THE UNIVERSITY OF CHICAGO

GREEDFLATION AND GROCERY RETAIL CONDUCT: EVIDENCE FROM COMMODITY-LIKE PRODUCT MARKUPS

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ABSTRACT

Recent inflationary pressures have sparked widespread allegations of “greedflation”—the notion that firms have exploited cost shocks to raise prices beyond what is justified by fundamentals. Among the sectors most frequently accused are grocery retailers, particularly in the pricing of essential, commodity-like consumer goods. This paper empirically investigates these claims by testing for the presence of coordinated or collusive pricing behavior among grocery retailers during a period of rising input costs. Using detailed store-, product-, and consumer-level data, I estimate a structural demand model and use it to recover mark-ups and test firm conduct. I examine whether price responses to commodity cost shocks are consistent with competitive pricing or indicative of joint profit maximization. The findings indicate that, for several product categories frequently highlighted in the media, pricing behavior is more consistent with competitive conduct than with collusion. Overall, despite rising prices and profits, the evidence indicates that pricing behavior remains consistent with competitive conduct, underscoring the importance for policymakers to account for demand conditions and cost pass-through before attributing inflation to coordinated market power.

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CHAPTER 1

GREEDFLATION AND GROCERY RETAIL CONDUCT: EVIDENCE FROM COMMODITY-LIKE PRODUCT MARKUPS

1.1 Introduction

Following the COVID-19 pandemic, both consumers and producers have faced substantial disruptions, none more visible than the sharp rise in food prices. As Handfield [2024] notes, consumer spending on food has reached its highest level since the early 1990s. Between 2020 and 2024 alone, U.S. food prices increased by 23.6 percent, as illustrated in Figure 1.1 [U.S. Department of Agriculture, Economic Research Service, 2025].

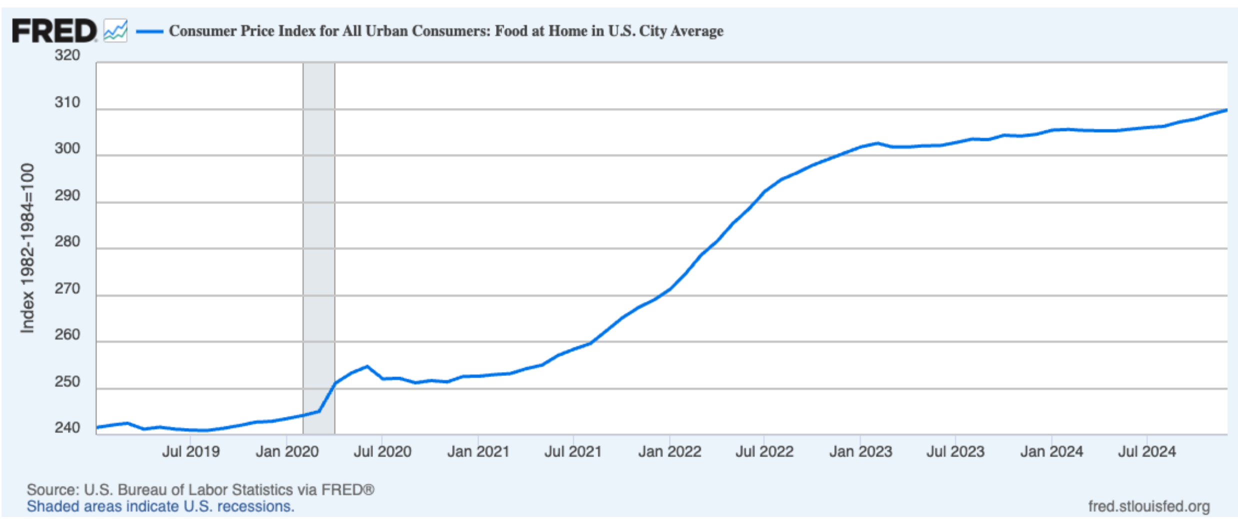

Figure 1.1: Consumer Price Index for All Urban Consumers: Food at Home in U.S. City Average [U.S. Bureau of Labor Statistics, 2025c].

In parallel with these inflationary pressures, a growing public narrative has emerged that blames corporate pricing behavior, particularly among grocery retailers, for elevated consumer costs. This discourse, shaped by behavioral responses and fairness concerns, has gained traction in political rhetoric and media coverage [Snir et al., 2025, Çakır et al., 2025]. From eggs and milk to packaged foods and household staples, basic grocery items have become symbols of perceived corporate opportunism during a period of economic uncertainty. A 2024 Federal Trade Commission (FTC) report reinforces these concerns, suggesting that some firms used rising in put costs as an opportunity to expand profit margins [Federal Trade Commission, 2024]. At the center of this conversation is the concept of "greedflation": the idea that firms exploited cost shocks and supply chain disruptions to raise prices beyond levels justified by competitive market forces [Demsas, 2024]. Recent work by Shapiro [2024] further underscores this narrative, showing how large retailers use intensive price monitoring and surveillance practices to track rivals' behavior, thereby facilitating tacit coordination and what Weber and Wasner [2023] terms "seller's inflation."

This paper empirically examines the extent to which such claims reflect actual pricing behavior of grocery retailers. Specifically, I assess whether price responses to commodity input cost shocks in key food categories are consistent with non-coordinated oligopoly behavior or instead exhibit patterns indicative of joint profit maximization. Leveraging rich store-, product-, and consumer-level data from U.S. grocery retailers, I estimate a structural demand model that enables the recovery of price-cost mark-ups and firm conduct parameters. This framework allows for formal testing of whether firms behave as independent Bertrand competitors or engage in coordination. By applying this approach to inflationary periods rather than tax shocks, where most recent conduct testing has focused, this paper contributes to a deeper understanding of strategic pricing behavior in times of macroeconomic disruption. In doing so, it informs broader policy discussions on market concentration, antitrust enforcement, and consumer welfare.

Narratives of greedflation have been reinforced by high-profile examples, as shown in Figure 1.2 [Food & Water Watch, 2025, Food & Power, 2024]. In these accounts, firms are portrayed not as passive responders to inflation but as strategic actors expanding margins under the guise of rising costs. Some commentators interpret these patterns as signs of tacit collusion or coordinated pricing among dominant players in increasingly concentrated markets. Recent empirical work supports these interpretations. Davis [2024] finds that the pandemic-era mark-up gains extended beyond the top firms in later years, indicating a diffusion of pricing power across the firm distribution. Likewise, Weber and Wasner [2023] argue that macroeconomic models alone cannot explain recent inflation and instead emphasize the role of strategic pricing and market structure.

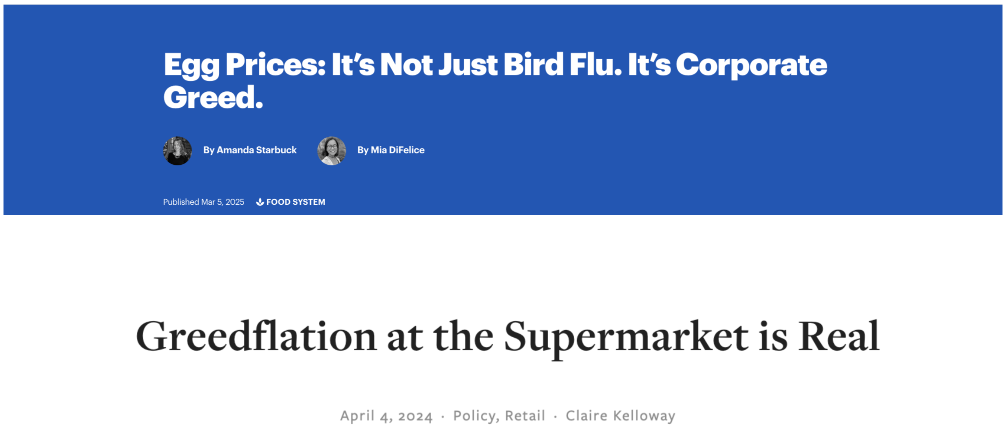

Figure 1.2: Greedflation News Articles [Food & Water Watch, 2025, Food & Power, 2024].

However, many economists remain skeptical of the greedflation narrative, arguing that it oversimplifies complex inflationary dynamics. As reported by Selyukh [2024], rising retailer margins can often be explained by traditional factors such as supply disruptions, demand shocks, and anticipatory pricing. Glover et al. [2023], for example, highlight how firms may raise prices in expectation of future cost increases, while **?** find that total mark-ups remained broadly stable due to offsetting behavior between manufacturers and retailers. Extending this evidence cross-nationally, Alvarez et al. [2025] show that although retail prices rose during the COVID-19 and post-pandemic inflation, overall markups remained stable because manufacturer and retailer margins moved in opposite directions, challenging the idea of widespread margin expansion. Although profit shares increased during 2021–2022, Çakır et al. [2025] attribute this primarily to supply-side frictions and precautionary strategies rather than explicit margin growth. Similarly, Nikiforos et al. [2024] emphasize that "profit-led inflation" can arise even without rising mark-ups, as firms seek to maintain pre-shock profitability in the face of higher costs. Related work further points to structural forces that mechanically raise profits without implying increased market power: pandemic-era non-marginal costs normalized, lowering average costs and boosting measured profits [Fernald and Li, 2022]; post-pandemic productivity and operational efficiencies compressed markups [Garga et al., 2024]; competitive pressures tightened cost pass-through during inflation [Note, 2022]; and demand normalization heightened price sensitivity, limiting firms' ability to sustain elevated margins [Cerrato and Gitti, 2023].

Adding further complexity, inflation is not experienced uniformly across products, retailers, or households. Price increases vary widely across categories and shopping formats, with low-income households often facing higher effective inflation rates [Dekimpe and van Heerde, 2023, Sangani, 2023]. Cavallo and Kryvtsov [2024] reveal that while households attempted to adapt through substitution and discount-seeking behavior, inflation in budget categories frequently undermined these coping strategies. In turn, policy and legal responses to price gouging concerns have shaped firm behavior. Scheitrum et al. [2023] document how litigation risks led U.S. food retailers to prioritize price rigidity over supply availability, resulting in reduced access to key staples such as eggs, particularly for lower-income consumers.

Taken together, the divergence between public narratives and academic evidence raises important questions about the underlying drivers of price increases in concentrated retail markets during periods of inflation. Although some scholars emphasize traditional supply-side explanations, others point to strategic pricing in the presence of market power. As Dekimpe and van Heerde [2023] note, the academic literature has historically devoted limited attention to inflationary episodes, particularly with regard to consumer–retailer interactions. Çakır et al. [2025] similarly argue that concepts like greedflation remain central to both public perception and economic experience, yet require deeper theoretical and empirical development to disentangle behavioral responses, cost pass-through, and firm conduct.

This paper contributes to this effort by empirically testing whether grocery retailers engaged in coordinated or collusive pricing behavior during recent inflationary periods. I examine whether price responses to commodity input cost shocks in key food categories are consistent with competitive oligopoly behavior or instead reflect pricing patterns indicative of joint profit maximization. Using detailed store-, product-, and consumer-level data from U.S. grocery retailers, I estimate a structural demand model that enables recovery of price-cost mark-ups and firm conduct parameters. This framework provides a formal empirical test of whether firms behave as Bertrand competitors or exhibit pricing consistent with tacit coordination.

This approach is motivated by three key observations. First, the product categories most frequently cited in media narratives of greedflation tend to be homogeneous or commodity-like goods, conditions that can facilitate coordination among retailers. Second, while aggregate profit trends and anecdotal reports suggest rising mark-ups, these measures do not account for differences in demand elasticity, input cost pass-through, or competitive intensity—factors that structural models can explicitly incorporate. Third, most recent empirical work on firm conduct has focused on tax shocks, leaving the inflation context underexplored. By applying this framework to inflationary episodes, this paper advances the understanding of price-setting behavior in concentrated markets and contributes to ongoing policy discussions on market power, inflation, and consumer welfare.

This paper proceeds as follows. Section 1.2 describes the institutional features of the grocery retail market. Section 1.3 reviews the related literature on firm conduct, cost pass-through, and pricing behavior under inflationary conditions. Section 1.4 describes the data sources and variable construction. Section 1.5 provides descriptive evidence on input cost trends and inflation patterns. Section 1.6 describes the conduct testing procedure. Section 1.7 outlines the empirical framework used to estimate demand and supply-side margins. Section 1.8 presents the main results and tests for firm conduct. Section 1.9 concludes.

1.2 Institutional Setting & Industry Background

1.2.1 Market Structure & Competition

U.S. grocery retailing is concentrated and organized around a small number of large, multi-store chains (e.g., Kroger, Walmart, Albertsons, Ahold Delhaize) that compete locally within metropolitan areas. Although firms operate nationally, pricing competition occurs at the market level because consumers substitute across nearby stores. Retailers set prices centrally at the chain or regional level rather than store-by-store, implying that observed prices reflect firm-level optimization over many products and locations simultaneously [DellaVigna and Gentzkow, 2019].

