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An Investigation of Bidder Behaviour in WIC Infant Formula Rebate Auctions

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AN INVESTIGATION OF BIDDER BEHAVIOUR IN WIC INFANT FORMULA REBATE AUCTIONS

BY

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This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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To my dear parents and siblings – Bidur Prasad Pandey, an amazing dad who has supported me every single day and granted me the freedom to live my life in every way possible; Sanju Pandey, my mom, for being my unwavering source of strength; Aashika Pandey and Aashosan Pandey, my two hearts' halves – thank you for always being there for me.

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LIST OF ABBREVIATIONS

ERS	Economics Research Service
FRED	Federal Reserve Economic Data
FPL	Federal Poverty Line
FY	Fiscal Year
MJ	Mead Johnson
NCHS	National Center of Health Statistics
OLS	Ordinary Least Square
SD	Standard Deviation
SNAP	Supplemental Nutrition Assistance Program
TFT	Tit for Tat
USDA	United States Department of Agriculture
VAR	Vector Autoregression
WIC	Women, Infants, and Children

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ABSTRACT

AN INVESTIGATION OF BIDDER BEHAVIOUR IN WIC INFANT FORMULA REBATE AUCTIONS

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This research investigated the competitive bidding dynamics for infant formula rebate contracts within the Special Supplemental Nutrition Assistance Program for Women, Infants, and Children (WIC). I begin by focusing on the differences between winning and losing bids. The study employs multiple regression to predict rebate bids submitted by major manufacturers when they win a contract. I next conduct a paired t-test for each manufacturer – revealing statistically significant differences between predicted bids (based on the parameters from the winning model) and actual bids when a manufacturer did not win. This suggests that each manufacturer bids significantly lower rebates (higher net prices, wholesale price – rebate) from their expected bids based on the winning bid functions when they lose a contract auction.

I next engage is a number of tests meant to detect evidence of tacit collusion as suggested by game theoretic models. Specifically, I test for evidence that manufacturers engage in tit-for-tat punishment strategies meant to dampen competition for contracts. For example, I examined the distributions of differences between actual bids and predicted bids and found they are skewed negative for rebates and positive for net prices. I defined "fake bid" as a bid lower than one standard deviation and two standard deviations below the mean predicted bid (above the mean for net prices) and found that manufacturers are less likely to submit fake bids on contracts they previously controlled. This suggests a strategic bidding approach, potentially indicating tacit collusion, where competitors are more likely to engage in non-serious bidding when attempting to win contracts from each other. Moreover, I conduct Granger causality tests to assess the strategic interactions, particularly looking for evidence of a tit-for-tat strategy where manufacturers react to each other's market share changes. The results showed significant interdependencies, confirming that changes in one manufacturer's market share could predict changes in another's. The insights gained from this research contribute to a deeper understanding of the dynamics surrounding infant formula contract bidding in the WIC program, offering potential avenues for enhancing its efficiency and fairness.

Key words: *WIC, infant formula, auction, manufacturers, winning bid, losing bid, fake bid*

CHAPTER ONE

INTRODUCTION

1.1 Background on WIC

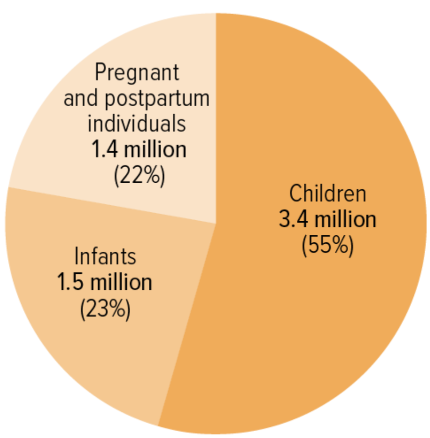
WIC stands for the Special Supplemental Nutrition Assistance Program for Women, Infants, and Children, which is a federal assistance program that provides low-income pregnant women, new mothers, and young children under 5 years of age with nutrition education, healthy and supplement foods packages, health care referrals, and other support. WIC has been a part of the nation's nutrition safety net for almost 45 years, and it now serves over 6 million individuals annually (Carlson & Neuberger, 2021). The United States Department of Agriculture (USDA) oversees the program. 89 WIC State territorial and tribal agencies manage WIC on a local level. These organizations cover the District of Columbia, 33 Indian Tribal Organizations, American Samoa, Guam, the Commonwealth Islands of the Northern Marianas, Puerto Rico, and the U.S. Virgin Islands in addition to the 50 States (Oliveira et al., 2004).

Who is eligible for WIC?

WIC ensures that children receive proper nutrition at a critical time in their development, as well as providing families with resources and support to help them live healthy lives. To qualify for WIC, applicants must be women during pregnancy and up to six weeks after delivery, breastfeeding women up to one year after delivery, non-breastfeeding women up to six months postpartum, an infant up to his/her first birthday, or children up to age five (Oliveira, Frazao, & Smallwood, 2011). Eligible participants are given a WIC card to use at participating grocery stores to purchase approved foods. In fiscal year (FY) 2021, WIC provided services to over 6.2 million people each month, including approximately 43% of all infants in the country. In FY 2021, the federal program costs for WIC were $5 billion (USDA/ERS, 2022).

Individuals who do not receive aid from other relevant means-tested programs must have a gross household income at or below 185 percent of the federal poverty line (FPL) (currently $42,606 per year for a family of three) in order to qualify for WIC benefits. To ease program administration, those who are already enrolled in the Supplemental Nutrition Assistance Program (SNAP, formerly food stamps), Medicaid, or receive monthly Temporary Assistance for Needy Families (TANF) cash assistance payments are automatically considered eligible for WIC based on income, regardless of whether the program's income limit exceeds 185 percent of the FPL. The vast majority of eligible WIC individuals (77.2 percent) also participate in one of these additional programs (CBPP, 2022).

WIC Serves 6 Million Low-Income Pregnant or Postpartum Individuals, Infants, and Children



Children	Number of participants	Share of total participants
4 years old	0.5 million	8%
3 years old	0.8 million	12%
2 years old	0.9 million	14%
1 year old	1.3 million	21%
Infants	1.5 million	23%
Individuals		
Pregnant	0.5 million	8%
Breastfeeding	0.5 million	8%
Other postpartum	0.4 million	6%

Source: CBPP analysis of U.S. Department of Agriculture administrative data for fiscal year 2021. Number of children aged 1 to 4 estimated using WIC Participation and Program Characteristics 2020.

CENTER ON BUDGET AND POLICY PRIORITIES | CBPP.ORG

Source:(CBPP, 2022)

1.2 Rebates and bidding procedure

A component of the WIC program is the distribution of infant formula to qualified families. This is accomplished through a bidding procedure in which formula producers compete for the opportunity to supply their goods through the program.

In the United States, WIC is the main purchaser of infant formula. WIC State agencies implement a cost-containment strategy for acquiring infant formula to reduce costs. In the middle of the 1980s, infant formula retail prices were rising faster than the prices of other foods, accounting for roughly 40% of the total WIC food expenses (Oliveira et al., 2004). This prompted states to investigate cost-containment strategies to lower infant formula costs.

WIC state agencies receive significant discounts from manufacturers in the form of rebates for each can of infant formula purchased by WIC participants. There is a rebate contract which is a legal agreement between an infant formula manufacturer and a state which is implemented through bidding. The rebate program's goal is to keep the cost of the formula provided to eligible families through the WIC program as low as possible. Manufacturers submit bids for their infant formula products under the rebate program, and the government awards contracts to the lowest bidders. The rebates are then paid to WIC by the manufacturers based on the number of cans sold through WIC. Manufacturers receive exclusive permission to provide their goods to WIC members in the State in exchange for rebates.

Approximately every three to four years, WIC state agencies rebid for infant formula contracts. The brand of formula provided through WIC and the manufacturer both frequently change from contract to contract in various states (Oliveira et al., 2004). An alliance of states or a state undertakes a competitive bidding procedure to choose a WIC provider. These sole-source contracts are chosen based on open bidding; the company with the lowest net wholesale price (which is equal to the manufacturer's wholesale price minus the rebate) is given the WIC contract for that State. Given the significant cost savings for the WIC program from the rebates, it's essential to understand the variables and trends related to the net price bids made by the formula makers**.**

Furthermore, the winning bidder on each infant formula contract receives an immediate benefit. Researchers at the USDA's Economic Research Service found that when a contract is awarded in a market, the winning manufacturer's market share increases by an average of 74 percentage points (Oliveira, Frazao, & Smallwood, 2011). While the companies are known to bid for WIC contracts, the specific strategies they employ in their negotiations are unknown. For instance, it is unclear how much the companies are willing to lower their prices to win the contract. Concerns have also been raised about conflicts of interest and unethical bidding practices. Additionally, the Federal Trade Commission has raised suspicions about potential collusion or coordination among participants in the infant formula market (Khan, 2023).

Given the complexities of the bidding process, this study aims to explore the underlying strategic behaviors that influence market shifts following contract awards. Specifically, the research questions will delve into whether a tit-for-tat strategy, like a repeated prisoners' dilemma scenario, plays a role in the bidding processes for these contracts.

Therefore, in response to this gap, we have the following research questions that we'll address in our research:

- Winning and losing rebate bids are different from what we would predict based on the losing and winning bid functions, respectively.
- Winning and losing net prices are different from what we would predict based on the losing and winning net price functions, respectively.
- Do changes in bidding patterns over time support the existence of a tit-for-tat strategy among manufacturers, indicating tacit collusion?

1.3 Research Objectives

- To determine whether the manufacturers are bidding the same when they lose as when they win i.e. whether they are bidding competitively or not.
- To know the specific negotiation strategies, used by infant formula manufacturers to bid for WIC contracts.
- To investigate the bidder behavior in WIC Infant Formula rebate auctions.

1.4 Major players in WIC infant formula

The infant formula market consolidated prior to the start of WIC's use of competitive bidding to procure infant formula. At first, Wyeth, Ross Laboratories, and Mead Johnson were the only three manufacturers to submit bids for WIC contracts. By purchasing Carnation in 1989, Nestlé made its entry into the market, and starting in 1990, it made a few offers. But in 1996, Wyeth pulled out of the WIC program to concentrate on selling generic-branded formulas, bringing the total number of competitors back to three. Even after over three decades, the same companies—Abbott, Mead Johnson, and Nestlé (Gerber)—continue to receive state contracts for WIC (Betson, 2009). Only three manufacturers are participating in bidding and providing infant formula through WIC:

Abbott (Ross), Mead Johnson, and Gerber (Carnation). Increasing the visibility of contract opportunities is one step that the USDA can take to attract more manufacturers to the program. With WIC infants receiving more than half of the country's formula supply, diversifying the source of WIC formula would strengthen the nation's formula supply and help ensure there is always a sufficient supply (Stacy, 2022).

