An Investigation into the Bidding Process for WIC Infant Formula Contracts*

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Abstract

Motivated by the FTC's ongoing investigation, this paper examines whether infant formula manufacturers colluded in bidding for WIC infant formula contracts. Using auction data from 2003 to 2021, we compare bidders' behavior during a competitive benchmark period (2003–2013) with that observed in the alleged collusive period (2016–2021). Descriptive patterns reveal that participation declined in the alleged period—consistent with reduced competition—yet when Abbott and MJ met head-to-head, winning bids fell even more sharply. Incumbents were more likely to retain contracts, but only by bidding more aggressively, not through rivals' restraint. To formally test for collusion, we implement state-of-the-art collusion screens that target two behaviors central to the FTC's allegation: bid rotation and cover bidding. These include tests from Kawai et al. (2023), Porter and Zona (1993), Huber and Imhof (2019) and Clark et al. (2025). Across these methods, we find little evidence of systematic bid rigging in WIC auctions during the alleged period.

Keywords— Auctions; Collusion; Bid Rigging; WIC; Infant Formula; FTC

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1 Introduction

In 2022, the Federal Trade Commission (FTC) launched an investigation into whether participants in the infant formula market, which is dominated by a handful of manufacturers, have engaged in collusion or coordination when bidding for government contracts (Whyte et al., 2023). The investigation specifically targets contracts with the U.S. Department of Agriculture's (USDA) Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), which provides free baby formula to low-income families.[1]

The WIC program serves approximately half of all infants born in the United States and is the primary purchaser of infant formula (Davis and Oliveira, 2015). To reduce costs, WIC state agencies hold auctions every three to four years for the procurement of baby formula. During these auctions, formula manufacturers submit sealed bids for the exclusive right to supply their products to WIC participants in that state. Eligible participants receive WIC vouchers for the winning manufacturer's formula, which they can redeem at WIC-authorized retail vendors.[2]

The FTC's core allegation is that "incumbent WIC contract holders agree not to bid against each other so that they can continue enjoying dominant positions in non-WIC markets in their respective states" (FTC, 2023). Here, incumbents are firms that previously won the WIC contract conducted by the same state agency. The incentive to collude, however, does not stem from WIC sales themselves, where deep rebates leave little room for profit. Rather, it arises from the spillover benefits that accompany a WIC victory, extending to the more profitable non-WIC market in which infant formula sells at full price and yields substantially higher margins (FTC, 2023). Winning a WIC contract typically ensures prominent shelf space and brand visibility across retail outlets, strengthening a manufacturer's position among non-WIC consumers and reinforcing its overall market dominance. In this sense, WIC auctions serve as gateways to the lucrative retail segment. Consequently, coordination in WIC bidding alone may be sufficient to preserve profits and sustain market power, even without explicit collusion in downstream pricing or output.

Reflecting these concerns, on January 27, 2023, the FTC requested data from Abbott covering 2016 to the present, including both WIC and non-WIC markets. Abbott resisted, arguing that providing non-

[1] Legal disclaimer: This paper analyzes the alleged cartel case strictly from an economic perspective. The investigation and prosecution of the firms involved in the alleged conspiracy are ongoing, and the allegations have not been proven in a court of law. However, for the purpose of this paper, we take these facts as established. The analysis is preliminary and incomplete, and the findings are subject to change.

[2] These vouchers specify the brand, quantity, form, type, and package size of products eligible for redemption through the WIC program.

WIC and pre-2020 data was unduly burdensome, but the FTC rejected this objection in April 2023, emphasizing that non-WIC data are critical for assessing market power and that a seven-year window is necessary to detect unusual bidding patterns.

The empirical analysis that follows tests the FTC's theory directly by analyzing the bidding process for WIC infant formula contracts and assessing whether the data show signs of bidder collusion. Consistent with the FTC's investigation window, we designate 2016 onward as the alleged collusive period in our empirical analysis. We close this window in 2021 since Nestlé submitted its final WIC bid in November 2021 and subsequently exited, fundamentally altering the market structure. Thus, our alleged period (2016–2021) captures the last years in which all three major manufacturers—Abbott, Mead Johnson (MJ), and Nestlé—actively participated in WIC bidding.

For the competitive benchmark, we follow the USDA study of 2003–2013, which concluded unequivocally that "the bidding for WIC infant formula rebate contracts is highly competitive" (Davis and Oliveira, 2015). According to Davis and Oliveira (2015), during that decade all three major manufacturers consistently participated in bidding, bids varied widely across firms and over time, contracts turned over frequently (about 38% changed suppliers), and rebates were exceptionally large (averaging 92% of wholesale price in 2013). The study explicitly found "no evidence of any anti-competitive contract-sharing scheme" (Davis and Oliveira, 2015). These features—full participation, wide bid dispersion, frequent turnover, and aggressive rebates—stand in sharp contrast to classic collusive markers such as reduced entry (De Leverano, 2019), tightly clustered bids (Clark et al., 2025), persistent incumbency (Porter and Zona, 1999; Kawai et al., 2023), or elevated prices (Connor and Lande, 2008).

Taken together, the USDA's documented competitive era (2003–2013) and the FTC's alleged collusive window (2016–2021) provide the empirical backdrop that we leverage for our statistical analysis.[3] The intervening years 2014–2015 fall outside both windows; we therefore exclude them from our analysis. We begin by comparing bidding outcomes across the two windows. While these comparisons across periods are informative, they are not ideal, since other market conditions may also have shifted between the two windows. Even so, a clear pattern emerges: in the alleged period, wholesale prices were higher, but rebates rose even more sharply, driving average bids close to zero and often pushing winning bids

[3]In its allegations, the FTC cited the same USDA study of 2003–2013 as support, claiming it revealed patterns "potentially indicative of noncompetitive bidding" (FTC, 2023). This reading is difficult to reconcile with the USDA's actual conclusion, which was unambiguous: the study found "no evidence of any anti-competitive contract-sharing scheme" and affirmed competitive outcomes (Davis and Oliveira, 2015). At the same time, the FTC limited its data request to 2016 onward. If the Commission truly believed that suspicious patterns extended back to 2003, it would have sought the full historical record. This tension further underscores why 2003–2013 is the appropriate competitive benchmark, a period already rigorously examined and shown to reflect vigorous competition.

into negative territory. Participation patterns also shifted: Abbott and MJ entered less frequently, while Nestlé became more active.

To probe the FTC's allegation more directly, we focus on head-to-head competition and incumbency across the two periods. If incumbents were collusively allocating markets by refraining from bidding against one another, we would expect to see two patterns during the alleged period: systematically less head-to-head competition, and higher winning bids for incumbents who could retain contracts without bidding aggressively. The data partly align with the first prediction—Abbott and MJ did compete against each other less often—but the pricing patterns move in the opposite direction. When they did meet head-to-head, winning bids declined even more sharply—both in simple comparisons and in regressions that account for market and cost conditions. Incumbents remained more likely to retain contracts, but only by bidding more aggressively to defend them, not because rivals held back. These patterns diverge from the collusive market-allocation narrative and provide little support for the FTC's allegation.

To move beyond descriptive comparisons, we turn to formal collusion screens. Our choice of screens is guided by the FTC's allegations, which focus on market allocation through non-competition among incumbents. If such coordination were present, it would most plausibly manifest in two ways. First, through bid rotation, where incumbents are systematically favored in contract awards by avoiding direct rivalry in one another's territories, ensuring that each maintains dominance in its existing markets. Second, through complementary or cover bidding, where rivals still participate in the auction but submit deliberately uncompetitive bids at inflated levels. This strategy preserves the appearance of competition while effectively leaving outcomes predetermined.

Our empirical analysis applies a set of collusion screens designed to detect these behaviors. The regression discontinuity test of Kawai et al. (2023) tests for bid rotation by examining whether incumbents are disproportionately likely to win contracts in near-tie auctions. The underlying intuition is that, under competitive bidding, winning and losing should be "as-if random" once bids are sufficiently close. The tests developed by Porter and Zona (1993) target cover bidding by relating bids to underlying cost conditions. The Level Test assesses whether bids are less responsive to cost shifters than expected under competition—since colluding firms may coordinate bids rather than adjusting them to their own cost changes. The Rank Test examines whether the ordering of bids corresponds to the cost rankings; under collusion, firms may take turns winning or submit cover bids that break this natural alignment. Finally, Huber and Imhof (2019) and Clark et al. (2025) propose tests that detect anomalies such as isolated winning bids or clustering that can arise under complementary bidding arrangements.

We implement each screen separately for the competitive benchmark period (2003–2013) and the alleged collusive period (2016–2021). The logic is straightforward: competition should not be rejected in the benchmark period, while rejection in the alleged period would be consistent with collusive conduct. Across all screens, however, we find little evidence of systematic bid rigging in WIC auctions during the alleged period. A key limitation of this analysis is the relatively small number of observations available for testing, which might limit the statistical power of these screens. Nonetheless, the consistency of results across multiple screens indicates that the observed bidding patterns remain broadly consistent with competitive behavior.

This paper is closely related to the literature on detecting collusion in auctions. A key strand of this literature relies on prior knowledge of the existence and structure of cartels. For example, Porter and Zona (1993) apply the Level and Rank tests to New York state highway construction auctions and reject the null of no cover bidding. Porter and Zona (1999) study Ohio school milk auctions in the 1980s, identifying collusion from systematic deviations from competitive bidding. Pesendorfer (2000) analyzes the Florida and Texas school milk cartels between 1980 and 1991, showing how cartel presence shapes bidding behavior. More recently, Huber and Imhof (2019) compare cartel and non-cartel periods in Swiss procurement data, using simple distributional screens to detect evidence of bid rigging.

Another line of research develops tests to detect collusive bidding without requiring prior knowledge of cartel activity. Notable applications include federal auctions for drainage leases in the United States (Hendricks and Porter, 1988), timber auctions in the United States and Canada (Baldwin et al., 1997; Schurter, 2017), seal coat auctions in the Midwest (Bajari and Ye, 2003), Internet Guaranteed Investment Certificates auctions (Kaplan et al., 2017), roadwork auctions in Italy (Athey et al., 2011), asphalt auctions in Montreal (Clark et al., 2025), and public works procurement auctions in Japan (Ishii, 2009; Chassang and Ortner, 2019; Kawai and Nakabayashi, 2022; Chassang et al., 2022; Kawai et al., 2023). This paper contributes to the literature by examining collusion in baby formula auctions, making it one of the first empirical studies to apply a broad family of "screens" to test for collusion in this market.

Since we investigate the bidding process for WIC infant formula contracts, we consider this work closely related to research on WIC and its infant formula rebate program. For instance, Prell (2004) develops a theoretical model that examines retail prices for infant formula, predicting that retailers charge higher prices when the relative size of WIC increases. Utilizing different datasets, Oliveira et al. (2011) and Huang and Perloff (2014) document that when the WIC contract brand switches from one manufacturer to another, the market share of the new contract brand increases substantially. They illustrate

that this increase is partially due to spillover effects, where sales of formula purchased outside the WIC program also rise. Similarly, Davis (2012) models infant formula wholesale prices in the context of the rebate program and demonstrates that winning the WIC contract enhances a firm's prominence in stores, leading to a significant increase in sales to non-WIC participants. A recent study by An et al. (2023) also confirms the sizable benefits of winning the auction, including a notable spillover effect on non-WIC demand, significant reductions in marginal costs, and higher retail prices for the WIC brand. Our work complements these studies by investigating whether the bidding process for WIC infant formula contracts is competitive.

The remainder of the paper is organized as follows. Section 2 provides background on the U.S. infant formula market, the WIC rebate program, and the FTC's investigation. Section 3 describes the auction data. Section 4 presents descriptive evidence. Section 5 implements several collusion tests from the literature and reports the results. Section 6 concludes.

2 Background

In this section, we describe the U.S. infant formula market, the WIC's infant formula rebate program, and the FTC's investigation into collusion.

2.1 The Infant Formula Market

Although infant formula was first introduced in the United States in the early 1900s, large-scale commercial production did not emerge until the baby boom following World War II (Oliveira et al., 2004). In 1980, Congress passed the Infant Formula Act to strengthen the safety of commercial formula, establishing mandatory testing, nutritional standards, and quality control procedures, and granting the Food and Drug Administration (FDA) authority to enforce these regulations. The resulting regulatory framework, combined with high tariff barriers, effectively insulated domestic producers from foreign competition and made entry by overseas formula companies nearly impossible.

Protected by these barriers, the infant formula industry has long been one of the most concentrated manufacturing sectors in the United States. By 1987, before the widespread adoption of the WIC infant formula rebate program, three manufacturers—each owned by a pharmaceutical company—produced roughly 99 percent of the domestic supply: Ross Laboratories (Abbott Laboratories), Mead Johnson (Bristol-Myers), and Wyeth-Ayerst Laboratories (American Home Products) (U.S. General Accounting

Office, 1990).[4]

Since the late 1980s, the U.S. infant formula market has undergone several notable changes. Nestlé entered the market in 1989, while Wyeth-Ayerst exited the domestic branded formula market in 1996, re-entering the following year as a private-label supplier with a market share of roughly 1% (Betson, 2009).[5] Since then, no new significant competitors have entered. The industry's leading players have remained largely stable: Ross Laboratories rebranded as Abbott Nutrition in 2007 (Wilson, 2007), and Nestlé acquired Wyeth Nutrition in 2012 (Nestlé, 2012).[6] Despite decades of effort, Nestlé struggled to gain a strong foothold and ultimately sold its U.S. and Canadian infant formula business to Perrigo in November 2022 (DiNapoli, 2022). Today, Abbott and Mead Johnson together account for roughly 80 percent of the U.S. market (Ketels, 2022).

On the product side, most infant formulas are cow's-milk-based and are modified to approximate the composition and nutritional profile of human milk. Soy-based options serve as an alternative for infants who cannot tolerate cow's-milk protein, while specialized products include hypoallergenic, lactose-free, and formulations for premature infants or those with particular medical needs. Formulas are sold in three forms—powder, liquid concentrate, and ready-to-feed—with powdered formula the least expensive and by far the most common in the United States (Oliveira et al. (2010); Davis and Oliveira (2015)). Packages span a range of sizes to accommodate household preferences.

A particularly important development in the past two decades has been the widespread adoption of formulas supplemented with two fatty acids—docosahexaenoic acid (DHA) and arachidonic acid (ARA). These occur naturally in breast milk, and numerous studies have linked them to improved visual acuity and cognitive development in infants (see, for example, Hoffman et al. (2009); Lien et al. (2018)). Abbott pioneered the launch of DHA/ARA-supplemented formulas in 2002, followed shortly by Mead Johnson and Nestlé. Although these products carried a premium price relative to standard formulas, sales grew rapidly. By 2008, DHA/ARA-supplemented products accounted for 98 percent of all infant formula sales in the U.S. (Oliveira et al., 2010). Given their near-universal adoption, our analysis focuses exclusively on contracts for supplemented formulas.

[4]The estimated individual market shares were: Ross, 55 percent; Mead Johnson, 35 percent; and Wyeth-Ayerst, 9 percent (U.S. General Accounting Office, 1990).

[5]Among the reasons the company cited for exiting were rising competitive costs and the rapid expansion of the WIC program (Moore, 1996).

[6]Pfizer owned Wyeth Nutrition at the time, following its 2009 acquisition of Wyeth (formerly American Home Products, rebranded in 2002).

2.2 WIC's Infant Formula Rebate Program

Administered by the Food and Nutrition Service (FNS) of the United States Department of Agriculture (USDA), the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) is a federal assistance program aimed at safeguarding the health of low-income pregnant, postpartum, and breastfeeding women, as well as infants and children under the age of five who are at nutritional risk. WIC provides three primary benefits: supplemental foods, nutrition education, and referrals to health care and other social services.

Approximately half of all newborns in the U.S. participate in the WIC program (FNS, 2023a). While WIC promotes breastfeeding as the preferred feeding method, it also provides iron-fortified infant formula for infants who are not exclusively breastfed (FNS, 2023b). According to estimates by the USDA's Economic Research Service (ERS), 56 percent of all formula sold in the U.S. in 2018 was purchased by WIC participants (ERS, 2023). Given this scale, the pricing of infant formula represent major cost drivers for the program.

To contain these costs, federal law requires WIC State agencies with more than 1,000 infant participants to use a cost-containment system for formula procurement. This system is structured as a single-supplier competitive bidding process, under which a single manufacturer is granted the exclusive contract to serve WIC infant participates in that State.[7,8] In exchange, the manufacturer provides the State agency with a rebate on the wholesale price of each unit of formula purchased through WIC.

Under single-supplier competitive bidding, a WIC State agency—or a group of agencies acting jointly as an "alliance"—solicits sealed rebate bids from infant formula manufacturers every three to four years.[9] Within an alliance, all participating State agencies receive the same rebate. As part of the solicitation, the agency specifies a standardized number of units of infant formula, which represents the total ounces of formula required to cover the maximum monthly allowance for the average number of infants by physical form (powder, liquid concentrate, ready-to-feed). These averages are calculated from at least six months

[7]WIC State agencies may operate an alternative cost-containment system if it generates savings equal to or greater than those under a single-supplier system (7 CFR §246.16a(d)). No State agency currently operates an alternative system.

[8]Solicitations for bids may take one of two forms: a single solicitation or separate solicitations. Federal law requires States and alliances serving more than 100,000 infants per month (based on the preceding 12 months) to issue separate solicitations for milk-based and soy-based infant formula (7 CFR §246.16a). Smaller States, by contrast, may issue a single solicitation for an iron-fortified, milk-based formula, in which case the rebate percentage discount offered on milk-based formula also applies to soy-based formula. As of March 2023, only three States (California, Florida, and New York) and two alliances (the Western States Contracting Alliance and the Southwest/Mountain Plains/Midwest Region Alliance) issued separate solicitations.