Prices adjust frequently and rely heavily on temporary promotions, with weekly revisions common in scanner data [Hitsch et al., 2021, Ellickson and Misra, 2008]. This high frequency supports modeling pricing as static, multi-product Bertrand competition at the weekly horizon. Consistent with supermarket practice, firms optimize profits jointly across product portfolios rather than product-by-product, so markups emerge from category-level substitution and strategic interactions. These features motivate modeling retailers as multi-product firms competing strategically in local markets.

1.2.2 Cost Shocks & Pass-Through

Retail prices are strongly tied to upstream costs—agricultural inputs, energy, transportation, and processing—which fluctuate at high frequency and are largely determined outside local demand conditions. For staple and relatively homogeneous categories such as eggs and milk, these costs provide plausibly exogenous supply shifters that transmit to retail prices through pass-through.

Empirical evidence shows that retailers adjust prices systematically but not one-for-one with costs, reflecting endogenous markups and strategic pricing [Nakamura, 2008, Hitsch et al., 2021]. The post-2021 inflation episode generated large, common cost shocks across firms, creating variation well suited to identifying pass-through and firm conduct. Because these shocks affect all competitors simultaneously, differences in observed pass-through primarily reflect competitive behavior rather than demand changes. Accordingly, input prices serve as instruments for marginal costs in the structural model.

1.2.3 Pricing Institutions & Retail Behavior

Supermarket pricing relies heavily on temporary promotions and feature/display activity. Chains frequently alternate between regular prices and short-lived discounts, generating substantial short-run price variation [Pesendorfer, 2002]. Promotions are used to trade off margins against store traffic and basket size, implying that profitability depends on portfolio performance rather than margins on any single item [Ellickson and Misra, 2008].

This institutional structure implies that higher prices need not correspond to higher markups or profits. Observed price changes may reflect cost pass-through, strategic traffic-building, or portfolio rebalancing. These considerations motivate decomposing prices into marginal costs and markups within a structural framework rather than interpreting raw price movements as evidence of market power.

1.3 Related Literature

1.3.1 Testing Pricing Conduct

A central objective in industrial organization is to distinguish empirically between competitive and non-competitive firm behavior. Structural approaches estimate demand and recover mark-ups implied by alternative supply-side conduct assumptions, allowing researchers to test whether observed pricing is consistent with competition, coordination, or other forms of market power. Foundational work by Bresnahan [1982] and Lau [1982], and later formalized by Berry and Haile [2014], shows that conduct is testable under appropriate exclusion restrictions that shift mark-ups but not marginal costs.

Empirical applications span a wide range of settings. Studies have tested for collusion and oligopoly behavior [Porter, 1983, Genesove and Mullin, 1998, Nevo, 2001], vertical pricing and channel power [Berto Villas-Boas, 2007, Bonnet and Dubois, 2010, Lee et al., 2021], price discrimination [D'Haultfœuille et al., 2019], and common ownership [Backus et al., 2021]. A consistent finding is that high price-cost margins do not necessarily imply coordination: differentiated products, multiproduct pricing, and vertical mark-ups can rationalize substantial margins under non-collusive oligopoly.

Recent econometric work refines inference in these environments. Model comparison and falsification tests such as Vuong [1989] and Rivers and Vuong [2002], and extensions addressing weak instruments and degeneracy [Shi, 2015, Schennach and Wilhelm, 2017, Liao and Shi, 2020, Andrews et al., 2019], improve the reliability of conduct testing. Together, this literature establishes structural demand and supply estimation as the primary framework for identifying firm behavior.

1.3.2 Measuring Pass-Through

A complementary tradition infers market power from cost pass-through. Different models of oligopoly predict different pass-through elasticities [Bulow and Pfleiderer, 1983, Weyl and Fabinger, 2013], motivating reduced-form regressions of prices on taxes or other cost shifters. However, pass-through alone provides limited identification of conduct, since it depends jointly on demand curvature, cost structure, and competitive interaction [MacKay et al., 2014, Miravete et al., 2023].

Importantly, empirical evidence shows that full or greater-than-100% pass-through is common even in competitive retail settings. In quantitative marketing, a large literature studies promotion pass-through in consumer packaged goods markets. Retailers frequently pass manufacturer discounts fully or more than fully to consumers, with substantial heterogeneity across brands and categories [Ailawadi et al., 2009, Besanko et al., 2005, Kumar et al., 2001]. These findings demonstrate that overshifting can arise from strategic pricing, category competition, and traffic-building motives rather than coordination.

Similar patterns appear in the tax incidence literature. Studies of cigarette and alcohol excise taxes consistently find complete or over-shifting of taxes to consumers [Sumner, 1981, Delipalla and O'Donnell, 2001], outcomes that standard oligopoly models can rationalize without collusion. Theoretical work emphasizes that pass-through depends critically on demand curvature and strategic complements [Bulow and Pfleiderer, 1983, Weyl and Fabinger, 2013]. Consequently, high pass-through is not, by itself, evidence of conspiracy. These insights motivate structural approaches that jointly model demand, marginal costs, and mark-ups to interpret observed pricing behavior.

1.3.3 Inflation and Firm Response

A recent literature studies whether rising mark-ups contributed to post-pandemic inflation. The "greedflation" hypothesis, rooted in Lerner [1958], argues that firms with market power exploited cost shocks to expand margins. Descriptive evidence shows rising profit shares and mark-ups during the inflationary period [Nikiforos et al., 2024, Bivens, 2022], and some studies interpret these patterns as consistent with opportunistic pricing [Davis, 2024].

However, alternative explanations emphasize competitive or forward-looking behavior. Firms may adjust prices in anticipation of future costs or supply disruptions [Glover et al., 2023, Conlon et al., 2023], or respond mechanically to common cost shocks that raise prices across the sector without coordinated conduct. Experimental and behavioral evidence suggests that consumers perceive cost-driven price increases as more acceptable, potentially relaxing competitive constraints without implying collusion [Snir et al., 2025, Scanlon, 2024, Estelami et al., 2001, Allender et al., 2021].

Overall, this literature highlights the difficulty of distinguishing coordinated mark-up expansion from competitive cost pass-through using aggregate evidence alone. Structural methods that recover demand, costs, and conduct are therefore essential for interpreting pricing behavior during inflationary episodes. By integrating conduct estimation with pass-through analysis, the present paper contributes to this broader effort to separate competitive responses from changes in firm behavior.

1.4 Data

I focus my empirical analysis on commodity-like product categories over the period 2008–2023. These categories were selected for several reasons. First, media narratives around greedflation often highlight homogeneous or commodity-like goods, markets where coordination among firms may be more feasible. Second, my primary interest lies in retailer behavior, and commodity products are less influenced by brand-driven cost variation, allowing me to abstract from firm-specific input heterogeneity. Third, wholesale costs in commodity-based product categories can be reasonably proxied using observable input price indices, reducing the need for detailed cost accounting data. This assumption is particularly valid in these markets because marginal costs are largely determined by a small set of well-identified and widely reported commodity inputs. Accordingly, I use direct components of marginal cost as instruments for retail prices.

1.4.1 Retail Scanner Data

This section describes the construction of markets, products, and variables used in the empirical analysis. The aggregation and sample construction procedures are applied consistently across all product categories, although the main text focuses on eggs as the primary case study. Eggs provide a particularly clean empirical setting: products are highly homogeneous, input costs are largely driven by common upstream shocks, and within-brand differentiation across stock-keeping units (SKUs) is limited. These features imply that substitution occurs primarily at the brand level and that marginal costs can be more reliably inferred from prices and estimated elasticities, making the category well suited for markup recovery and conduct analysis.

The analysis uses the Kilts Nielsen Retail Scanner Dataset for 2008–2023 and covers six Designated Market Areas (DMAs): Boston, Chicago, Denver, Phoenix, Richmond, and Charlotte. These regions provide geographic diversity and, consistent with Backus et al. [2021], exhibit high Nielsen coverage of supermarket sales. The raw data are observed at the UPC–store–week level and include unit sales and an "average price" measure.[1]

Markets are defined at the *DMA–year–quarter* level, yielding 384 distinct markets. This definition reflects the geographic and temporal scale at which retailers set prices and face local demand conditions. Prices are aggregated to the DMA–parent chain level, consistent with evidence that pricing is largely centralized within retail chains [DellaVigna and Gentzkow, 2019].

Across all categories, products are constructed by aggregating individual SKUs along the observable dimensions that drive both consumer substitution and cost differences. The guiding principle is to group together SKUs that are close substitutes from the consumer's perspective and share similar production costs, while separating products that differ on attributes likely to generate meaningful variation in willingness to pay or marginal cost. Finer SKU-level variation that does not correspond to economically distinct products—such as minor pack-size differences—is absorbed by product fixed effects in the demand model.

For eggs, products are defined at the *brand–housing–organic–parent* level. Specifically, all SKUs sharing a common brand name, housing type (e.g., conventional, cage-free, free-range, pasture-raised), organic status, and parent company are combined into a single product within each market. Housing and organic attributes represent the primary dimensions of

1. The average price reflects within-week price variation, retailer coupons, and loyalty discounts, but excludes manufacturer coupons. See Kilts documentation for details.

differentiation in this category: they are prominently displayed on packaging, command distinct price premia, and correspond to differences in production costs such as feed, housing infrastructure, and certification requirements.

Market shares are constructed relative to a measure of potential market size derived from NielsenIQ's household projection factors. For each DMA–year, the sum of projection factors across panelists yields an estimate of the total household population in that market. Market size is then defined as projected households multiplied by a per-household consumption norm calibrated from USDA data on grocery-channel egg purchases, ensuring a meaningful outside option representing non-purchase, alternative channels, and untracked products. For each DMA–quarter–product, the market share equals total eggs sold divided by market size. Prices are computed as sales-weighted averages of unit prices standardized to a per-dozen basis within each DMA–quarter–product cell.

To focus on economically meaningful competitors, brands are screened based on total volume and geographic coverage. I rank brands by total egg sales across all markets and retain the top 20 brands that appear in all six DMAs, along with store brands (CTL BR) which are retailer-specific. All housing and organic variants of selected brands are kept as separate products. Remaining brands are dropped, and product-market observations with shares below 10^{-5} or prices below \$2.50 per dozen are excluded to reduce noise and avoid negative implied marginal costs in the structural model.

The same market definitions, aggregation procedures, and variable constructions are applied to milk and orange juice. Category-specific summaries and additional product details are reported in Appendix A.8.

Across categories, markets typically contain 8–15 parent firms and 65–220 products, reflecting the finer product definitions that distinguish housing, organic, fat content, and concentrate type within brands. Concentration varies across categories: leading egg brands account for roughly 7–14% of inside sales, while milk markets are more concentrated, with top brand shares reaching 20–48% depending on the DMA. Orange juice concentration is moderate, with top brand shares of 8–16%. Outside shares are substantial across all categories—typically 48–88%—indicating that non-purchase, alternative channels, and untracked products remain important margins of substitution. Prices are broadly comparable across DMAs within each category: egg prices average \$3.23–\$3.70 per dozen, milk prices \$2.88–\$4.04 per gallon, and orange juice prices \$6.53–\$7.17 per gallon. These common institutional features, together with cross-market variation in concentration and pricing, provide useful variation for identifying demand and supply behavior.

1.4.2 Upstream price and commodity series.

In addition to the scanner data, I incorporate publicly available macroeconomic, commodity, and labor market series from the Bureau of Labor Statistics (BLS) and the Federal Reserve Bank of St. Louis FRED database. These data serve three roles in the analysis: reduced-form descriptive evidence, demand-side instruments, and supply-side cost shifters for the conduct test.

Descriptive analysis. The Consumer Price Index (CPI) and Producer Price Index (PPI) for each category are used in a reduced-form analysis to compare downstream retail prices with upstream cost movements. Both indices are normalized to 2008 as a common base year for comparability.

Category-specific commodity input prices. For eggs and milk, I use the prepared animal feeds PPI, corn prices, and soybean meal prices, which account for the majority of production costs and are widely used as proxies for marginal cost movements in livestock and dairy production [Egg Industry Center, 2023, U.S. Department of Agriculture, Economic Research Service, 2013]. For orange juice, I use frozen concentrated orange juice (FCOJ) producer price indices, which capture raw input cost shocks [Dutta et al., 2002]. Because national cost series are absorbed by market fixed effects in the demand model, I interact these commodity prices with product characteristics—organic status and housing type—to generate product-varying cost instruments that provide identifying variation for the price coefficient.

Retail sector cost shifters. I also incorporate grocery wholesale wages (BLS average hourly earnings for grocery stores) and a supermarket services PPI, which capture industry-wide labor and operational cost trends that affect retail marginal costs.

Regional cost shifters. To capture geographic variation in distribution and operating costs, I use DMA-level energy and gasoline consumer price indices from BLS area-level CPI series. For Charlotte and Richmond, where DMA-specific series are unavailable, I use the South region B/C proxy.

Demand rotators. Finally, I collect DMA-level unemployment rates from BLS metropolitan area statistics and demographic moments—household income quantiles and the share of households with children—from the Nielsen HMS panelist files. These variables shift demand but do not directly affect production costs, making them valid excluded instruments for the conduct test.