1.5 New contribution to the literature

Understanding the history and structure of WIC's competitive bidding process for infant formula, as well as the resulting federal savings, can assist policymakers in ensuring that this critical component of WIC's design remains strong (Carlson, Greenstein, & Neuberger, 2017). Knowledge gaps in the bidding process can give rise to the potential for unfair advantage or bias, whether done so knowingly or unknowingly. The bidding process can be made more open and fair for all parties by identifying and filling in the gaps. Effective, transparency, and fair competitive bidding for infant formula remains a key cost-containment mechanism. It increases the number of eligible women and young children who can receive WIC, improves the program's efficiency and effectiveness, and lowers federal expenses. Both WIC members and general taxpayers benefit from the program's improvement of low-income families' nutrition and health, which results in healthier babies, more nutrient-dense diets, better child health care, and children who perform better academically (Carlson, Greenstein, & Neuberger, 2017). The newly acquired information about the WIC infant formula bidding process can support the creation of effective policies and advocacy efforts, as well as better the operation of the WIC program. This research delves into the ethical concerns and potential collusion aspects, offering insights into the regulatory implications and the impact of competitive behaviors on market dynamics.

CHAPTER TWO

LITERATURE REVIEW

2.1 History and background of WIC

WIC's origins can be traced back to the 1960s, when the government recognized that many low-income Americans were suffering from malnutrition. This is mainly after the US emerged from World War II (Kennedy & Dwyer, 2020). The Commodity Supplemental Food Program, which provided supplemental foods and targeted comparable demographics, was already in place when the WIC program was authorized in 1972 by Congressional legislation (P. L. 92433, was sponsored by Senator Hubert Humphrey (D) of Minnesota) as a preliminary two-year pilot program.

Administration officials at the USDA said that WIC was superfluous since it duplicated that program. But ultimately it became clear that the existing food assistance programs, such as the Commodity Supplemental Food Program and the Food Stamp Program, were unable to adequately address the specific requirements of pregnant mothers and young children (Oliveira & Frazao, 2009). The first WIC clinic opened in 1974 in Pineville, Kentucky when the agency was successfully sued to release the funds allotted for WIC. WIC was in operation in 45 States by the end of the year (USDA, 1999).

The WIC program provides nutrition education, healthy food packages, and other support to low-income pregnant women, new mothers, and young children under 5 years of age. WIC is the main purchaser of infant formula in the country and implements a cost-containment strategy to acquire formula at a lower cost through manufacturer rebates and contracts offering the lowest net price. WIC state agencies receive significant discounts from manufacturers in the form of rebates for each can of infant formula purchased by WIC participants, and contracts are given to those who offer the lowest net price (Wholesale price minus rebates). However, it is uncertain how the net price bid varies among WIC state agencies (Davis & Oliveira, 2015).

2.2 Rebate program and bidding process

Manufacturer rebates for infant formula have become a crucial part of the WIC program. The amount of rebates in nominal terms has increased annually since the use of rebates started in the late 1980s (Oliveira & Frazao, 2009).

Oliveira et al. (2004) found in a multiple regression analysis that retail prices rose as a brand received a WIC contract and that they also increased with the size of the WIC market. The study conducted by Betson (2009) found that there are no significant differences between the bids of Mead Johnson and Ross lab. Using the OLS regression, they also suggested that the firm’s wholesale pricing decision wouldn’t affect the net price (wholesale price minus rebate) of the formula to the government. He discovered data to support the idea that bids submitted in response to an initial solicitation do differ from bids submitted in response to subsequent solicitations (early solicitations resulted in smaller rebate amounts). Although the empirical results largely agreed with the theoretical model's predictions in his study, the effect of having more firms submit bids for the solicitation is still unclear.

Davis (2011) estimated manufacturers' marginal costs and found that they are low in comparison to wholesale prices. He discovered a significant spillover effect that suggests a brand's share of non-WIC demand will rise by 50–60% once it secures a WIC contract.

WIC participants buy most of the infant formula in the United States from three main manufacturers: Abbott, Mead Johnson (MJ), and Nestlé. These manufacturers compete in each state to win exclusive service rights for WIC members via a first-price auction. During the auction, manufacturers bid on rebates for their primary contract brands. The manufacturer with the lowest net price, determined as the wholesale price minus the rebate, receives a multi-year contract to exclusively serve WIC members in that state. Notably, the auction data shows a clear trend: manufacturers offer very significant discounts in contrast to their wholesale costs in order to acquire WIC contracts. More particular, submitted rebates exceed 80% and 90% of wholesale prices for more than 75% and 25% (An, Davis, & Ruli Xiao, 2023).

2.3 Change in retail price of infant formula

Oliveira et al. (2004) in their study conducted a multivariate regression analysis to measure the net effect of an independent variable i.e. median household income, the poverty rate, the wholesale price, and a measure of number of discount stores, on the dependent variable i.e. retail price of infant formula in supermarkets. They choose the average real retail price of infant formula in supermarkets in a particular market area as a dependent variable. And they choose numerous independent variables including relative size of WIC if contract brand, relative size of WIC[1] if noncontract brand, change in contract brand etc.

Regression analysis findings reveal that, after accounting for all other variables, the relative size of WIC had a statistically significant positive impact on the retail price of the contract brand of infant formula. Also, results showed the greater the relative size of WIC, the greater the price of non-contract formula. Holding other factors constant, a manufacturer's brand of infant formula has a higher retail price when it is the contract brand than when it

[1] relative size of WIC = the number of WIC formula-fed infants in the State containing the market area / the number of non-WIC formula-fed infants in the State containing the market area

is the noncontract brand at any given level of relative WIC size. Oliveira et al. (2004) termed this price difference as the contract brand effect.

Oliveira, Frazao and Smallwood (2010) in their paper revealed that WIC State agencies were paying more for infant formula in recent contracts due to rising wholesale pricing. This has resulted in considerable increased expenses for the WIC program, the equivalent of supporting thousands of people for a full year. The study also showed that future expenses will be determined by WIC's share of the formula market, which will be impacted by things such as economic situations and changes in food packaging. Balancing these issues will be critical in order to properly continue WIC's support for mothers and infants.

Davis and Oliveira (2015) tried to understand the factors and patterns associated with the net prices offered by formula manufacturers to WIC state agencies. They also attempt to determine whether bidding for a WIC infant formula rebate contract is competitive. Furthermore, the paper also wanted to explore if manufacturers were more likely to win a contract if they were the previous winner or not. To provide insight on some of the causes and implications of intra- and interagency net pricing variation, they document and analyze the net price bids submitted by infant formula manufacturers pursuing infant formula contracts with WIC agencies between 2003 and early 2013.

To find the relationship between state/alliance size and net price bid, Davis and Oliveira (2015) conducted a linear regression analysis, taking net price as dependent variable and infant participation as an independent variable. Since there are three firms (Mead Johnson, Abbott, and Nestle/Gerber), three separate regression equations were estimated. Figure 1 indicates that there is a negative relationship between state alliance size and net price bid.

Figure 1: Net price bid and number of wic infants in state / alliance, 2003-13

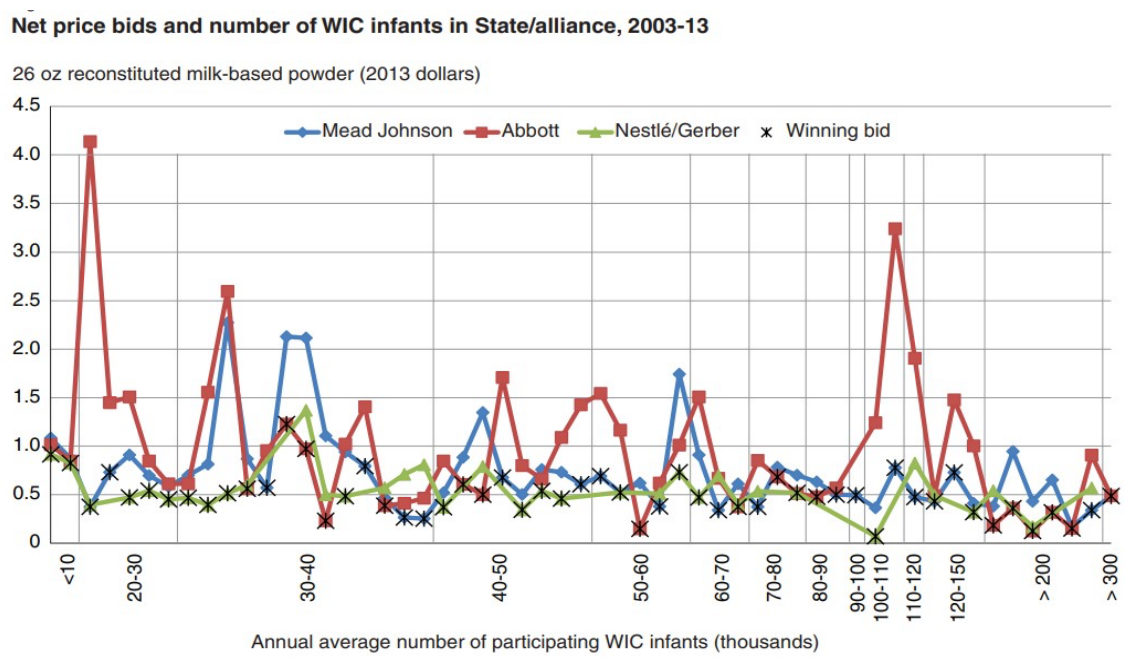


Figure 1 :Net price bid and number of wic infants in state / alliance, 2003-13

Source: Davis and Oliveira (2015)

Once again, they found a negative relationship using a regression (Figure 2). The regression results indicate that larger States/alliances may receive lower net price bids from Mead Johnson and Abbott, even though the report is unable to draw a firm conclusion about a connection between State/alliance size and the net prices offered by Nestlé/Gerber. Moreover, for larger States/alliances, lower bids appear to be associated with lower winning net prices.

