_1), which better captures common product costs but suffers from missing data in some cases. Alternatively, μ_2 uses the average price of the same product in the same week across all states contracting with the same WIC brand (IV_2), which avoids missing data but has less power in capturing common costs. The robustness check results, presented in Table 10, show that for the mixed logit model with a lognormal specification, the estimation is insensitive to the choice of instrument. For the normal specification, the final instrument choice yields results that fall between those of the alternative instruments, confirming the reliability of the baseline estimation

Table 4 presents the sample average elasticities implied by these results. Cross-elasticity is higher between products produced by the same manufacturer or of the same type. Additionally, hypoallergenic formulas, which are targeted at infants with special needs, are not easily substitutable with other types of formula. Demand for two store-brand products is inelastic, as their prices are significantly lower than those of other products of the same type. Consequently, consumers are less responsive to price changes for these two products.

7 Consumer Welfare

The goal of this study is to examine potential policies that can make the WIC program more beneficial. Theoretically, consumers benefit from lower price and the perceived value from the "WIC product" signal. I conduct counterfactual exercises from the both the product eligibility hand and the mandatory participation hand.

I make the following assumptions when conducting counterfactual analysis. First, I assume the consumer preferences remain stable before and after the counterfactual change. This assumption simplifies the analysis and ensures that any observed changes in consumer behavior can be attributed to changes in the market condition. Second, I assume that there is no strategic behavior of firms. That is to say, firms do not change their pricing or marketing strategies in response to the policy changes. The relaxation of this assumption by incorporating price dynamics will be discussed in the robustness check section. Third, I assume there is no changes to market structure or consumer's budget, and retail stores always ensure product availability.

Consumer surplus (CS) with the random coefficient α is expressed as

$$CS = \int \frac{1}{\alpha} ln \left[\sum_j e^{-\alpha P_{ij} + X'_{ij}\beta} + 1 \right] f(\alpha), d\alpha \tag{16}$$

Given α's probability distribution, the Monte Carlo Integration method is employed by generating 100 random numbers from the distribution $f(\alpha)$, evaluate the integrand for each random number, and ake average of the 100 random numbers. Welfare change is determined by substituting the original CS equation with counterfactual attributes and the new price equilibrium.

7.1 Product Eligibility

Increase Product Variety

In this section, I explore a counterfactual scenario aimed at assessing the potential impacts of adopting a multi-source contract strategy within the WIC program. Currently, the WIC program contracts with a single manufacturer for infant formula, limiting product variety for participants. This scenario posits what might happen if, instead, the WIC program were to contract with multiple manufacturers, thereby broadening the range of WIC-eligible infant formula products. The discussion of cost to contract with more manufacturers falls outside the scope of this study.

The counterfactual analysis addresses the question: How would increasing product variety by adopting a multi-source contracting approach affect social welfare, nutritional outcomes for infants, and the infant formula market dynamics for both WIC participants and nonparticipants?

The motivation for this counterfactual exploration is rooted in the hypothesis that a greater diversity of infant formula products available through WIC could enhance participant satisfaction, potentially improving nutritional outcomes by accommodating varied dietary needs and preferences. Moreover, for nonparticipants, an increase in products carrying the "WIC" endorsement might influence market perceptions of quality and affordability, possibly affecting broader consumer behavior.

To study the effect of increasing product variety, I first introduce Abbott and MeadJohnson's basic type products as the new WIC products in all states separately, then study the effect of adding both firm's products as WIC eligible products for all states. In this counterfactual, price does not change, except for newly selected WIC eligible products, whose price will be set to $0 for WIC consumers.

As the result of this counterfactual, we observed a significant enhancement in consumer welfare, as measured by consumer surplus, which increased by 15% on average for each purchase across the sample population when adding Abbott's basic type products as the WIC eligible products for all states. Adding MeadJohnson products can incraese consumer welfare by 8.7% per purchase on average. Adding both brands' products as WIC eligible product increase consumer welfare more than adding a single brand. However, the increase in consumer surplus is not additive, indicating diminishing benefits.