[9]In 2004, Congress prohibited the formation of new multi-State alliances serving more than 100,000 infants. Alliances above this threshold as of October 2003 were exempted (Public Law 108-265). A list of existing alliances and their member States is provided in Appendix A.

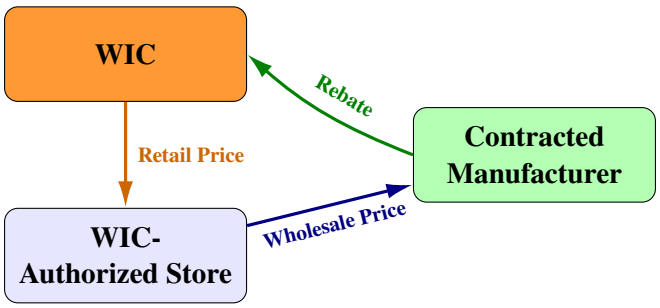
of the most recent participation and issuance data.

Manufacturers then submit bid sheets reporting the lowest national wholesale price per unit for a full truckload of formula, together with the rebates they will provide for each of the three formula types.[10] Using these inputs, the bid sheet automatically calculates the total monthly net price—defined as the wholesale price minus the rebate, weighted by the number of units in each form. Once submitted, all bid sheets are opened and read aloud in a public session, and the contract is awarded to the manufacturer offering the lowest total monthly net price (see Table B1 for an example).

The winning contract then governs pricing for the duration of the agreement. If the manufacturer's reported wholesale price changes after bid opening, the rebate adjusts on a cent-for-cent basis, keeping the net wholesale price fixed even as the rebate expressed as a percentage of wholesale price fluctuates. In practice, however, reported wholesale prices rarely change. Contracts typically last three to five years before being rebid, with optional extensions that may be exercised by the State or by mutual agreement.

Beyond manufacturer rebates, states employ additional measures to control WIC formula costs at the retail level. Because participants receive formula free of charge, they are insensitive to price differences—creating an incentive for retailers to raise prices on WIC-approved brands, potentially undermining the savings achieved through rebates. To mitigate this risk, states impose retail price controls. The most common approach is vendor peer grouping, where authorized vendors are classified by characteristics such as store size (e.g., based on the number of cash registers) and geographic location. Each peer group is assigned a Maximum Allowable Redemption Level (MARL), which sets the highest per-unit price the state will reimburse. MARLs are periodically updated to reflect market conditions. For example, New York sets MARLs monthly from peer-group redemption data via the eWIC payment system, and any price submitted above the MARL is automatically reduced to the MARL at the time of payment (New York State WIC Program, 2024).

Figure 1: WIC payment flow



[10] Unless otherwise specified, all subsequent references to the wholesale price denote the lowest national wholesale price per unit for a full truckload of infant formula.

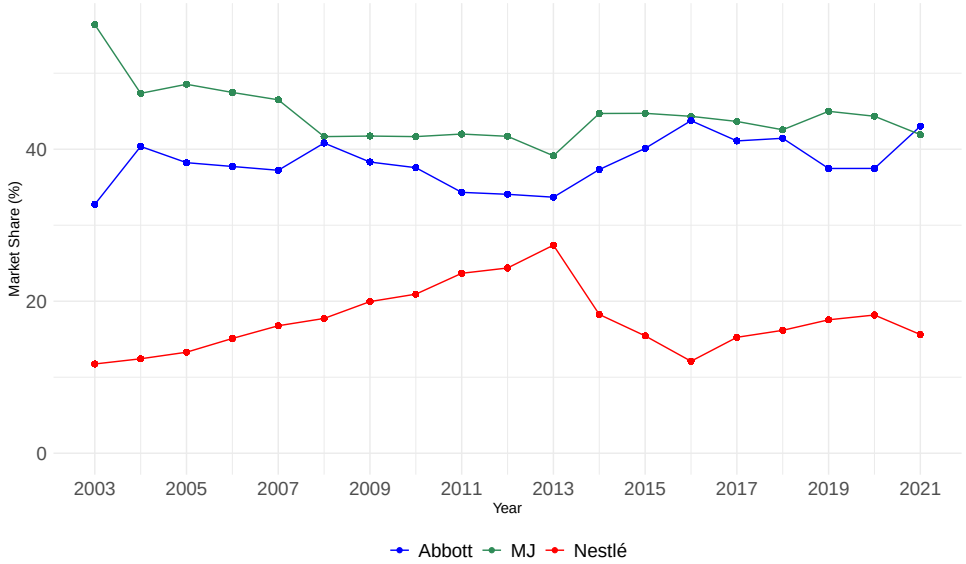
To illustrate how these contracting arrangements translate into payments, Figure 1 presents the flow of payments under the WIC infant formula program. WIC-authorized vendors purchase formula from the contracted manufacturer at wholesale prices, which can vary by volume and need not match the reported wholesale price on the bid sheet. Eligible participants redeem food vouchers at these stores, which collect the vouchers and submit them to the State agency. The State agency reimburses the stores for the full retail price (WIC and non-WIC consumers face the same posted shelf price, in accordance with 7 CFR §246.12(h)(3)(iii)). The State agency subsequently invoices the contracted manufacturer for rebates on the redeemed formula. As a result, the program's net cost per unit equals the retail prices paid to stores minus the manufacturer rebate.

Turning to the competitive landscape, the structure of the WIC infant formula market has remained remarkably stable over time. Initially, only three formula manufacturers bid for states' early WIC contracts: MJ, Ross, and Wyeth-Ayerst. A fourth competitor, Nestlé, entered the bidding process in 1992, but in 1996 Wyeth-Ayerst exited, reducing the number of bidders back to three. Decades later, the same three firms—MJ, Abbott (formerly Ross), and Nestlé—continued to dominate state WIC contracts.

Figure 2 below shows how WIC infant formula market shares for Abbott, MJ, and Nestlé evolved from 2003 to 2021.[11] Abbott and MJ have consistently held around 40% each, establishing themselves as clear market leaders. Nestlé's share grew steadily until about 2013, after which it began to decline. In November 2022, Nestlé sold its formula business to Perrigo and stopped bidding for new WIC contracts, although it committed to honoring its existing agreements to ensure uninterrupted supply, with Perrigo supplying products through its Gateway plant. The last WIC auction in which Nestlé participated took place in November 2021. Since this exit significantly reshaped the market, our analysis focuses on contracts awarded before that date.

[11] Figure C1 plots the flow of WIC market share for all bidders over the same period, measuring the annual percentage of new contracts awarded rather than cumulative contract coverage.

Figure 2: WIC Infant Formula Market Share by Bidder, 2003 - 2021



Note: This figure plots the market share for each bidder from the year 2003 to 2021. Market share is defined as the ratio of the number of WIC infants served (both existing and new contracts) by each bidder to the total number of WIC infants in a given year.

2.3 The FTC's Investigation

In late 2022, the FTC launched an investigation into whether Abbott and other infant formula manufacturers engaged in collusion or coordination in bidding for WIC infant formula contracts (Whyte et al., 2023). On January 27, 2023, as part of this inquiry, the FTC issued a Civil Investigative Demand (CID) to Abbott requesting a wide range of materials, including all records related to WIC bids submitted by the company, correspondence with competitors, and documents concerning competition in the manufacture, marketing, or sale of infant formula products. The CID also sought datasets on non-WIC sales, costs, and other financial information from January 2016 onward (FTC, 2023). The investigation extends beyond Abbott: according to ABC News, both Nestlé and MJ confirmed that they received similar requests for information from the FTC regarding their WIC contract bidding processes and have responded accordingly (Pezenik and Yu, 2023).

Abbott soon pushed back against the breadth of these requests. On March 16, 2023, the company petitioned the FTC to narrow the CID, arguing that requests for non-WIC and pre-2020 data were unduly burdensome. The FTC rejected this petition. In the *Order Denying Petition to Limit CID*, Commissioner Alvaro Bedoya explained that non-WIC data were critical for assessing the relationship between winning WIC contracts and non-WIC sales, including potential spillover effects, and for evaluating whether incumbents had incentives to avoid bidding against one another (FTC, 2023). He further emphasized

that because WIC state agencies typically solicit rebate bids every three to four years on cycles that do not perfectly overlap, a seven-year window was needed to capture multiple bidding rounds and identify potential anomalies.

Taken together, these points clarify why our analysis designates 2016–2021 as the alleged collusive period. The FTC's CID explicitly begins its data request in January 2016, reflecting its view that potential coordination could have been operative from that time forward. We set the endpoint at 2021, the year of Nestlé's last participation in WIC bidding, which marked the start of its withdrawal and culminated in its formal exit in 2022. This timing ensures that the designated period captures the full span during which all three major manufacturers were active participants in WIC auctions under the FTC's inquiry.

The FTC also made explicit its theory of harm. In the same order, it expressed concern that "incumbent WIC contract holders agree not to bid against each other so that they can continue enjoying dominant positions in non-WIC markets in their respective states" (FTC, 2023). At its core, this theory reflects market allocation through non-competition among incumbents. The incentive to collude does not arise from the WIC program itself, where deep rebates leave little profit on each unit sold. Rather, the value of coordination lies in the much larger non-WIC market, where formula is sold at full price and margins are far higher. Because winning a WIC contract typically secures the manufacturer a dominant share of non-WIC sales—often close to 80%—the WIC auctions function as the gateway to the profitable non-WIC market. In this sense, collusion in WIC bidding is sufficient to safeguard profits without requiring extensive coordination elsewhere.

If such coordination were present, it would most plausibly manifest through two channels: (i) bid rotation, whereby incumbents are systematically favored in contract awards, often by avoiding direct rivalry in one another's territories; and (ii) complementary or cover bidding, in which rivals may still participate but submit deliberately uncompetitive bids at inflated levels, thereby preserving the appearance of competition while leaving outcomes predetermined. Guided by this framework, our empirical analysis applies collusion screens tailored to detect bid rotation and cover bidding.

3 Data

Motivated by the FTC's allegation, the analysis examines bids submitted to WIC State agencies during two windows: 2003–2013 as a competitive benchmark and 2016–2021 as the alleged collusive period. Auctions held in 2014–2015 are excluded because they fall between these windows and cannot be clearly

assigned to either. The auction data include each firm's winning and losing rebate bids, wholesale prices, and key auction characteristics such as the WIC agency identifier, bidding system type, and formula type (milk- or soy-based). As noted earlier, sole-source contracts are awarded to the manufacturer offering the lowest net price bid, calculated by weighting rebates across the three product forms—powder, liquid concentrate, and ready-to-feed. The dataset, however, does not report bid information for ready-to-feed bottles or the precise weights applied to each form.

Because of these limitations, our analysis focuses on contracts for supplemented milk-based powdered formulas—the primary type used in the WIC program. This focus is appropriate, as powdered formula accounts for the vast majority of WIC prescriptions (98.4 percent in 2018) (Gleason et al., 2021), and the data show that the lowest powdered bid always determines the contract winner. Moreover, since container sizes and reconstitution yields (the liquid obtained after mixing powder or concentrate with water) vary across brands—and may change over time even within the same product—we standardize all monetary values for comparability by converting wholesale prices, rebates, and net price bids to a common unit of 26 reconstituted fluid ounces, which corresponds to WIC's daily maximum allowance during the study period. Throughout the paper, all prices and bids are expressed on this basis.

Table 1 reports descriptive statistics for the two periods of interest, based on 55 auctions held during the competitive period and 35 during the alleged period. Average wholesale prices increased from $4.11 in the competitive period to $4.57 in the alleged collusive period, while average rebates rose from $3.27 to $4.55. As rebates rose faster than wholesale prices, the average net bid declined sharply—from $0.84 to nearly zero—driven in part by very low or even negative bids during the alleged period. The average winning bid, in particular, shifted from a positive $0.54 in the competitive period to a negative $0.28 in the alleged period, suggesting that manufacturers bid more aggressively to secure contracts, even as the average number of bidders per auction fell modestly from 2.6 to 2.4.

These patterns raise a key question: why would manufacturers offer such large rebates, even to the point of submitting negative net bids?[12] One important factor is the spillover effect of WIC contracts: winning a contract often increases shelf space and brand visibility in retail stores, which can, in turn, boost non-WIC sales where manufacturers earn full margins without offering rebates (Davis, 2012; Oliveira et al., 2011; Huang and Perloff, 2014; An et al., 2023). The relative size of the WIC market also matters: when WIC accounts for a smaller share of births, firms have stronger incentives to bid

[12]It is important to note that the wholesale prices reported on bid sheets reflect full-truckload bulk transactions, which receive sizable volume discounts. Smaller retailers purchasing in less-than-truckload quantities often pay higher per-unit prices, sometimes exceeding the rebate amount. Consequently, even when the net bid appears negative in the auction, manufacturers can still earn positive margins on some sales.

aggressively, since only a small portion of revenue is at risk while spillover gains in the larger non-WIC market remain substantial (Hodges et al., 2025). With WIC participation around 40 percent—the current national average—equilibrium bids can even be negative, meaning firms accept losses on WIC sales because non-WIC gains compensate (Hodges et al., 2024). Another cost-based motivation stems from the structure of the infant formula industry: large, capital-intensive plants with substantial fixed costs benefit from maintaining scale, so a drop in demand can push production below efficient capacity and raise per-unit costs. Aggressively bidding for WIC contracts thus helps firms preserve these scale economies, even if it requires unusually large rebates (Hodges et al., 2025).

Table 1: Summary Statistics by Period

Variable	N	Mean	Std. Dev.	Min	Max
Competitive Period (2003–2013)					
Wholesale Price	144	4.108	0.158	3.852	4.616
Rebate	144	3.269	0.612	0.313	4.241
Net Price Bid	144	0.840	0.549	0.078	3.602
Winning Bid	55	0.544	0.249	0.078	1.376
Nbr. of Bidders	55	2.618	0.527	1	3
Alleged Period (2016–2021)					
Wholesale Price	83	4.572	0.170	4.244	4.928
Rebate	83	4.548	0.706	2.059	6.202
Net Price Bid	83	0.024	0.672	−1.657	2.440
Winning Bid	35	−0.276	0.598	−1.657	0.709
Nbr. of Bidders	35	2.371	0.843	1	3

Notes: Wholesale prices, rebates, and bids are adjusted to constant 2020 dollars using the Consumer Price Index for All Items and are reported in dollars per 26 fl. oz. of reconstituted formula.

While Table 1 highlights broad shifts in prices, rebates, and bids, bidder-level patterns in Table 2 reveal how individual firms behaved across the two periods. Only three bidders—Abbott, MJ, and Nestlé—participated throughout both periods. During the competitive period, average wholesale prices were broadly similar, ranging from $4.04 for Abbott to $4.17 for MJ. Rebates varied more: Nestlé offered the highest on average ($3.50), followed by MJ ($3.35) and Abbott ($3.03). These differences translated into higher net bids for Abbott ($1.02) compared with MJ ($0.82) and Nestlé ($0.61).

Participation rates were high for Abbott (96%) and MJ (100%) but lower for Nestlé (66%). Even so, Nestlé's aggressive rebate strategy enabled it to win half of the auctions it entered, compared with win rates of 30% for Abbott and 38% for MJ. In terms of market shares, MJ led with about 45%, Abbott followed with 37%, and Nestlé accounted for 19%.

In the alleged period, wholesale prices increased for all three firms, with Nestlé posting the highest

Table 2: Bidder-Level Summary Statistics by Period

Variable	Abbott	MJ	Nestlé
Competitive Period (2003–2013)			
Avg. Wholesale Price	4.044	4.170	4.110
Avg. Rebate	3.029	3.351	3.496
Avg. Net Price Bid	1.015	0.819	0.613
Avg. Winning Bid	0.510	0.567	0.547
Participation Rate	96.4%	100.0%	65.5%
Win Rate	30.2%	38.2%	50.0%
Avg. WIC Market Share	36.8%	44.9%	18.5%
Alleged Period (2016–2021)			
Avg. Wholesale Price	4.499	4.503	4.718
Avg. Rebate	4.686	4.376	4.594
Avg. Net Price Bid	−0.187	0.126	0.124
Avg. Winning Bid	−0.371	−0.160	−0.327
Participation Rate	77.1%	82.9%	77.1%
Win Rate	48.1%	48.3%	29.6%
Avg. WIC Market Share	40.7%	43.6%	15.8%

Notes: Wholesale prices, rebates, and bids are expressed in constant 2020 dollars per 26 fl. oz. of reconstituted formula. Participation rate is the fraction of auctions in which the firm submitted a bid; win rate is conditional on participation. WIC market share is measured as the proportion of WIC infants served—accounting for both existing and new contracts—relative to the total number of WIC infants in a given year, averaged over the period.

level ($4.72 compared with $4.50 for Abbott and MJ). Rebates also rose sharply, averaging between $4.38 for MJ and $4.69 for Abbott. These higher rebates drove net bids close to zero or negative: Abbott submitted the most aggressive bids on average (–$0.19), while MJ and Nestlé both hovered just above zero ($0.13 and $0.12, respectively). Winning bids were negative for all three firms, ranging from –$0.37 for Abbott to –$0.16 for MJ, consistent with rebates often exceeding wholesale prices in this period.

Participation converged across firms during this period, with all three entering roughly 77–83% of auctions. This represented a decline for Abbott and MJ relative to their near-universal participation earlier, but an increase for Nestlé compared with its lower involvement in the competitive period. Abbott and MJ each won close to half of the auctions they entered (48%), while Nestlé's win rate fell to 30%, reflecting a weaker position than in the earlier period. This shift in performance is mirrored in market outcomes: Abbott and MJ dominated with roughly equal shares of 41% and 44%, while Nestlé's share declined to about 16%.

Overall, the alleged collusive period featured higher wholesale prices, substantially larger rebates, and negative winning bids, along with reduced participation by Abbott and MJ and increased activity

by Nestlé. The next section provides additional descriptive evidence to evaluate whether these patterns reflect competitive bidding or instead point to coordinated behavior.