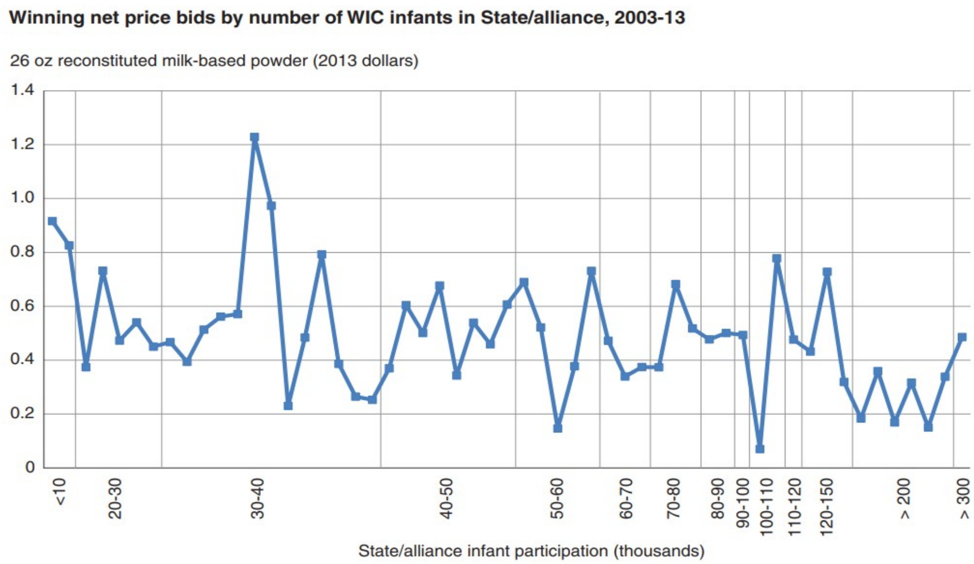


Figure 2:Winning net price bids by number of wic infants in state/alliance, 2003-13

Source: Davis and Oliveira (2015)

The report emphasizes that this study just highlights statistical regularity, and that the relationship between the two should not be seen as a cause and effect. In this case, while the data may show a pattern between the size of a State/alliance and lower net prices, there may be other variables that contribute to lower prices, and it's essential to examine those factors to determine the actual drivers of price reductions.

2.4 Margin of victory

Davis and Oliveira (2015) utilized statistical analysis to reveal that, since 2008, the victory margins in WIC infant formula contracts have decreased from 2.0 times the winning bid to 1.6 times the winning bid, suggesting increased market competitiveness. According to Davis and Oliveira (2015), margins of victory are crucial because they predict the outcome of the auction and the final price of the infant formula if the closest rival had won.

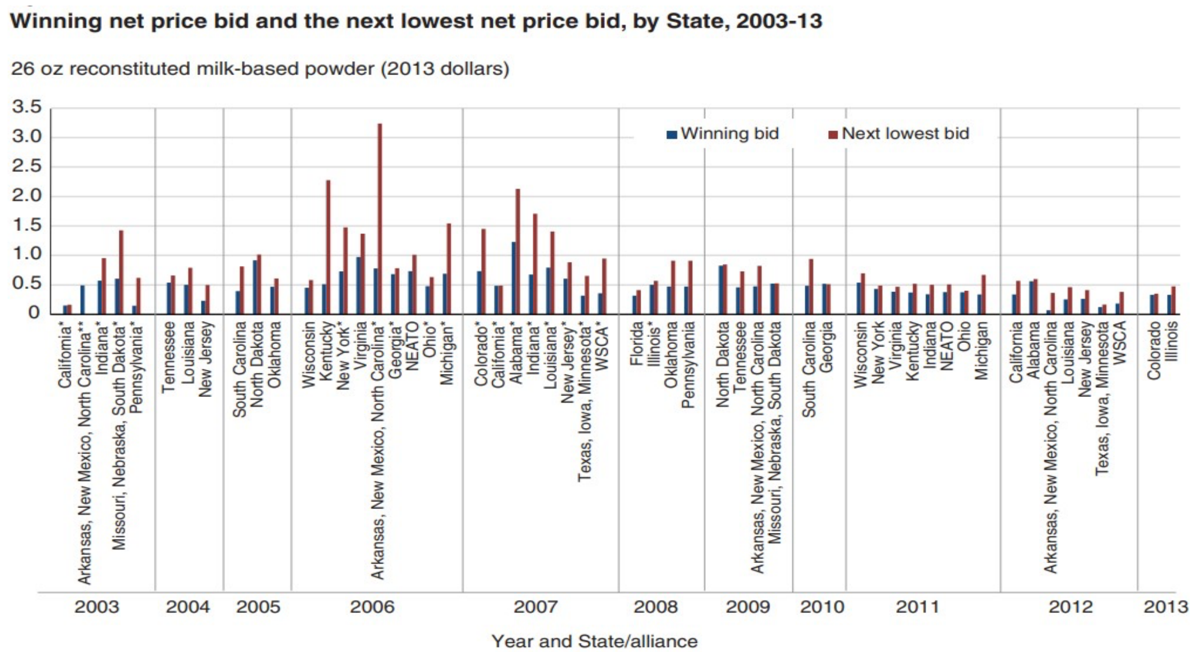


Figure 3: Victory Margin

Source: Davis and Oliveira (2015)

According to the research, each year's State/alliance WIC infant formula contract has regularly received bids from all three of the main infant formula producers and contract is awarded to whoever bids the lower net price. But, having a contract does not ensure that the same manufacturer will win the contract the following round, although after winning a contract, a manufacturer is more likely than its rivals to win the following round of bidding. Factors like supply chains, good working relationships, and familiarity may also play a role in this.

Also, Davis and Oliveira (2015) find no evidence of any anti-competitive contract sharing mechanism, despite variances in net price bids for the same contract. This is due to the various bids that were received for each contract and the frequent firm rotation of contracts.

2.5 Interstate factors shaping WIC food package costs

Davis and Leibtag (2005) in their study provide insights into the factors influencing the average monthly costs of the WIC food assistance program across different states. They revealed that differences in food prices between states play a crucial role in shaping the variations observed in average monthly costs. States with higher-than-average WIC expenses generally have higher food prices, while those with lower-than-average costs tend to have more affordable food prices. Interestingly, the composition of WIC participants in each state has a lesser impact on cost differences compared to the influence of food prices. They also discovered that the same cost-containment measures can generate varying levels of cost reductions across states. This occurs due to differences in consumer preferences and the effectiveness of these practices in curbing purchasing behavior. By examining specific cost-containment practices in California and Texas, they observed that even when identical measures are applied, the effects on average monthly costs can differ between regions. Based on these outcomes, they highlighted that even with equivalent food packages and caseloads, disparities in average monthly costs would persist due to varying food prices. Furthermore, the study highlighted the difficulties of accommodating WIC members in places with higher food prices, even if food grants remain the same.

2.6 WIC expands state flexibility in response to formula shortage

In response to the shortage of infant formula caused by Abbott's recall of formula manufactured at a Michigan factory in February 2022, the USDA and other federal policymakers, along with formula manufacturers, implemented several measures. USDA provided waivers to states allowing WIC participants to buy other brands and types of formula without the usual medical documentation requirements, which was approved in states with Abbott contracts and most other states. The federal government worked to obtain specialty formula for infants with medical conditions, with limited stock being released on a case-by-case basis. Companies sent formula to places where there were shortages, while Abbott kept WIC costs down by offering refunds on other brands in states where there were contracts. Recent legislation enhanced the WIC program's ability to respond to supply disruptions, allowing for program flexibilities during emergencies and requiring contract provisions to protect against disruptions. USDA also offered nationwide waivers to authorize and issue imported formulas that may not meet all WIC requirements, ensuring access for WIC participants (Neuberger, Bergh, & Hall, 2022).

2.7 Auction theory

The discipline of auction theory is dynamic and quickly changing, producing new ideas and applications all the time. It has served as the foundation for a great deal of essential theoretical work and has helped us better understand how prices are formed, especially when they are prominently displayed and when they are negotiated during active conversations between the buyer and the seller. Klemperer (1999) provides an elementary, non-technical, survey of auction theory with the most fundamental concept.

There are four types of auctions that are used and analyzed. They are the ascending bid auction (English Auction), the descending bid auction (the Dutch auction), the-first price sealed bid-auction, and the second price sealed bid auction.

In the ascending bid auction, bids are made orally. The auctioneer begins the bidding at a certain price. Bidders announce successively higher bids until no one is willing to bid any higher. The bidder who submitted the final bid wins and pays the bid price. This auction is frequently used for art, used cars, and other items. The descending bid auction works exactly the opposite way; the auctioneer starts at a very high price and gradually lowers it. The objects are awarded to the first bidder who declares that she will accept the current price.

A first-price sealed bid is an auction where bidders submit sealed bids without knowing the other participants' bids. In this kind of auction, the highest bidder receives the good or service and pays the sum they offered. And lastly, a second-price sealed bid auction, often referred to as a Vickrey auction, is a type of auction in which players submit sealed bids without knowing the other bidders' amounts, but the winner pays the second-highest amount rather than their own.

Goeree and Offerman (2003) in their paper mentioned private value and common value are two terms used in the context of auctions to describe two different ways of valuing the good or service that is being auctioned, and these values have an effect on how bidders behave. In the private-value model, each bidder has a private and unique valuation for the item being auctioned, which is unknown to the other bidders or the seller. This means that each bidder bids based on their private information and willingness to pay, without knowing how much the other bidders are willing to pay. In contrast in a common value auction, the value of the item is the same for all bidders, but each bidder has different private information about of this. In this case, a bidder would change her estimate of the value if she learned another bidder’s signals.

Klemperer (1999) presented the basic analysis of optimal auctions, revenue equivalence, and marginal revenue. If any potential buyer of an object has a privately known signal drawn independently from a common distribution, then any auction mechanism in which the object always goes to the buyers with the highest signal and any bidder with the lowest feasible signal except zero surplus yields the same expected revenue: (Revenue Equivalence Theorem).

Oliveira and Frazao (2009) showed that if the bidders are risk-neutral and their information signals are independent, the expected revenue from any standard auctions equals the expected marginal revenue of the winning bidder.

2.8 Collusion screens in auctions

Chassang et al. (2022) investigates public works procurement auctions in Japan and reveal a significant lack of margin of victory near zero, implying collusion. They demonstrate that the missing mass of bids increases in auctions with high winning bids and decreases after regulatory scrutiny. They create a dynamic auction model to show that this pattern is not consistent with competitive bidding. They discover that under competition, the elasticity of bidders' residual demand should be less than -1, but the observed data suggest it is close to zero, indicating collusion.

Bajari and Ye (2003) analyze competitive and collusive bidding in procurement auctions with asymmetric bidders. They propose two conditions for bids to be rationalized by competitive bidding: conditional independence and exchangeability. Conditional independence requires that bids are not correlated after accounting for publicly observed information. Exchangeability implies that all bidders behave similarly when faced with the same cost structure. They implement tests for these conditions by estimating reduced form bid functions and testing residual correlations and coefficient equality. In their analysis, bids fail the conditional independence test but pass the exchangeability test, suggesting that while bids are not conditionally independent, they are exchangeable, indicating competitive behavior.

Kawai, Nakabayshi and Ortner (2023) introduce a test to detect collusive bid rotation patterns in procurement auctions using regression discontinuity (RD) design. They aim to distinguish between competitive and collusive bidding by analyzing discontinuities in the distribution of relevant covariates (e.g., incumbency status, backlog) around close winners and close losers. The test focuses on detecting whether winning and losing bids are "as-if-random" when bids are very close. They implement the test in the form of a RD test, where bidder-specific characteristics are regressed on bid differences. The test statistic is designed to detect collusion based on patterns of incumbency status, backlog, or distance. They find that none of the point estimates are statistically significant, indicating that the null hypothesis of competition is not rejected. However, they note that their test does not consider all possible collusive strategies, and further research is needed to explore other potential collusive behaviors.