It is also worth noting that the change in consumer surplus varied considerably depending on WIC participation status. For WIC consumers, who benefited from a direct reduction in price to $0 for the newly eligible products, there was a substantial increase in consumer surplus of 26%. This notable rise was primarily attributable to the direct price reductions, indicating a strong positive impact of increased product eligibility on WIC participants' economic welfare. Furthermore, the expansion of the WIC signal to more products also positively influenced the consumer surplus for non-WIC participants, which saw an increase of 8.5%. This suggests that the WIC endorsement not only serves as a significant indicator of product quality and affordability but also has a broader market influence, enhancing perceived value among non-WIC consumers. Thus, extending the WIC signal to a wider range of products can have a ripple effect, improving consumer confidence and perceived value across the market.

Decrease Product Variety

Moreover, I investigate a counterfactual scenario to understand the implications of maintaining the existing product variety versus entirely eliminating WIC support. This counterfactual analysis seeks to answer the question: What would be the economic consequences if the WIC program did not exist? By considering a scenario where families must bear the full cost of infant formula, we can more fully appreciate the value and impact of the WIC program. In this scenario, I assume that firms' current pricing strategies remain unchanged, as it would be more profitable for firms in an oligopolistic market to avoid initiating a price cuts in the long run.

The average change in consumer surplus was a significant decrease of 22% throughout the sample. This decline in welfare was particularly pronounced among WIC consumers, who experienced an average decrease in consumer surplus of 55%. Such a substantial reduction highlights the critical role that WIC benefits play in the financial well-being of these consumers. Non-WIC consumers also encountered a decrease in consumer surplus, albeit a smaller one, amounting to 12%. This decline was observed in the absence of products carrying the WIC endorsement, which underscores the value that the WIC signal adds to products in terms of perceived quality and affordability.

It is crucial to note that the negative impact of eliminating the current WIC program's benefits is larger in magnitude compared to the positive effects observed in the previous counterfactual scenario of adding more eligible products. This contrast further underscores the essential nature of the WIC program in supporting not only the direct beneficiaries but also in influencing the broader consumer market, reflecting how deeply the WIC program is interwoven with economic stability and consumer perception within this sector.

7.2 Mandatory Participation

In addition to product variety consideration, I also investigate a counterfactual scenario to understand the potential impacts of universal coverage by the WIC program for all income, and household composition eligible households. Despite meeting the income criteria and having young child at home, a significant portion of eligible households are not enrolled in the WIC program, suggesting the presence of non-financial barriers to access. These barriers may include lack of awareness, perceived stigma, bureaucratic complexities, or logistical challenges that deter eligible families from participating.

My counterfactual analysis seeks to answer the question: What if all WIC subsidy eligible households, which are households with young kids that meet the income criteria were automatically covered by the program? This hypothetical scenario allows me to explore the broader implications for social welfare, nutritional outcomes for infants and children, and economic efficiencies. By comparing the current state with this counterfactual, I aim to isolate the effects of complete program coverage on both the demand for infant formula and the overall effectiveness of subsidy programs in achieving their public health and economic objectives.

The current WIC consumers are not affected in this counterfactual scenario. However, non-WIC consumers who are eligible for the subsidy will experience an average increase of 10% in consumer surplus if they participate in the WIC program. In my sample, about 45% of WIC-eligible families were not participating in the WIC program. This indicates a substantial opportunity for the WIC program to extend its outreach to these households, which could enhance their economic welfare without the need for additional budget allocations or contract negotiations with manufacturers. Therefore, focusing on maximizing enrollment among these families is a practical and efficient first step to increase welfare.