4 Descriptive Analysis

As discussed above, the FTC's theory of harm centers on the claim that incumbents refrained from bidding against one another, thereby allocating WIC markets to protect dominance in their respective non-WIC sales. Such coordination could manifest through bid rotation (avoiding head-to-head rivalry) or complementary bidding (submitting deliberately inflated bids). To explore whether the observed bidding patterns align with this theory, we begin with a descriptive analysis of the data. Specifically, we examine bidder participation, head-to-head competition, pricing behavior (wholesale prices and net bids), and the role of incumbency in contract retention.

Participation and head-to-head competition. As shown above, participation patterns shifted in the alleged period, with Abbott and MJ entering less frequently while Nestlé became more active. We now examine how these changes affected the intensity of head-to-head competition. Table 3 reports the frequency of head-to-head competition for different firm pairs and reproduces participation rates from Table 2 for ease of comparison. If incumbents were allocating markets by refraining from bidding against one another, we would expect head-to-head competition between major rivals to decline sharply in the alleged period. Consistent with this, Abbott and MJ faced each other far less often, with their head-to-head presence falling from 96% in the competitive period to 63% in the alleged period. By contrast, Abbott–Nestlé and MJ–Nestlé competition remained relatively stable, occurring in roughly two-thirds of auctions in both periods.

This decline is closely tied to the rise of one-bidder auctions. Whereas only 2% of auctions (1 out of 55) in the competitive benchmark featured a single bidder, the share rose to 23% (8 out of 35) in the alleged period. Of these eight cases, three involved Abbott, four involved MJ, and one involved Nestlé. Importantly, all of the one-bidder auctions occurred in relatively small states and only in years when large, high-volume contracts were also on offer and attracted multiple bidders. These patterns may reflect capacity constraints, with firms prioritizing larger, more lucrative contracts, but they could also indicate a more systematic reduction in head-to-head rivalry. To illustrate these patterns in greater detail, Table E2 reports the full distribution of bidder sets and winners, while Appendix Table E4 provides the breakdown by incumbent identity.

Table 3: Summary of Participation and Bidding Behavior by Period

	Competitive (2003–2013)	Alleged (2016–2021)	Difference
Participation (% of auctions)			
Abbott	96.364	77.143	−19.221**
MJ	100	82.857	−17.143***
Nestlé	65.455	77.143	11.688
Head-to-head (% of auctions)			
Abbott vs MJ	96.364	62.857	−33.507***
Abbott vs Nestlé	63.636	65.714	2.078
MJ vs Nestlé	65.455	68.571	3.116
Head-to-head Avg. Wholesale Price			
Abbott vs MJ	4.104	4.486	0.382***
Abbott vs Nestlé	4.082	4.613	0.531***
MJ vs Nestlé	4.164	4.612	0.448***
Head-to-head Avg. Bid			
Abbott vs MJ	0.923	−0.073	−0.997***
Abbott vs Nestlé	0.788	−0.069	−0.857***
MJ vs Nestlé	0.718	0.156	−0.562***
Head-to-head Avg. Winning Bid			
Abbott vs MJ	0.546	−0.484	−1.030***
Abbott vs Nestlé	0.522	−0.360	−0.882***
MJ vs Nestlé	0.497	−0.312	−0.809***

Notes: "Participation" is the share of auctions in which a firm submitted a bid. "Head-to-head" is the share of auctions in which both firms in a pair were present. Average wholesale price and average bid are conditional on both firms participating in the same auction; average winning bid is conditional on both being present and one of them winning. All bid values are per 26 fl. oz. of reconstituted formula. "Difference" is computed as the mean in the alleged period minus the mean in the competitive period (Alleged − Competitive). Statistical significance for differences in proportions (Participation and Head-to-head) is based on Fisher's exact test, while differences in means (Average wholesale price, bid, and winning bid) are assessed using two-sample t-tests. Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

To assess whether the descriptive patterns reflect systematic differences once observable factors are taken into account, we estimate two regression models of bidder participation (Table 4). The dependent variable is an indicator for whether a bidder submitted a bid in a given auction. Because the FTC's allegation centers on incumbents coordinating to avoid competing against one another, Model (1) tests whether incumbents were systematically more or less likely to participate during the alleged collusive period. Model (2) allows for bidder-specific responses by interacting the alleged-period dummy with firm identities. Both specifications control for capacity, distance, WIC and non-WIC market size, and input prices, and include state/alliance and bidder fixed effects. Here, capacity refers to a bidder's ability to take on new contracts relative to its workload, while distance captures proximity from production plants to the

auctioning state.[13] WIC and non-WIC market size correspond to the number of infants in each category within a state-year. Input prices are national commodity prices for nonfat dry milk, whey protein, lactose, and vegetable oils.

Table 4: Effect of Alleged Period on Bidder Participation

	Dep. Var: Participate	
	(1)	(2)
Main variables		
Incumbent	0.158***	0.136***
	(0.031)	(0.038)
Alleged (overall)	−0.034	
	(0.096)	
Incumbent × Alleged	−0.038	
	(0.083)	
Alleged × Abbott		−0.197*
		(0.111)
Alleged × MJ		−0.113
		(0.105)
Alleged × Nestlé		0.208*
		(0.106)
Controls		
Capacity, Distance	Yes	Yes
Market Size (WIC/Non-WIC)	Yes	Yes
Main Input Prices	Yes	Yes
Fixed Effects		
State/Alliance FE	Yes	Yes
Bidder FE	Yes	Yes
Observations	270	270
R^2	0.281	0.331

Notes: Standard errors clustered at the auction level in parentheses. Participate =1 if bidder enters. Model (1) includes an interaction between the alleged-period dummy and incumbency status. Model (2) interacts the alleged-period dummy with bidder identities to allow for heterogeneous effects. "Main Input Prices" include nonfat milk, lactose, oils, and whey protein prices.
Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

Model (1) shows that during the competitive benchmark period, incumbents were about 16 percentage points more likely to participate than non-incumbents, holding other factors constant. The interaction term *Incumbent* × *Alleged* is small and statistically insignificant (–0.038), suggesting that incumbents did not systematically alter their participation behavior during the alleged collusive period.

Turning to bidder-specific responses, Model (2) shows patterns consistent with the raw data. Abbott's participation fell by roughly 20 percentage points, closely matching the decline reported earlier. MJ's

[13]Capacity is defined as $capacity_{i,t} = 1 - \frac{backlog_{i,t}}{max\ backlog_i}$, where $backlog_{i,t}$ is the total value of contracts won by firm i over the preceding six months and $max\ backlog_i$ is the highest backlog observed for that firm across the sample. The auction for a new contract typically begins three to six months before the current contract expires, so the backlog measure reflects a firm's unfinished work over a six-month period. We also tried three-month and twelve-month backlogs, and the results remained consistent. Distance is measured from the bidder's nearest plant to the largest city (by population) in a state; for multi-state alliances, weighted averages are calculated using the number of WIC infants as weights.

coefficient is also negative (−0.113) but statistically insignificant, suggesting that its decline is not robust once controls are included. By contrast, Nestlé's participation increased by about 21 percentage points, significant at the 10% level, again in line with the trends reported in Table 3.

Taken together, the results indicate that incumbents generally had higher participation rates in the competitive period, but there is no evidence that incumbents systematically altered their behavior in the alleged collusive period. Instead, participation changes appear to have been bidder-specific: Abbott reduced its activity, Nestlé expanded its participation, and MJ's decline was not statistically significant. Nevertheless, the parallel decline in participation by Abbott and MJ may warrant further scrutiny, as it could suggest the possibility of coordination between the two firms. To assess this possibility, we next examine their pricing behavior, which provide direct evidence on how firms competed when they did participate.

Pricing behavior Table 3 shows that reported wholesale prices rose significantly across all firm pairs, increasing by about \$0.40–\$0.50 (per 26 fl. oz. of reconstituted formula), while average net and winning bids fell by nearly a dollar—far exceeding the rise in reported wholesale prices. The decline was most pronounced in Abbott–MJ competition, where average winning bids dropped from \$0.546 to –\$0.484, with smaller declines in Abbott–Nestlé and MJ–Nestlé competition.

To verify that this pattern is not driven by differences in states or auction characteristics, Table 5 reports regressions of wholesale prices on an alleged-period indicator with fixed effects and controls. The results confirm a systematic wholesale price increase of roughly \$0.46–\$0.51 during the alleged period, robust to cost shifters and market size controls. Table 6 complements this analysis by focusing on winners' reported wholesale prices and winning bids, relative to Abbott–Nestlé competition in the benchmark period. In the baseline specifications (Models 1 and 3, with only state/alliance fixed effects), reported wholesale prices for winners in Abbott–MJ and MJ–Nestlé competition rose by about \$0.30–\$0.34, while winning bids fell sharply by roughly \$0.56–\$0.58, both highly significant. Once controls for input costs and market size are added (Models 2 and 4), these effects shrink but remain statistically significant: wholesale prices are higher by about \$0.09–\$0.13, while winning bids are lower by about \$0.12. Overall, the regression evidence reinforces a consistent pattern of rising wholesale prices coupled with falling net bids, even after accounting for observable cost and market factors.

To interpret this pattern, it is important to clarify the role of the reported wholesale price in the bidding process. The figure listed on the bid sheet—the "lowest national wholesale price"—is not necessarily the price any retailer actually pays, nor is it directly enforceable in the non-WIC market. Instead, it serves

primarily as an accounting input to the net bid calculation. This design, however, might create scope for misreporting: by inflating the reported wholesale benchmark, firms can present larger rebates on paper and potentially anchor higher charges in the more profitable non-WIC retail market, all while leaving the effective net bid unchanged.[14]

What makes the results puzzling, however, is the coexistence of increased wholesale prices with sharply lower net bids. If firms were colluding, one would expect them to take advantage of higher wholesale prices by offering only moderate rebates—enough to satisfy WIC agencies but without eroding margin. Instead, net bids fell by much more than the increase in wholesale prices, indicating that firms competed aggressively on the rebates that determined contract awards.

Table 5: Effect of Alleged Period on Wholesale Prices

	Dep. Var: Wholesale Price	
	(1)	(2)
Main variables		
Alleged	0.485***	0.508***
	(0.022)	(0.051)
Controls		
Capacity, Distance	No	Yes
Main Input Prices	No	Yes
Market Size (WIC/Non-WIC)	No	Yes
Incumbent	No	Yes
Fixed Effects		
State/Alliance FE	Yes	Yes
Bidder FE	Yes	Yes
Observations	227	227
R^2	0.762	0.792

Notes: Standard errors clustered at the auction level are reported in parentheses. "Main Input Prices" include nonfat milk, lactose, oils, and whey protein prices. All bid values are expressed in dollars per 26 fl. oz. of reconstituted formula.
Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

A natural concern is that the decline in winning bids could simply reflect changes in bidder composition. During the alleged period, Abbott and MJ almost never competed in isolation—there was only one two-bidder auction—so nearly all of their interaction took place in three-bidder settings with Nestlé

[14]Figure D2 indicates that reported wholesale price changes did not closely track the main observable input costs. During the alleged period, wholesale prices rose slightly even as input prices declined (see Figure D2). The Producer Price Index for "Processed Foods and Feeds: Fat Free or Skim Milk" (FRED series WPU02310303) also displays a marked downturn beginning in 2015, often attributed to a global oversupply of milk following the removal of EU milk quotas in April 2015 and continued strong U.S. production. Of course, infant formula production relies on a wide range of ingredients and inputs beyond dairy proteins, and it is possible that increases in some of these other costs offset the decline in dairy prices, contributing to higher reported wholesale prices.

Table 6: Effect of Alleged Period on Winner's Reported Wholesale Prices and Winning Bids by Rivalry

Dep. Var:	**Winner Wholesale Price**		**Winning Bid**	
	(1)	(2)	(3)	(4)
Main variables				
Alleged × (MJ, Nestlé)	0.338***	0.127***	−0.556***	−0.121***
	(0.040)	(0.039)	(0.080)	(0.045)
Alleged × (Abbott, MJ)	0.302***	0.090***	−0.581***	−0.117***
	(0.038)	(0.030)	(0.084)	(0.043)
Controls				
Market Size (WIC/Non-WIC)	No	Yes	No	Yes
Main Input Prices	No	Yes	No	Yes
Fixed Effects				
State/Alliance FE	Yes	Yes	Yes	Yes
Observations	193	193	193	193
R^2	0.503	0.720	0.654	0.848

Notes: Standard errors clustered at the auction level are reported in parentheses. The omitted category is Abbott–Nestlé competition in the competitive benchmark period. For wholesale prices and winning bids, Model (1) includes only state/alliance fixed effects, while Model (2) adds controls for WIC and non-WIC market size and main input prices (nonfat milk, lactose, oils, and whey protein). All bid values are expressed in dollars per 26 fl. oz. of reconstituted formula.
Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

present (Table E2). If Nestlé's entry systematically pushed bids downward, then the observed decline might reflect its more frequent participation rather than a shift in competition between Abbott and MJ. Table 7 evaluates this possibility and shows that, once input costs, bidder characteristics, contract size, and state/alliance fixed effects are accounted for, Nestlé's presence does not have a statistically significant impact on Abbott's or MJ's bids. The most consistent result is that bids were systematically lower in the alleged period, regardless of Nestlé's entry, which rules out Nestlé's participation as the main driver of lower bids.

The role of incumbency in contract retention Having established how participation and pricing evolved across periods, we now examine how incumbency shaped outcomes. Table 8 reports retention rates, average reported wholesale prices, and average winning bids by firm and period, distinguishing between incumbent and non-incumbent victories.

Incumbent retention rates were high in both periods. Conditional on holding the previous contract, the probability of retaining it was 47.6% for Abbott, 66.7% for MJ, and 76.9% for Nestlé during the competitive benchmark, compared with 63.6%, 73.3%, and 55.6%, respectively, during the alleged collusive period. These figures suggest that incumbency is associated with a substantial advantage in WIC auctions.

At first glance, one might worry that the high retention rates reflect collusive coordination, with

Table 7: Effect of Nestlé Participation on Bids

	Dep. Var: Bid	
	(1)	(2)
Main variables		
Alleged Period	−1.050***	−0.439*
	(0.177)	(0.229)
Nestlé Present	−0.235**	0.021
	(0.113)	(0.147)
Alleged × Nestlé Present	0.136	−0.215
	(0.195)	(0.210)
Controls		
Capacity, Distance	No	Yes
Main Input Prices	No	Yes
Market Size (WIC/Non-WIC)	No	Yes
Incumbent	No	Yes
Fixed Effects		
State/Alliance FE	Yes	Yes
Bidder FE	Yes	Yes
Observations	164	164
R^2	0.566	0.644

Notes: Standard errors clustered at the auction level are reported in parentheses. "Main Input Prices" include nonfat milk, lactose, oils, and whey protein prices. The sample is restricted to bids submitted by Abbott and MJ. All bid values are expressed in dollars per 26 fl. oz. of reconstituted formula.
Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

incumbents retaining contracts because rivals refrained from bidding aggressively. If this were the case, incumbents should consistently win with higher net bids, since they could hold on without offering large rebates. Table 8, however, shows no such pattern. In both periods, incumbents' average winning bids were not systematically higher than those of non-incumbents; indeed, during the alleged period, incumbents often prevailed with lower bids (e.g., Abbott at $–0.431 vs. $–0.301 for non-incumbent wins, and MJ at $–0.257 vs. $0.195). At the same time, and consistent with the results above, reported wholesale prices were uniformly higher in the alleged period for all bidders. These patterns suggest that while incumbents retained a strong advantage, it was not sustained through rivals' forbearance. Instead, incumbents often had to undercut competitors to retain contracts.

We examine this relationship more formally by estimating regressions of reported wholesale prices and winning bids on incumbency status and the alleged-period indicator. Table 9 reports the results: reported wholesale prices rose by about $0.53 in the alleged period, while winning bids fell by roughly $0.46, both highly significant. Incumbency alone has no effect on wholesale prices or winning bids in

Table 8: Incumbent Retention Rates, Average Wholesale Prices, and Winning Bids by Firm and Period

			Avg. Wholesale Price		Avg. Winning Bid	
Period	**Bidder**	**Retention Rate (%)**	**Non-Incumbent**	**Incumbent**	**Non-Incumbent**	**Incumbent**
Competitive (2003–2013)	Abbott	47.619	4.009	4.089	0.506	0.512
	MJ	66.667	4.118	4.219	0.608	0.547
	Nestlé	76.923	4.102	4.063	0.486	0.596
Alleged (2016–2021)	Abbott	63.636	4.429	4.513	−0.301	−0.431
	MJ	73.333	4.539	4.512	0.195	−0.257
	Nestlé	55.556	4.679	4.785	0.076	−0.568

Notes: Retention rate is the percentage of contracts won by the previous incumbent (i.e., the probability of winning conditional on holding the prior contract). Average wholesale prices and winning bids are reported separately for cases in which the non-incumbent wins and the incumbent wins. For example, during the competitive period, when Abbott won as a non-incumbent, the average wholesale price was \$4.009 and the average winning bid was \$0.506. All values are expressed in dollars per 26 fl. oz. of reconstituted formula.

the benchmark period, but the interaction term indicates that incumbents' bids declined by an additional \$0.34 in the alleged period. Thus, in line with the descriptive evidence presented above, all bidders lowered their bids during the alleged period, with incumbents cutting theirs even more sharply.