The study conducted by Huang (2023), examined the process for WIC infant formula contracts in the United States from 2013 to 2015 focusing on potential collusion among major manufacturers – Mead Johnson, Ross (Abbott) and Carnation (Gerber). By applying various collusion detection screens proposed by prior research, including those of Chassang et al. (2022), Bajari and Ye (2003) and Kawai, Nakabayshi and Ortner (2023) his main objective was to assess whether bidding behavior suggests non-competitive practice of those manufacturers. The results indicate that there is no systematic evidence of bid rigging or collusion among these manufacturers during the study period. Despite this, the analysis acknowledges the possibility that a sophisticated cartel could evade detection through these tests. Additionally, it recognizes the limitations imposed by the small sample size, which may affect the power of the tests to detect certain forms of collusion.

2.9 Tit-for-Tat strategy and tacit collusion

The principle of tit-for-tat strategy is based on cooperating on the first move and then mirroring whatever the other player did in the preceding round. Thus, tit-for-tat (TFT) is a strategy of cooperation based on reciprocity (Baarslag, Hindriks, & Jonker, 2011). TFT is a strategy option in a repeated Prisoner's Dilemma game in which a player starts by cooperating with their opponent and then does whatever the opponent did on the previous move for the rest of the game, thereby maintaining trust with those who deserve it and punishing betrayers (Singer, 2015).

The repeated prisoner's dilemma is an extension of the general form except the game is repeatedly played by the same participants. A repeated prisoner's dilemma differs from the original concept of a prisoner's dilemma because participants can learn about the behavioral tendencies of their counterparty. Since the game is repeated, one individual can formulate a strategy that does not follow the regular logical convention of an isolated round. Tit for tat is a common iterated prisoner's dilemma strategy (Halton, 2022).

Tacit collusion refers to an implicit understanding among competitors, where they indirectly coordinate actions to limit competition and maximize profits without explicit communication or formal agreement. In an oligopoly, firms may use a TFT strategy to support tacit collusion (Crowley & Sargent, 1996). This strategy starts with all firms agreeing to keep prices high to maximize profits. If one firm lowers prices to attract more customers, the others do the same in retaliation, making the first firm lose out. This cycle of mimicry keeps all firms in line, encouraging them to stick to the agreement to keep prices high (Ekman et al., 2014).

2.10 Granger causality test

Granger causality is a popular concept of statistics that is commonly used in multiple fields such as economics, geography, and environmental that is based on causal relationship (He, 2009). It is a statistical hypothesis test for determining whether one time series is useful in predicting another. Basically, it is based on the notion how well past values of a time series Y_t could predict future values of another series X_t. According to Granger causality, if a signal X_1 "Granger-causes" a signal X_2, then past values of X_1 should contain information that helps predict X_2 above and beyond the information contained in past values of X_2 alone (Seth, 2007). In my study, we examine whether one manufacturer's market share provides useful information for predicting another manufacturer's future market share. Specifically, we investigate whether there is evidence of a "tit-for-tat" strategy between the manufacturers.

2.11 Summary

The WIC program in the United States, established in the 1960s to combat malnutrition among low-income Americans, has evolved significantly over the years. Central to the program is the acquisition of infant formula, with WIC being the main purchaser in the country. To secure formula at lower costs, WIC employs a cost-containment strategy involving manufacturer rebates and contracts with the lowest net price. However, there is uncertainty regarding how net price bids vary among WIC state agencies. The bidding process for these contracts involves manufacturers competing in first-price auctions, where the lowest net price bidder receives a multi-year contract. Studies have shown that bids often exceed 80% and 90% of wholesale prices, indicating significant discounts to acquire WIC contracts. The literature also explores factors influencing retail prices of infant formula, margin of victory in WIC auctions, and auction theory. Overall, the literature highlights the complexities of the WIC program, its impact on infant formula markets, and ongoing efforts to ensure competitive bidding practices. While there have been concerns about collusion in WIC infant formula auctions, scant research has addressed collusion, and none have found evidence of systematic evidence of bid rigging or collusion among major manufacturers. These insights set the stage for our research objective, which aims to delve deeper into the bidding behavior of manufacturers in WIC auctions. By examining whether manufacturers bid differently when they win compared to when they lose and looking on the insights on tit for tat strategy among the manufacturers, our research seeks to contribute to the existing knowledge on competitive practices within the WIC program's procurement process.

CHAPTER THREE
METHODOLOGY

3.1 Introduction

This chapter presents the model used in this study. It mainly consists of the methods of study, the specification of the model, the estimation procedure, and describes the process of data analysis.

3.2 Data set layout

Each observation in the data consists of a bid by a manufacturer for a sole-source auction in a state. The data include each state in the United States along with the District of Columbia for 1987-2022. Some state WIC programs have joined together to form alliances, through which they can negotiate combined deals with infant formula vendors. A state's affiliation with an alliance or independence is indicated by a variable in the data set. Data contains four[2] different types of formulas, but the study focuses on milk powder, as this is the most commonly purchased type of infant formula. The data identify the name of the contract winner and the previous winner according to the year. There are other variables are described in next section (3.3).

3.3 Variables description

We used four dependent variables and ten independent variables in our study.

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[2] LC-M = milk-based liquid concentrate, LC-S= Soy-based liquid concentrate, PW-M= milk-based powder, and PW- S= soy-based powder

Table 1: Variables and its description

Variables	Description
Dependent variables	
Winning rebate bid	It represents the bid amount that the infant manufacturers firms (Mead Johnson, Ross, and Carnation) offer to win a bid and to distribute the formula in each state. It is a continuous variable that can take any positive value.
Losing rebate bid	This is the rebate amount that manufacturers submit when they lose the auction. It is also a continuous variable that can take any positive value.
Winning net price	This is the net price of the milk formula when the manufacturer wins the auction, computed as wholesale price minus the rebate.
Losing net price	This is the net price of milk formula when the manufacturer loses the auction.
Independent variables	
Wholesale price (WP):	This is a continuous variable that represents the cost of the infant formula of the same manufacturers whose rebate we take as a response variable.
Rival wholesale price (RWP)	This is the cost of the milk formula of a rival manufacturer. Including this as our independent variable gives us a sense of its impact on the rebate amount and understand how competitive pricing dynamics affect the auction outcomes.

Average distance (AD)	It is the mean distance between manufacturer firms and the central location where bidding is conducted within the state.
Rival average distance (RAD)	It is the mean distance between rival manufacturer firms and the central location where bidding is conducted within the state.
Number of bidders (numbid)	This is the number of bidders who took part in the auction.
Number of WIC infants (WIC)	This is discrete variables that represent the number of infants who participated in the WIC program.
Number of non-WIC infants (NWIC)	It represents total number of infants who do not participate in the WIC, and it is measured as the number of total births in state minus total WIC infants.
Income (I)	Refers to the average income of individuals within the state where the bidding is taking place.
Previous winner	This refers to a manufacturer who has won the most recent contract by a WIC agency.

3.4 Sources of data

The study relied on existing sources and secondary data for its foundation and analysis to achieve its objectives. The data contains several variables which were obtained from different sources. The dependent variables (winning rebate bid, losing rebate bids, winning net price, and losing net price) and seven independent variables (wholesale price, rival wholesale price, years (1996-2020), average distance and rival average distance and number of WIC infants) were collected from USDA Food and Nutrition Service (USDA, 2023). These data are auction-specific data. And for the number of non-WIC infants, we first collected the data of total births by state from the National Centre of Health Statistics (NCHS, 2023). Then, we subtracted the number of WIC infants from the total births to get the data of the number of non-WIC infants. Similarly, we collected data for state income from Federal Reserve Economic Data (FRED).

3.5 Conceptual framework

I look for evidence in bidding behaviors suggestive of tacit collusion. First, if bidders are engaged in a market sharing strategy, I expect firms to offer bids that are not intended to win. I test for behavior two ways:

1. Bids wins differ from bid lost.
2. Non-serious bids should be offered less frequently in auctions which a manufacturer held a previous contract.

Second, one method for firms to tacitly collude is to play a tit-for-tat strategy as in a repeated prisoners dilemma. In a tit-for-tat strategy, a bidder mimics the other bidder's action in the previous period which can support collusion. In this strategy, a player cheating should be met with a response. I look for evidence of tit-for-tat strategy, I used Granger Causality I examined the causality test between two largest manufacturers: Mead Johnson and Ross. These statistical tools help reveal whether past changes in one manufacturer's market share can predict future changes in another's.

<u>Hypothesis 1</u>

H_0: $\widehat{NP}_{\text{win}} - NP_{\text{lose}} = 0$

where, $\widehat{NP}_{win}$ = Net Price predicted to bid using coefficient from winning model, but characteristics of contracts lost

NP_{lose} = Net Price submitted bid in auctions that were lost

A. If firms bid their value, our model is properly specified, then $\widehat{NP}_{win} - NP_{lose} = 0$ should be true.

B. If $\widehat{NP}_{win} - NP_{lose} > 0$ then firms are bidding below their predicted value in the auction they lose.

C. If $\widehat{NP}_{win} - NP_{lose} < 0$, then firms are bidding above their predicted value in auctions they lose.

Hypothesis 2

H_0: $\hat{R}_{win} - R_{lose} = 0$

$\hat{R}_{win}$ = Rebate bid predicted from winning model, but characteristics of contracts lost

R_{lose} = Rebate bid submitted in auctions that were lost

If our model is correctly specified, I expect the difference between the predicted rebate bid for auctions based on the winning model and the actual rebate bid in the auctions lost should be zero. If the difference ($\hat{R}_{win} - R_{lose}$) is greater than zero, it indicates that firms are bidding below their predicted value in auctions they lose. If the difference ($\hat{R}_{win} - R_{lose}$) is less than zero, it suggests that firms are bidding above their predicted value in auctions they lose.

Hypothesis 3

H_0: $\widehat{NP}_{lose} - NP_{win} = 0$

where, $\widehat{NP}_{lose}$ = Net Price predicted to bid based in coefficient from losing model, but characteristics of contracts won

NP_{win}= Net Price submitted in auctions that were won

If our model is correctly specified, I expect the difference between the predicted net price from losing auction and the actual net price when they won to be zero. A difference ($\widehat{NP}_{lose}$ - NP_{win})) greater than zero would suggest that firms are bidding net price below their predicted value in the auction they win. A difference ($\widehat{NP}_{lose}$ - NP_{win}) less than zero would indicate that firms are bidding net price above their predicted value in the auction they win.