8 Robustness Check

Counterfactual with Price Dynamics

Price change is an important factor to consumer welfare change. I use a prediction approach to model price dynamics in counterfactual scenarios involving changes in product variety. First, I assume the functional form of price

$$\begin{aligned}\text{price} = {} & \alpha_0 + \alpha_1\text{brand} + \alpha_2\text{type} + \alpha_3\text{size} + \alpha_4\text{quarter} + \alpha_5\text{state} + \alpha_6\text{county} \\ & + \beta_1\text{wicproduct} + \beta_2 \text{ \# of WIC products of the same brand} \\ & + \beta_3 \text{ \# of WIC products of the rival brand} \\ & + \beta_4 \text{ \% of WIC products in the choice set (market share)} + \epsilon \end{aligned} \tag{17}$$

I obtain the linear relationship between price and related variables. I then update these variables to reflect the counterfactual scenario and predict new price using the estimated relationship, such that

$$\begin{aligned}\text{updated price} = {} & \text{price} + \beta_1\Delta\text{wicproduct} \\ & + \beta_2\Delta\text{number of WIC products of the same brand} \\ & + \beta_3\Delta\text{number of WIC products of the rival brand} \\ & + \beta_4\Delta \text{ \% of WIC products in the choice set} \end{aligned} \tag{18}$$

The variables chosen for price prediction are selected because they capture market conditions that influence price and are likely to change in the counterfactual scenario. Variables that remain constant between the baseline and counterfactual, such as the number of products in the market, are omitted from the model.

The regression results in Table 11 show that with product, county, and week fixed effects, the selected regressors have an insignificant impact on price, suggesting that prices remain relatively stable when a product's WIC-eligibility status changes. Based on the regression results, I use the model from column (4) for price adjustment, as it includes all key variables for price prediction.

I then adjust the counterfactual prices using the estimated relationship from equation (17). Table 12 shows the average price change by manufacturer when different brands are added as nationwide WIC brands. Prices for all brands decrease when the WIC program contracts with more brands, with a more significant price drop for the brand selected as the nationwide WIC brand. Figure 3 illustrates the price distribution in both baseline and counterfactual scenarios, showing that my modeling approach ensures the counterfactual price distribution remains similar to the baseline, adding realism to the analysis.

With the counterfactual prices updated, I conduct the welfare analysis using the new parameters. The pattern of consumer surplus changes is similar to the results without price adjustment, showing that adding two brands as nationwide WIC brands increases welfare more than adding a single brand. However, the total welfare gain from adding two brands is less than the sum of gains from adding each brand individually. WIC consumers particularly benefit from the increased product selection. A novel finding in the counterfactual with price changes is the wider distribution of welfare changes. Some consumers may experience a decrease in consumer surplus due to price increases for certain products they purchase, with non-WIC consumers potentially facing up to a 40% decrease. On the positive side, the maximum welfare gain for both WIC and non-WIC consumers is much higher due to price decreases for certain products. For example, the maximum welfare gain for WIC households when both brands are added as nationwide WIC brands increases by 82 percentage points, from 105% to 187%.

9 Conclusion

My research provides a clearer understanding of the value of the current WIC subsidy program in the infant formula market and explores how changes to the program can impact consumer welfare. The WIC program offers a limited selection of infant formula to eligible households. I find that increasing product selection by introducing a nationwide brand can lead to a consumer surplus increase of 2.3% to 6.3% per purchase for non-WIC participants, depending on the brand introduced. If multiple brands are added as nationwide WIC brands, non-WIC consumers could see up to a 41.5% increase in consumer surplus per purchase. WIC participants benefit even more from expanded product selection, as they can access a broader range of products at no additional cost. Moreover, the analysis reveals a significant welfare loss if the WIC program were eliminated, with WIC participants experiencing more than double the welfare loss compared to the welfare gain from introducing multiple brands, highlighting the program's importance. Lastly, expanding WIC enrollment to all eligible households could increase consumer surplus by an average of 10%, with a potential increase of up to 158.5% per purchase.

This study contributes to the literature on WIC program welfare by using a novel estimation method to better understand consumer demand and offer clear, actionable welfare calculations. It also provides policy implications, suggesting various ways to enhance the welfare impact of the WIC program. Policymakers can use these findings as a guide to optimize the program within budget constraints.

However, my work has limitations. First, in estimating demand within a discrete choice framework, I simplified purchases into dummy variables, which may lead to underestimating demand elasticity for a small subset of observations. While the mixed logit model captures preference heterogeneity, the choice of distribution for random coefficients is critical. If the actual distribution deviates significantly from the assumed one, the results may not accurately reflect consumer behavior. Second, the counterfactual analysis assumes price stability when the WIC program is removed, which could oversimplify market dynamics, as firms may adjust their pricing strategies in response to the loss of WIC-induced demand. Third, the analysis does not account for potential cost implications, including increased costs to the government for contracting with multiple brands or the administrative costs of reaching out to eligible households, both of which could affect the feasibility and net benefits of the proposed program changes.