Table 9: Effect of Alleged Period and Incumbency on Wholesale Prices and Winning Bids

	Wholesale Price	**Winning Bid**
	(1)	(1)
Main variables		
Incumbent	0.004	0.082
	(0.018)	(0.109)
Alleged Period	0.526***	−0.458***
	(0.055)	(0.168)
Incumbent × Alleged	−0.043	−0.342**
	(0.047)	(0.165)
Controls		
Capacity, Distance	Yes	Yes
Market Size (WIC/Non-WIC)	Yes	Yes
Main Input Prices	Yes	Yes
Fixed Effects		
State/Alliance FE	Yes	Yes
Bidder FE	Yes	Yes
Observations	227	90
R^2	0.794	0.846
Within R^2	0.756	0.741

Notes: Standard errors clustered at the auction level are reported in parentheses. "Main Input Prices" include nonfat milk, lactose, oils, and whey protein prices. All bid values are expressed in dollars per 26 fl. oz. of reconstituted formula. Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

Taken together, even as Abbott and MJ's participation declined, we find no evidence that competition softened in a manner consistent with collusion. Reported wholesale prices did rise, but winning bids in their head-to-head competition fell more sharply during the alleged period, both in simple comparisons

and in regressions that account for market and cost conditions. This stands in direct contrast to the classic collusion narrative in procurement auctions, where reduced entry is typically associated with higher winning bids (see, for example, De Leverano (2019)). Moreover, incumbents retained an advantage, yet not because rivals held back; rather, they had to undercut competitors to keep contracts. Overall, the descriptive evidence does not support the FTC's allegation. We next turn to formal collusion screens that provide direct statistical tests of whether observed bidding behavior departs from competitive benchmarks.

5 Screens for Collusion

We apply a series of well-established collusion screens to WIC infant formula auctions, implementing each test separately for a competitive benchmark period and the alleged collusive period. The logic of our approach is straightforward: screens should not reject the hypothesis of competition during the benchmark period but should signal collusion if the alleged period exhibits noncompetitive conduct.

Our focus is on screens designed to capture two collusive strategies: bid rotation, in which firms avoid head-to-head competition by allocating wins, and cover bidding, in which losing bids are submitted without any intention of winning. The regression discontinuity design of Kawai et al. (2023) detects bid rotation by testing whether incumbents disproportionately win contracts in near-tie auctions. The tests of Porter and Zona (1993) capture cover bidding by examining whether alleged colluders submit bids that are less responsive to cost shifters (Level Test) or whether bid ranks systematically diverge from cost rankings (Rank Test). Screens proposed in Huber and Imhof (2019) and Clark et al. (2025) provide complementary evidence by identifying anomalous patterns in the dispersion and shape of the bid distribution that may result from cover bidding. By focusing on these targeted screens, we sharpen our analysis to the dimensions of collusion most consistent with the allegations in this market.

5.1 Kawai et al. (2023)

5.1.1 Overview

Kawai et al. (2023) develop a regression discontinuity (RD) design to detect collusive bid rotation. In such schemes, cartels often rotate winners or favor incumbents to allocate projects, leading incumbents to win disproportionately more often than non-incumbents. However, similar patterns may also emerge under competition: incumbents may have genuine cost advantages—such as established supplier networks or lower distribution costs—that enable them to bid more aggressively and secure contracts without

collusion.

The RD approach distinguishes between these explanations by testing for discontinuities in the distribution of economically relevant bidder characteristics (e.g., backlog, incumbency status) around marginal winners and losers. The key intuition is that when bids are nearly tied, outcomes should be "as-if random." Under competition, incumbents should be marginal winners roughly half the time and marginal losers the other half. By contrast, if a bidding ring allocates contracts to incumbents, incumbents will appear disproportionately as marginal winners. This logic extends to other bidder characteristics as well.

5.1.2 Implementation and Results

In their applications to Ohio school milk and Japanese municipal procurement auctions, Kawai et al. (2023) use incumbency status and backlog as outcome variables, reflecting the dimensions along which collusion was suspected. In the WIC infant formula setting—and consistent with the FTC's concern that incumbent contract holders may have avoided bidding against one another—we focus on incumbency status as the outcome variable.[15] Formally, the test statistic used to detect potential collusion is defined as

$$\beta = \lim_{\Delta^1_{i,a} \searrow 0^+} \mathbb{E}[Y_{i,a} \mid \Delta^1_{i,a}] - \lim_{\Delta^1_{i,a} \nearrow 0^-} \mathbb{E}[Y_{i,a} \mid \Delta^1_{i,a}], \tag{1}$$

where $Y_{i,a}$ denotes the outcome variable of interest—in our case, whether bidder i is the incumbent in auction a—and $\Delta^1_{i,a}$ is the running variable, defined as the difference between bidder i's bid and the lowest rival bid in auction a:

$$\Delta^1_{i,a} = b_{i,a} - \wedge \mathbf{b}_{-i,a}, \tag{2}$$

with $b_{i,a}$ denoting the bid of firm i in auction a, and $\wedge \mathbf{b}_{-i,a}$ the minimum bid submitted by all rivals. Intuitively, the test examines whether incumbents are disproportionately likely to win when $\Delta^1_{i,a}$ is close to zero; a significant discontinuity at this point provides evidence against competitive bidding.

To estimate β, we use a local linear regression as in Kawai et al. (2023):

$$\hat{\beta} = \hat{b_0^+} - \hat{b_0^-}, \tag{3}$$

[15] In addition to incumbency status, we also examined backlog levels and distance as alternative outcomes. As reported in Tables G6–G9, the null hypothesis of $\beta = 0$ cannot be rejected in any case.

with

$$(\hat{b_0^+}, \hat{b_1^+}) = \arg\min \sum_{i,a} (Y_{i,a} - \hat{b_0^+} - \hat{b_1^+}\Delta_{i,a}^1)^2 \mathbf{K}\left(\frac{\Delta_{i,a}^1}{h_n}\right) \mathbb{1}_{\Delta_{i,a}^1 > 0} \tag{4}$$

$$(\hat{b_0^-}, \hat{b_1^-}) = \arg\min \sum_{i,a} (Y_{i,a} - \hat{b_0^-} - \hat{b_1^-}\Delta_{i,a}^1)^2 \mathbf{K}\left(\frac{\Delta_{i,a}^1}{h_n}\right) \mathbb{1}_{\Delta_{i,a}^1 < 0}, \tag{5}$$

where $\mathbf{K}$ is the kernel, and h_n is the bandwidth. We pool across bidder i and auction a when estimating $\hat{\beta}$. For the baseline estimates, we use a coverage error rate optimal bandwidth and a triangular kernel with a bias correction procedure as proposed in Calonico et al. (2014). We implement the RD test separately for the competitive and alleged collusive periods. The null hypothesis is $H_0 : \beta = 0$; rejection provides evidence against competition, with a negative discontinuity indicating that incumbents win near-tied auctions more often than expected.[16]

Table 10 reports the main RD estimates with standard errors clustered at the auction level. In the competitive period, the estimated discontinuity is negative but small and statistically insignificant ($\hat{\beta} = -0.202$, p-value $= 0.399$), indicating no evidence that incumbents were disproportionately more likely to be marginal winners than marginal losers, as expected under competition. In the alleged collusive period, the point estimate switches sign ($\hat{\beta} = 0.506$, p-value $= 0.249$), implying incumbents were, if anything, less likely to win near-tie auctions. Overall, these results provide no statistically significant evidence of collusive favoritism toward incumbents, though the estimates are imprecise, as reflected in the large standard errors. Full results, including conventional and bias-corrected estimates and bandwidth details, are reported in Tables G10–G11.

Table 10: Regression Discontinuity Estimates of Incumbency Status

	Competitive Period	**Alleged Period**
$\hat{\beta}$	−0.202	0.506
	(0.240)	(0.439)
Bandwidth h	0.440	0.432
p-value	0.399	0.249
95% C.I.	[−0.671, 0.268]	[−0.354, 1.367]
Observations	143	75

Notes: Robust estimates from local linear RD using a triangular kernel at cutoff $c = 0$ with bid difference as the running variable. Robust standard errors clustered at the auction level are reported in parentheses.

[16]From the definition of β in (1), the right-hand limit ($\Delta_{i,a}^1 \searrow 0^+$) corresponds to marginal losers, while the left-hand limit ($\Delta_{i,a}^1 \nearrow 0^-$) corresponds to marginal winners. Equivalently, $\beta = \Pr(\text{incumbent} \mid \text{loser near tie}) - \Pr(\text{incumbent} \mid \text{winner near tie})$. If incumbents are systematically favored, the probability of being an incumbent is higher for marginal winners than for marginal losers, which implies $\beta < 0$.

5.1.3 Discussion

The RD test provides an intuitive way to assess whether incumbents disproportionately secure marginal victories, which would be consistent with collusive bid allocation. In our setting, however, the estimates are imprecise, particularly during the alleged collusive period, where the sample size is smaller ($N = 75$ vs. $N = 143$ in the competitive period). The wide confidence intervals suggest that the test may lack statistical power to detect favoritism toward incumbents. This limitation is evident when compared to Kawai et al. (2023), who apply the same test to Ohio school milk auctions with 266 observations—the smallest of their samples—and to Japanese municipal procurement auctions with roughly 60,000 observations. Relative to these applications, the WIC dataset is far more limited, which might constrain the precision of our estimates.

To further examine this issue, we conducted a Monte Carlo simulation tailored to the WIC auction structure. The exercise varied the share of collusive auctions from 0% to 100% and evaluated the rejection frequency of the RD test. The results, reported in Figure G3, confirm that the RD design can detect systematic bid rotation when collusion is prevalent. However, statistical power declines sharply as the share of competitive auctions increases, and rejection rates remain sensitive to bandwidth choice in small samples.

Moreover, the RD test targets bid rotation. In practice, such schemes are typically sustained through cover bidding, whereby rivals submit losing bids at inflated levels to preserve the appearance of competition. To capture this complementary dimension of collusion, we supplement the RD test with regression- and distribution-based screens designed to detect cover bidding, including those developed by Porter and Zona (1993), Huber and Imhof (2019), and Clark et al. (2025).

5.2 Porter and Zona (1993)

5.2.1 Overview

Porter and Zona (1993) propose two econometric procedures—the Level Test and the Rank Test—to detect cover bidding in procurement auctions. The Level Test examines whether firms' bids respond to cost-related variables in a manner consistent with competition. In their application, Porter and Zona (1993) exploited information on suspected cartel members to compare the bidding behavior of collusive firms with that of competitive firms. If cartel bids are genuine, their determinants should resemble those of competitive bids, whereas cover bids submitted with no intention of winning will not respond

systematically to cost factors. To test this, they estimate three models—using all bids, only competitive bids, and only cartel bids—and apply a Chow test to evaluate whether the coefficients are equal across groups.

The Rank Test builds on the intuition that under competition, bid rankings should correspond to cost rankings: the lowest-cost firm should typically submit the lowest bid, the next-lowest-cost firm should submit the second-lowest bid, and so on. In this case, observable cost-related variables should consistently explain why some bids are lower and others higher across the distribution. Under collusion, however, this alignment breaks down. The designated winning bid may still reflect underlying costs, but cover bids are chosen strategically to lose and thus need not respond systematically to cost factors. Porter and Zona (1993) implement this test by examining how observable variables affect the probability of submitting the lowest bid versus a higher-ranked bid, separately for competitive and suspected cartel firms. Systematic differences across groups provide evidence consistent with cover bidding.

5.2.2 Implementation and Results

Level Test Porter and Zona (1993) implement the Level Test by contrasting the bidding behavior of identified cartel members with that of competitive firms. In our context, we lack prior knowledge of which bidders may have colluded. We therefore adapt the approach by comparing behavior across two periods: a competitive benchmark and an alleged collusive period. The underlying intuition is the same: under competition, bids should respond systematically to observable cost drivers, whereas under collusion these relationships may weaken or disappear. In addition, because the traditional Chow test used by Porter and Zona (1993) assumes homoskedastic, i.i.d. errors, it is not appropriate for our setting, where bids from the same auction are likely to have correlated errors. To account for this dependence, we instead implement a cluster-robust Wald test by stacking the two samples and estimating a pooled regression with interaction terms.

We also tailor the Level Test to the FTC's allegation concerning incumbents' bidding behavior. Specifically, we estimate

$$b_{ia} = \alpha_a + \gamma_i + \theta \,\text{Incumbent}_{ia} + \eta \left(\text{Alleged}_a \times \text{Incumbent}_{ia}\right) + \mathbf{Z}_{ia}^{\top}\boldsymbol{\beta} + \varepsilon_{ia}, \tag{6}$$

where b_{ia} is firm i's bid in auction a, α_a are auction fixed effects, and γ_i are bidder fixed effects. The coefficient θ captures the effect of incumbency in the competitive benchmark, while η is the coefficient of interest, indicating whether this effect shifts during the alleged collusive period. The vector $\mathbf{Z}_{ia}$

contains both bidder- and rival-specific cost shifters. Bidder-level variables include the wholesale price, the logarithm of the bidder's distance to the auctioning state, and the bidder's production capacity. Rival-level variables include the minimum distance among rival plants and the maximum rival production capacity. The error term is represented by ε_{ia}.

The test therefore asks whether the role of incumbency in shaping bids changed across periods. Under competition, incumbency may confer cost advantages, but its influence should remain stable absent changes in market fundamentals. Once auction fixed effects, bidder fixed effects, and observable cost shifters are accounted for, any residual change in the incumbency effect would be difficult to reconcile with competitive behavior.

Table 11 reports the adapted Level Test results. In the competitive benchmark, incumbents submit significantly lower bids than non-incumbents, consistent with an incumbency advantage. The interaction between incumbency and the alleged collusive period is negative but statistically insignificant, indicating no systematic change in incumbent bidding behavior. Overall, we find little support for the FTC's allegation that incumbents avoided bidding aggressively. Robustness checks using wild cluster bootstrap-t confidence intervals (Table G12) also confirm that the effect is not statistically significant.

Table 11: Adapted Level Test Results

	Dep. Var: Bid
Main variables	
Incumbent	−0.231***
	(0.085)
Incumbent × Alleged	−0.154
	(0.146)
Controls	
Capacity, Distance	Yes
Rival Capacity, Rival Distance	Yes
Wholesale Price	Yes
Fixed Effects	
Auction FE	Yes
Bidder FE	Yes
Observations	218
R^2	0.720

Notes: Standard errors clustered at the auction level are reported in parentheses.
Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

Rank Test As in the Level Test, we examine whether the relationship between bidder characteristics and bid ranks shifts during the alleged collusive period relative to the competitive benchmark. Under competition, bid ranks should be systematically related to cost-based variables such as wholesale price, distance, capacity, and incumbency status. By contrast, if some bids are cover bids submitted without any intention of winning, their ranking will no longer reflect underlying cost conditions.

Formally, consider auctions indexed by $a = 1, \ldots, A$, each with $\mathcal{I}_a$ participating bidders. For bidder i in auction a, let $\mathbf{Z}_{ia}$ denote a vector of bidder-specific cost shifters. Let $r_m(a)$ denote the bidder submitting the mth lowest bid in auction a. The probability of observing a complete ranking of bids follows the Plackett–Luce (rank-ordered logit) form:

$$P\big(r_1(a) < r_2(a) < \cdots < r_{\mathcal{I}_a}(a)\big) = \prod_{m=1}^{\mathcal{I}_a} \frac{\exp\big(\beta^\top \mathbf{Z}_{r_m(a),a}\big)}{\sum_{j=m}^{\mathcal{I}_a} \exp\big(\beta^\top \mathbf{Z}_{r_j(a),a}\big)}. \tag{7}$$

Aggregating over all auctions yields the likelihood function, and taking logs gives the sample log-likelihood:

$$\ell(\beta) = \sum_{a=1}^{A} \sum_{m=1}^{\mathcal{I}_a} \left[\beta^\top \mathbf{Z}_{r_m(a),a} - \log\left(\sum_{j=m}^{\mathcal{I}_a} \exp\big(\beta^\top \mathbf{Z}_{r_j(a),a}\big) \right) \right]. \tag{8}$$

Porter and Zona (1993) show that the rank likelihood in (7) can be decomposed into two components: (i) the probability of observing the lowest-ranked (winning) bid and (ii) the probability of the ordering among the remaining bids. This motivates three estimators:

1. *All-ranks model:* estimate β from the full likelihood,

$$\ell_{\text{all}}(\beta) = \ell(\beta).$$

2. *Lowest-only model:* focus only on the winning bidder,

$$\ell_{\text{low}}(\beta) = \sum_{a=1}^{A} \left[\beta^\top \mathbf{Z}_{r_1(a),a} - \log\left(\sum_{j=1}^{\mathcal{I}_a} \exp\big(\beta^\top \mathbf{Z}_{r_j(a),a}\big) \right) \right],$$

   which corresponds to a conditional logit for the winner.

3. *Higher-only model:* focus on the ordering among non-winning bids,

$$\ell_{\text{high}}(\beta) = \sum_{a=1}^{A} \sum_{m=2}^{\mathcal{I}_a} \left[\beta^\top \mathbf{Z}_{r_m(a),a} - \log\left(\sum_{j=m}^{\mathcal{I}_a} \exp\big(\beta^\top \mathbf{Z}_{r_j(a),a}\big) \right) \right].$$

Each model is estimated by maximum likelihood. To test whether bidder characteristics explain ranks in the same way for winning and non-winning bids, we compute a likelihood ratio statistic:

$$LRT = -2\left[\ell_{\text{all}}(\hat{\beta}) - \left(\ell_{\text{low}}(\hat{\beta}) + \ell_{\text{high}}(\hat{\beta})\right)\right],$$

where $\ell_{\text{all}}(\hat{\beta})$, $\ell_{\text{low}}(\hat{\beta})$, and $\ell_{\text{high}}(\hat{\beta})$ are the maximized log-likelihood values from the all-ranks, lowest-only, and higher-only models, respectively. Note that the rank-based test requires variation in ranks to be meaningful. If an auction has only one bidder, there is no ranking to model. With two bidders, we observe only a winner and a single loser, so there is no ordering among higher-order bids. Accordingly, we restrict the sample to auctions with at least three bidders.