Hypothesis 4

H_0: $\hat{R}_{lose}$ - R_{win} = 0

where $\hat{R}_{lose}$ = Rebate bid predicted using coefficient from losing model, but characteristics of contracts won

R_{win} = Rebate submitted in auctions that were won

If our model is correctly specified and accurately predicts rebate bids, I expect the difference between the predicted rebate bid from the losing model and the actual rebate bid when they won to be zero. If the difference ($\hat{R}_{lose}$ - R_{win}) is greater than zero, it indicates that firms are bidding below their predicted value in auctions they win. If the difference ($\hat{R}_{lose}$ - R_{win}) is less than zero, it suggests that firms are bidding above their predicted value in auctions they win.

Hypothesis 5: Being a previous bid winner decreases the likelihood of making a non-serious bid indicating tacit collusion.

Non-Serious (0,1) = f (previous winner)

To test this hypothesis, I conducted regression analysis focusing on bids where the winner matches the previous winner. Non-serious bids were identified by comparing bid values to statistical thresholds: bids one standard deviation below the predicted mean in rebate cases (termed 'Rebate fake bid 1') and two standard deviations below (termed 'Rebate fake bid 2'), as well as bids one standard deviation above the predicted mean in net price cases (termed 'Net Price fake bid 1') and two standard deviations above (termed 'Net Price fake bid 2'). Bids meeting these criteria were labeled as non-serious ('fake_bid = 1'), while bids that did not meet the criteria were labeled as serious ('fake_bid = 0'). Additionally, the variable 'previous winner' distinguishes between bidders who have previously won bids (coded as 1) and those who have not (coded as 0).

Collectively, Hypotheses 1 through 5 address whether bids are high or low for non-winning auctions, suggesting that manufacturers may be engaging in a repeated prisoners' dilemma game using a tit-for-tat strategy. To further investigate why manufacturers, appear to be submitting non-serious bids and whether this reflects a tit-for-tat strategy, we utilized our monthly data. By employing a Vector Autoregression (VAR) model and conducting a Granger causality test, we aimed to discover any predictive relationships between the changes in market shares of different manufacturers. In this test we were only looking the causality test between two largest manufacturers: Mead Johnson and Ross. These statistical tools help reveal whether past changes in one manufacturer's market share can predict future changes in another's, potentially indicating strategic bidding behaviors influenced by competitors' previous actions. The results from the Granger causality tests if significant will suggest that the manufacturers are not merely reacting spontaneously but are strategically responding to each other's previous behaviors, which is a hallmark of the tit-for-tat strategy in repeated game scenarios. Thus, we aimed to test the following hypothesis:

Hypothesis 6

Null Hypothesis (H_0): $\gamma_{ijk}=0$ for all k, which implies that changes in the market share of manufacturer j do not Granger-cause changes in the market share of manufacturer i. Therefore, there is no evidence of tit for tat strategy among the manufacturers.

where,

γijk are the coefficients of lagged terms of changes in market share for manufacturer j (reflecting the potential influence of manufacturer j on i) and i and j represents manufacturers i.e. Mead Johnson and Ross respectively.

3.6 Analytical model

We used a multiple linear regression model to estimate the rebate bid and net price for both winning and losing auctions as a function of independent variables for each manufacturer. In our study, we applied a logarithmic transformation of all variables in each model.

Winning rebate model using only winning bid

Here, the winning rebate bid was estimated as a function of the wholesale price (WP), rival wholesale price (RWP), average distance (AD), rival average distance (RAD), income (I), number of bids (numbid), number of WIC infants in a state (WIC), number of non-WIC infants in a state (NWIC), and dummy variables for each year.

$\widehat{\boldsymbol{WinningRebatebid}}_{\mathbf{i,\,k}} = \beta_0 + \beta_1 WP_{\mathbf{i}} + \beta_2\, RWP_{\mathbf{j}} + \beta_3\, AD_{\mathbf{i}} + \beta_4\, RAD_{\mathbf{j}} + \beta_5 I + \beta_6 numbid_{\mathbf{k}}$

$+ \beta_7 WIC_{\mathbf{k}} + \beta_8 NWIC_{\mathbf{k}} + \sum_{n=1}^{T} \delta_n$

Where i, represents each manufacturer (Mead Johnson, Ross, and Carnation), k represents auction.

Winning net price model using only winning bid

The winning net price was estimated as a function of average distance (AD), rival average distance (RAD), income (I), number of bids (numbid), number of WIC infants in an state (WIC), number of non-WIC infants in a state (NWIC), and dummy variables for each year (Tdum).

$$\widehat{WinningNetPrice}_{i,k} = \gamma_0 + \gamma_1 AD_i + \gamma_2 RAD_j + \gamma_3 I + \gamma_4 numbid_k + \gamma_5 WIC_k + \gamma_6 NWIC_k + \sum_{n=1}^{T} \delta_n$$

Losing rebate model using losing bid

Similarly, the losing rebate bid was estimated as a function of the wholesale price (WP), rival wholesale price (RWP), average distance (AD), rival average distance (RAD), income (I), number of bids (numbid), number of WIC infants in a state (WIC), number of non-WIC infants in an state (NWIC), and dummy variables for each year.

$$\widehat{LosingRebatebid}_{i,k} = \beta_0 + \beta_1 WP_i + \beta_2 RWP_j + \beta_3 AD_i + \beta_4 RAD_j + \beta_5 I + \beta_6 numbid_k + \beta_7 WIC_k + \beta_8 NWIC_k + \sum_{n=1}^{T} \delta_n$$

Losing net price model using losing bid

The losing net price was estimated as a function of average distance (AD), rival average distance (RAD), income (I), number of bids (numbid), number of WIC infants in a state (WIC), number of non-WIC infants in a state (NWIC), and dummy variables for each year (Tdum).

$$\widehat{LosingeNetPrice}_{i,k} = \gamma_0 + \gamma_1 AD_i + \gamma_2 RAD_j + \gamma_3 I + \gamma_4 numbid_k + \gamma_5 WIC_k + \gamma_6 NWIC_k + \sum_{n=1}^{T} \delta_n$$

We then predicted each winning and losing rebate bid and net price based on separate regression models for winning and losing bids. Additionally, we applied a bootstrap procedure to create multiple bootstrap samples (reps) to estimate the standard error of the predicted variables to account for potential generated variability. To be clear, for instance, we estimated the winning rebate bid for “MJ”, and we applied a bootstrap procedure to estimate the standard error of the predicted variables based on that winning regression function of the rebate bid.

Fake bid model

We modeled fake bids (indicating nonserious bids) for winners as a function of the previous winner variable, which indicates whether the previous bid winner was the respective manufacturer, for both the rebate and net price cases:

$$\text{Fake\_Bid } (0,1)_i = f(\text{previous\_winner})$$

where i represents manufacturers, MJ, Ross and Carnation.

In our analysis of fake bids for the rebate scenario, we categorized bids into two distinct groups based on their deviation from the mean rebate value: 'Rebate fake bid 1' represents bids that are one standard deviation below the predicted mean from winning auction, indicating a less competitive or strategic bid. 'Rebate fake bid 2' represents bids that are two standard deviations below the predicted mean, suggesting a further deviation towards non-competitive bidding strategies. Similarly, for the net price scenario, 'Net Price fake bid 1' includes bids that are one standard deviation above the predicted mean, while 'Net Price fake bid 2' encompasses bids that are two standard deviations above the predicted mean.

Here fake bids are dummy variables where 0 represents a bid that is considered competitive, aligning closely with the expected mean values. 1 represents a bid identified as non-serious, deviating significantly from the expected competitive norms, either below or above the mean, as specified in our criteria for rebate and net price scenarios respectively. Additionally, we examined the distribution of residuals through histograms comparing scenarios where manufacturers won the auction versus when they did not.

3.7 Evaluation of model

3.7.1 Paired t-test

I conducted a paired t-test to compare the mean of the predicted winning and losing rebate bids with the actual bids when the manufacturers lost and won the auction, respectively. Similarly, I compared the predicted winning and losing net prices with the actual net prices when the manufacturers lost and won the auction, respectively. These calculations were performed manually using the formula of paired t-test as done in (XU, 2017).

$$\text{T-test} = \frac{\overline{\widehat{X_1}} - \overline{X_2}}{\sqrt{\frac{SD_1{}^2}{n1} + \frac{SD_2{}^2}{n2}}}$$

where,

$\overline{\widehat{X_1}}$ *and* $\overline{X_2}$= Mean of predicted and actual samples, respectively

$\overline{X_2}$= is the actual mean of rebate or net price of manufacturers when they bid on the auctions, whereas $\overline{\widehat{X_1}}$ is the predicted rebate or net price of manufacturers from either the winning or losing model.

SD_1 and SD_2 = Standard deviations of predicted and actual samples, respectively

n_1 and n_2 = Total number of observations of predicted and actual samples, respectively

3.7.2 Granger causality Test

I employed a rigorous statistical approach to test our hypothesis 6 concerning strategic bidding behavior among manufacturers, specifically investigating a potential 'tit for tat' strategy. Utilizing a Vector Autoregression (VAR) model, we analyzed the interdependencies among changes in the market shares of different manufacturers over time. To statistically determine the presence of causative relationships, we conducted a Granger causality test, where the null hypothesis stated that changes in the market share of one manufacturer do not predict changes in another's market share. The results from these tests provided insights into whether manufacturers react to each other's market movements, indicating strategic responses.

CHAPTER FOUR

RESULTS

4.1 Introduction

This chapter presents the empirical estimations of the models. The chapter also presents the results of hypotheses tests to know whether the predicted bid and net price from winning and losing regression functions are different from their actual bid when they lose and win auctions respectively.

4.2 Regression analysis

The focus of this study is to find the relationship between factors affecting winning and losing rebate bids and net price of each manufacturer (MJ, Ross, and Carnation). In this section, the study presents the main findings from the multiple linear regression analyses. The results of the estimations conducted in this study are presented in the Tables below.

4.2.1 Winning and losing rebate bid

The regression models for MJ, Ross, and Carnation's winning and losing rebate bids demonstrate high statistical significance at 5% significant level. For MJ's winning rebate bid, the F-test statistic is notably high at 80.85 as shown in Table 1, indicating that the model's independent variables explain a significant portion of the variance in the bid. The R-squared value of 0.9645 further confirms this, revealing that the model accounts for 96.45% of the variance in the winning rebate bid. Overall, the model indicates that the wholesale price of MJ's infant milk formula, the number of WIC infants, the number of bidders, and the year have a significant impact on the winning rebate bid for MJ, whereas other factors such as the rival's wholesale price, average distance to stores, rival average distance, non-WIC infants alliance, and income have non-significant effects. Similarly, MJ's losing rebate bid model is highly significant, with an F-test statistic of 44.70 and an R-squared value of 0.9193, explaining 91.93% of the variance.