A potential extension of this research involves examining the supply side to better understand how policy changes impact firm pricing and the auction process, which plays a critical role in determining market outcomes. First, a supply-side model could be developed using the demand estimates and profit-maximizing equations to calculate firms' marginal costs. This would allow for an analysis of how firms adjust their prices in response to new market conditions, such as changes in WIC product selection or broader participation. By adjusting firms' prices under different policy scenarios, we can recalculate consumer welfare and assess how supply-side dynamics affect overall welfare outcomes. Additionally, obtaining historical WIC auction data would enable the estimation of the relationship between a firm's pricing and profitability with its likelihood of winning a WIC contract. This would provide insights into how to design the auction process to increase product variety while keeping costs within budget, ensuring maximum improvement in net benefits for both WIC participants and the broader market.

Figures and Tables

	mean	sd	min	max	count
Non-WIC					
income	66.86	28.73	2.5	100	711
education	15.25	2.04	6	18	711
# of children	0.75	0.81	0	3	711
hh size	3.26	1.52	1	9	711
# of trips	3.46	3.76	1	25	711
WIC					
income	41.88	25.51	2.5	100	80
education	14.65	1.82	10	18	80
# of children	1.21	0.88	0	3	80
hh size	4.04	1.63	1	8	80
# of trips	5.67	5.89	1	31	80

Table 1: Household Characteristics

alt	firm	type	size	mean	sd	min	max	count
1	Abbott	basic	13	1.32	0.47	0.14	2.49	2684
2	Abbott	basic	23	1.27	0.47	0.13	2.48	2773
3	Abbott	basic	31	1.25	0.48	0.13	2.49	2693
4	Abbott	comfort	12.5	1.32	0.48	0.19	2.45	2152
5	Abbott	comfort	30	1.28	0.48	0.20	2.50	2619
6	Abbott	hypoallergenic	12	1.50	0.66	0.17	2.83	2572
7	MeadJohnson	basic	12.5	1.32	0.47	0.17	2.48	2265
8	MeadJohnson	comfort	12.5	1.35	0.48	0.26	2.94	2427
9	MeadJohnson	hypoallergenic	12.5	1.49	0.64	0.29	3.44	2567
10	Nestle	basic	12	1.35	0.49	0.29	2.50	1973
11	Storebrand	basic	33	1.11	0.55	0.20	2.49	2531
12	Storebrand	basic	34	1.06	0.55	0.41	2.49	846
13	Storebrand	basic	35	1.13	0.56	0.08	2.49	2503
14	Storebrand	basic	48	1.01	0.58	0.33	2.48	673
Total				1.29	0.54	0.08	3.44	31278