1.5 Descriptive Analysis

1.5.1 CPI–PPI Dynamics and Pass-Through

This section provides reduced-form descriptive evidence on how retail prices respond to upstream cost shocks before turning to the structural model. Under competitive or demand-constrained pricing, consumer prices should co-move with producer costs, with incomplete pass-through and temporary margin compression when costs rise. In contrast, a "greedflation" or coordinated pricing hypothesis predicts retail prices rising faster than costs, implying a widening CPI–PPI spread and markup expansion during inflationary periods. To distinguish between these predictions, I compare CPI and PPI dynamics over time and estimate regime-specific pass-through regressions. Interpreting these relationships as equilibrium responses treats producer price indices as plausibly exogenous cost shifters. This assumption is reasonable because upstream input markets are national or global and unlikely to be influenced by pricing decisions of individual local retailers.

Figure 1.3 compares the Consumer Price Index (CPI, blue), which reflects retail prices paid by consumers, to the Producer Price Index (PPI, red), which proxies for upstream input costs for eggs, over time. Shaded regions indicate inflation regimes: red for high inflation, yellow for moderate inflation, and blue for deflation. I define a time as high inflation if the year to year percent change in prices exceed 4%, mild inflation if the year to year percent change is between 0% to 4%, and deflation if the year to year percent change is less than 0%. If retailers were expanding market power or engaging in coordinated pricing during inflation, one would expect consumer prices to rise faster than costs, implying CPI pulling away from PPI and a widening gap between the two series. Instead, the opposite pattern emerges. During high-inflation periods, particularly 2021–2023, PPI spikes sharply while CPI rises more gradually, compressing the gap between the two indices. This narrowing spread implies that costs increase faster than retail prices, consistent with shrinking markups and incomplete pass-through rather than margin expansion. By contrast, during deflationary or low-cost periods (e.g., 2016–2017), PPI falls while CPI declines much less or remains relatively stable, widening the gap and implying higher retail margins.

Interpreting the CPI–PPI spread as a proxy for the retail markup, the figure therefore suggests countercyclical margins: markups tend to decrease when input costs surge and increase when costs fall. Economically, this pattern is consistent with competitive or demand-constrained pricing, where retailers cannot fully pass through sharp cost increases during inflation but are slower to pass through cost reductions during deflation. Taken together, the evidence contradicts the "greedflation" narrative—higher prices and profits during inflation do not appear to stem from expanding markups, but rather from elevated costs with compressed margins.

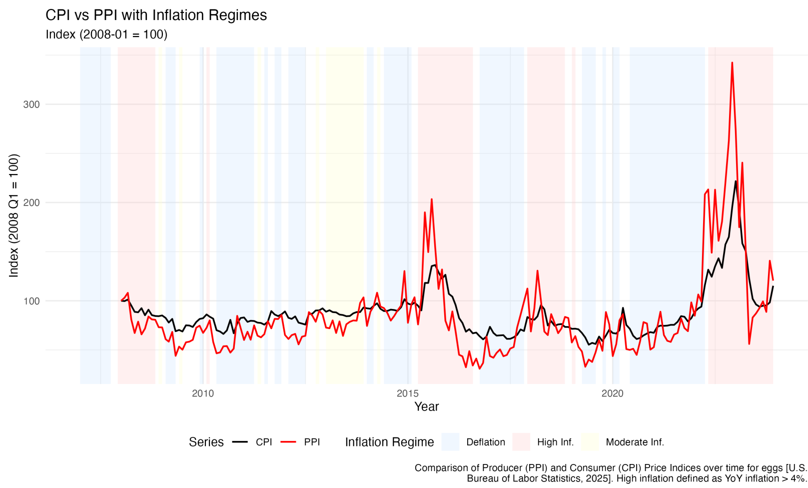

Figure 1.3: Comparison of Producer (PPI) and Consumer (CPI) Price Indices over time for eggs [U.S. Bureau of Labor Statistics, 2025b,a]. High inflation defined as YoY inflation $> 4\%$.

Furthermore, to quantify how retail prices respond to upstream cost shocks across inflationary environments, I estimate the following reduced-form specification:

$$\log P_t^C = \alpha + \beta \log P_t^P + \gamma_D D_t + \gamma_H H_t + \delta_D D_t \log P_t^P + \delta_H H_t \log P_t^P + \lambda_y + \varepsilon_t, \quad (1.1)$$

where D_t and H_t are indicator variables for deflation and high-inflation regimes, respectively. P_t^C denotes the CPI, P_t^P denotes the PPI, and λ_y are year fixed effects. The indicator variables classify months into inflation regimes based on year-over-year CPI inflation: deflation ($< 0\%$), moderate inflation, and high inflation ($> 4\%$). The interaction terms allow the degree of pass-through from producer to consumer prices to vary with the inflation environment.

Table 1.1 reports the estimates. In the baseline (moderate inflation) regime, the elasticity of consumer prices with respect to producer prices is 0.514 and statistically significant ($p < 0.05$), indicating incomplete but meaningful cost pass-through: a 10 percent increase in producer prices is associated with approximately a 5 percent increase in consumer prices. The interaction terms reveal that pass-through does not increase during high-inflation episodes. The high-inflation interaction is small (-0.028) and statistically insignificant, implying that the pass-through elasticity during high inflation is approximately $0.514 - 0.028 = 0.49$, essentially unchanged from the baseline. During deflationary periods, pass-through weakens somewhat ($0.514 - 0.352 = 0.16$), though the interaction is only marginally significant.

These patterns are informative for evaluating the greedflation hypothesis. If retailers were exploiting inflationary episodes to expand margins, one would expect pass-through to exceed one—prices rising faster than costs—during high-inflation periods. Instead, pass-through remains stable and well below unity, consistent with incomplete cost transmission and compressed margins rather than coordinated markup expansion. The regime level effects are positive but statistically insignificant, providing no evidence that retail price levels systematically shift beyond what is explained by cost movements and year effects.

While these reduced-form results provide useful descriptive evidence on pass-through and margin dynamics, they do not directly identify firm conduct or recover economically meaningful markups. The CPI–PPI gap is only an imperfect proxy for marginal costs and cannot disentangle demand substitution, multi-product pricing, or strategic interactions among retailers. To distinguish between competitive and coordinated pricing behavior, it is therefore necessary to move beyond reduced-form correlations and estimate a structural demand and supply model that explicitly recovers marginal costs and markups from observed prices and quantities. Refer to Table A.4 and Table A.5 for similar results for milk and orange juice in the Appendix.

	Estimate	**Std. Err.**	**t**
Regime: Deflation	1.477	0.839	1.761*
Regime: High	0.161	0.821	0.195
log(PPI)	0.514	0.192	2.673**
Regime: Deflation $\times$ log(PPI)	-0.352	0.193	-1.819*
Regime: High $\times$ log(PPI)	-0.028	0.190	-0.145
Year FE		Yes	
Adj. R^2		0.895	

Table 1.1: Reduced-Form Pass-Through Results for Eggs.

1.5.2 Price, Quantity, and Revenue Trends

To further assess pricing behavior, I examine DMA-level time series of average prices, total quantities, and total revenues within each category. These aggregates provide a simple reduced-form view of how markets adjust to cost or demand shocks while abstracting from within-category composition. Under competitive or cost-driven pricing, increases in prices during inflation should primarily reflect higher marginal costs, with relatively stable quantities for staple goods due to inelastic demand, implying revenues rise mainly through price rather than strategic margin expansion. In contrast, a coordinated pricing or greedflation hypothesis predicts price increases accompanied by systematic quantity contractions or disproportionate revenue growth consistent with higher markups. Plotting these series separately by DMA allows me to test these predictions and verify that observed patterns are not driven by aggregation across heterogeneous markets. The resulting trends serve as descriptive stylized facts that motivate, the subsequent structural recovery of costs and markups.

To characterize pricing and demand dynamics within each market, I construct DMA-level time series of average prices, quantities, and revenues for each category. Specifically, for each DMA–quarter pair, I compute the sales-weighted average price across products, total units sold, and total category revenue. These measures summarize the evolution of category-level outcomes faced by consumers and retailers within each local market while abstracting from within-category product composition. Plotting these series separately by DMA allows me to examine both common time trends and heterogeneity in market responses across locations. For brevity, I present the DMA-level plots for eggs in the main text and report analogous figures for milk and orange juice in the Appendix. The qualitative patterns are similar across categories, with each exhibiting rising prices and revenues after 2020 alongside comparatively stable quantities (refer to Figure A.4 and Figure A.5 in the Appendix for more information).

Figure 1.4 reveals several patterns. Prices are relatively stable in the $3 - -4$ per dozen range across most DMAs from 2008 through 2020, with periodic short-lived spikes. Beginning around 2022, all DMAs exhibit a sharp price spike, with average prices reaching $4.50 - -5.00$ or higher before partially reverting. This pattern is consistent with the well-documented avian influenza supply shock and broader inflationary pressures during this period. Notably, the price movements are transitory rather than persistent: prices rise sharply and then retreat, rather than shifting permanently to a higher level.

Quantities also exhibit pronounced spikes in several DMAs during the 2022–2023 window, with total eggs sold increasing substantially before returning to prior levels. Rather than declining in response to higher prices, quantities rise alongside them, amplifying the revenue impact. This co-movement of prices and quantities is consistent with a supply-shock-driven episode in which retail demand remains strong even as input costs surge. Revenue trends reflect both channels, with sharp spikes during 2022–2023 driven by simultaneous increases in prices and quantities.

Examining these trends at the DMA level is informative for two reasons. First, the price spike patterns are common across all six DMAs, indicating that the inflationary episode reflects national cost shocks rather than idiosyncratic local demand conditions. Second, the degree of price adjustment varies across markets, providing useful cross-market variation for the structural model by allowing me to observe how common cost shocks translate into different pricing outcomes under differing competitive environments.

Taken together, these descriptive facts motivate the structural analysis that follows. The sharp but temporary price spikes suggest that price movements are driven primarily by cost shocks rather than permanent changes in market structure or conduct. However, price movements alone cannot distinguish cost pass-through from strategic markup adjustments. Disentangling these channels requires estimating demand elasticities and recovering marginal costs and markups within an explicit model of firm conduct.

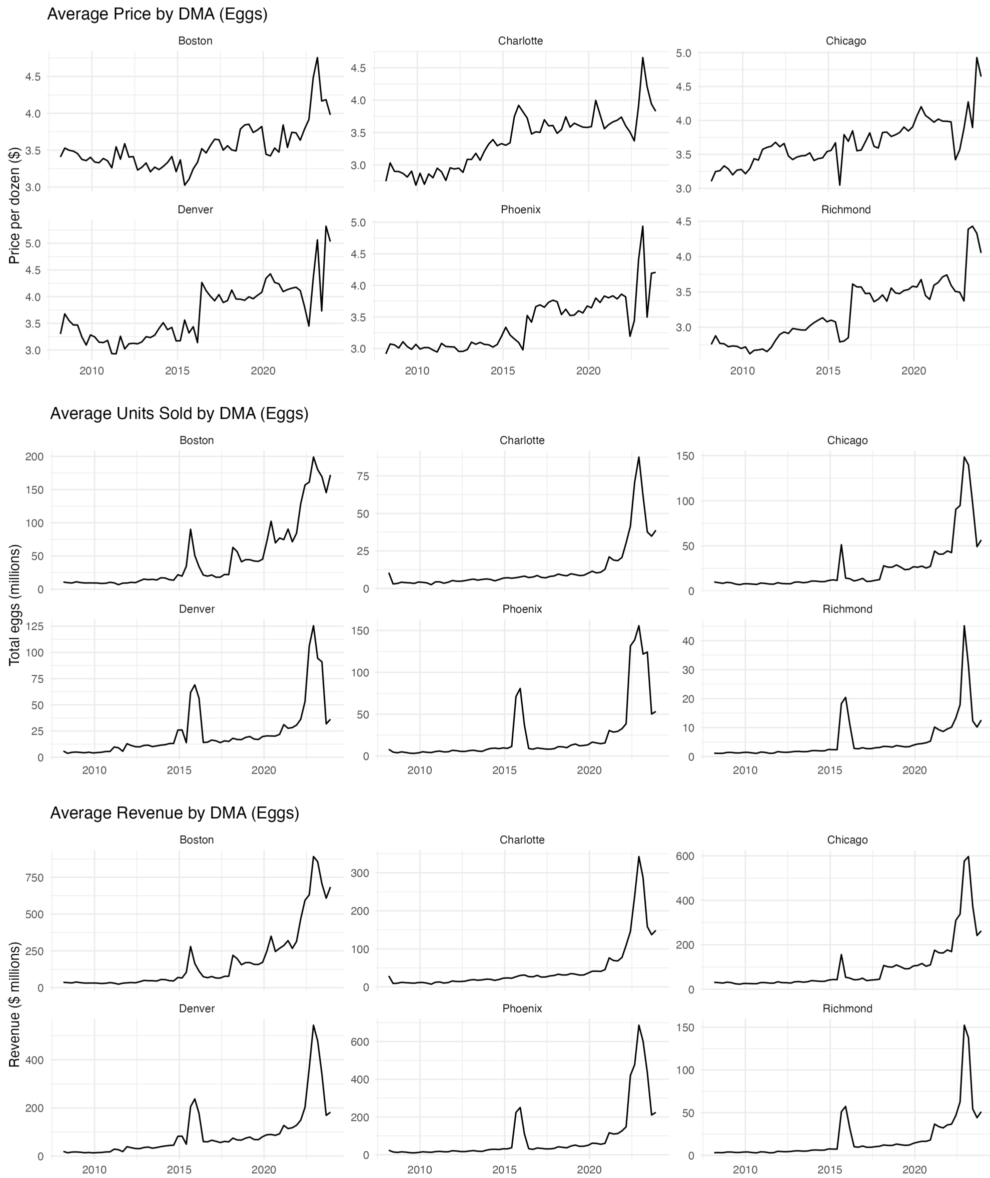

Figure 1.4: Price, Quantity, and Revenue Trends for Eggs Over Time.