Moving to Ross shown in table 2, the model for their winning rebate bid is highly significant, with a low p-value (<0.05) and an F-test statistic of 36.78, explaining 92.46% of the variance. However, Ross's losing rebate bid model, though significant, has a lower F-test statistic of 3.78 and explains 46.84% of the variance. Only WIC -infants alliance is significant out of all independent variables for winning rebate and for losing rebate bid case, Ross wholesale price and rival wholesale price i.e. MJ wholesale price is significant. Carnation's winning and losing rebate bid models are both highly significant, with p-values of <0.05 and F-test statistics of 181.58 and 128.57, respectively. These models explain 99.47% and 97.56% of the variance in the winning and losing rebate bids, respectively. These results collectively indicate strong explanatory power in the models for all three manufacturers' rebate bids, showcasing the impact of their independent variables.

Table 2: Multiple linear regression results for MJ

Variables	**(1) Winning Rebate**	**(2) Losing Rebate**	**(3) Winning netprice**	**(4) Losing netprice**
constant	-3.412***	-8.79***	20.02	28.53***
mjwholesaleprice	2.09*** (0.23)	3.37*** (0.64)	-	-
roswolesaleprice	-0.20* (0.31)	-2.54*** (0.69)	-	-
mjavgdist	-0.01** (0.01)	-0.087* (0.04)	0.11 (0.16)	0.37** (0.17)
rossavgdist	-0.005* (0.02)	0.10*** (0.06)	0.01 (0.23)	-0.45* (0.25)
income	0.17* (0.09)	0.77** (0.11)	-1.79*** (0.32)	-2.38*** (0.37)
allaincewicinfants	0.04*** (0.009)	0.08*** (0.02)	-0.40*** (0.08)	-0.16* (0.09)
allaincenonwicinfants	-0.01* (0.0098)	-0.019 (0.02)	0.202** (0.085)	-0.08 (0.089)

numofbidders	0.03*** (0.007)	0.06** (0.03)	-0.50*** (0.071)	-0.41*** (0.0836)
observations	144	193	142	184
R-squared	0.9645	0.9193	0.8875	0.8470
F-test	(36, 153) 80.85	(39, 153) 44.70	(33, 108) 25.82	(35, 148) 23.40

Note: Standard errors in parentheses. *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$

4.2.2 Winning and losing net price

The regression models for MJ, Ross, and Carnation's winning and losing net prices demonstrate significant statistical findings, with all models displaying low p-values for the F-Statistics. For MJ's winning net price, the model is highly significant, with an F-test statistic of 25.82, explaining 88.75% of the variance. Conversely, MJ's losing net price model, though significant, has a slightly lower F-test statistic of 23.40 and explains 84.70% of the variance.

Moving to Ross, both the winning and losing net price models are significant, with p-values of 0.0000. The winning net price model has an F-test statistic of 14.76, explaining 83.90% of the variance, while the losing net price model has an F-test statistic of 10.56, explaining 69.48% of the variance.

Carnation's winning net price model is also significant, with an F-test statistic of 5.51, explaining 84.64% of the variance. Similarly, Carnation's losing net price model is significant, with an F-test statistic of 43.69, explaining 86.19% of the variance. These results underscore the impact of the independent variables on the net prices for all three manufacturers, highlighting the explanatory power of the models.

Table 3:Multiple linear regression results for Ross

Variables	**(1) Winning Rebate**	**(2) Losing Rebate**	**(3) Winning net price**	**(4) Losing net price**
constant	-2.58***	11.3*	19.3***	20.4***
rosswholesaleprice	2.023 (0.889)	17.11*** (3.22)	-	-
mjwholesaleprice	-0.983 (0.831)	-13.88*** (3.38)	-	-
rossavgdist	0.005 (0.07)	-0.305 (0.269)	0.0422 (0.3326)	0.03 (0.3)
mjavgdist	0.002 (0.05)	0.130 (0.18)	-0.0721 (0.240)	0.163 (0.20)
income	0.145 (0.10)	-1.37 (0.870)	-1.54*** (0.412)	-2.02*** (0.47)
allaincewicinfants	0.08*** (0.02)	-0.06 (0.1)	-0.26** (0.11)	0.08 (0.12)
alliancenonwicinfants	-.0082 (.0026)	0.043 (0.103)	-0.113 (0.1115)	-0.09 (0.11)
numofbidder	0.0432* (0.02)	0.164* (0.09)	-0.186** (0.09)	-0.53*** (0.08)
Observations	141	202	116	204
R-Squared	0.9246	0.4684	0.8390	0.6948
F-test	(35, 105) 36.78	(38, 163) 3.78	(30, 85) 14.76	(36, 167) 10.56

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4:Multiple linear regression results for Carnation

Variables	**(1) Winning Rebate**	**(2) Losing Rebate**	**(3) Winning net price**	**(4) Losing net price**
constant	-2.5*** (0.59)	-8.37*** (0.87)	-3.34 (12.9)	32.6** (5.8)
carnwholesaleprice	1.50*** (0.12)	1.03*** (0.1)	-	
mjwholesaleprice	-0.84 (0.67)	-0.15 (0.12)	-	
carnavgdist	0.004 (0.02)	-0.03** (0.015)	-1.57*** (0.52)	-0.052 (0.07)
mjavgdist	-0.028 (0.025)	0.026 (0.018)	1.19* (0.6063)	-0.08 (0.09)
income	0.26*** (0.09)	0.73*** (0.08)	-0.136 (0.99)	-2.77*** (0.55)
alliancewicinfants	0.046*	-0.023	0.6014	0.004

	(0.023)	(0.018)	(0.53)	(0.10)
alliancenonwicinfants	-0.003	0.062***	0.061	-0.006
	(0.018)	(0.020)	(0.46)	(0.09)
numbidder	0.027**	-0.007	-0.148	-0.96***
	(0.012)	(0.02)	(0.33)	(0.08)
Observations	56	119	51	273
R-squared	0.9947	0.9756	0.8464	0.8619
F-test	(28,27)	(28, 90)	(25, 25)	(34, 238)
	181.58	128.57	5.51	43.69

Note: Standard errors in parentheses. *** p < 0.01, **p < 0.05, *p < 0.1

A study conducted by Davis and Oliveira (2015) included separate regression analyses for three firms, with net price as the dependent variable and infant participation in the WIC as the independent variable. The results revealed that the number of WIC infant participants had a statistically significant relationship with net price for Mead Johnson and Ross, while Carnation (Gerber) did not show statistically significant results.

4.3 Hypothesis testing of rebate bid and net price

Hypothesis 1: H_0: $\widehat{NP}_{win} - NP_{lose} = 0$

Hypothesis 2: H_0: $\hat{R}_{win} - R_{lose} = 0$

Hypothesis 3: H_0: $\widehat{NP}_{lose} - NP_{win} = 0$

Hypothesis 4: H_0: $\hat{R}_{lose} - R_{win} = 0$

The analysis focused on comparing the actual winning and losing rebate and net price bid amounts with the predicted bids based on separate regression models for losing and winning bids respectively. The mean differences between the actual and predicted bid amounts were calculated for each manufacturer and tested using a paired t-test.

4.3.1 Paired t-test result

Table 5: Paired t-test results

Manufacturers	Variables	Mean Differences	t-test
Winning rebate case			
MJ	Pred. mj rebate-win	0.084	2.38**
	Winner! = "MJ"		
Ross	Pred. ross rebate-win	0.1985	4.603***
	Winner! = "R"		
Carnation	Pred. carn rebate-win	-0.03935	-0.51
	Winner! = "C"		
Winning net price case			
MJ	Pred. mj netprice-win	-0.6692	-5.68***
	Winner != "MJ"		
Ross	Pred. ross netprice-win	-1.0419	-10.05***
	Winner! = "R"		
Carnation	Pred. carn netprice-win	-1.2429	-0.324
	Winner != "C"		
Losing rebate case			
MJ	Pred. mj rebate-lose	-0.0443	-1.80*
	Winner = "MJ"		
Ross	Pred. ross rebate-lose	-0.192	-2.17***
	Winner = "R"		
Carnation	Pred. carn rebate-lose	-0.189	-2.09***
	Winner = "C"		
Losing net price case			
MJ	Pred. mj netprice-lose	0.4542	3.91***
	Winner = "MJ"		
Ross	Pred. ross netprice-lose	0.8021	5.62***
	Winner = "R"		
Carnation	Pred. carn netprice -lose	0.978	4.81***
	Winner = "C"		

*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$

Winning rebate bid case

For MJ, the mean difference between the predicted bid based on the winning regression function and the actual losing rebate bid was 0.084, with a t-value of 2.383, indicating a significant difference at less than the 5% level. In other words, on average, manufacturer

MJ could have bid around 8.4% higher than what they actually bid when they lost the auction in order to have a chance to win.

For Ross, the mean difference of 0.1985 with a t-value of 4.6037 indicates that, on average, Ross could have bid around 19.85% higher than what they actually bid when they lost the auction in order to have a chance to win. Also, this difference was found to be statistically significant at 1% significant level. Carnation, however, had a mean difference of -0.03935 with a t-value of -0.5131, which was not significant.

Winning net price case

For MJ, the mean difference between the predicted net price based on the winning net price function and the actual losing net price was -0.6692, with a t-value of -5.6813, indicating a significant difference at the 1% level. This also means the net price of MJ when they lose should be 66.92% lower than MJ's actual losing net price. Ross had a mean difference of -1.0419 with a t-value of -10.053, showing a significant difference. Carnation had a mean difference of -1.2429 with a t-value of -0.32417, which was not significant.

Losing rebate bid case

For MJ, the mean difference between the predicted bid based on the losing rebate function and the actual winning rebate bid was -0.0443, with a t-value of -1.8030, indicating a significant difference at the 10% level. This means that, on average, MJ's actual winning rebate bid was 4.43% higher than what was predicted by the losing rebate function. Ross had a mean difference of -0.192 with a t-value of -2.1702, also showing a significant difference and they should have bid rebates approximately 19% lower than what they actually bid for the chance to win that auction. Carnation had a mean difference of -0.1899 with a t-value of -2.0965, which was significant.

Losing net price Case

For MJ, the mean difference between the predicted net price based on the losing function and the actual winning net price was 0.4542, with a t-value of 3.915, indicating a significant difference at the 5% level. This means that, on average, MJ's actual winning net price was 45.42% lower than what was predicted by the model based on the losing regression function. Ross had a mean difference of 0.8021 with a t-value of 5.6215, also showing a significant difference. Carnation had a mean difference of 0.978 with a t-value of 4.818, which was significant.

4.3.2 Fake bid (Non serious bid) model result

The focus of this study is to find the estimation of fake bid with respect to previous winner. The dependent variable, fake bids, are dummy variables where 0 represents a bid that is considered competitive, aligning closely with the expected mean values. A value of 1 represents a bid identified as non-serious, deviating significantly from the expected competitive norms, either below or above the mean, as specified in our criteria for rebate and net price scenarios respectively. This analysis utilizes a Linear Probability Model (LPM) to quantify the relationship between previous winning status and the probability of placing a fake bid, allowing for a clear interpretation of how previous outcomes influence subsequent bidding actions.