Table 2: Per Ounce Retail Price by Alternatives

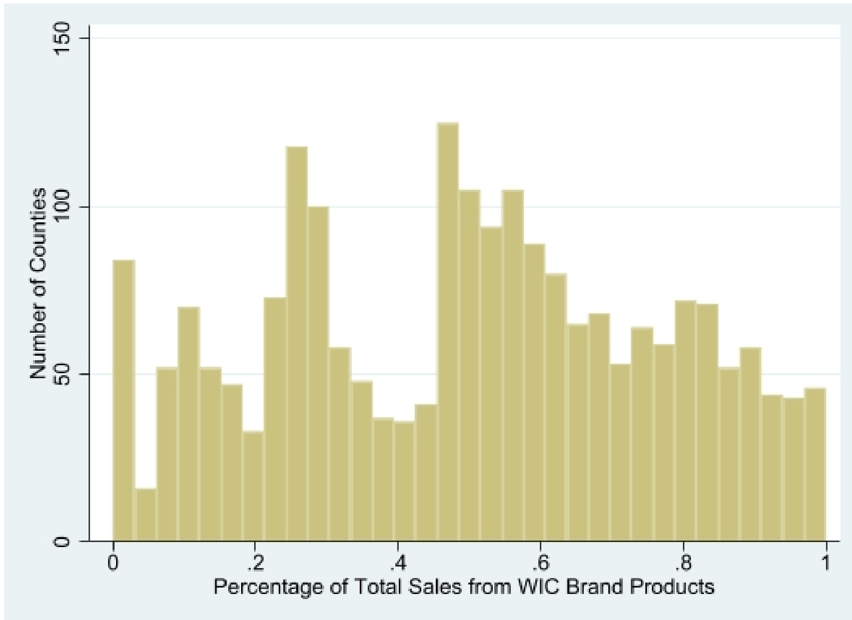

Figure 1: WIC brand product sales as a percentage of total sales

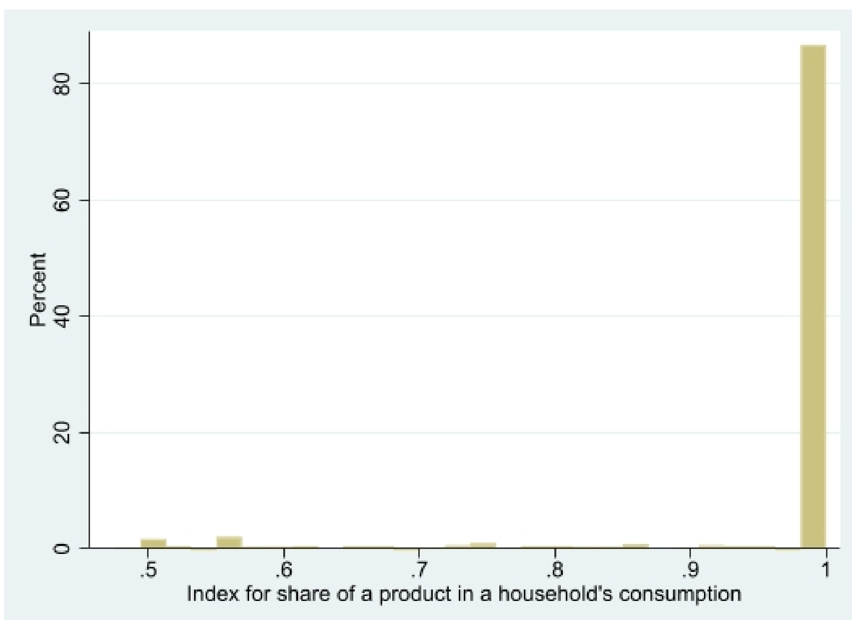

Figure 2: Share of a brand in a household's consumption

Random parameter distribution	Logit	Mixed Logit Lognormal	Mixed Logit Normal
price	-2.827***	-1.309***	-3.040***
	(-4.41)	(11.45)	(-3.88)
residual μ	1.944**	2.590***	1.418*
	(2.84)	(-7.73)	(1.82)
wicproduct	0.924***	0.843***	1.076***
	(5.97)	(8.57)	(6.11)
sd(price)		0.840***	2.474***
		(8.16)	(19.19)
HH, State, Week, Product FE	Y	Y	Y
N	31160	30170	30170

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Discrete Choice Model Results