Table 12 presents the results of the Rank Test. For both the competitive and alleged periods, the p-values (0.637 and 0.304, respectively) are far above conventional significance levels. Thus, we cannot reject the null hypothesis that bidder characteristics affect winning and non-winning bids in the same way. Put differently, we find no evidence that higher-order (non-winning) bids were less responsive to cost factors during the alleged collusive period.

Table 12: Porter–Zona Rank Test

Sample	LR statistic	df	p-value
Competitive	4.293	6	0.637
Alleged	7.190	6	0.304

Notes: The likelihood ratio test evaluates whether bidder characteristics affect winning and non-winning bids in the same way. The restricted model imposes a common set of coefficients across all ranks, while the unrestricted model allows separate coefficients for the lowest-ranked (winning) bid and higher-ranked bids. Covariates include wholesale price, log(distance), capacity, rival capacity, log(rival distance), and incumbency status.

5.2.3 Discussion

While the tests in Porter and Zona (1993) provide valuable insights by linking bids to observable cost shifters and rank orderings, they remain regression-based and hinge on the correct specification of bidder-level covariates. Moreover, these tests can miss certain collusive strategies. For instance, if cartel members simply scale their competitive bids upward by the same percentage, their rank orderings would remain unchanged, allowing them to pass the Rank Test undetected. To broaden the analysis beyond

regression-based approaches, we next turn to statistical screens that focus directly on the distribution of bids, following Huber and Imhof (2019) and Clark et al. (2025).

5.3 Huber and Imhof (2019)

5.3.1 Overview

Huber and Imhof (2019) develop statistical screens that exploit the distribution of bids to detect deviations from competitive behavior. The intuition is straightforward: in competitive settings, bids reflect heterogeneous costs and strategies, producing a reasonable degree of dispersion. Under collusion, by contrast—particularly through practices such as cover bidding—bids often exhibit abnormal regularities, clustering too closely around the designated winner or showing unusually low variance. The screens in Huber and Imhof (2019) therefore focus on characteristics of the bid distribution—such as its spread and skewness—and compare these patterns across the competitive and alleged periods.

Not all of these screens are feasible in our setting, as some require at least four bidders, whereas WIC formula contract auctions involve at most three. We therefore focus on the subset of screens that can be implemented with two or three bidders. Specifically, we implement five: (i) Bid dispersion, capturing overall variation in submitted bids; (ii) Skewness, measuring asymmetry in the bid distribution that may signal an isolated winning bid; (iii) Absolute difference, the raw gap between the lowest and second-lowest bids; (iv) Relative difference, the same gap normalized by the standard deviation of losing bids; and (v) Normalized distance, the gap between the two lowest bids divided by the average spacing across all adjacent bids. The exact formulas for these measures are summarized in Table F5.

5.3.2 Implementation and Results

We compute these screens separately for the competitive and alleged collusive periods. Table 13 reports the summary statistics. The most notable change is that the relative difference is markedly lower in the alleged period (1.963 vs. 3.099), which may reflect a smaller gap between the winning and second-lowest bids, greater dispersion among losing bids, or a combination of the two. Bid dispersion and skewness are also slightly higher on average, while the other measures remain broadly similar across the two periods.

To formally assess whether the distributions differ, we employ a permutation-based test suited to small samples. The idea is as follows: if the two groups are drawn from the same underlying distribution, the assignment of observations to "competitive" or "alleged" is arbitrary. By repeatedly shuffling the

group labels and recalculating the difference in medians—a robust measure of central tendency under non-normality—we generate the distribution of differences that would be expected by chance. Comparing the observed difference to this reference distribution then allows us to determine whether the observed period differences are statistically meaningful rather than random fluctuations.

Table 13: Descriptive Statistics of Bidding Screens by Period

Period	Variable	Mean	Std. Dev.	Min	Max	Obs.
Competitive (2003–2013)	Bid dispersion	0.376	0.339	0.003	1.935	54
	Bid skewness	0.375	1.057	−1.724	1.731	35
	Absolute difference	0.394	0.486	0.004	2.736	54
	Relative difference	3.099	7.151	0.021	37.320	35
	Normalized distance	0.852	0.488	0.029	1.927	35
Alleged (2016–2023)	Bid dispersion	0.448	0.335	0.013	1.259	27
	Bid skewness	0.444	1.023	−1.678	1.698	21
	Absolute difference	0.396	0.375	0.019	1.587	27
	Relative difference	1.963	3.185	0.113	13.923	21
	Normalized distance	0.836	0.435	0.149	1.816	21

Notes: Table reports summary statistics for bidding-screen variables during the competitive period (2003–2013) and the alleged period (2016–2023). "Obs." denotes the number of auctions used in each calculation.

Table 14 reports the results of the permutation tests. For bid dispersion, the observed median difference is essentially zero, with the confidence interval including zero and a p-value of 1. For bid skewness, the median difference is positive but not statistically significant ($p = 0.682$). The absolute difference between the two lowest bids shows a very small positive difference across periods, again not significant ($p = 0.809$). For the relative difference and the normalized distance, the observed differences are slightly negative, but both confidence intervals span zero and p-values are far from conventional significance thresholds ($p = 0.688$ and $p = 0.686$, respectively). Overall, none of the five screens detect systematic differences in the distribution of bids between the competitive and alleged periods.

5.3.3 Discussion

While the screens in Huber and Imhof (2019) offer a model-free way to detect unusual bid dispersion, they focus on the overall distribution without distinguishing between winners and losers. By contrast, Clark et al. (2025) refine the approach by directly comparing gaps that involve the winning bid with those among losing bids. This distinction matters because collusion is most likely to distort the margin between the winner and runner-up, while leaving the distribution of losing bids relatively unaffected. We now

Table 14: Permutation Test Results Comparing Alleged vs. Competitive Bids

	Test Results			Sample Size	
Variable	**Obs. Median Diff.**	**95% CI**	**p-value**	**Competitive**	**Alleged**
Bid dispersion	0.0001	[−0.115, 0.249]	1	54	27
Bid skewness	0.230	[−0.745, 0.807]	0.682	35	21
Absolute difference	0.016	[−0.119, 0.163]	0.809	54	27
Relative difference	−0.158	[−0.522, 0.572]	0.688	35	21
Normalized distance	−0.085	[−0.300, 0.263]	0.686	35	21

Notes: Entries report two-tailed permutation tests (9,999 iterations) comparing bid characteristics between the competitive and alleged periods. Reported intervals are 95% bootstrap confidence intervals for the *median difference* (Alleged − Competitive). No test is statistically significant at $\alpha = 0.05$.

turn to the screen developed by Clark et al. (2025).

5.4 Clark et al. (2025)

5.4.1 Overview

Building on Chassang et al. (2022) and Kawai et al. (2023), Clark et al. (2025) propose a screening method for detecting collusion in settings with cover bidding. Their approach assumes that both bids and bid differences follow smooth distributions under the null of competition. In addition to the bid differences defined in (2), they construct a second set of bid differences that exclude the winning bids. The two distributions are then compared, with the intuition that under competition they should be approximately equivalent within a narrow interval around zero. The key insight is that while a cartel may strategically create a gap between the winning bid and the second-lowest bid, it has little incentive to manipulate the gap among losing bids. The screen can be implemented either parametrically or nonparametrically.

Although designed for settings with cover bidding, the screen of Clark et al. (2025) is flexible enough to capture a broader range of bid-rigging arrangements. It does so by comparing two bid-difference distributions within a narrow interval around zero, while also accounting for zeros that may arise when firms coordinate to submit tied or nearly identical bids.

5.4.2 Implementation and Results

We begin by constructing the second set of bid differences, denoted as $\Delta^2_{i,a}$, which excludes winning bids. These two sets of bid differences—$\Delta^1_{i,a}$, which includes all bids, and $\Delta^2_{i,a}$—form the sample used for the screening procedure. Under the assumption of competitive bidding, the null hypothesis is stated as follows: H_0: $\Delta^1_{i,a}|\Delta^1_{i,a} \in [-H, +H] = \Delta^2_{i,a}|\Delta^2_{i,a} \in [-H, +H]$, where $-H$ and $+H$ are the lower and

upper bound of the interval, respectively.

Because the screen is only informative in a small interval around zero, the choice of interval width H is crucial. If H is too small, too few observations remain and the test lacks power; if H is too large, the window admits outliers and undermines the smoothness assumption near the cutoff. To balance these concerns, we consider several candidate values of H and use descriptive statistics to guide a sensible choice.

Table 15 provides descriptive statistics for the distribution of bid differences. Relative to the competitive period, the alleged period shows a modest upward shift in central tendency (mean 0.168 vs. 0.109; median 0.185 vs. 0.077). The interquartile ranges—$[-0.187, 0.378]$ in the competitive period and $[-0.259, 0.498]$ in the alleged period—suggest that a window of about ±0.4 already captures the bulk of the data. Coverage calculations reinforce this point: within ±0.4, 63% of bids are preserved in the competitive period and 57% in the alleged period; expanding to ±0.6 increases coverage to 72% and 68%, respectively, and at ±0.8 the shares exceed 80% in both periods. These patterns indicate that most observations lie close to zero, motivating our focus on windows of ±0.4, ±0.6, and ±0.8 in the analysis.

Table 15: Summary Statistics of Bid Differences

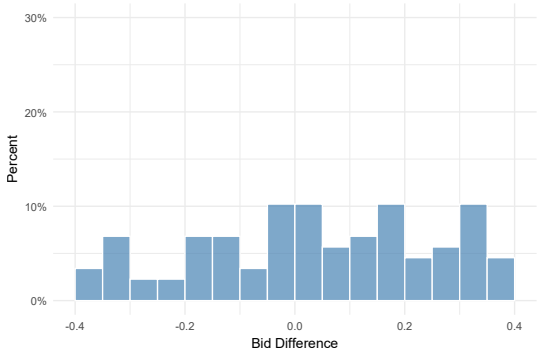
Period	N	Min	Q1	Median	Mean	Q3	Max
Competitive	213	−2.736	−0.187	0.077	0.109	0.378	2.736
Alleged	117	−1.805	−0.259	0.185	0.168	0.498	2.517

Clark et al. (2025) emphasize that clustered losing bids combined with isolated winning bids are hallmarks of cover bidding, which generates distinct differences between $\Delta^1_{i,a}$ and $\Delta^2_{i,a}$. To assess whether similar patterns emerge in our data, Figure 3 plots the distributions of bid differences in the competitive and alleged periods, using an interval of ±0.4 with bin width 0.05 as an illustrative example; additional figures in G4–G8 present results for alternative intervals and bin widths.

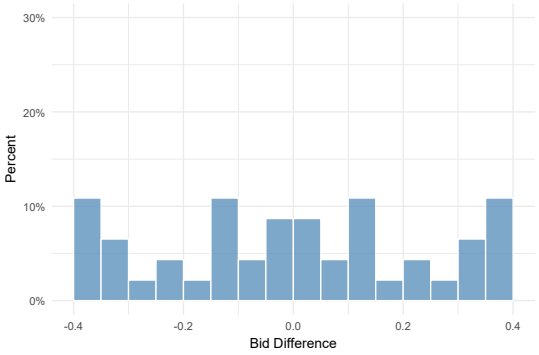
In the competitive period (panels a and b), both $\Delta^1_{i,a}$ and $\Delta^2_{i,a}$ are relatively flat and dispersed around zero, with clear mass at zero and no strong divergence between the two distributions. In the alleged period (panels c and d), by contrast, $\Delta^1_{i,a}$ shows reduced mass at zero and more clustering further away, while $\Delta^2_{i,a}$ exhibits a sharper dip around zero and heavier concentration at larger spacings. These contrasts suggest that the distribution of bid differences in the alleged period may differ from the competitive period. That said, sample sizes in the alleged period are quite limited (45 for $\Delta^1_{i,a}$ and 22 for $\Delta^2_{i,a}$). For $\Delta^1_{i,a}$ in particular, only a single observation falls in each of the two bins immediately adjacent to zero. Thus, the apparent "missing mass" near zero should be interpreted with caution.

Figure 3: Bid Difference Distributions

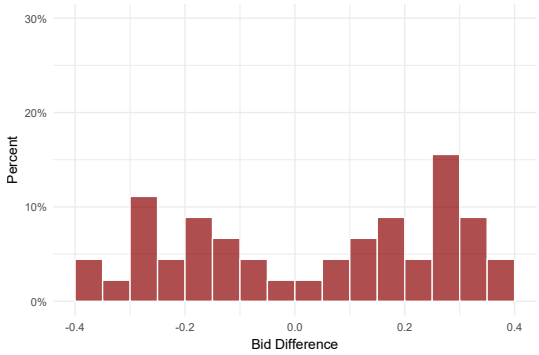
(a) Competitive Period: $\Delta^1_{i,a}$



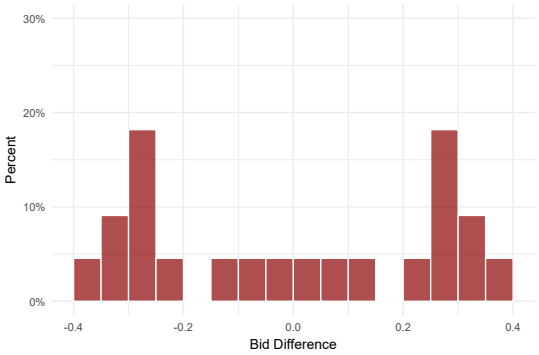
(b) Competitive Period: $\Delta^2_{i,a}$



(c) Alleged Period: $\Delta^1_{i,a}$



(d) Alleged Period: $\Delta^2_{i,a}$



Notes: Bid differences are measured in dollars per 26 fl. oz. of reconstituted formula. The interval of bid differences is ±0.4 and bin width is 0.05.

While these figures provide useful descriptive evidence, they cannot establish whether the observed contrasts are statistically meaningful. For this, we turn to formal testing. We employ the Kolmogorov–Smirnov (KS) test to compare the two bid-difference distributions separately within each period. A practical challenge is that the standard KS test relies on asymptotic properties, which may perform poorly with relatively small samples. To address this concern, we implement a permutation-based version of the two-sample KS test, similar to our approach for the screens in Huber and Imhof (2019). Under the null hypothesis that both groups are drawn from the same distribution, the assignment of observations to Δ^1 or Δ^2 is arbitrary. By repeatedly reassigning labels at random, we obtain an empirical p-value that provides more reliable inference in small samples than the standard asymptotic KS test.

We first implement the screen without additional controls, and the resulting nonparametric p-values are reported in Table 16. Across all window choices, the p-values remain large, suggesting that the null hypothesis of equal distributions cannot be rejected in either period.

Table 16: Nonparametric Implementation of the Screen

	Bid-difference window		
	$[-0.4, 0.4]$	$[-0.6, 0.6]$	$[-0.8, 0.8]$
Competitive	0.735	0.553	0.451
Alleged	0.885	0.575	0.407

Notes: Entries report permutation-based p-values from two-sample Kolmogorov–Smirnov tests comparing the Δ^1 and Δ^2 distributions across the competitive and alleged periods. Each test uses $B = 9{,}999$ random permutations of group labels.

For the parametric version of the screen, the distributions of $\Delta^1_{i,a}$ and $\Delta^2_{i,a}$ are discretized into Q intervals. Following Clark et al. (2025), we estimate a set of linear probability models:

$$y_{i,a,q} = \alpha_q + \gamma_q \mathbb{1}\{\Delta^1_{i,a}\} + \mathbf{Z}\beta + \varepsilon_{i,a,q}, \tag{9}$$

where $y_{i,a,q}$ equals 1 if $\Delta^1_{i,a}$ lies in interval q and 0 if it lies outside interval q but within $[-H, H]$. The variable $\mathbb{1}\{\Delta^1_{i,a}\}$ is an indicator that equals 1 if the observation is drawn from $\Delta^1_{i,a}$ and 0 if it is drawn from $\Delta^2_{i,a}$. The vector $\mathbf{Z}$ contains covariates such as auction and bidder characteristics. We test the null hypothesis of equal distributions using two-sided t-tests, with standard errors clustered at the auction level.

When applying the test parametrically, we focus first on the interval ± 0.4, which we partition into eight equal-sized subintervals, each of width 0.1 per 26 fl. oz. Because no bids in the sample are exactly

tied, there is no separate bin for zero. The upper panel of Table 17 reports results for the competitive period, and the lower panel reports results for the alleged period. In both cases, most coefficients on the indicator variable $\mathbb{1}f(\Delta^1_{i,a})$ are small and statistically insignificant, suggesting that the two bid-difference distributions are approximately equivalent within this window. To conserve space, results for the wider intervals (±0.6 and ±0.8) are reported in Tables G13 and G14.