1.6 Conduct Test

This section evaluates whether observed prices are more consistent with competitive (Bertrand) pricing or coordinated conduct. The key idea is simple. Holding demand fixed, different conduct assumptions imply different markups, and therefore different implied marginal costs. If a conduct model is correct, the marginal costs recovered under that model should behave like true costs: they should co-move with observable input prices and be orthogonal to unobserved shocks. If a conduct model is incorrect, the markup error contaminates the recovered costs, causing them to move systematically with variables that should not affect true production costs. The preferred conduct model is therefore the one whose implied costs are most consistent with exogenous cost shifters.

Throughout, I partition observables into three groups. Let w_{jt} denote variables that affect only costs (e.g., commodity input prices such as feed or juice concentrate), x_{jt} denote variables that may affect both demand and costs (e.g., product characteristics or market conditions), and v_{jt} denote variables that shift demand only (e.g., demographics). I collect these into $Z_{jt} = (w_{jt}, x_{jt}, v_{jt})$.

1.6.1 Setup and intuition

Let j index products and t index markets. Denote the observed price by p_{jt} and the demand-estimated implied markup under conduct model m by η_{jt}^{m}[2]. Fixing the estimated demand system, each conduct model maps observables into markups and thus into implied marginal costs:

$$mc_{jt}^{m} \equiv p_{jt} - \eta_{jt}^{m}. \tag{1.2}$$

Following Backus et al. [2021], I parameterize marginal costs flexibly as a function of observed cost shifters and an unobserved cost shock:

$$mc_{jt}^{m} = h(x_{jt}, w_{jt}) + \omega_{jt}^{m}, \tag{1.3}$$

where x_{jt} collects exogenous product characteristics that may enter both demand and costs, w_{jt} denotes cost shifters excluded from demand, and ω_{jt}^{m} captures unobserved marginal cost

2. Details on how to get markups under Bertrand and coordinated conduct can be found in Appendix A.6.2

variation implied by conduct model m. This flexibility is important. If the true cost function is nonlinear or heterogeneous, imposing a linear or quadratic specification can mechanically generate residual patterns that have nothing to do with conduct. A flexible $h(\cdot)$ reduces the risk that misspecified cost functional form is mistaken for evidence of collusion or competition. The key point is that, because mc_{jt}^m is constructed from p_{jt} and η_{jt}^m, the unobserved shock ω_{jt}^m depends on the conduct assumption through the implied markup.

The test is built on an orthogonality restriction: under the correct conduct model, the implied cost residual should be mean independent of valid instruments $A(Z_t)$ constructed from exogenous shifters.[3] When the conduct model is misspecified, the implied markup error contaminates mc_{jt}^m and generates systematic correlation between ω_{jt}^m and appropriately chosen functions of Z_t. The conduct test selects the model for which this orthogonality violation is smallest.

1.6.2 Instrument choice: predictable markup disagreement

The conduct test relies on instruments that isolate exogenous cost variation. A natural approach, following Berto Villas-Boas [2007], is to use factor prices w_{jt} directly and evaluate which model produces costs that best "fit" a regression on those inputs. This works well when the cost function is correctly specified, but can have low power or be sensitive to functional form assumptions.

Backus et al. [2021] propose a different strategy that targets conduct more directly. Rather than asking whether costs fit a regression, they construct moments that emphasize where conduct models disagree. Specifically, they exploit predictable differences in implied markups across models. Intuitively, if two conduct assumptions imply systematically different pricing rules, the variation in those differences is exactly what helps distinguish which model is correct.

3. Under correct specification, $\mathbb{E}[\omega_{jt}^m \mid Z_t] = 0 \Rightarrow \mathbb{E}[\omega_{jt}^m \cdot A(Z_t)] = 0$ for any measurable function $A(\cdot)$.

To implement this idea, I project the difference in implied markups across models onto exogenous variables Z_{jt} and use the predictable component as an instrument. This removes unobserved cost shocks while retaining variation driven by observables. Relative to using raw factor prices alone, this approach improves power because the instrument is explicitly designed to highlight markup disagreement, not just generic cost variation.

Specifically, the raw difference in implied markups across two conduct models,

$$\Delta\eta_{jt}^{1,2} \equiv \eta_{jt}^{1} - \eta_{jt}^{2},$$

I isolate the predictable component by projecting $\Delta^{1,2}\eta_{jt}$ onto exogenous shifters Z_t and using the fitted values

$$A(Z_t) = \mathbb{E}[\Delta^{1,2}\eta_{jt} \mid Z_t]$$

as the instrument. This projection filters out the unobserved shock component while retaining variation driven by observables, yielding an instrument that is both relevant (loads on markup disagreement) and valid (orthogonal to ω_{jt}^{m}). Operationally, I estimate $A(Z_t)$ flexibly using a nonparametric projection of $\Delta\eta_{jt}^{1,2}$ on Z_t, and use the fitted values $\hat{g}(Z_t)$ as the instrument in the scalar moment.

1.6.3 Scalar GMM criterion and model comparison

I define the sample moment under conduct model m as

$$\hat{M}(\eta^{m}) \equiv \frac{1}{n}\sum_{j,t} \hat{\omega}_{jt}^{m}\, \hat{g}(Z_t), \tag{1.4}$$

where $\hat{\omega}_{jt}^{m}$ are the estimated marginal cost residuals implied by model m after flexibly fitting the marginal cost function $h(\cdot)$ in Equation (1.3). The corresponding scalar GMM criterion is simply the squared sample moment:

$$\tilde{Q}(\eta^m) \equiv \left(\hat{M}(\eta^m)\right)^2 = \left(\frac{1}{n}\sum_{j,t} \hat{\omega}^m_{jt}\, \hat{g}(Z_t)\right)^2. \tag{1.5}$$

This criterion captures violations of cost orthogonality implied by conduct model m. A smaller value indicates that the implied marginal costs are more consistent with exogenous variation in Z_t.

1.6.4 Vuong-style test statistic

To compare two conduct models (e.g., $m = 1$ Bertrand and $m = 2$ collusion), I compute the difference in scalar criteria. Under standard regularity conditions for GMM moments [Hansen, 1982, Newey and McFadden, 1994] and the non-nested comparison logic of Vuong [1989], Backus et al. [2021] establish that

$$\sqrt{n}\left(\tilde{Q}(\eta^1) - \tilde{Q}(\eta^2)\right) \xrightarrow{d} \mathcal{N}(0, \sigma^2), \tag{1.6}$$

where σ^2 is the asymptotic variance of the criterion difference. I estimate σ via a bootstrap that resamples markets (or market$\times$time blocks) to respect within-market correlation in the residuals.

The resulting standardized statistic is

$$T = \sqrt{n}\,\frac{\tilde{Q}(\eta^1) - \tilde{Q}(\eta^2)}{\hat{\sigma}} \xrightarrow{d} \mathcal{N}(0, 1). \tag{1.7}$$

The decision rule follows directly. A significantly positive T indicates $\tilde{Q}(\eta^1) > \tilde{Q}(\eta^2)$, i.e., model 2 yields smaller orthogonality violations and is preferred. A significantly negative T favors model 1. If T is close to zero, I fail to distinguish the two models. In my application, model 1 corresponds to Bertrand competition and model 2 corresponds to coordinated conduct. Therefore, a significantly negative statistic favors Bertrand pricing, whereas a significantly positive statistic favors collusion.

1.6.5 Remarks

This approach has three practical advantages emphasized by Backus et al. [2021]. First, it accommodates flexible functional forms for marginal costs and for the instrument construction, reducing sensitivity to parametric misspecification. Second, because the comparison is based on a scalar moment, it avoids choices about high-dimensional optimal weighting matrices while still delivering valid non-nested inference. Third, the test has a clear economic interpretation: it selects the conduct model whose implied marginal costs are most consistent with exogenous variation in cost shifters, i.e., the model that best satisfies cost orthogonality. Refer to Appendix A.6 to the full algorithm for this testing procedure.

1.7 Empirical Framework

1.7.1 Demand Specification

I estimate a standard random coeffcients logit demand model. For completeness, I outline the components of the model here and explain the general model in detail in the Appendix A.9. In each period t, consumer i chooses among N_t differentiated products sold across retailers. The indirect utility from choosing product j in period t is

$$U_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{ijt}$$

where ϵ_{ijt} is an idiosyncratic preference shock assumed i.i.d. Type I Extreme Value. The mean utility δ_{jt} aggregates the components of product quality observed and unobserved by the econometrician:

$$\delta_{jt} = \beta_p \log(p_{jt}) + \beta_f \text{Feature}_{jt} + \beta_d \text{Display}_{jt} + \alpha_t + \gamma_j + \xi_{jt},$$

where β_p captures price sensitivity on the log-price scale. Feature and display promotions enter additively. The market fixed effects α_t are defined at the DMA–year–quarter level, absorbing all location-specific and time-specific variation including local demand shocks and common cost trends. Product fixed effects γ_j absorb time-invariant product characteristics such as brand identity, housing type, and organic status. The unobserved demand shock ξ_{jt} captures residual product attributes observed by consumers but not by the econometrician.

Heterogeneity in preferences across consumers enters through the random-coefficients term

$$\mu_{ijt} = \sigma_p \log(p_{jt})\nu_i + \pi_{\text{income}} \log(p_{jt}) \cdot \text{income}_i + \pi_{\text{child}} \log(p_{jt}) \cdot \text{child}_i$$

where ν_i is an unobserved consumer-specific draw from a standard normal distribution, income_i is household income (in \$10,000 units), and child_i is an indicator for the presence of children in the household. The demographic interactions allow price sensitivity to vary systematically with household characteristics: higher-income households and households with children may respond differently to price changes. Together with the unobserved heterogeneity ν_i, these interactions generate flexible cross-price substitution patterns that depart from the restrictive independence of irrelevant alternatives property of the standard logit model.

Consumers choose the product that yields the highest utility, including an outside option whose mean utility is normalized to zero. Let M_t denote the market size in period t and q_{jt} the observed quantity sold. Observed market shares are

$$s_{jt} = \frac{q_{jt}}{M_t}$$

where q_{jt} is the observed quantity sold of product j in week t. Under the i.i.d. Type I Extreme

Value assumption for ϵ_{ijt}, the implied choice probabilities correspond to a mixed logit model, integrating over the joint distribution of demographics and unobserved heterogeneity. The resulting share inversion and GMM estimation follow the canonical BLP procedure.

Consumers are assumed to purchase one unit of the good that yields the highest utility. Therefore, the market share of product j is given by the probability that product j is chosen:

$$s_{jt} = \int \mathbb{I}\left(U_{ijt} \geq U_{iht}, \forall h \in \{0, 1, \ldots, N_t\}\right) dF(\epsilon) dF(\nu) dF(D)$$

Here, D_i represents observed consumer demographics, such as income and the presence of children, which interact with log price to capture systematic heterogeneity in price sensitivity across consumers, while ν_i captures unobserved heterogeneity. If one assumes that both D_i and ν_i are fixed and that consumer heterogeneity enters only through the i.i.d. shock ϵ_{ijt} with a Type I Extreme Value distribution, this reduces to the standard multinomial logit model.

To address the endogeneity of prices arising from unobserved demand shocks ξ_{jt}, I construct instruments that satisfy both relevance and exclusion restrictions. Because the demand model absorbs product and market fixed effects, instruments must vary across products within a market to provide identifying variation. National cost series and market-level demographics, while exogenous, are collinear with the market fixed effects and therefore cannot serve directly as demand instruments. I exploit three sources of product-varying exogenous price variation.

First, I interact commodity input prices with product characteristics to generate *cost–characteristic instruments* that vary across products within a market. Specifically, I interact feed PPI, corn prices, and soybean meal prices with organic status and housing type (cage-free, free-range, or pasture-raised versus conventional). These interactions capture the fact that input cost shocks affect products differentially depending on their production technology—for example, organic and cage-free eggs have different feed cost structures than conventional eggs. This yields five instruments: feed × organic, corn × organic, soybean × organic, feed × housing, and corn × housing.