alt	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	**-2.5**	0.54	0.44	0.36	0.39	0.37	0.33	0.35	0.37	0.29	0.38	0.14	0.40	0.09
2	0.27	**-2.97**	0.28	0.19	0.22	0.19	0.17	0.19	0.19	0.15	0.20	0.07	0.21	0.04
3	0.25	0.32	**-2.82**	0.25	0.26	0.22	0.18	0.20	0.21	0.16	0.22	0.08	0.22	0.05
4	0.15	0.16	0.19	**-2.35**	0.19	0.15	0.12	0.13	0.14	0.11	0.13	0.05	0.13	0.03
5	0.19	0.22	0.24	0.20	**-2.85**	0.26	0.18	0.18	0.19	0.14	0.19	0.06	0.19	0.04
6	0.08	0.09	0.09	0.08	0.12	**-3.05**	0.11	0.09	0.12	0.08	0.07	0.02	0.07	0.02
7	0.15	0.17	0.17	0.11	0.18	0.23	**-2.40**	0.22	0.18	0.12	0.15	0.04	0.15	0.04
8	0.18	0.20	0.19	0.13	0.20	0.20	0.25	**-2.59**	0.27	0.16	0.19	0.05	0.18	0.04
9	0.07	0.08	0.08	0.06	0.08	0.10	0.07	0.11	**-3.10**	0.08	0.07	0.02	0.06	0.01
10	0.16	0.19	0.17	0.13	0.16	0.17	0.14	0.17	0.23	**-2.18**	0.19	0.06	0.15	0.04
11	0.28	0.31	0.32	0.22	0.31	0.27	0.24	0.27	0.31	0.27	**-2.51**	0.13	0.55	0.09
12	0.09	0.10	0.09	0.08	0.10	0.09	0.08	0.09	0.09	0.09	0.13	**-0.83**	0.14	0.01
13	0.17	0.18	0.17	0.12	0.17	0.15	0.14	0.14	0.15	0.12	0.31	0.08	**-2.76**	0.06
14	0.10	0.10	0.10	0.07	0.10	0.09	0.09	0.09	0.09	0.08	0.13	0.01	0.15	**-0.56**

Table 4: Own and Cross Price Elasticities

	CS_0	CS_1^{Abbott}	CS_1^{MJ}	CS_1^{Both}
sample total	1163.77	1271.75	1195.8	1303.4
Δ CS		107.98	32.03	139.63
% Δ CS		9.28	2.75	12.00

Table 5: Increase WIC product selection: Sample Δ CS by Brands

	Non-WIC			WIC		
	min	mean	max	min	mean	max
CS_0 per purchase		0.41			0.73	
Δ CS - Abbott	0.00	0.03	0.16	0.00	0.16	0.68
% Δ CS - Abbott	0.00	6.34	39.02	0.00	21.92	93.15
Δ CS - MJ	0.00	0.01	0.08	0.00	0.05	0.40
% Δ CS - MJ	0.00	2.32	11.85	0.00	6.44	37.74
Δ CS - Both	0.00	0.04	0.17	0.00	0.19	0.77
% Δ CS - Both	0.00	8.54	41.46	0.00	26.03	105.48

Table 6: Increase WIC product selection: Sample Δ CS By Household WIC Status

	CS0	CS Remove WIC
Sample total	1350.27	1048.96
Δ CS		-301.31
% Δ CS		-22.31

Table 7: Decrease WIC product selection: Sample ΔCS by Brands

	Non-WIC			WIC		
	min	mean	max	min	mean	max
CS0 per purchase	0.07	0.41	0.65	0.04	0.73	1.06
Δ CS	-0.18	-0.05	0.00	-0.76	-0.40	0
%Δ CS	-43.90	-11.71	0.00	-104.11	-54.79	0

Table 8: Decrease WIC product selection: Δ CS By WIC Status

	Non-WIC		
	min	mean	max
CS_0 per purchase		0.41	
Δ CS	0	0.04	0.65
$\%\Delta$ CS	0	10.00	158.54

Table 9: Δ CS Under Mandatory Participation Policy

Table 10: Mixed Logit Robustness Check

	(1) Lognormal	(2) Lognormal	(3) Lognormal	(4) Normal	(5) Normal	(6) Normal
price	-1.309***	-1.313***	-1.378***	-3.040***	-1.968**	-4.006***
	(11.45)	(9.25)	(11.44)	(-3.88)	(-2.05)	(-4.79)
wicproduct	0.843***	0.977***	0.799***	1.076***	1.410***	0.877***
	(8.57)	(8.07)	(7.47)	(6.11)	(6.71)	(4.72)
residual μ	2.590***			1.418*		
	(-7.73)			(1.82)		
resudual μ_1		2.814***			0.617	
		(-6.28)			(0.64)	
resudual μ_2			2.810***			2.387***
			(-7.19)			(2.87)
sd(price)	0.840***	0.679***	0.786***	2.474***	2.164***	2.473***
	(8.16)	(6.48)	(7.58)	(19.19)	(16.75)	(19.19)
County FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
N	30170	21410	30170	30170	21410	30170