Table 17: Parametric Implementation of the Screen in Clark et al. (2025)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var	Pr[−0.4, −0.3]	Pr(−0.3, −0.2]	Pr(−0.2, −0.1]	Pr(−0.1, 0]	Pr(0, 0.1]	Pr(0.1, 0.2]	Pr(0.2, 0.3]	Pr(0.3, 0.4]
Competitive Period (N = 134)								
$\mathbb{1}\{\Delta^1_{i,a}\}$	−0.072	−0.020	0.006	0.006	0.029	0.040	0.037	−0.026
	(0.059)	(0.046)	(0.050)	(0.056)	(0.054)	(0.055)	(0.043)	(0.063)
Constant	0.174***	0.065*	0.130**	0.130**	0.130**	0.130**	0.065*	0.174***
	(0.050)	(0.036)	(0.047)	(0.047)	(0.047)	(0.047)	(0.036)	(0.050)
R^2	0.010	0.002	0.000 07	0.000 07	0.001	0.003	0.004	0.001
Controls	NO	NO	NO	NO	NO	NO	NO	NO
Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO
Alleged Period (N = 67)								
$\mathbb{1}\{\Delta^1_{i,a}\}$	−0.070	−0.072	0.110*	−0.024	−0.024	0.110*	−0.027	−0.003
	(0.076)	(0.084)	(0.057)	(0.077)	(0.077)	(0.057)	(0.089)	(0.088)
Constant	0.136*	0.227**	0.045	0.091	0.091	0.045	0.227**	0.136*
	(0.069)	(0.078)	(0.045)	(0.060)	(0.060)	(0.045)	(0.078)	(0.069)
R^2	0.013	0.008	0.025	0.002	0.002	0.025	0.001	0.000 02
Controls	NO	NO	NO	NO	NO	NO	NO	NO
Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO

Notes: Each column reports results from a linear probability model where the dependent variable equals one if the observation falls in the indicated bid-difference bin (width 0.1, overall window ±0.4). $\mathbb{1}f(\Delta^1_{i,a})$ is an indicator that equals 1 if the observation is from $\Delta^1_{i,a}$. Reported coefficients are for $\mathbb{1}\{\Delta^1_{i,a}\}$ (top row) and the constant (baseline probability, second row). Standard errors clustered at the auction level are in parentheses. Significance levels: $^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

We also implement the screen including additional controls. Tables G15 and G16 report the results for the nonparametric and parametric tests, respectively, after controlling for bidder capacity, distance, the number of WIC and non-WIC infants, and prices of key formula inputs. In addition, we include year and bidder fixed effects in the estimations. Once these controls are incorporated, the null hypothesis of competition is not rejected in either specification.

5.4.3 Discussion

As previously noted, the screen proposed by Clark et al. (2025) relies on the assumption that bids and bid-difference distributions exhibit smoothness under competition. The authors suggest that this assumption holds in contexts such as first-price sealed-bid auctions with symmetric bidders and independent private values, where bidders' costs are drawn independently and identically from a distribution within the same bounded interval. However, if bidders' costs originate from significantly different distributions, the bid-difference distributions Δ^1 and Δ^2 may not be smooth, rendering the screen inapplicable.

In our analysis, it is reasonable to assume that the bid smoothness condition is satisfied. As illustrated in Table 2, reported wholesale prices are highly similar across bidders in the infant formula market, indicating minimal variation in their manufacturing costs. Furthermore, the primary inputs used in producing baby formula are standardized, and products in this industry have remained largely unchanged for decades. Therefore, it is unlikely that the cost distributions among bidders vary dramatically, supporting the validity of the smoothness assumption in this context.

6 Conclusion

This paper investigates whether infant formula manufacturers colluded in bidding for WIC contracts, as alleged by the FTC. Using auction data from 2003–2021, we compare a competitive benchmark period (2003–2013) with the alleged collusive period (2016–2021) and evaluate bidder behavior through both descriptive evidence and formal collusion screens.

During the alleged period, reported wholesale prices were higher for all bidders, but rebates rose even more sharply, pushing average bids close to zero and often into negative territory. Although elevated wholesale prices could, in principle, facilitate collusion by anchoring higher prices in the non-WIC market, colluding firms would have little reason to pair them with such large rebates. The combination instead points to continued rivalry over the rebate margin that determined contract awards. Moreover, while Abbott and MJ entered fewer auctions, competition intensified when they did: head-to-head bids fell rather than rose, and incumbents retained contracts by undercutting challengers rather than benefiting from rivals' restraint. Taken together, these patterns are difficult to reconcile with the notion of market allocation through reduced competition.

To complement this descriptive analysis, we implement a suite of state-of-the-art collusion screens that target behaviors central to the FTC's allegation—namely, bid rotation and cover bidding. These include the regression discontinuity approach of Kawai et al. (2023), the regression-based tests of Porter and Zona (1993), and the distributional methods of Huber and Imhof (2019) and Clark et al. (2025). Importantly, we apply each screen separately to the competitive and alleged collusive periods, and across all tests, we find little evidence of coordinated bidding in WIC contract auctions during the alleged collusive period. Nonetheless, these findings should be interpreted with caution: the relatively small number of auctions limits the statistical power of the tests, leaving open the possibility that collusion, if present, went undetected.

Finally, as the FTC has noted, any coordinated conduct in this industry would likely have been more profitably directed toward the non-WIC segment of the market. Because manufacturers earn the bulk of their profits from non-WIC sales—where formula is sold at full price without rebates—collusive gains would most plausibly stem from raising the actual wholesale prices charged to retailers, which lie outside the WIC program's oversight. If such coordination had occurred, higher actual wholesale prices would be expected to pass through to consumers in the form of higher retail prices. Yet recent evidence indicates that, after adjusting for inflation, the average price of milk-based powder formula remained broadly stable between 2013 and 2020 and then declined by about 11 percent, from $6.15 per 26 reconstituted fl. oz. in 2020 to $5.48 in 2023 (U.S. Government Accountability Office, 2025). This sustained stability, followed by a marked decline, is difficult to reconcile with collusion, which would typically lead to higher prices.

Overall, the combined evidence—both from our analysis and from price patterns in the broader formula market—suggests that the WIC infant formula auctions remained largely competitive during the alleged period.

Appendix A Multi-State Alliances

There are six multi-State alliances during the study period:

- The Western States Contracting Alliance (WSCA) is comprised of 14 States (Alaska, Arizona, Delaware, Hawaii, Idaho, Kansas, Maryland, Montana, Nevada, Oregon, Utah, Washington, West Virginia, and Wyoming), the District of Columbia, 4 territories (American Samoa, Guam, the Virgin Islands, the Commonwealth of the Northern Mariana Islands), and three Indian Tribal Organizations (ITO).
- The New England and Tribal Organization (NEATO) is comprised of five States (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island), and two ITOs. In October 2008, one of the ITOs, Chicksaw, left NEATO. The former NEATO states remained the same. Vermont joined NEATO starting with 2021 Contract.
- The Mountain Plains Region is comprised of three States (Missouri, Nebraska, and South Dakota). North Dakota joined this alliance starting with 2021 contract.
- The Southwest/Southeast Region is comprised of three States (Arkansas, New Mexico, and North Carolina).
- The Southwest/Mountain Plains/Midwest Regions is comprised of three States (Iowa, Minnesota, Texas), and one ITO.
- The Southwest Region is comprised of one State (Oklahoma) and five ITOs.

Appendix B How is the Winner Determined?

Table B1: Monthly Net Price Calculations by Bidder—New York State, 2016

Abbott	**Total Ounces**	**Wholesale Price**	**Rebate**	**Net Price**	**Percentage Rebate**	**Monthly Net Price**
Powder (13 oz can)	2,880,000	$14.38	$13.55	$0.83	94.23%	$183,876.92
Liquid Concentrate (13 oz can)	806,000	$4.43	$3.63	$0.80	81.94%	$49,600.00
Ready-to-Feed (36 oz can)	403,000	$6.50	$6.00	$0.50	92.31%	$5,597.22
					Total	**$239,074.14**
MJ	**Total Ounces**	**Wholesale Price**	**Rebate**	**Net Price**	**Percentage Rebate**	**Monthly Net Price**
Powder (13 oz can)	2,880,000	$14.38	$14.31	$0.07	99.51%	$15,507.69
Liquid Concentrate (13 oz can)	806,000	$4.33	$4.31	$0.02	99.54%	$1,240.00
Ready-to-Feed (36 oz can)	403,000	$6.00	$5.50	$0.50	91.67%	$5,597.22
					Total	**$22,344.91**
Nestlé	**Total Ounces**	**Wholesale Price**	**Rebate**	**Net Price**	**Percentage Rebate**	**Monthly Net Price**
Powder (13 oz can)	2,880,000	$14.80	$13.13	$1.67	88.72%	$369,969.23
Liquid Concentrate (13 oz can)	806,000	$4.43	$4.00	$0.43	90.29%	$26,660.00
Ready-to-Feed (36 oz can)	403,000	$6.20	$5.90	$0.30	95.16%	$3,358.33
					Total	**$399,987.56**

To illustrate the auction mechanism, consider the case of New York State in 2016. On the bid sheet, WIC State agencies specify the total number of ounces required for each type of primary contract infant formula. The primary contract formula is the product for which the rebate is bid—such as *Similac*® *Advance*® (Abbott), *Enfamil*® *Infant* (MJ), or Good Start® Gentle (Nestlé).

Bidders report the lowest national wholesale price per unit for a full truckload of formula, together with the rebates offered for a pre-specified quantity of each of the three formula forms: powder, liquid concentrate, and ready-to-feed. For each form, the monthly net price is calculated by dividing the total required ounces by the can size and multiplying by the net price per can. For example, Abbott's monthly net price for powdered formula is computed as $\frac{2{,}880{,}000}{13} \times \$0.83 = \$183{,}876.92$. The total monthly net price is then obtained by summing across all three forms. The contract is awarded to the manufacturer offering the lowest total monthly net price. In this example, Mead Johnson was selected as the winner, having submitted the lowest bid ($22,344.91 vs. $239,074.14 and $399,987.56).

In our auction data, not all information is available. In particular, ready-to-feed bids and total ounces are missing (denoted by red cells in the table). Since powdered formula is the predominant type consumed by WIC participants, and because the lowest powdered bid consistently determines the contract winner, our analysis focuses exclusively on powdered bids.

Once a contract is awarded, its terms govern pricing over the contract's life. If the manufacturer's wholesale price changes, the rebate adjusts on a cent-for-cent basis, keeping the net wholesale price fixed. This means that while the effective net price remains constant, the rebate expressed as a percentage of

wholesale price may fluctuate.

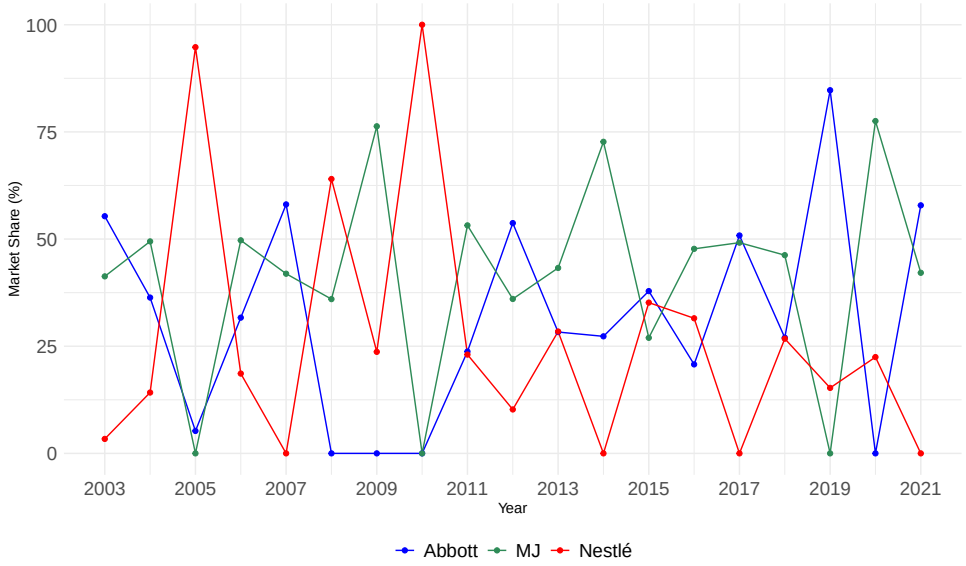
The scope of the contract extends beyond the primary formula. All other formulas (except exempt formulas) produced by the winning manufacturer are also considered contract formulas and must be rebated. For example, Abbott's contract line includes *Similac® Sensitive®*, while MJ's includes *Enfamil A.R.™* and *Enfamil® Reguline®*. WIC State agencies are required to issue the primary contract formula as the first choice but may decide whether participants can also access some or all of the manufacturer's other contract formulas. As a result, the set of formulas available to WIC participants can differ across States, even when they contract with the same manufacturer.

Finally, rebates on these additional contract formulas are linked to the same percentage discount as the primary contract formula within each physical form. For instance, if the rebate on the primary contract powdered formula is set at 90 percent of the wholesale price, that same 90 percent applies to all other powdered formulas produced by the manufacturer, including soy-based powder when covered under a single solicitation.

Appendix C Flow WIC Market Share

Figure C1 below plots the flow of WIC market share for all bidders from 2003 to 2021. Here, market share is defined as the percentage of new contracts secured by each bidder relative to the total value of new contracts awarded in a given year. The figure reveals significant spikes in market shares, suggesting substantial fluctuations over time. For instance, in 2010, Nestlé secured 100% of new contracts, only to see its share drop to around 10% by 2012. While Nestlé dominated new contracts during the first decade of the sample period, its market share declined sharply after 2013.

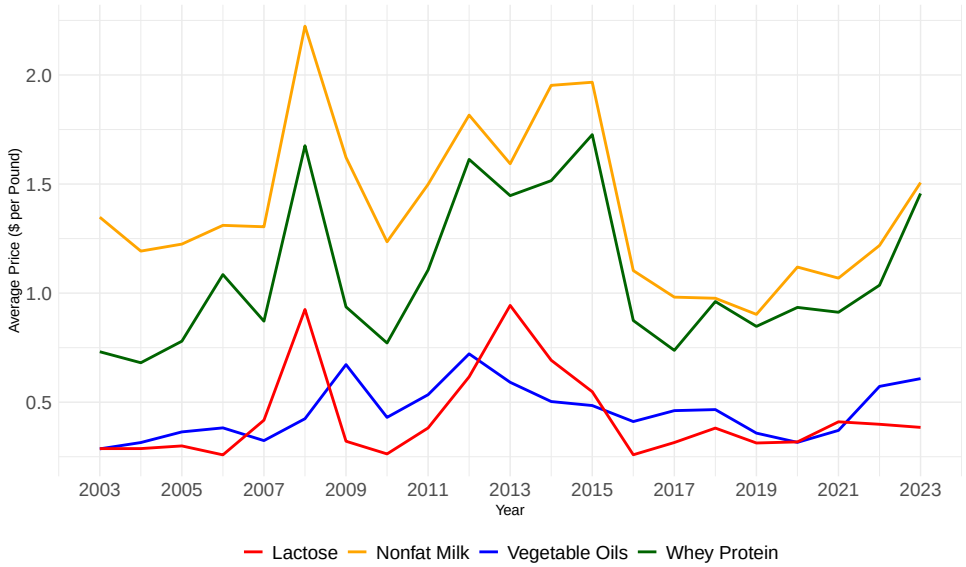
Figure C1: Flow WIC Market Share by Bidder, 2003–2021



Note: This figure plots the market share for each bidder spanning from the year 2003 to 2021. Market share is calculated as the proportion of new contracts secured by each bidder relative to the total size of new contracts issued in a given year.

Appendix D Additional Figures

Figure D2: Average Prices of Key Inputs into Baby Formula Production, 2003–2021



Notes: The figure plots average annual prices of selected inputs into baby formula production, including nonfat dry milk, lactose, whey protein, and vegetable oils. Data on input prices are from the Agricultural Marketing Service of the USDA (AMS Public Data).

Appendix E Participation

While Table 3 in the main text reports aggregate measures of participation and head-to-head competition, Table E2 provides a more detailed view of bidder composition and the distribution of winners across matchups. During the competitive period, nearly two-thirds of auctions (35 of 55) involved all three firms, and only one auction featured a single bidder. In the alleged period, however, rivalry declined markedly: single-bidder auctions rose to nearly one-quarter (8 of 35). Given the size of the market and the high stakes associated with winning a WIC contract, such limited participation appears highly unusual.

Table E3 examines these single-bid outcomes in greater detail. It shows that all one-bid auctions during the alleged period occurred in relatively small states and always in years when large, high-volume contracts attracted multiple bidders. For example, in 2018 three small states (IL, GA, PA) each drew only a single bid, while the large AR–NM–NC alliance auction in the same year attracted all three firms. A similar pattern appears in 2021, when Kentucky, Ohio, and Virginia each had only one bidder, yet New York's large contract again drew three participants. These patterns indicate that one-bid outcomes were concentrated in smaller markets and coincided with active competition over larger contracts.

Table E2: Auction Participation and Wins of Bidders by Period

Bidder Set	Competitive Period (2003–2013)				Alleged Period (2016–2021)			
	# Auctions	Winner			# Auctions	Winner		
		Abbott	MJ	Nestlé		Abbott	MJ	Nestlé
One-Bid Auctions								
Abbott	–	–	–	–	3	3	0	0
MJ	1	0	1	0	4	0	4	0
Nestlé	–	–	–	–	1	0	0	1
Two-Bid Auctions								
Abbott–MJ	18	8	10	0	1	0	1	0
Abbott–Nestlé	–	–	–	–	2	0	0	2
MJ–Nestlé	1	0	1	0	3	0	3	0
Three-Bid Auctions								
Abbott–MJ–Nestlé	35	8	9	18	21	10	6	5

Notes: Each row shows a unique bidder combination, with the number of auctions and the number of times each firm won in that combination. Results are shown separately for the competitive and alleged periods. "–" indicates no such auctions in that period.

Table E3: One-Bid Auctions and Contemporaneous Large Auctions

Year	One-Bid Auction	Large Contemporaneous Auction(s)
2016	AL (34,099; 1 bidder; winner: MJ)	NY (102,806; 3 bidders; winner: MJ)
2018	IL (56,270; 1 bidder; winner: MJ) GA (57,907; 1 bidder; winner: MJ) PA (54,376; 1 bidder; winner: Abbott)	AR–NM–NC (85,282; 3 bidders; winner: Nestlé)
2020	SC (24,614; 1 bidder; winner: Nestlé)	FL (104,792; 3 bidders; winner: MJ)
2021	KY (25,825; 1 bidder; winner: Abbott) OH (37,063; 1 bidder; winner: MJ) VA (28,135; 1 bidder; winner: Abbott)	NY (80,682; 3 bidders; winner: MJ)

Notes: "Large" auctions are defined as those in the top quartile of WIC infants served. Numbers in parentheses show the number of WIC infants, the number of bidders, and the winner.