Second, I implement a differentiation-based strategy following Gandhi and Houde [2019]. For each product j in market t, I compute the sum of squared characteristic distances between j and all rival products k in the same market:

$$z_{jt}^{\text{diff},\ell} = \sum_{k \neq j} \left(x_{jt}^{(\ell)} - x_{kt}^{(\ell)} \right)^2,$$

using three characteristics: average pack size, organic status, and housing type. I also construct all pairwise cross terms. These differentiation measures capture local competitive pressure: products surrounded by many similar rivals face more elastic demand and lower markups. Because rival product positioning affects equilibrium markups through substitution patterns rather than through ξ_{jt}, these instruments satisfy the exclusion restriction.

Third, following Backus et al. [2021], I project observed prices onto cost shifters and differentiation measures using a random forest regression and compute differentiation IVs on the predicted prices $\hat{p}_{jt}$. This captures expected price positioning and provides an additional instrument that combines cost and competitive variation.

Finally, I interact all differentiation IVs with market-level demographic moments—median income and the share of households with children—to generate instruments that vary both across products and across markets. Together, this instrument set provides strong and plausibly exogenous variation for identifying the log-price coefficient in the random-coefficients demand model. More details on differentiation instruments can be found in Appendix A.7.

1.7.2 Variables for Conduct Testing

To estimate marginal costs and implement the conduct test, I partition observed exogenous variables Z_{jt} into those that affect costs, both demand and costs, or demand only. This separation clarifies identification: the conduct test selects the model whose implied marginal cost residuals are orthogonal to appropriately chosen functions of Z_{jt}.

Cost shifters (w_{jt}). These variables enter the marginal cost equation but are excluded from consumer demand. They include commodity input prices (feed PPI, corn price, soybean meal price), regional cost shifters (DMA-level energy and gasoline CPI), and retail sector costs (grocery wholesale wages, supermarket services PPI). I also include interactions of commodity prices with product characteristics—feed × organic, corn × organic, soybean × organic, feed × housing, and corn × housing—which generate product-varying cost variation.

Shared shifters (x_{jt}). Some variables influence both demand and costs. These include product characteristics (organic status, housing type, average pack size) and promotional activities (feature and display). Product characteristics enter consumer utility through the product fixed effects and affect production costs through differences in feed, housing infrastructure, and certification requirements. Promotions shift consumer demand while also affecting retailers' effective marginal costs through advertising and merchandising expenditures.

Demand-only shifters (v_{jt}). These variables shift demand and markups but do not directly affect marginal costs, making them the key excluded instruments for the conduct test. They include local market demographics (income quantiles and the share of households with children), DMA-level unemployment rates, and differentiation IVs measuring local competitive pressure (characteristic distances in pack size, organic status, and housing type, plus cross terms and predicted-price differentiation). These factors capture variation in consumer preferences and substitution patterns without mechanically entering the cost function.

This partition is central for identification. Under the correct conduct model, the implied marginal cost residuals ω_{jt}^m should be orthogonal to the demand-only shifters v_{jt}. When conduct is misspecified, the markup error contaminates implied costs and generates systematic correlation with v_{jt}. The test therefore exploits the excluded instruments to distinguish competitive from coordinated pricing.

1.8 Results

1.8.1 Demand Estimates, Elasticities, and Implied Markups

I first estimate a random-coefficients logit demand model for eggs. The model is estimated using DMA–year–quarter markets and brand–housing–organic–parent products, yielding 39,167 product–market observations across 326 markets and 1,517 products.

Mean utility coefficients. Table 1.2 reports the estimated demand parameters. The log-price coefficient is negative and precisely estimated ($\hat{\beta}_p = -4.525$, $p < 0.01$), confirming economically meaningful price sensitivity. The income interaction is positive and significant ($\hat{\pi}_{\text{income}} = 0.236$, $p < 0.01$), indicating that higher-income households are less price-sensitive. The child interaction is small and not statistically significant. The random coefficient on log price (sigma) converges to its lower bound of zero, indicating that unobserved taste heterogeneity in price sensitivity is not identified beyond the demographic interactions.

Feature advertising has a positive and statistically significant effect on mean utility (1.090, $p < 0.01$), consistent with demand shifts from retail promotions in commodity grocery categories. The display coefficient is imprecisely estimated and not statistically significant.

	Estimate	Std. Err.
Mean Utility		
log(Price)	-4.525^{***}	1.178
Feature	1.090^{***}	0.396
Display	-13.685	11.956
Random Coefficients		
SD(log(Price))	0.000	4.590
Demographic Interactions		
log(Price) $\times$ Income	0.236^{***}	0.064
log(Price) $\times$ Child	-0.178	3.130
Observations	39,167	
Markets	326	
Products	1,517	

Table 1.2: BLP Demand Estimates for Eggs.

Notes: Estimates from a random-coefficients logit demand model. Standard errors obtained via GMM. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Elasticities. Figure 1.5 plots share-weighted own-price elasticities over time. Elasticities range from approximately -1.3 to -1.9, indicating elastic demand at the product level.[4] The magnitude varies over time, with demand becoming less elastic (moving toward -1.3) during the 2016–2020 period before spiking sharply more elastic around 2022 during the price shock episode. This pattern is consistent with heightened consumer substitution across

4. These elasticities are larger in magnitude than category-level estimates in the literature (refer to Appendix A.12), which typically find inelastic demand for eggs as a whole. The difference reflects the finer product definition used here: with products differentiated by brand, housing type, and organic status, consumers can substitute across products within the egg category, generating higher product-level elasticities even when overall category demand is inelastic.

egg products when prices surge.

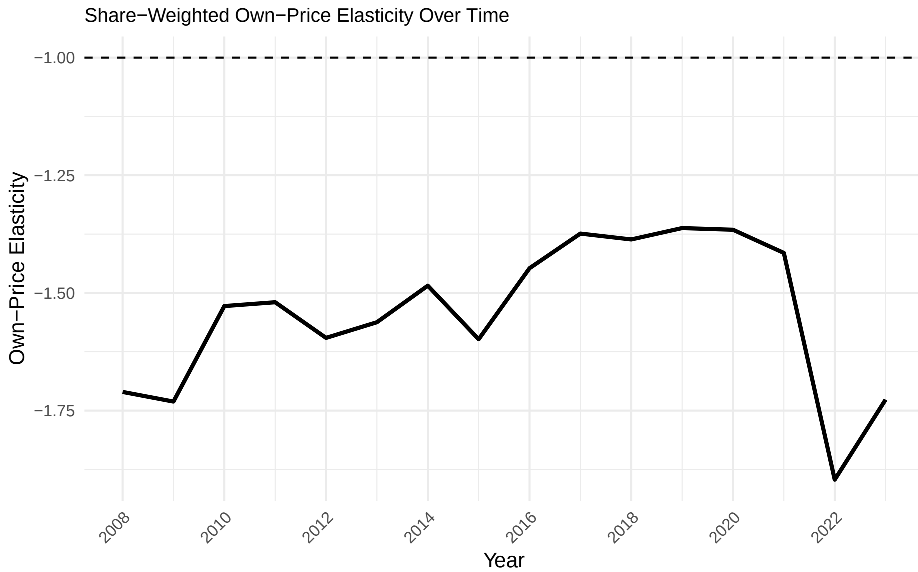

Figure 1.5: Share-Weighted Own Price Elasticity Over Time.

Implied markups. Using the estimated demand system, I compute implied markups under alternative conduct assumptions. Figure 1.6 shows share-weighted average markups over time. Markups implied by Bertrand competition are modest and relatively stable, whereas coordinated (joint-profit maximizing) conduct yields substantially higher markups. The large gap between these two series illustrates how conduct assumptions translate directly into economically different pricing implications.

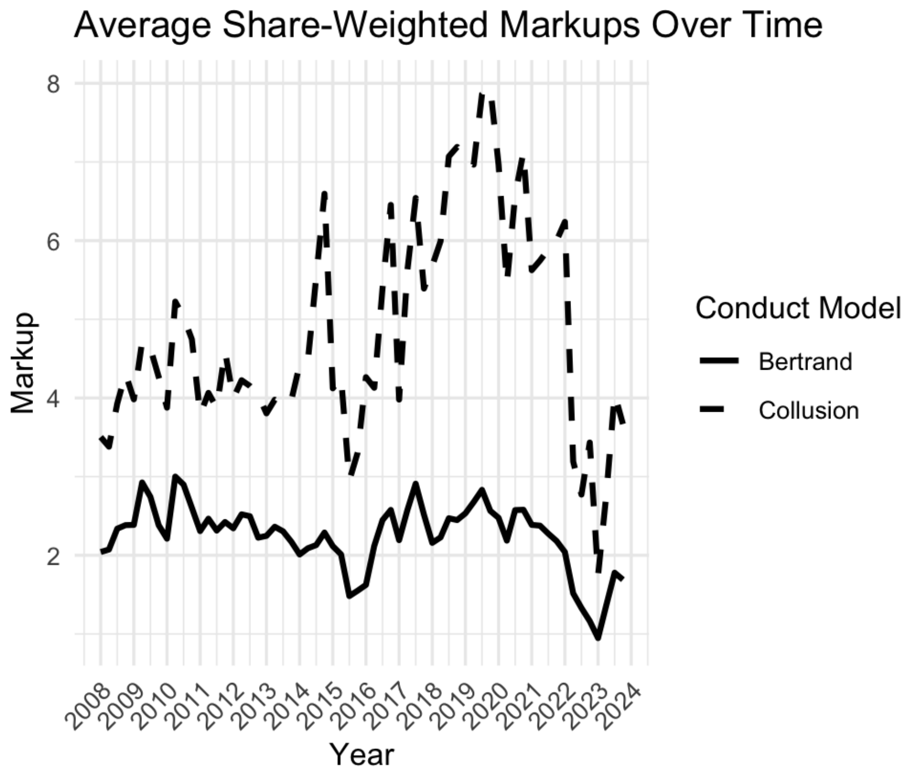

Figure 1.6: Average Share-Weighted Markups Over Time.

Interpretation. Taken together, these results indicate that (i) prices and promotions strongly affect demand, (ii) consumer price sensitivity weakens during inflation, and (iii) the demand system generates meaningful variation in implied markups across conduct models. These elasticities and markups serve as key inputs to the structural conduct test described in the next section. Parallel estimates for milk and orange juice are reported in Appendix A.10.

1.8.2 Conduct Test Results

I formally test firm conduct using the non-nested GMM comparison described in Section 1.6. Let $Q(\eta^B)$ and $Q(\eta^C)$ denote the scalar GMM criteria for the Bertrand (independent pricing) and coordinated (joint-profit maximization) models, respectively. Define the Vuong-style test statistic

$$T = \frac{\sqrt{n}\left(Q(\eta^B) - Q(\eta^C)\right)}{\hat{\sigma}}.$$

The hypotheses are:

$$\begin{aligned}
H_0 &: Q(\eta^B) = Q(\eta^C) \quad \text{(both models fit equally well)}, \\
H_A &: Q(\eta^B) < Q(\eta^C) \quad \text{(Bertrand fits better)}, \\
H_A' &: Q(\eta^B) > Q(\eta^C) \quad \text{(coordinated conduct fits better)}.
\end{aligned}$$

Because the statistic is proportional to $Q(\eta^B) - Q(\eta^C)$, negative and statistically significant values favor the Bertrand model, while positive values favor coordinated conduct.

Table 1.3 reports the results for the egg category. Across the full sample and both subsamples, the estimated differences are negative and highly statistically significant ($p < 0.01$), leading me to reject H_0 in favor of the Bertrand alternative. In the full period, the mean difference of -3.58 indicates substantially smaller moment violations under independent pricing. The same conclusion holds pre- and post-2020.

Although the magnitude of the difference declines in the post-2020 period, the sign and statistical significance are unchanged. This narrowing suggests that the separation between conduct models is smaller during the recent inflationary episode—potentially reflecting tighter margins or common cost shocks—but remains inconsistent with coordinated or collusive pricing. Overall, the evidence strongly supports competitive Bertrand conduct in the egg market.

Parallel results for milk and orange juice are reported in Appendix A.11.

Sample	Mean Diff.	Test	Conclusion
Full (2008–2023)	−3.58	$p < 0.01$	Bertrand preferred
Pre-2020	−1.39	$p < 0.01$	Bertrand preferred
Post-2020	−0.65	$p < 0.01$	Bertrand preferred

Table 1.3: Conduct Testing Results.

1.9 Conclusion

Recent public discussion has attributed rising grocery prices during the post-2020 inflationary episode to "greedflation," the idea that retailers exploited cost shocks to expand markups. Across eggs, milk, and orange juice, I find little support for this view. Both reduced-form evidence and structural conduct tests indicate that prices, elasticities, and recovered markups are most consistent with competitive (Bertrand) pricing rather than coordinated or joint-profit-maximizing behavior. Retail prices track upstream input costs closely, estimated demand is relatively elastic, and markups tend to compress—not expand—during high-inflation periods. Non-nested GMM tests consistently reject collusive conduct in favor of independent pricing across categories and markets.