Table 6: Estimation of fake bids

Manufacturers		**Rebate fake bid 1**	**Rebate fake bid 2**	**Net price fake bid 1**	**Net price fake bid 2**
Mead Johnson	Previous winner mj	-0.184**	-0.154**	-0.205**	-0.207**
		(0.05)	(0.049)	(0.051)	(0.042)
	const	0.43**	0.36**	0.47**	0.285**
		(0.032)	(0.030)	(0.032)	(0.026)
	R2	0.034	0.0268	0.0417	0.063

Ross	Previous winner ross	-0.091**	-0.027	-0.119**	-0.143**
		(0.32)	(0.2)	(0.05)	(0.045)
	const	0.117**	0.044**	0.588**	0.16**
		(0.018)	(0.011)	(0.031)	(0.025)
	R2	0.022	0.0046	0.012	0.027
Carnation	Previous winner carn	-0.193**	0.098**	-0.571**	-0.073
		(0.057)	(0.05)	(0.073)	(0.049)
	const	0.132**	0.098**	0.615**	0.883**
		(0.02)	(0.017)	(0.026)	(0.017)
	R2	0.0313	0.0108	0.14	0.0062

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Rebate Case

Based on the regression analysis for Mead Johnson, Ross, and Carnation for rebate bid case, the variable previous winner (indicating if the previous bid winner was the respective manufacturer) is statistically significant in predicting 'fake bid' (indicating a nonserious bid) for winners. In the rebate case when considering bids that are one standard deviation below the mean and two standard deviations below the mean, the regression analysis reveals a negative relationship between being a previous winner and the likelihood of making non serious bid. This suggests that being a previous winner decreases the probability of submitting non-serious bid. For instance, a coefficient of -0.184 and -0.154 means that being a previous winner as Mead Johnson decreases the probability of submitting a non-serious bid by 18.4 percentage for bids that are one deviation below the mean and 15.4 percentage points for bids that are two standard deviations below the mean. Similar analyses for Ross and Carnation show comparable patterns. This analysis shows that if a manufacturer currently holds a contract, it often expects to win it again without much competition from other firms. This may happen because of tacit collusion, where they avoid intense competition to keep the contract stable. For example, if Ross didn't aggressively bid against Mead Johnson previously, Ross expects Mead Johnson to do the same in return when Ross holds the contract. This kind of tit-for-tat strategy helps companies avoid conflicts and ensures that they take turns winning contracts.

Along with that, the residuals, when a winner is not MJ, the histogram are left-skewed (Fig 2) which indicates that while some rebate bids are close to the predictions, there are many instances where the actual bids of bidder are significantly lower than the predicted rebate bid based on the winning auctions. This observation may suggest non-serious bidding behavior, where bidders strategically submit lower rebate bids. It hints at a potential strategy among bidders to consistently underbid, possibly to avoid winning certain auctions, which could be interpreted as indicative of tacit collusion.

Similarly for Ross and Carnation, the histogram of residuals when they did not win the auction (Figure 4 and Figure 6 respectively) also exhibits a similar pattern (left-skewed). Hence, this pattern also shows the indication of a non-serious bid and aligns with tacit collusion.

Net price Case

Based on the regression analysis for Mead Johnson, Ross, and Carnation for net price case, the variable previous winner (indicating if the previous bid winner was the respective manufacturer) is statistically significant in predicting 'fake bid' (indicating a nonserious bid) for winners. For the net price case when considering fake bids that are one standard deviation above the mean and two standard deviations above the mean, the regression analysis revealed the negative coefficient for all the manufacturers. This negative relationship emphasizes that previous winners are less likely to submit non-serious bids. For instance, a coefficient of -0.205 and -0.207 for in the regression model for Mead Johnson indicates being a previous winner reduces a likelihood of submitting a non-serious (exaggeratedly high) bid by 20.5% when the bid is one standard deviation above the mean and 20.7% when the bid is two standard deviations above the mean. This bidding strategy reflects a likely adherence to tacit collusion principles, where firms restrain their bidding to maintain market stability and protect long-term market relationships among the manufacturers.

We can further see the histogram of residuals i.e. actual net price minus predicted net price for Net Price, in Figure 8, showing a right-skewed distribution when a winner is not MJ. This indicates that while some net prices are close to the predictions, there are many instances where the actual net price of bidder is significantly higher than the predicted net price, indicating nonserious bidding behavior. It suggests a potential strategy among bidders to consistently have higher net prices, possibly to avoid winning certain auctions, which aligns with the concept of tacit collusion. Similarly for Ross and Carnation, the histogram of residuals when they did not win the auction (Figure 10 and Figure 12 respectively) also exhibits a similar pattern (left-skewed). Hence, this pattern also shows the indication of a non-serious bid and aligns with tacit collusion.