Table E4: Participation, Win Rates (Conditional), and Winning Bids by Incumbent Identity

Incumbent	Bidder	Nbr. Participations	Participation (%)	Nbr. Wins	Win (%)	Avg. Winning Bid
Competitive (2003–2013)						
	Abbott	21	100	10	47.619	0.512
Abbott	MJ	21	100	6	28.571	0.639
	Nestlé	12	57.143	5	41.667	0.524
	MJ	21	100	14	66.667	0.547
MJ	Abbott	19	90.476	4	21.053	0.421
	Nestlé	11	52.381	3	27.273	0.422
	Nestlé	13	100	10	76.923	0.596
Nestlé	Abbott	13	100	2	15.385	0.675
	MJ	13	100	1	7.692	0.422
Alleged (2016–2021)						
	Abbott	10	90.909	7	70	−0.431
Abbott	MJ	8	72.727	1	12.500	0.661
	Nestlé	8	72.727	3	37.500	0.076
	MJ	15	100	11	73.333	−0.257
MJ	Abbott	11	73.333	4	36.364	−0.158
	Nestlé	13	86.667	0	0	–
	Nestlé	6	66.667	5	83.333	−0.568
Nestlé	Abbott	6	66.667	2	33.333	−0.585
	MJ	6	66.667	2	33.333	−0.038

Notes: Bold bidder = incumbent. "Nbr. Participations" counts auctions in which the bidder submitted a bid (given the incumbent). Participation (%) = Participations / Eligible Auctions. "Nbr. Wins" = number of auctions the bidder won. Win (%) is conditional: Wins / Participations. Avg. Winning Bid is the bidder's own average winning bid (per 26 fl. oz. reconstituted formula), conditional on winning. "–" indicates no wins in the sample.

Appendix F Screens in Huber and Imhof(2019)

Table F5: Summary of Statistical Screens in Huber and Imhof (2019)

Screen	Formula	Description
Bid dispersion (σ)	$\sigma_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(b_{it}-\mu_t)^2}$	Measures overall bid dispersion within a tender.
Bid skewness	$Skew(b_t) = \frac{n}{(n-1)(n-2)}\sum_{i=1}^{n}\left(\frac{b_{it}-\mu_t}{s_t}\right)^3$	Captures asymmetry in the bid distribution.
Absolute difference	$b_{2t} - b_{1t}$	Difference between the two lowest bids.
Relative difference (RD)	$RD_t = \frac{b_{2t}-b_{1t}}{s_{t,\text{losing bids}}}$	Normalizes gap by dispersion of losing bids.
Normalized distance (NormD)	$NORMD_t = \frac{b_{2t}-b_{1t}}{\frac{1}{n-1}\sum_{i=1}^{n-1}(b_{i+1,t}-b_{i,t})}$	Scales gap using average adjacent bid differences.

Appendix G Robustness Checks

G.1 RDD Test

G.1.1 Outcome variable: Log Backlog

Table G6: Regression Discontinuity Estimates, Competitive Period

Cutoff $c = 0$					
	Left of c	Right of c		Number of obs = 143	
				Kernel = Triangular	
Number of obs	54	89			
Eff. Number of obs	38	53			
Order est. (p)	1	1			
Order bias (q)	2	2			
BW est. (h)	0.443	0.443			
BW bias (b)	0.737	0.737			
ρ (h/b)	0.601	0.601			
Number of clusters	46	46			
Outcome: Log Backlog (6-month)				**Running variable: Bid Difference**	
Method	Coef.	Std. Err.	z	$P > \|z\|$	[95% C.I.]
Conventional	0.118	0.141	0.840	0.401	[−0.158, 0.394]
Bias-corrected	0.085	0.141	0.604	0.546	[−0.191, 0.361]
Robust	0.085	0.160	0.532	0.595	[−0.228, 0.398]

Notes: Robust clustered standard errors using auction-level clusters.

Table G7: Regression Discontinuity Estimates, Alleged Period

Cutoff $c = 0$					
	Left of c	Right of c		Number of obs = 75	
				Kernel = Triangular	
Number of obs	27	48			
Eff. Number of obs	18	23			
Order est. (p)	1	1			
Order bias (q)	2	2			
BW est. (h)	0.369	0.369			
BW bias (b)	0.603	0.603			
ρ (h/b)	0.612	0.612			
Number of clusters	21	21			
Outcome: Log Backlog (6-month)				**Running variable: Bid Difference**	
Method	Coef.	Std. Err.	z	$P > \|z\|$	[95% C.I.]
Conventional	0.561	0.456	1.229	0.219	[−0.334, 1.455]
Bias-corrected	0.635	0.456	1.392	0.164	[−0.259, 1.530]
Robust	0.635	0.569	1.116	0.264	[−0.481, 1.751]

Notes: Robust clustered standard errors using auction-level clusters.

G.1.2 Outcome variable: Log Distance

Table G8: Regression Discontinuity Estimates, Competitive Period

Cutoff $c = 0$					
	Left of c	Right of c	Number of obs = 143		
			Kernel = Triangular		
Number of obs	54	89			
Eff. Number of obs	37	52			
Order est. (p)	1	1			
Order bias (q)	2	2			
BW est. (h)	0.401	0.401			
BW bias (b)	0.606	0.606			
ρ (h/b)	0.662	0.662			
Number of clusters	44	44			
Outcome: Log Distance			**Running variable: Bid Difference**		
Method	Coef.	Std. Err.	z	$P > \|z\|$	[95% C.I.]
Conventional	0.120	0.263	0.455	0.649	[−0.396, 0.635]
Bias-corrected	0.159	0.263	0.605	0.545	[−0.357, 0.675]
Robust	0.159	0.301	0.528	0.598	[−0.432, 0.750]

Notes: Robust clustered standard errors using auction-level clusters.

Table G9: Regression Discontinuity Estimates, Alleged Period

Cutoff $c = 0$					
	Left of c	Right of c	Number of obs = 75		
			Kernel = Triangular		
Number of obs	27	48			
Eff. Number of obs	21	26			
Order est. (p)	1	1			
Order bias (q)	2	2			
BW est. (h)	0.423	0.423			
BW bias (b)	0.720	0.720			
ρ (h/b)	0.588	0.588			
Number of clusters	22	22			
Outcome: Log Distance			**Running variable: Bid Difference**		
Method	Coef.	Std. Err.	z	$P > \|z\|$	[95% C.I.]
Conventional	−0.675	0.494	−1.366	0.172	[−1.644, 0.294]
Bias-corrected	−0.869	0.494	−1.758	0.079	[−1.838, 0.100]
Robust	−0.869	0.556	−1.563	0.118	[−1.958, 0.221]

Notes: Robust clustered standard errors using auction-level clusters.

G.1.3 Outcome variable: Incumbency Status

Table G10: Regression Discontinuity Estimates, Competitive Period

Cutoff $c = 0$					
	Left of c	Right of c	Number of obs = 143		
			Kernel = Triangular		
Number of obs	54	89			
Eff. Number of obs	38	53			
Order est. (p)	1	1			
Order bias (q)	2	2			
BW est. (h)	0.440	0.440			
BW bias (b)	0.663	0.663			
ρ (h/b)	0.664	0.664			
Number of clusters	45	45			
Outcome: Incumbency Status			**Running variable: Bid Difference**		
Method	Coef.	Std. Err.	z	$P > \|z\|$	[95% C.I.]
Conventional	−0.219	0.204	−1.075	0.282	[−0.619, 0.180]
Bias-corrected	−0.202	0.204	−0.991	0.322	[−0.601, 0.198]
Robust	−0.202	0.240	−0.843	0.399	[−0.671, 0.268]

Notes: Robust clustered standard errors using auction-level clusters.

Table G11: Regression Discontinuity Estimates, Alleged Period

Cutoff $c = 0$					
	Left of c	Right of c	Number of obs = 75		
			Kernel = Triangular		
Number of obs	27	48			
Eff. Number of obs	21	27			
Order est. (p)	1	1			
Order bias (q)	2	2			
BW est. (h)	0.432	0.432			
BW bias (b)	0.653	0.653			
ρ (h/b)	0.661	0.661			
Number of clusters	22	22			
Outcome: Incumbency Status			**Running variable: Bid Difference**		
Method	Coef.	Std. Err.	z	$P > \|z\|$	[95% C.I.]
Conventional	0.439	0.363	1.210	0.226	[−0.272, 1.150]
Bias-corrected	0.506	0.363	1.396	0.163	[−0.205, 1.217]
Robust	0.506	0.439	1.153	0.249	[−0.354, 1.367]

Notes: Robust clustered standard errors using auction-level clusters.

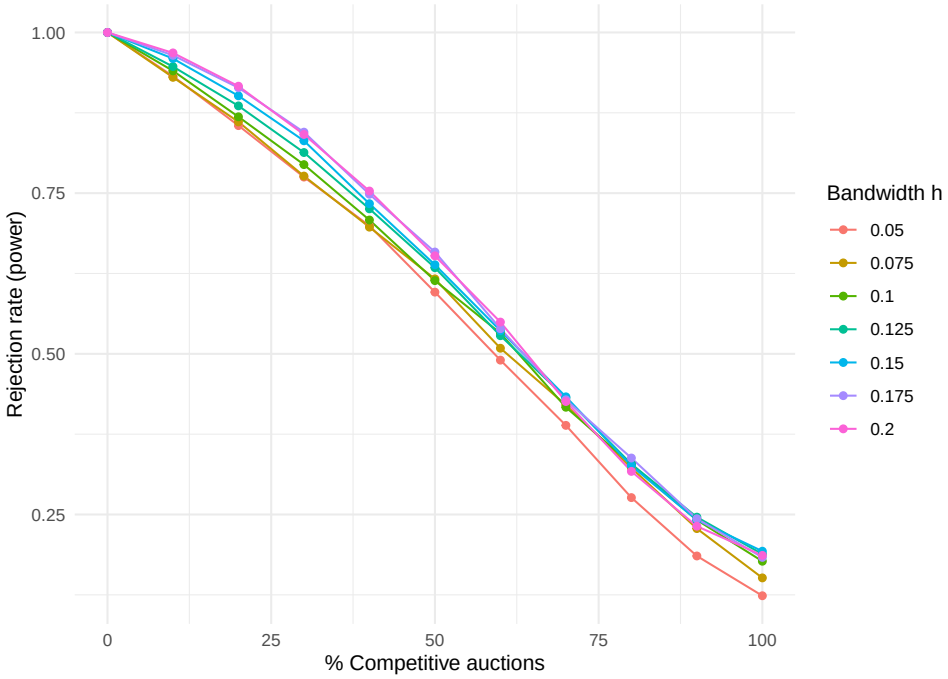
G.2 Simulation Design

We conducted a Monte Carlo exercise to evaluate the statistical power of the RD test in samples consistent with the WIC infant formula auction data. Specifically, we varied the intensity of collusion across replications—ranging from fully collusive to fully competitive markets—and assessed how often the test rejected the null hypothesis of competition. The design proceeds as follows:

- Auction structure: Each replication simulates $N = 27$ auctions, with 6 auctions involving two bidders and 21 auctions involving three bidders. This mirrors the composition of the WIC dataset during the alleged collusive period.
- Competitive auctions: In x% of auctions, all bidders draw bids independently from a normal distribution with mean $\mu = 1$ and standard deviation $\sigma = 0.2$.
- Collusive auctions: In the remaining $(100 - x)$%, the designated incumbent draws a bid from the same distribution, while non-incumbents submit cover bids equal to the incumbent's bid plus a random markup drawn uniformly from $[0.001, 0.15]$.
- Varying collusion intensity: The parameter x is varied from 0 to 100 (in increments of 10) to capture scenarios ranging from fully collusive to fully competitive markets.
- Estimation procedure: For each value of x, we generate 10,000 datasets, apply the RD test, and record whether the null hypothesis $H_0 : \beta = 0$ is rejected at the 5% level.

Figure G3 plots the rejection rates of the RD test across different collusion intensities and bandwidth choices. At 100% competitive auctions, the rejection rates for each bandwidth h are close to 5%, indicating that the test is correctly sized under competition. In contrast, when all auctions are collusive (0% competitive), the test rejects the null of competition at a high rate, demonstrating strong power to detect bid rotation. As the share of competitive auctions rises, the rejection rate declines, reflecting weaker signals of collusion in more mixed environments. The choice of bandwidth influences performance of the RD test.

Figure G3: Power Curve of the RD Test Under Varying Collusion Intensities



Notes: This figure plots rejection rates (at the 5% level) from Monte Carlo simulations of 27 auctions, where the share of competitive auctions varies from 0% (fully collusive) to 100% (fully competitive). Results are reported for different bandwidth choices.

G.3 Bootstrap Inference for Incumbency Effect

Table G12: Wild Cluster Bootstrap Inference for Incumbent × Alleged

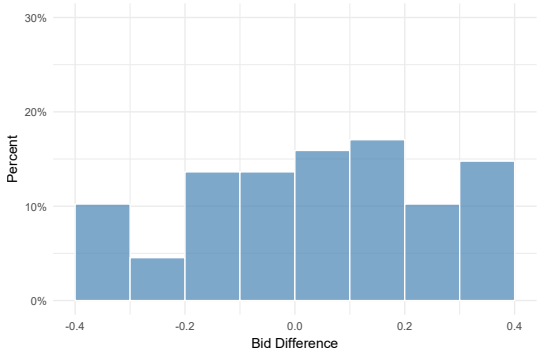
	(1)
Bootstrap p-value	0.230
95% CI	[-0.441, 0.132]

Notes: Wild cluster bootstrap-t test with 9,999 replications, Rademacher weights, and clustering at the auction level. Reported p-values and confidence intervals are based on the bootstrap distribution under the null hypothesis.

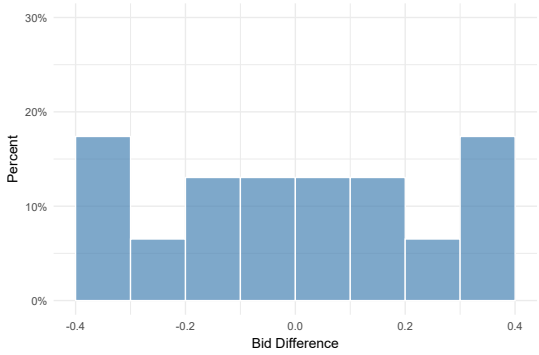
G.4 Additional Figures for Bid Difference Distributions

Figure G4: Bid Difference Distributions, Interval ±0.4, Bin Width = 0.1

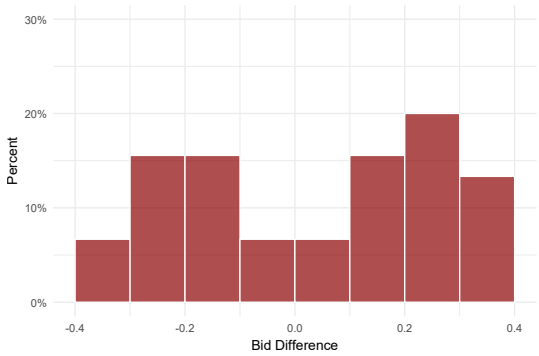
(a) Competitive: $\Delta^1_{i,a}$



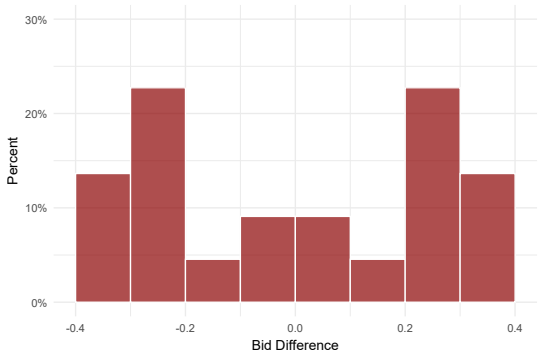
(b) Competitive: $\Delta^2_{i,a}$



(c) Alleged: $\Delta^1_{i,a}$



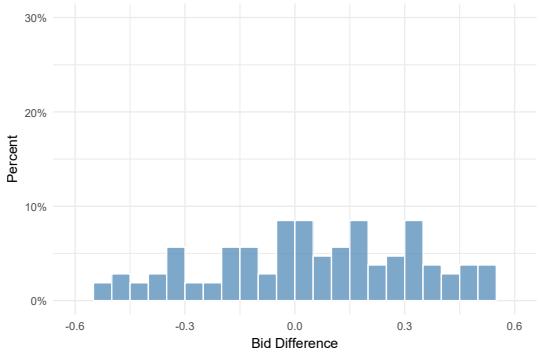
(d) Alleged: $\Delta^2_{i,a}$



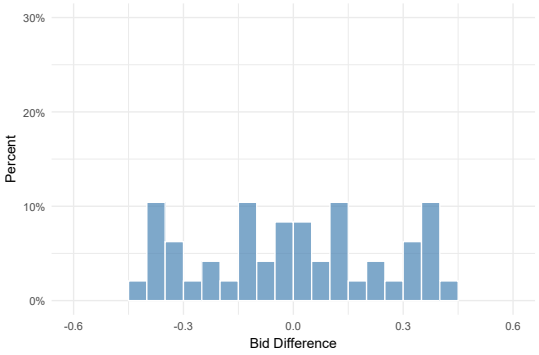
Notes: Bid differences are expressed in dollars per 26 fl. oz. of reconstituted formula. Histograms restrict bid differences to ±0.4 with bin width 0.1.