These results highlight two broader lessons. First, rising prices or revenues alone are not evidence of market power. In staple categories with inelastic demand and large input-cost shocks, competitive pass-through can mechanically raise prices and profits without any change in conduct. Second, properly diagnosing pricing behavior requires jointly accounting for demand, costs, and substitution patterns. Structural approaches that recover marginal costs and markups provide a more reliable basis for distinguishing competitive pass-through from strategic pricing than price levels alone.

From a policy perspective, my findings suggest caution in interpreting short-run price spikes as proof of collusion or as justification for conduct-focused interventions such as price controls or windfall profit taxes. In relatively homogeneous grocery markets, improving supply-side resilience—reducing input bottlenecks, transportation costs, or other cost pressures—may be more effective at lowering consumer prices. More broadly, the conduct-testing framework developed here can be applied to other retail settings to evaluate whether observed price movements reflect market power or underlying cost shocks.[5]

5. Researcher(s) own analyses calculated (or derived) based in part on (i) retail measurement data from Nielsen Consumer LLC ("NielsenIQ"); (ii) media data from The Nielsen Company (US), LLC ("Nielsen"); and (iii) marketing databases provided through the respective NielsenIQ and the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of NielsenIQ or Nielsen. Neither NielsenIQ nor Nielsen is responsible for, had any role in, or was involved in analyzing and preparing the results reported herein.

APPENDIX A

A.1 Differentiation Checks

These figures illustrate the distribution of observable product differentiation across brands within each year for each product category. For each brand, I compute the number of distinct styles, types, and organic claims offered, as well as the share of products labeled organic, and plot the within-year distributions of these measures. Across all attributes, the mass of the distribution is concentrated at one or two variants per brand, with very limited dispersion and few brands offering a wide assortment of differentiated products. Median values are close to one in every year, indicating that most brands sell essentially a single standardized product with minimal vertical or horizontal differentiation. Organic penetration is likewise limited and concentrated among a small subset of brands. Taken together, these patterns suggest that the category is largely commodity-like, with limited scope for differentiation-based market power, consistent with a competitive pricing environment.

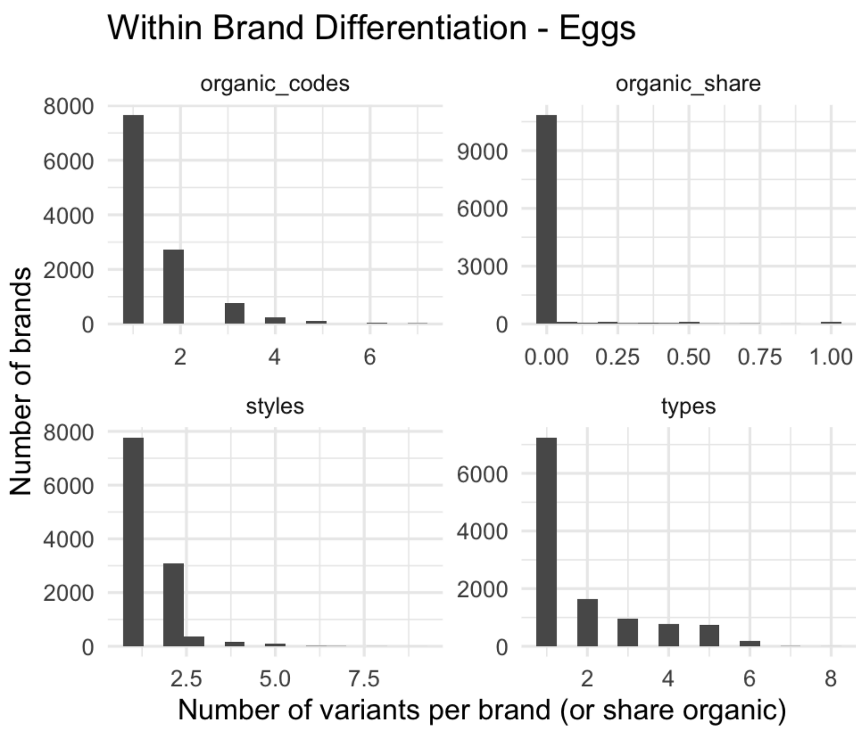

Figure A.1: Differentiation Checks for Eggs.

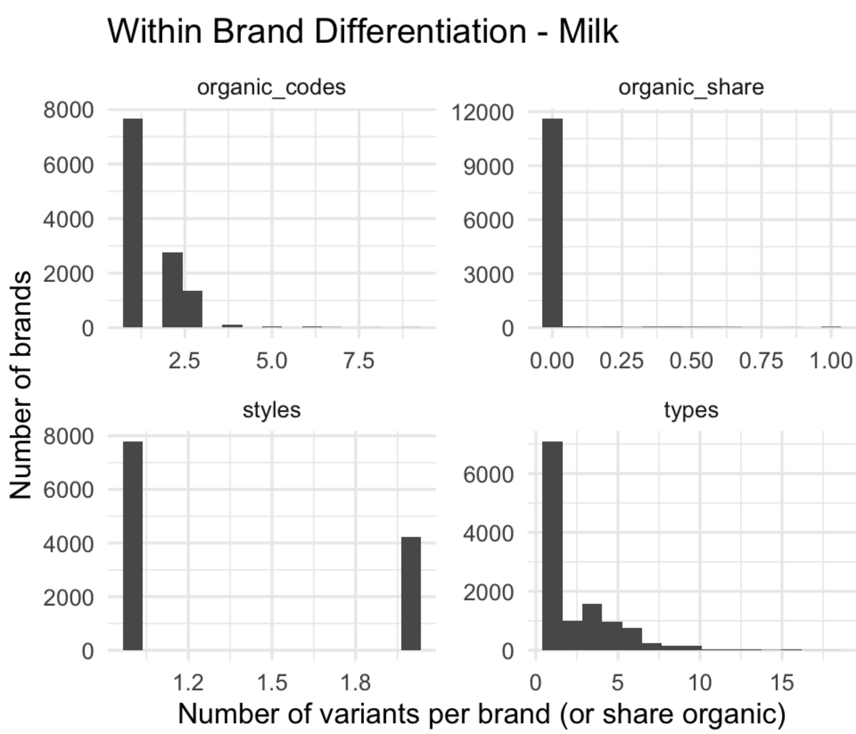

Figure A.2: Differentiation Checks for Milk.

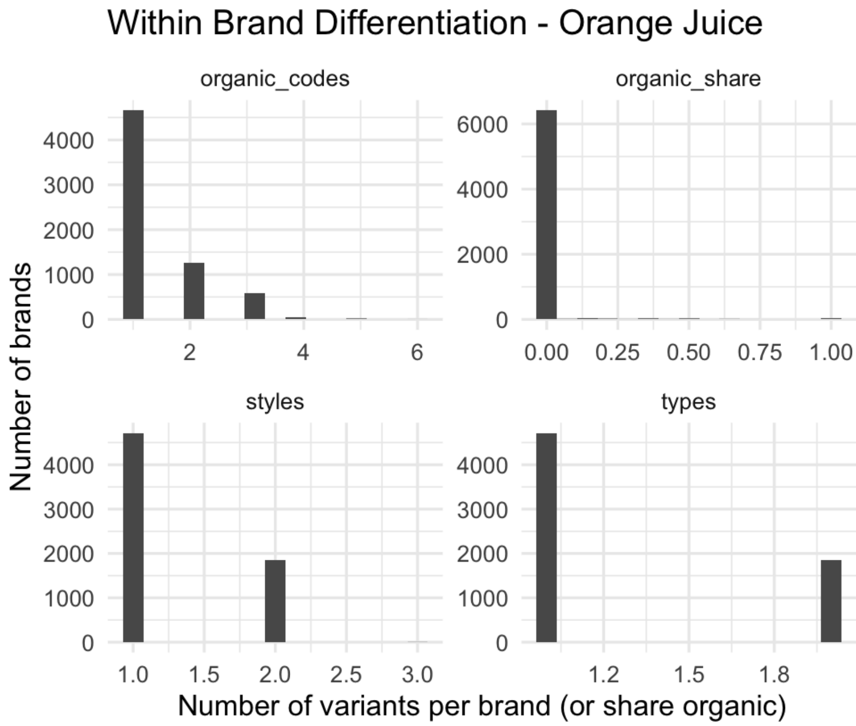

Figure A.3: Differentiation Checks for Orange Juice.

A.2 Summary Statistics

Statistic	Boston	Chicago	Charlotte	Phoenix	Richmond	Denver
Number of Markets	64	64	64	64	64	64
Average # of Brands per Market	6.4	5.9	5.5	5.5	5.5	5.9
Average # of Parent Firms per Market	14.2	10.0	15.3	13.6	12.3	9.8
Average Market Share of Top Brand (%)	20.2	18.6	20.6	27.9	29.8	9.8
Average Outside Share (%)	43.3	56.7	38.4	40.1	28.4	78.1
Average Price ($/dozen)	3.39	3.02	3.01	3.16	3.09	2.93
Mean Income ($)	68,764	58,500	67,122	64,822	59,967	59,092
Share of Households with Children (%)	29.6	31.9	33.3	31.6	31.2	30.9

Table A.1: Descriptive Statistics – Eggs.

Statistic	Boston	Chicago	Charlotte	Phoenix	Richmond	Denver
Number of Markets	64	64	64	64	64	64
Average # of Brands per Market	6.8	6.8	6.8	7.0	6.7	6.9
Average # of Parent Firms per Market	14.0	11.2	15.2	13.0	13.0	10.6
Average Market Share of Top Brand (%)	18.5	21.2	12.8	25.0	38.1	10.2
Average Outside Share (%)	46.4	54.7	59.9	51.0	26.9	78.4
Average Price ($/ounce)	0.65	0.68	0.64	0.62	0.66	0.67
Mean Income ($)	68,764	58,500	62,789	64,541	59,967	59,092
Share of Households with Children (%)	29.6	31.9	32.5	31.6	31.2	30.9

Table A.2: Descriptive Statistics – Milk.

Statistic	Boston	Chicago	Charlotte	Phoenix	Richmond	Denver
Number of Markets	64	64	64	64	64	64
Average # of Brands per Market	6.0	6.0	6.0	6.0	6.0	6.0
Average # of Parent Firms per Market	15.0	15.2	11.0	12.6	10.9	13.0
Average Market Share of Top Brand (%)	12.3	45.1	8.5	20.7	76.1	29.5
Average Outside Share (%)	41.8	93.3	93.3	89.2	94.8	100.9
Average Price ($/ounce)	0.94	0.81	0.93	0.89	0.95	1.01
Mean Income ($)	68,764	62,789	58,500	59,967	59,092	64,541
Share of Households with Children (%)	29.6	32.5	31.9	31.2	30.9	31.6

Table A.3: Descriptive Statistics – Orange Juice.

A.3 Milk and Orange Juice Trends

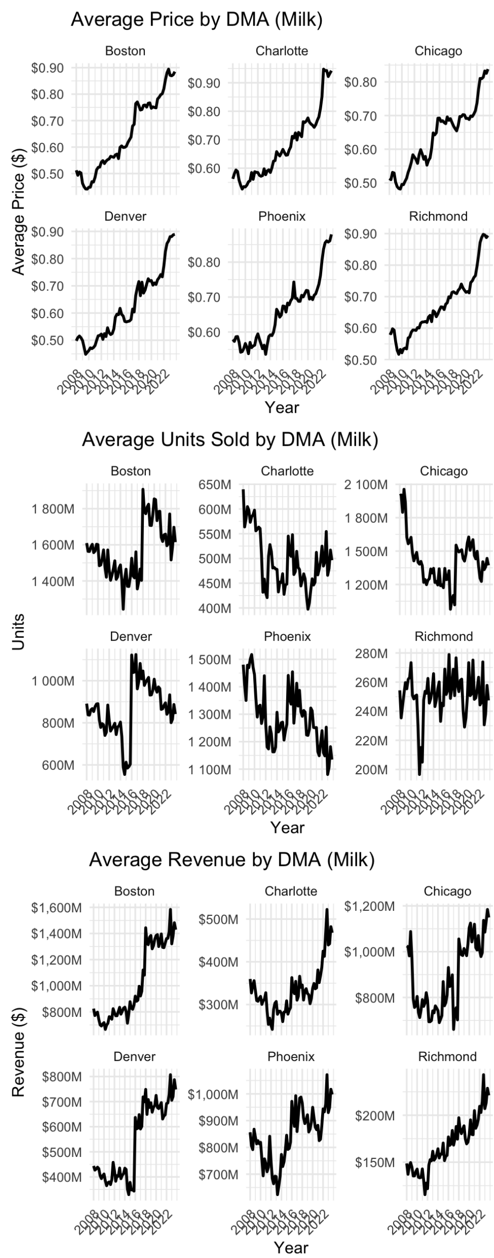

Figure A.4: Price, Quantity, and Revenue Trends for Milk Over Time.