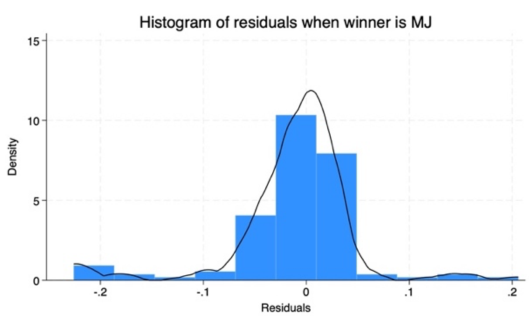

Figure 4

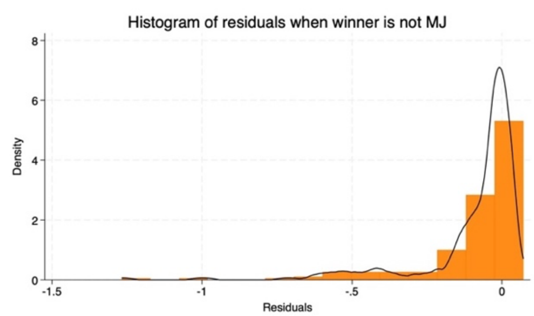

Figure 5

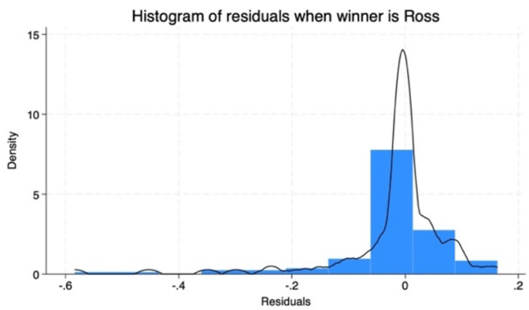

Figure 6

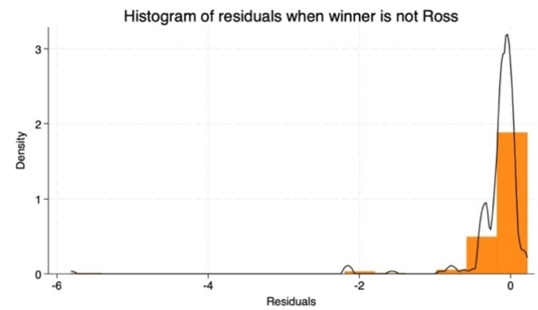

Figure 7

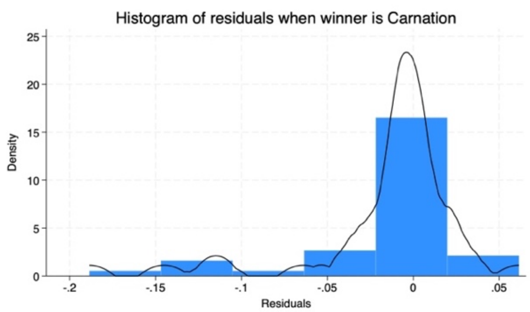

Figure 8

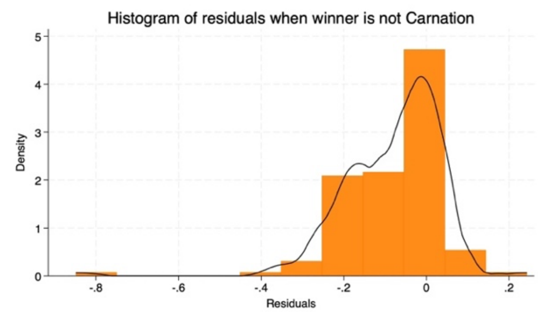

Figure 9

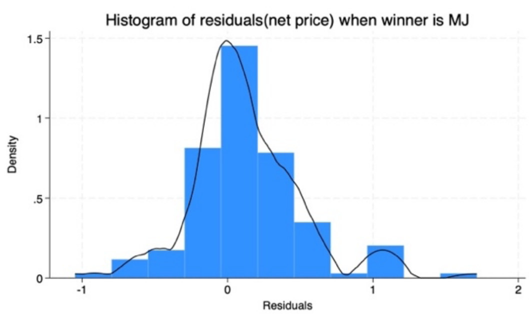

Figure 10

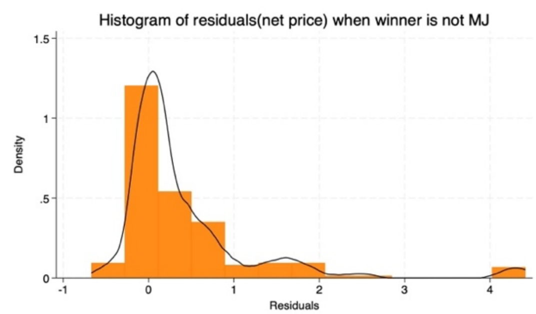

Figure 11

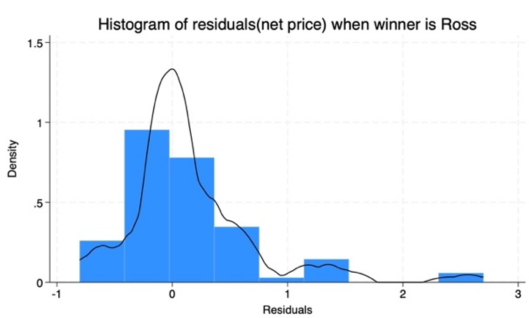

Figure 12

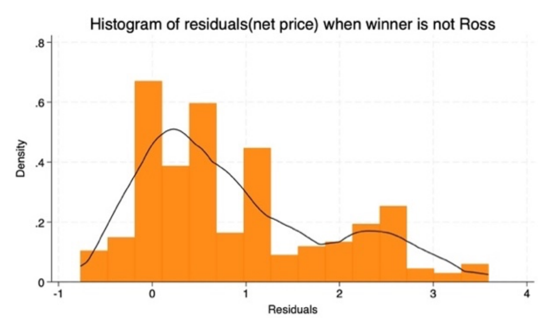

Figure 13

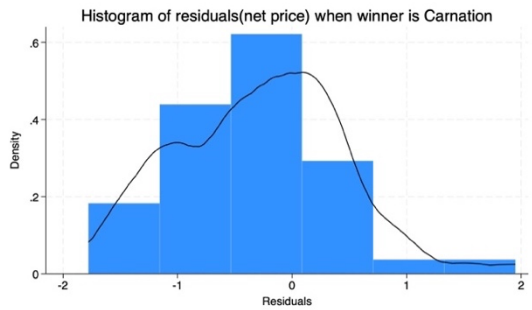

Figure 14

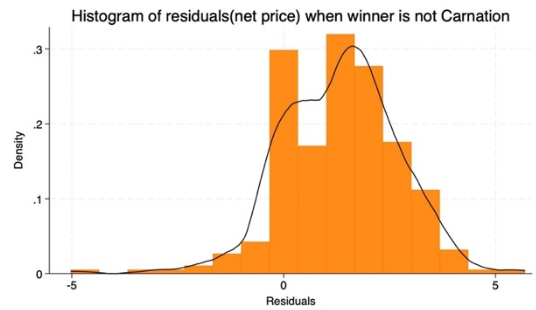

Figure 15

4.3.3 Granger causality test

To further explore the strategic interactions among bidders, we conducted Granger causality tests to assess the potential for tit for tat strategy or repeated prisoner's dilemma scenarios. We analyzed monthly data on manufacturers' shares of total WIC infants to identify whether changes in one manufacturer's, Mead Johnson, market share of total WIC infants' contracts could predict changes in another's, Ross, indicating strategic, responsive behaviors.

Prior to performing the Granger causality tests, we conducted Dickey-Fuller tests to ascertain the stationarity of our data, as stationarity is a requisite assumption for Granger causality. The initial tests indicated that the data was non-stationary. Consequently, we differentiated our monthly data to achieve stationarity and then re-applied the Granger causality test, which confirmed the data was stationary, allowing us to proceed with our causality analysis.

Table 7: Granger-Causality test for market share

Equation	Excluded	Chi2	df	Prob > chi2
dmjshare	drossshare	6.4677	1	0.011**
dmjshare	ALL	6.4677	1	0.011**
drossshare	dmjshare	13.068	1	0.000**
drossshare	ALL	13.068	1	0.000**

The variable dmjshare and drossshare represents the first difference of Mead Johnson's and Ross's market share respectively. In time series analysis, the first difference of a series is the series of changes from one period to the next. This can be expressed mathematically as:

$$dmjshare_t = mjshare_t - mjshare_{t-1}$$

where:

- $dmjshare_t$ is the value of the first difference of Mead Johnson's market share at time t,
- $mjshare_t$ is the value of Mead Johnson's market share at time t,
- $mjshare_{t-1}$ is the value of Mead Johnson's market share at time t−1.

In analyzing market share dynamics, the Granger causality tests revealed notable interdependencies between manufacturers. When excluding Ross's market share from the equation predicting Mead Johnson's market share, the results show a statistically significant Granger-causal impact on mead Johnson's market share at 5% significant effect. This implies changes in market share of manufacturer Ross Granger causes a change in market share of Mead Johnson.

Conversely, when excluding Mead Johnson's market share change from the equation predicting Ross's market share, the analysis yielded a chi-square 13.068 with p-value less than 0.001. This strongly suggests that changes in Mead Johnson's market share are a significant Granger-causal predictor of Ross's market share fluctuations. These results give evidence for a tit-for-tat strategy, where each manufacturers market share adjustments appear strategically linked to the actions of their competitors. The Granger causality test outcomes indicate that any significant change in Ross's market share influences subsequent changes in Mead Johnson’s market share, and vice versa. Such reciprocal behavior suggests that both companies are actively engaged in a cycle of reactive strategies, adjusting their market moves based on the competitive actions of the other.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.0 INTRODUCTION

This chapter summarizes the study's key findings on comparative analysis of winning and losing bids from major manufacturers in WIC rebate auctions. This is followed by the conclusions from the study and the possible recommendations for policymakers and research.

5.1 SUMMARY

This study examined whether the manufacturers are bidding competitively in WIC rebate auctions. The analysis included five dependent variables (winning and losing rebate bids, winning, losing net prices and fake bids) and ten independent variables (including wholesale price, rival wholesale price, average distance, rival average distance, income, number of bidders and previous winner). Data were collected from various sources, including USDA, NCHS, and FRED. Hypotheses were formulated and tested using multiple linear regression models, with separate models for winning and losing bids for each manufacturer. The study applied a bootstrap procedure and conducted paired t-tests to compare predicted and actual rebate bids and net prices. I also used linear probability model to predict non serious bid to look whether manufacturers as a previous bid winner is significant with the likelihood of making a non-serious bid indicating tacit collusion. To further explore the strategic dynamics between manufacturers, Vector Autoregression (VAR) and Granger causality tests were employed. These methods were useful in identifying potential tit for tat strategies, where each manufacturer's actions seem to influence and be influenced by their competitors' actions.

5.2 CONCLUSIONS AND RECOMMENDATIONS

The results of the regression analysis provide valuable insights into the factors influencing winning and losing rebate bids and net prices for manufacturers MJ, Ross, and Carnation. The models for all three manufacturers show high statistical significance, indicating that the independent variables have a significant impact on bid outcomes. Hypothesis testing further confirms the effectiveness of the models in predicting bid outcomes. The paired t-tests show significant differences between the actual and predicted bid amounts for all three manufacturers. For instance, we found that firms are bidding below their predicted value in auctions they lose, indicating that they could have bid differently to potentially improve their chances of winning auctions. These findings suggest that manufacturers may not always bid competitively.

To further understand the strategy, the study explored the notion of non-serious bids and tit-for-tat strategies among the competitors. The analysis of fake bids revealed that previous winners are less likely to submit non serious rebate bids, potentially indicative of tacit collusion. This pattern was consistent across all manufacturers, suggesting a strategic, possibly collusive behavior that affects how bids are placed depending on the auction context giving some hint on tit-for-tat strategy.

Moreover, Granger causality tests were conducted to assess the strategic interactions, particularly looking for evidence of a tit-for-tat strategy where manufacturers react to each other’s market share changes. The results showed significant interdependencies, confirming that changes in one manufacturer’s market share could predict changes in another’s. This highlights a responsive bidding behavior among the firms, where they adjust their strategies based on the actions of their competitors, further evidencing the complexity of competitive dynamics in this market.

5.3 LIMITATIONS OF OUR STUDY

Model misspecification: This suggests that there may be errors or inadequacies in the way the regression models were constructed, or the variables included in them. The model might be missing some important variables that can lead to biased estimates and inaccurate conclusions.

Firms are submitting shadow bids intending to lose: This refers to the possibility that some firms may intentionally submit bids that are higher than what they are willing to offer, with the intention of losing the auction. The reasons behind this behavior are not clear and require further research to understand.

Exclusion of Carnation from causality test: In our study, we focused on Mead Johnson (MJ) and Ross due to their dominant market shares in the WIC auction context, which suggested a more direct competitive interaction between them. Consequently, Carnation was excluded from the Granger causality tests. This exclusion may limit the scope of our findings, as it omits an analysis of how Carnation's actions might influence or be influenced by the market dynamics set by MJ and Ross.

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APPENDIX

Table 8: Summary of winning and losing rebate and net price

Manufacturers	Variables	Observations	Mean	Standard deviation
		Losing rebate case		
MJ	Winner! = “MJ”	193	1.409	0.3164
Ross	Winner! = “R”	202	1.3005	0.5288
Carnation	Winner! = “C”	119	1.450	0.2861
		Winning rebate case		
MJ	Winner = “MJ”	145	1.464	0.1483
Ross	Winner = “R”	141	1.519	0.290
Carnation	Winner = “C”	56	1.438	0.2404
		Losing net price case		
MJ	Winner! = “MJ”	184	-0.292	0.885
Ross	Winner! = “R”	204	-0.180	0.816
Carnation	Winner! = “C”	273	0.404	1.275
		Winning net price case		
MJ	Winner = “MJ”	142	-0.919	0.766
Ross	Winner = “R”	116	-0.922	0.843
Carnation	Winner = “C”	51	-1.137	1.065

Table 9: Predicted winning and losing rebate and net price

Manufacturers	Variables	replications	Predicted mean	Bootstrap S.E
		Winning rebate bid		
MJ	win_mjrebatehat	104	1.493	0.0269
Ross	win_rossrebatehat	105	1.499	0.02179
Carnation	win_carnrebatehat	100	1.41065	0.07207
		Losing rebate bid		
MJ	lose_mjrebatehat	108	1.4197	0.0212606
Ross	lose_rossrebatehat	103	1.327	0.0850298
Carnation	lose_carnrebatehat	111	1.2481	0.0846909
		Winning net price		
MJ	win_netpricemjhat	108	-0.9612	0.09807
Ross	win_netpricerosshat	100	-1.2219	0.08646
Carnation	win_netpricecarnhat	102	-0.8389	0.74531
		Losing net price		
MJ	lose_netpricemjhat	102	-0.4648	0.09658
Ross	lose_netpricerosshat	104	-0.1199	0.1193
Carnation	lose_netpricecarnhat	108	-0.159	0.1377

Total observation each = 363

Dickey-Fuller Test

Table 10: Dickey-Fuller test results for unit root analysis

Variable	Observations	Test Statistics	Critical value (1%)	Critical value (5%)	Critical value (10%)	MacKinnon Approximate P-value
dmjshare	463	-21.094	-3.981	-3.421	-3.13	<0.0001
drossshare	463	-20.815	-3.981	-3.421	-3.13	<0.0001

Vector Autoregression (VAR) results for dmjshare and drossshare

Table 11: Summary statistics of VAR model for dmjshare and drossshare

Variable	Parameters	RMSE	R-squared	Chi-squared	p-value
dmjshare	3	0.0244	0.0248	9.395	0.0091
drossshare	3	0.24025	0.0363	13.9036	0.0010

Table 12:Coefficients for Vector Autoregression (VAR) Model

Equation	Coefficient	Estimate	Std. Error	z-value	P-value	95% Confidence Interval
dmjshare						
	dmjshare L12	0.324	0.106	3.06	0.002	[0.1163, 0.5316]
	drossshare L12	0.2737	0.1076	02.54	0.011	[0.0627, 0.4847]
	constant	0.0007	0.0012	0.57	0.571	[-0.00177, 0.0032]
drossshare						
	dmjshare L12	-0.376	0.104	-3.61	0.000	[-0.579, -0.1721]
	drossshare L12	-0.379	0.1056	-3.59	0.000	[-0.586, -0.172]
	constant	0.000067	0.0012	0.05	0.957	[-0.0023, 0.0025]