Figure G5: Bid Difference Distributions, Interval ±0.6, Bin Width = 0.05

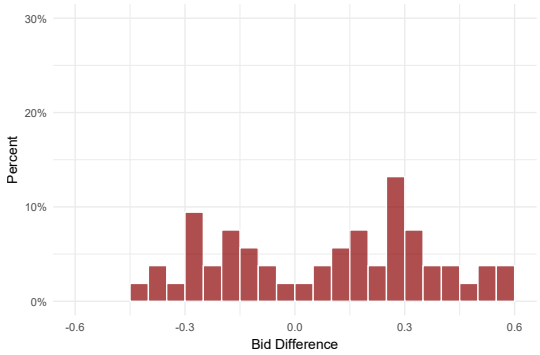
(a) Competitive: $\Delta^1_{i,a}$



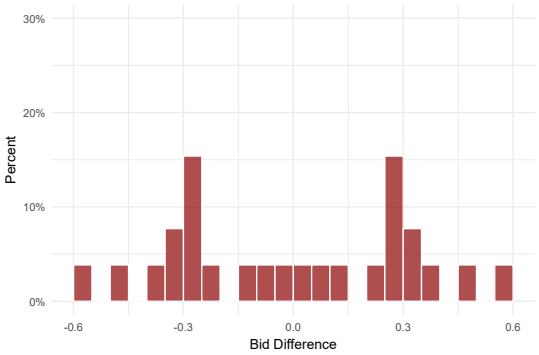
(b) Competitive: $\Delta^2_{i,a}$



(c) Alleged: $\Delta^1_{i,a}$



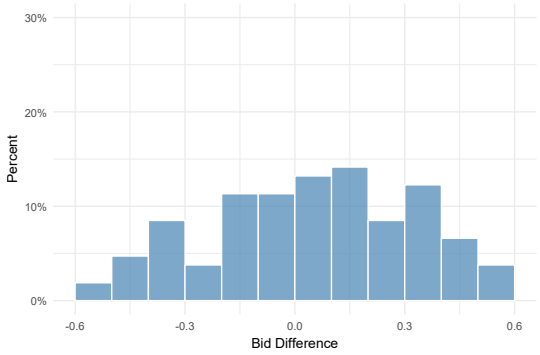
(d) Alleged: $\Delta^2_{i,a}$



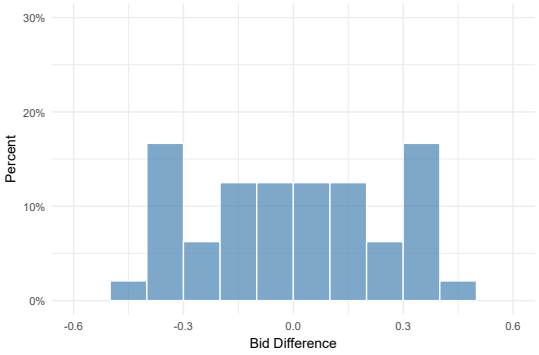
Notes: Bid differences are expressed in dollars per 26 fl. oz. of reconstituted formula. Histograms restrict bid differences to ±0.6 with bin width 0.05.

Figure G6: Bid Difference Distributions, Interval ±0.6, Bin Width = 0.1

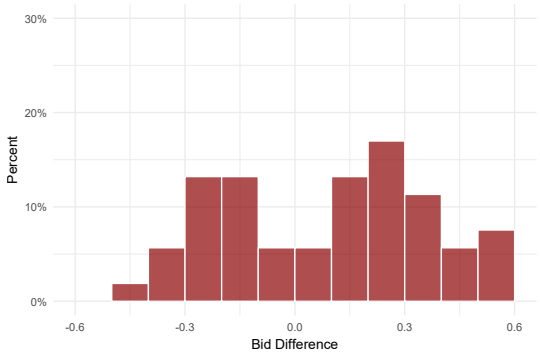
(a) Competitive: $\Delta^1_{i,a}$



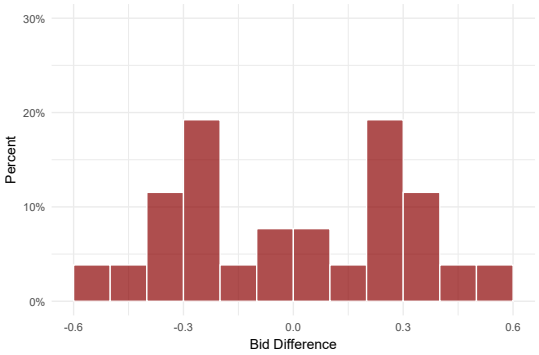
(b) Competitive: $\Delta^2_{i,a}$



(c) Alleged: $\Delta^1_{i,a}$



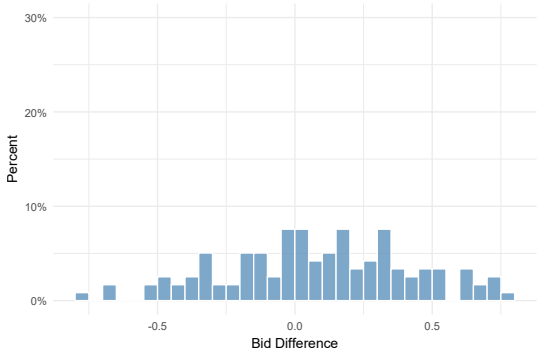
(d) Alleged: $\Delta^2_{i,a}$



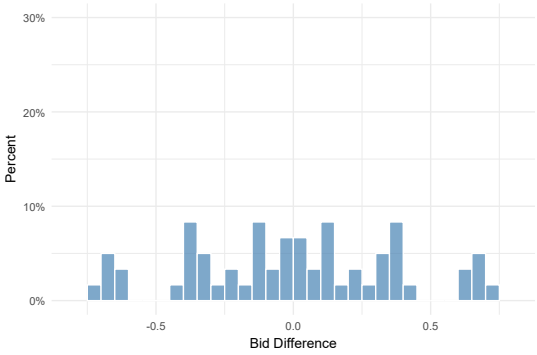
Notes: Bid differences are expressed in dollars per 26 fl. oz. of reconstituted formula. Histograms restrict bid differences to ±0.6 with bin width 0.1.

Figure G7: Bid Difference Distributions, Interval ±0.8, Bin Width = 0.05

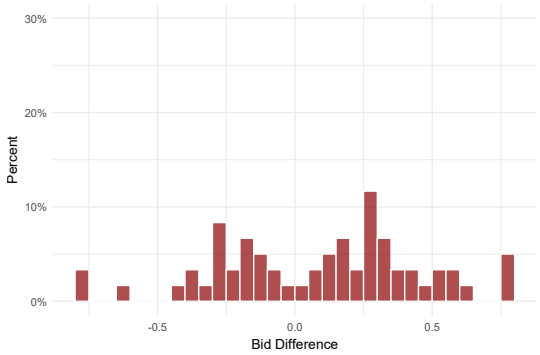
(a) Competitive: $\Delta^1_{i,a}$



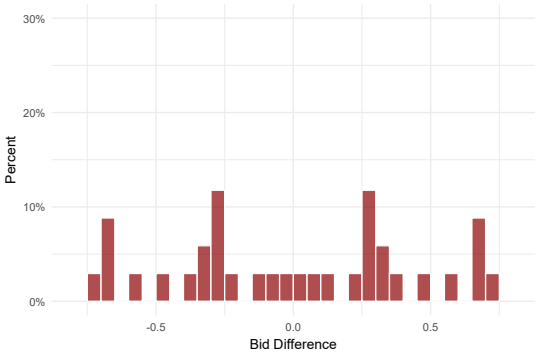
(b) Competitive: $\Delta^2_{i,a}$



(c) Alleged: $\Delta^1_{i,a}$



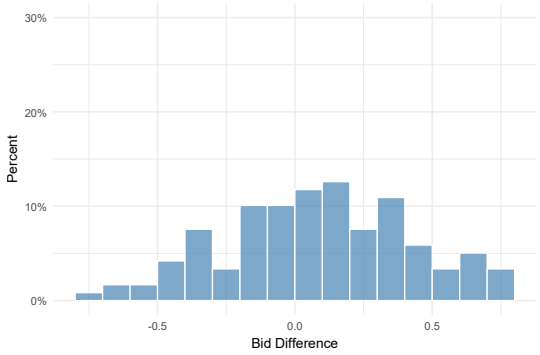
(d) Alleged: $\Delta^2_{i,a}$



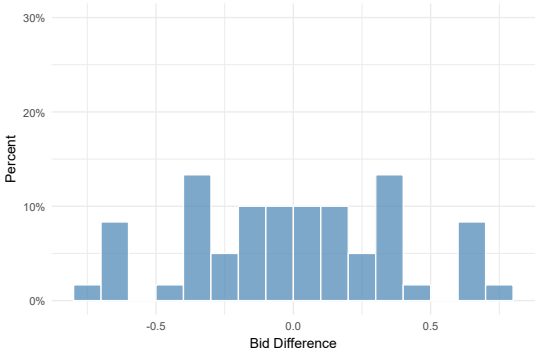
Notes: Bid differences are expressed in dollars per 26 fl. oz. of reconstituted formula. Histograms restrict bid differences to ±0.8 with bin width 0.05.

Figure G8: Bid Difference Distributions, Interval ±0.8, Bin Width = 0.1

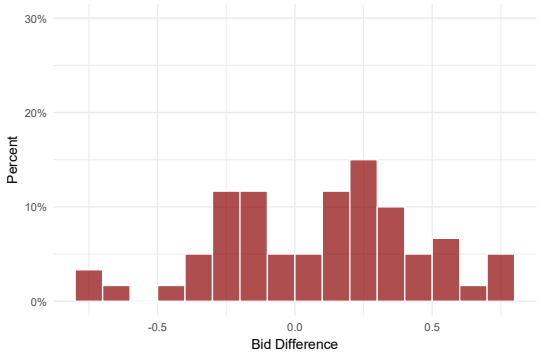
(a) Competitive: $\Delta^1_{i,a}$



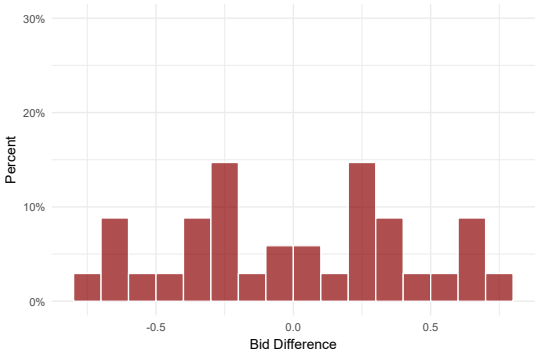
(b) Competitive: $\Delta^2_{i,a}$



(c) Alleged: $\Delta^1_{i,a}$



(d) Alleged: $\Delta^2_{i,a}$



Notes: Bid differences are expressed in dollars per 26 fl. oz. of reconstituted formula. Histograms restrict bid differences to ±0.8 with bin width 0.1.

G.5 Implementation of Clark et al. (2025)

Table G13: Parametric Implementation of the Screen in Clark et al. (2025), $\Delta \in [-0.6, 0.6]$

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var	$\Pr[-0.6,-0.4]$	$\Pr(-0.4,-0.2]$	$\Pr(-0.2,0]$	$\Pr(0,0.2]$	$\Pr(0.2,0.4]$	$\Pr(0.4,0.6]$
Competitive Period (N = 154)						
$\mathbb{1}\{\Delta^1_{i,a}\}$	0.045	−0.107*	−0.024	0.024	−0.022	0.083**
	(0.032)	(0.058)	(0.058)	(0.055)	(0.060)	(0.036)
Constant	0.021	0.229***	0.250***	0.250***	0.229***	0.021
	(0.021)	(0.052)	(0.052)	(0.052)	(0.052)	(0.021)
R^2	0.009	0.019	0.001	0.001	0.001	0.021
Controls	NO	NO	NO	NO	NO	NO
Fixed Effects	NO	NO	NO	NO	NO	NO
Alleged Period (N = 79)						
$\mathbb{1}\{\Delta^1_{i,a}\}$	−0.058	−0.119	0.073	0.073	−0.025	0.055
	(0.055)	(0.083)	(0.082)	(0.082)	(0.096)	(0.063)
Constant	0.077	0.308***	0.115*	0.115*	0.308***	0.077
	(0.052)	(0.070)	(0.060)	(0.060)	(0.070)	(0.052)
R^2	0.020	0.018	0.009	0.009	0.001	0.007
Controls	NO	NO	NO	NO	NO	NO
Fixed Effects	NO	NO	NO	NO	NO	NO

Notes: Each column reports results from a linear probability model where the dependent variable equals one if the observation falls in the indicated bid-difference bin (width 0.2, overall window ±0.6). $\mathbb{1}f(\Delta^1_{i,a})$ is an indicator that equals 1 if the observation is from $\Delta^1_{i,a}$. Reported coefficients are for $\mathbb{1}\{\Delta^1_{i,a}\}$ (top row) and the constant (baseline probability, second row). Standard errors clustered at the auction level are in parentheses. Significance levels: $^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table G14: Parametric Implementation of the Screen in Clark et al. (2025), $\Delta \in [-0.8, 0.8]$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var	$\Pr[-0.8,-0.6]$	$\Pr(-0.6,-0.4]$	$\Pr(-0.4,-0.2]$	$\Pr(-0.2,0]$	$\Pr(0,0.2]$	$\Pr(0.2,0.4]$	$\Pr(0.4,0.6]$	$\Pr(0.6,0.8]$
Competitive Period (N = 179)								
$\mathbb{1}\{\Delta^1_{i,a}\}$	−0.075*	0.042	−0.074	0.002	0.044	0.002	0.076**	−0.016
	(0.040)	(0.028)	(0.052)	(0.049)	(0.047)	(0.052)	(0.031)	(0.041)
Constant	0.100***	0.017	0.183***	0.200***	0.200***	0.183***	0.017	0.100***
	(0.037)	(0.017)	(0.045)	(0.045)	(0.045)	(0.045)	(0.017)	(0.037)
R^2	0.026	0.009	0.011	0.000 004	0.002	0.000 004	0.020	0.001
Controls	NO	NO	NO	NO	NO	NO	NO	NO
Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO
Alleged Period (N = 94)								
$\mathbb{1}\{\Delta^1_{i,a}\}$	−0.068	−0.042	−0.069	0.078	0.078	0.015	0.058	−0.051
	(0.059)	(0.045)	(0.080)	(0.065)	(0.065)	(0.087)	(0.053)	(0.062)
Constant	0.118**	0.059	0.235***	0.088*	0.088*	0.235***	0.059	0.118**
	(0.053)	(0.040)	(0.062)	(0.047)	(0.047)	(0.062)	(0.040)	(0.053)
R^2	0.015	0.013	0.007	0.012	0.012	0.000 03	0.009	0.008
Controls	NO	NO	NO	NO	NO	NO	NO	NO
Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO

Notes: Each column reports results from a linear probability model where the dependent variable equals one if the observation falls in the indicated bid-difference bin (width 0.2, overall window ±0.8). $\mathbb{1}f(\Delta^1_{i,a})$ is an indicator that equals 1 if the observation is from $\Delta^1_{i,a}$. Reported coefficients are for $\mathbb{1}\{\Delta^1_{i,a}\}$ (top row) and the constant (baseline probability, second row). Standard errors clustered at the auction level are in parentheses. Significance levels: $^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table G15: Nonparametric Implementation of the Screen, with controls

	Bid-difference window		
	[−0.4, 0.4]	[−0.6, 0.6]	[−0.8, 0.8]
Competitive	0.211	0.150	0.052
Alleged	0.665	0.414	0.417

Notes: Reported values are permutation-based p-values from two-sample Kolmogorov–Smirnov tests comparing the Δ^1 and Δ^2 distributions between the competitive and alleged periods. Each test is based on $B = 9{,}999$ random permutations of group labels and controls for log(Distance), Capacity, log(WIC Infants), log(Non-WIC), input prices (vegetable oils, whey protein, nonfat milk, lactose), as well as Year and Bidder fixed effects.

Table G16: Parametric Implementation of the Screen in Clark et al. (2025), with controls, $\Delta \in [-0.6, 0.6]$

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var	Pr[−0.6, −0.4]	Pr(−0.4, −0.2]	Pr(−0.2, 0]	Pr(0, 0.2]	Pr(0.2, 0.4]	Pr(0.4, 0.6]
Competitive Period (N = 154)						
$\mathbb{1}\{\Delta^1_{i,a}\}$	−0.0002	−0.112*	−0.060	0.080	0.011	0.082**
	(0.032)	(0.065)	(0.069)	(0.060)	(0.070)	(0.040)
Constant	−0.033	−0.596*	1.051*	1.420***	−1.090**	0.248
	(0.398)	(0.355)	(0.570)	(0.477)	(0.442)	(0.473)
R^2	0.229	0.152	0.088	0.222	0.142	0.120
Controls	YES	YES	YES	YES	YES	YES
Bidder FE	YES	YES	YES	YES	YES	YES
State/Alliance FE	YES	YES	YES	YES	YES	YES
Alleged Period (N = 79)						
$\mathbb{1}\{\Delta^1_{i,a}\}$	−0.058	−0.144	0.068	0.074	−0.004	0.064
	(0.052)	(0.114)	(0.086)	(0.086)	(0.123)	(0.076)
Constant	−0.140	2.236	−0.150	−0.395	−0.346	−0.206
	(1.025)	(2.925)	(2.351)	(2.338)	(3.502)	(1.679)
R^2	0.198	0.151	0.141	0.140	0.075	0.145
Controls	YES	YES	YES	YES	YES	YES
Bidder FE	YES	YES	YES	YES	YES	YES
State/Alliance FE	YES	YES	YES	YES	YES	YES

Notes: Each column reports results from a linear probability model where the dependent variable equals one if the observation falls in the indicated bid-difference bin (width 0.2, overall window ±0.6). $\mathbb{1}f(\Delta^1_{i,a})$ is an indicator that equals 1 if the observation is from $\Delta^1_{i,a}$. Reported coefficients are for $\mathbb{1}\{\Delta^1_{i,a}\}$ (top row) and the constant (baseline probability, second row). Controls include log(Distance), Capacity, log(WIC Infants), log(Non-WIC), and input prices (vegetable oils, whey protein, nonfat milk, lactose). Standard errors clustered at the auction level are in parentheses. Significance levels: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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