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	price	price	price	price
wicproduct	-0.00435	-0.00144	-0.000673	0.000357
	(-0.47)	(-0.14)	(-0.07)	(0.03)
% of wic in market	-0.0329	-0.0417	-0.0270	-0.0337
	(-0.90)	(-1.08)	(-0.73)	(-0.82)
# rival brand WIC		0.00100		0.000618
		(0.68)		(0.38)
# same brand WIC			-0.00125	-0.000991
			(-0.81)	(-0.59)
Product, County, Week FE	Y	Y	Y	Y
Adjusted R^2	0.026	0.026	0.026	0.026
N	30762	30762	30762	30762

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Regression with Price Predictors

Price change by firms	Add the brand as the nationwide WIC brand		
	Abbott	MeadJohnson	Both
Abbott	-0.0061	-0.00094	-0.0045
MeadJohnson	-0.0026	-0.0025	-0.0067
Nestle	-0.0029	-0.00095	-0.0054
Storebrand	-0.0024	-0.00094	-0.005

Table 12: Price Change by firms Across Scenarios

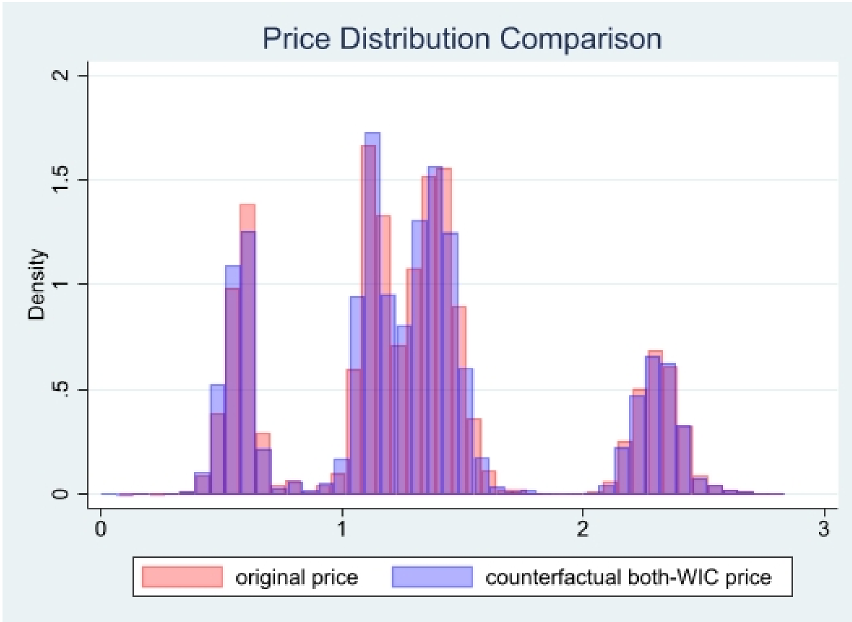

Figure 3: Original prices vs. counterfactual price: 2 brands as nationwide WIC brands

	CS_0	CS_1^{Abbott}	CS_1^{MJ}	CS_1^{Both}
Sample total	1350.27	1488.15	1392.91	1526.77
Δ CS		137.88	42.64	176.5
% Δ CS		10.21	3.16	13.07

Table 13: Increase WIC product selection with price dynamics: sample ΔCS by Brands

	Non-WIC			WIC		
	min	mean	max	min	mean	max
CS_0 per purchase		0.41			0.73	
Δ CS1 - Abbott	-0.19	0.03	0.19	-0.01	0.16	0.69
% Δ CS - Abbott	-46.34	6.34	46.34	-2.68	39.02	168.29
Δ CS - MJ	-0.17	0.01	0.12	-0.05	0.05	0.40
% Δ CS - MJ	-41.46	2.10	29.27	-11.95	11.46	97.56
Δ CS - Both	-0.15	0.04	0.20	-0.01	0.19	0.77
% Δ CS - Both	-36.59	8.54	48.78	-2.68	46.34	187.80

Table 14: Increase WIC product selection with price dynamics: Δ CS by WIC Status

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