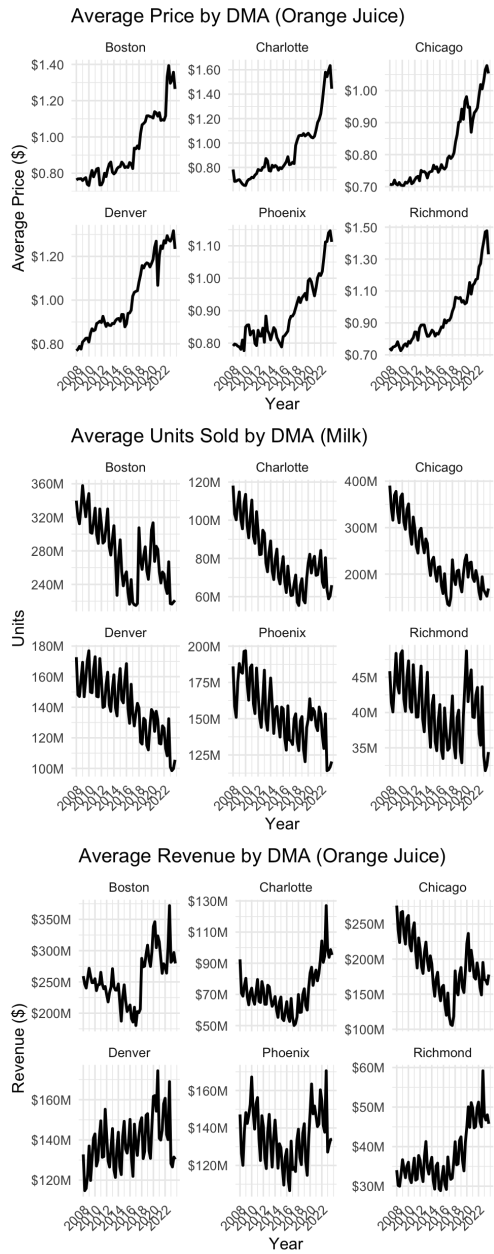

Figure A.5: Price, Quantity, and Revenue Trends for Orange Juice Over Time.

A.4 Extra CPI and PPI Graphs

A.4.1 Milk

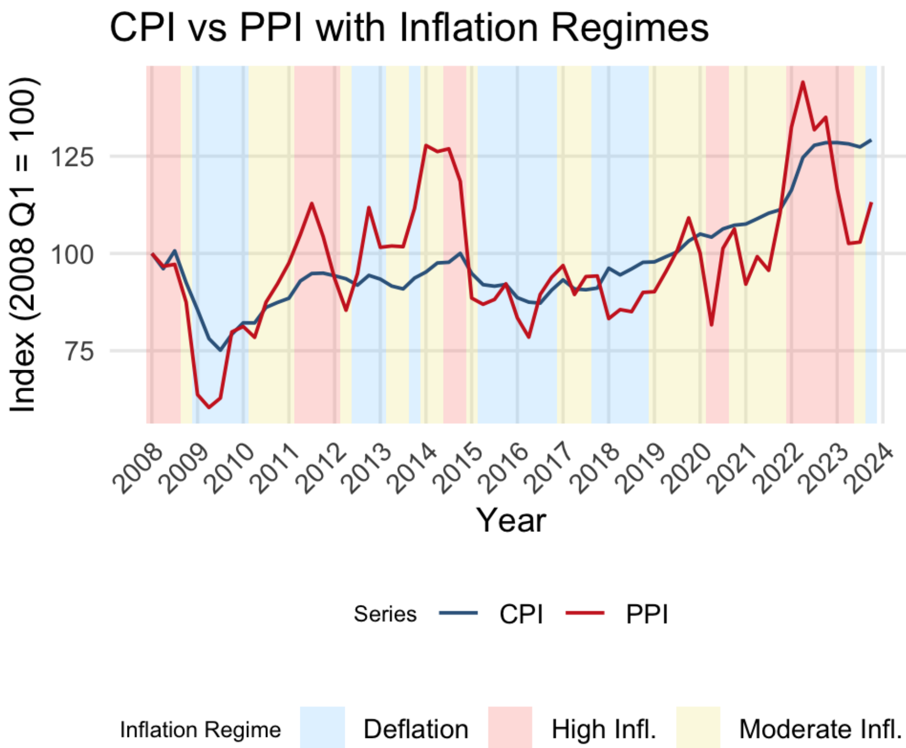

Figure A.6: Comparison of Producer (PPI) and Consumer (CPI) Price Indices over time for milk [U.S. Bureau of Labor Statistics, 2025a].

A.4.2 Orange Juice - Constructing Cost Indices and Predicting Producer Prices

To evaluate whether retail prices track underlying input costs, I construct monthly measures of producer costs and related commodity fundamentals. Producer prices for eggs are obtained from the Bureau of Labor Statistics Producer Price Index (PPI) series. The index is normalized to equal 100 in January 2008:

$$\text{PPI}_t^{\text{norm}} = \frac{\text{PPI}_t}{\text{PPI}_{\text{Jan 2008}}} \times 100.$$

However, for orange juice, I only have PPI for years 2008-2020. Therefore, I estimate the PPIs for years 2021-2023 using futures. Specifically, I merge the PPI series with futures prices.

I estimate predictive regressions of the form

$$\text{PPI}_t^{\text{norm}} = \alpha + \beta_0\,\text{Future}_t + \sum_{k=1}^{K} \beta_k\,\text{Future}_{t-k} + \gamma\,\text{InputIndex}_t + \delta\,\text{Inflation}_t + \lambda_s + \varepsilon_t,$$

where λ_s denotes month-of-year fixed effects capturing seasonality. In addition, moving averages and short-run volatility measures of futures prices are included to capture persistent and transitory cost dynamics.

Fitted values from this model closely track realized PPI movements (Figure A.7), indicating that producer prices are largely explained by observable cost fundamentals rather than discretionary pricing behavior. This tight fit supports the interpretation of PPI as a valid proxy for marginal cost in the main conduct and pass-through analysis.

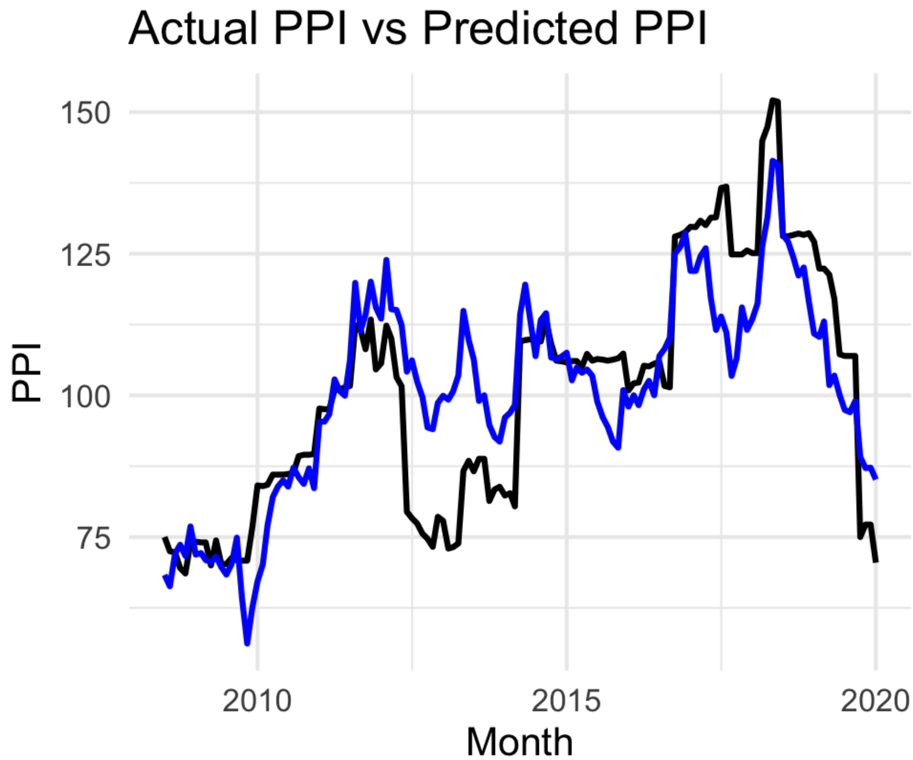

Figure A.7: Actual PPI vs. Predicted PPI.

The final plot to compare CPI and PPI with inflation regimes is the following:

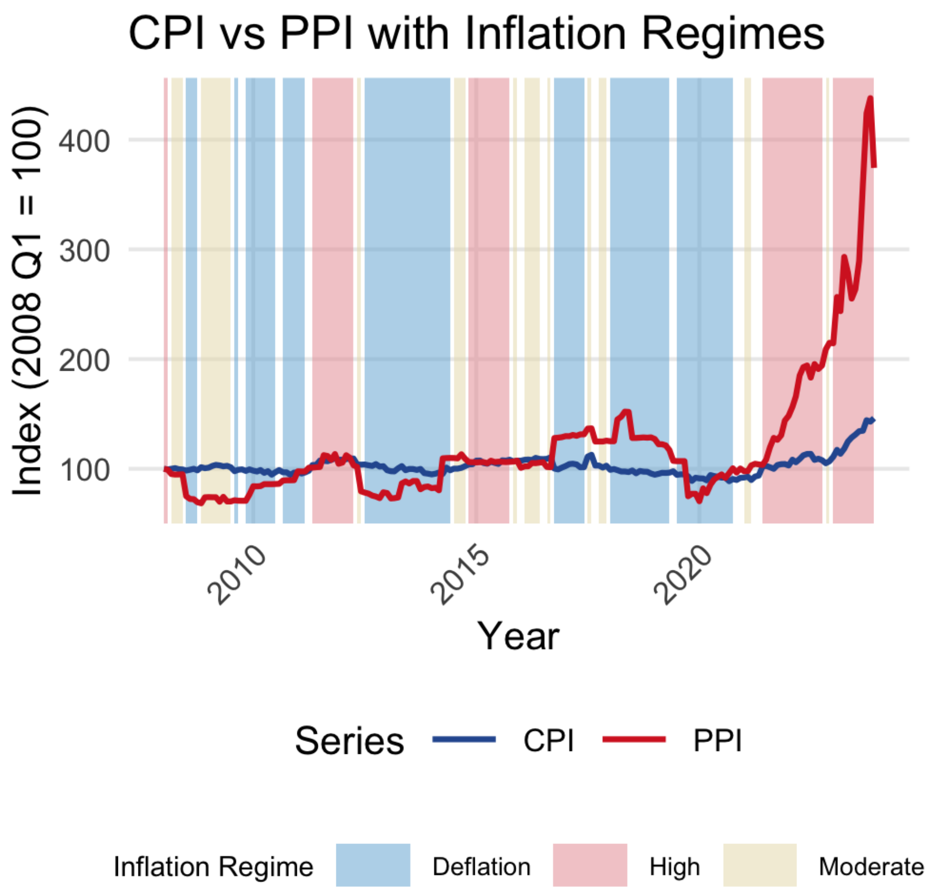

Figure A.8: Comparison of Producer (PPI) and Consumer (CPI) Price Indices over time for orange juice [U.S. Bureau of Labor Statistics, 2025a].

A.5 Reduced Form Regressions

A.5.1 Milk

	Estimate	**Std. Err.**	**t**
Regime: Deflation	-0.132	0.101	-1.300
Regime: High	-0.254	0.121	-2.101*
log(PPI)	-0.007	0.020	-0.367
Regime: Deflation $\times$ log(PPI)	0.028	0.023	1.229
Regime: High $\times$ log(PPI)	0.060	0.026	2.274*
Year FE		Yes	
Adj. R^2		0.846	

Table A.4: Reduced Form Regressions - Milk.

A.5.2 Orange Juice

	Estimate	**Std. Err.**	**t**
Regime: Deflation	0.387	0.112	3.443***
Regime: High	-0.655	0.124	-5.282***
log(PPI)	0.130	0.024	5.536***
Regime: Deflation $\times$ log(PPI)	-0.091	0.025	-3.707***
Regime: High $\times$ log(PPI)	0.145	0.026	5.525***
Year FE		Yes	
Adj. R^2		0.846	

Table A.5: Reduced Form Regressions - Orange Juice.

A.6 Conduct Testing Details

A.6.1 Algorithm

Step 1: Estimate demand to recover predicted markups η^1_{jt} and η^2_{jt} under two conduct models.

Step 2: Estimate marginal cost function:

$$\hat{h}^s(x_{jt}, w_{jt}) = p_{jt} - \eta^m_{jt} - \omega^m_{jt}$$

Step 3: Compute residuals:

$$\omega^m_{jt} = p_{jt} - \eta^m_{jt} - \hat{h}^s(x_{jt}, w_{jt})$$

Step 4: Regress $\Delta\eta^{1,2}_{jt}$ on z_t to get:

$$\hat{g}(z_t) \approx \mathbb{E}[\Delta\eta^{1,2}_{jt} \mid z_t]$$

Step 5: Compute scalar moment:

$$Q(\eta^m) = \left(\frac{1}{n}\sum_{j,t} \omega^m_{jt} \cdot \hat{g}(z_t)\right)^2$$

Step 6: Bootstrap to estimate standard error $\hat{\sigma}$ of $Q(\eta^1) - Q(\eta^2)$.

Step 7: Compute test statistic:

$$T = \frac{\sqrt{n}\left(Q(\eta^1) - Q(\eta^2)\right)}{\hat{\sigma}}$$

A.6.2 Markup Calculations Under Alternative Conduct Assumptions

This appendix details how implied markups are computed under alternative conduct assumptions. Following standard multi-product pricing models in differentiated product demand systems [Berry et al., 1995, Nevo, 2001], markups are recovered from firms' first-order conditions using the estimated demand system.

Let $j = 1, \ldots, J$ index products within a market t. Denote by $s_{jt}(p)$ the market share of product j and define the $J \times J$ matrix of price derivatives

$$\mathcal{H}_t \equiv \frac{\partial s_t}{\partial p_t} = \left[\frac{\partial s_{jt}}{\partial p_{kt}}\right]_{j,k},$$

which captures substitution patterns across products. Let s_t denote the vector of shares and Ω_t denote the ownership matrix, where

$$(\Omega_t)_{jk} = \begin{cases} 1 & \text{if products } j \text{ and } k \text{ are jointly priced by the same decision maker,} \\ 0 & \text{otherwise.} \end{cases}$$

Different conduct assumptions correspond to different ownership structures and therefore different pricing first-order conditions.

General first-order condition. Under standard Bertrand-type price competition with multi-product firms, the vector of markups μ_t satisfies

$$\mu_t = -\left(\Omega_t \odot \mathcal{H}_t\right)^{-1} s_t, \tag{A.1}$$

where $\odot$ denotes the Hadamard (elementwise) product. Intuitively, $\Omega_t \odot \mathcal{H}_t$ determines which substitution effects are internalized by the pricing decision maker, and inverting this matrix translates demand sensitivities into optimal markups.

Below I specialize this expression to the two conduct models considered in the paper.

Bertrand competition

Under Bertrand competition, each firm sets prices to maximize profits for its own products, taking rivals' prices as given. Substitution effects across competing firms are not internalized. The ownership matrix therefore equals the identity:

$$(\Omega_t)_{jk} = \mathbf{1}\{j = k\}.$$

Substituting into Equation (A.1) yields

$$\mu_t^B = -\left(\Omega_t \odot \mathcal{H}_t\right)^{-1} s_t. \tag{A.2}$$

Markups depend only on own-price derivatives and on substitution among products owned by the same firm. This corresponds to standard competitive pricing behavior in differentiated product markets.

Coordinated conduct (joint-profit maximization)

Under coordinated conduct, firms internalize substitution across all products and choose prices to maximize joint industry profits. Economically, this corresponds to full collusion or industry-wide coordination. The ownership matrix becomes

$$(\Omega_t)_{jk} = 1 \quad \forall j, k,$$

so all substitution effects are internalized.

In this case,

$$\Omega_t \odot \mathcal{H}_t = \mathcal{H}_t,$$

and the markup formula simplifies to

$$\mu_t^C = -\mathcal{H}_t^{-1} s_t. \tag{A.3}$$

Relative to Bertrand pricing, this specification produces larger markups because firms account for the profit lost from diverting demand to any competing product.

A.6.3 Generalized Method of Moments as a Testing Framework

This appendix reviews the Generalized Method of Moments (GMM) framework that underlies both estimation and the conduct tests implemented in the main text. While GMM is commonly introduced as an estimator, it is equally useful as a model evaluation and specification testing device. The central idea is that an economic model implies population moment restrictions, and competing models can be compared by how well their implied moments satisfy these orthogonality conditions in the data. The discussion follows Hansen [1982], Chamberlain [1987], and Newey and McFadden [1994].

Moment conditions

Let W_t denote observed data and let θ denote model parameters. An economic model typically implies population restrictions of the form

$$\mathbb{E}[g(W_t, \theta_0)] = 0, \tag{A.4}$$

where $g(\cdot)$ is a vector of moment functions and θ_0 is the true parameter value. These conditions state that certain residuals or errors are mean independent of observable variables under correct specification.

In practice, population moments are replaced by their sample analogues,

$$\bar{g}_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} g(W_t, \theta),$$

and GMM selects parameters that minimize the distance between these sample moments and zero:

$$\hat{\theta} = \arg\min_{\theta}\ \bar{g}_T(\theta)' W \bar{g}_T(\theta), \tag{A.5}$$

where W is a positive semi-definite weighting matrix.

Orthogonality and instruments

A common form of moment restriction arises from orthogonality between structural errors and exogenous variables. Suppose the model implies an error term ε_t satisfying

$$\mathbb{E}[\varepsilon_t \mid Z_t] = 0, \tag{A.6}$$

where Z_t are exogenous instruments. Then for any measurable function $A(Z_t)$,

$$\mathbb{E}[\varepsilon_t \cdot A(Z_t)] = 0. \tag{A.7}$$

These moment conditions form the basis for identification.

Instrument validity requires that $A(Z_t)$ be exogenous so that the orthogonality restriction holds under the correct model. However, not all valid instruments are equally informative. Test power and efficiency depend on choosing functions $A(Z_t)$ that load strongly on directions where competing models differ. As shown by Chamberlain [1987], optimal instruments are conditional expectations of model sensitivities given the instruments.

GMM for model comparison and specification testing

Although GMM is often used for parameter estimation, it can also be used to compare models. Competing structural models typically imply different moment conditions or generate different residuals. The preferred model is the one whose implied moments are closest to satisfying orthogonality.

Formally, let $\varepsilon_t^{(m)}$ denote residuals implied by model m. Define the corresponding sample moment

$$\bar{g}_T^{(m)} = \frac{1}{T}\sum_t \varepsilon_t^{(m)} A(Z_t).$$

A simple scalar criterion is

$$Q^{(m)} = \left(\bar{g}_T^{(m)}\right)^2, \tag{A.8}$$

which measures violations of the orthogonality condition. Smaller values indicate that the model is more consistent with exogenous variation in Z_t.

This logic underlies classical overidentification tests (e.g., Hansen's J-test), non-nested model comparisons, and the conduct tests used in this paper. In the non-nested setting, differences in GMM criteria across models can be compared using Vuong-style asymptotics [Vuong, 1989, Rivers and Vuong, 2002], yielding formal inference on which model better fits the moment restrictions.

A.6.4 Vuong-Style Tests for Non-Nested Model Comparison

This appendix describes the non-nested testing framework used to compare alternative conduct models. The procedure follows the classical likelihood-based comparison of Vuong [1989] and the moment-based adaptation developed by Rivers and Vuong [2002] and Backus et al. [2021]. The key feature of this setting is that the competing models are *non-nested*: neither model can be obtained as a special case or parameter restriction of the other. Standard likelihood ratio or Wald tests are therefore not applicable.

Non-nested conduct models

In the conduct context, different behavioral assumptions imply distinct pricing first-order conditions and therefore different mappings from observables to markups and marginal costs. Because these pricing rules are structurally different, one conduct model cannot be embedded within the other through parameter restrictions. Consequently, the models generate separate residual processes and separate moment conditions.

Let $\omega_{jt}^{(m)}$ denote the marginal cost residual implied by conduct model m. Each model implies a distinct orthogonality restriction of the form

$$\mathbb{E}\Big[\omega_{jt}^{(m)} \cdot A(Z_t)\Big] = 0, \tag{A.9}$$

where $A(Z_t)$ is an instrument constructed from exogenous shifters. If model m is correctly specified, these moments should be close to zero. When the model is misspecified, systematic moment violations remain.

Criterion-based comparison

The Vuong framework compares models using a model-fit criterion rather than asking whether any single model is exactly correct. In likelihood settings, the comparison is based on differences in log-likelihoods. In GMM settings, the analogous comparison uses differences in moment violations.

Let

$$\hat{g}^{(m)} = \frac{1}{n}\sum_{j,t} \hat{\omega}_{jt}^{(m)} A(Z_t)$$

denote the sample moment under model m, and define the scalar GMM criterion

$$\tilde{Q}^{(m)} = \left(\hat{g}^{(m)}\right)^2. \tag{A.10}$$

This quantity measures how far the model's implied moments deviate from the orthogonality restriction. Smaller values indicate better fit.

The comparison focuses on the difference

$$\Delta Q = \tilde{Q}^{(1)} - \tilde{Q}^{(2)}.$$

If $\Delta Q > 0$, model 2 produces smaller moment violations; if $\Delta Q < 0$, model 1 performs better.

Asymptotic distribution and test statistic

Under regularity conditions for GMM sample moments [Hansen, 1982, Newey and McFadden, 1994] and the non-nested asymptotics developed by Vuong [1989] and Rivers and Vuong [2002], the scaled difference in criteria satisfies

$$\sqrt{n}\left(\tilde{Q}^{(1)} - \tilde{Q}^{(2)}\right) \xrightarrow{d} \mathcal{N}(0, \sigma^2). \tag{A.11}$$

Let $\hat{\sigma}$ denote a consistent estimate of σ, obtained via bootstrap or influence-function methods. The standardized statistic

$$T = \frac{\sqrt{n}\left(\tilde{Q}^{(1)} - \tilde{Q}^{(2)}\right)}{\hat{\sigma}} \xrightarrow{d} \mathcal{N}(0, 1) \tag{A.12}$$

provides a formal test.

Decision rule and interpretation

The decision rule mirrors a standard two-sided z-test:

- $T > 1.96$: prefer model 2,

- $T < -1.96$: prefer model 1,

- otherwise: fail to distinguish the models.

Importantly, the Vuong-style test does not attempt to determine whether either model is "true." Instead, it selects the model that is *closer to the data-generating process* in the sense of producing smaller violations of the implied moment restrictions. Thus, the procedure is best interpreted as a relative model comparison rather than an absolute specification test.

A.7 Differentiation-Based Instruments (Gandhi–Houde)

Following Gandhi and Houde [2019], I construct differentiation-based instruments that exploit the idea that product positioning in characteristic space determines competitive pressure and therefore equilibrium markups and prices. Products that are closer substitutes face stronger competition and lower markups, while more isolated products can sustain higher prices. Variation in relative product distances thus shifts prices through supply-side substitution patterns rather than through unobserved demand shocks, making these measures valid instruments for price.

Let $x_{jt}^{(\ell)}$ denote observable characteristics of product j in dimension ℓ. For each product–rival pair (j, k), define the distance in characteristic space as

$$d_{jk,t}^{(\ell)} = \left| x_{jt}^{(\ell)} - x_{kt}^{(\ell)} \right|.$$

These distances summarize how close two products are along economically meaningful attributes.

I then aggregate distances across all rivals to form differentiation measures that capture both proximity and isolation. Specifically, I construct linear and quadratic sums of distances:

$$z_{jt}^{\text{diff}} = \sum_{k \neq j} \left(d_{jk,t}^{(\ell)},\ d_{jk,t}^{(\ell)\,2} \right),$$

which provide flexible measures of how crowded the local competitive environment is around each product. Intuitively, products surrounded by many similar alternatives have small average distances and face more elastic demand, while more differentiated products have larger distances and greater pricing power.

To strengthen instrument relevance and mitigate measurement error in observed prices, I follow Gandhi and Houde [2019] and first project prices onto cost shifters and differentiation measures to obtain predicted prices:

$$\hat{p}_{jt} = \mathbb{E}\Big[p_{jt} \mid \text{cost shifters},\ z_{jt}^{\text{diff}}\Big].$$

I then use $\hat{p}_{jt}$ (and functions of it) as instruments for observed prices in the demand estimation. Because differentiation and cost shifters affect equilibrium prices through substitution patterns and marginal costs rather than through the unobserved demand shock ξ_{jt}, these instruments satisfy the exclusion restriction under standard assumptions.

Consistent with Berry et al. [1995] and Backus et al. [2021], this approach provides strong and economically interpretable sources of exogenous price variation, particularly in categories such as eggs and other commodity-like products where observable characteristics largely determine substitution patterns.

A.8 Product Detail

	Milk	Orange Juice
Number of markets (DMA–year–quarter)	384	384
Number of products	436	401
Number of observations	17,576	21,305

Table A.6: Market and Product Summary Statistics by Category.

Notes: Markets are defined at the DMA–year–quarter level and products are aggregated to the parent store–brand level.

A.9 BLP Demand Model and Estimation Details

This section describes the random-coefficients logit demand system used to recover substitution patterns, elasticities, and implied markups. I follow the framework of Berry et al. [1995], commonly referred to as the BLP model, which allows flexible substitution across products while accommodating consumer heterogeneity.

Utility specification. Consumer i's indirect utility from product j in market t is given by

$$u_{ijt} = x_{jt}\beta - \alpha p_{jt} + x_{jt}\Sigma\nu_i + p_{jt}\Pi D_i + \xi_{jt} + \varepsilon_{ijt}, \tag{A.13}$$

where x_{jt} denotes observed product characteristics (e.g., promotions and fixed effects), p_{jt} is price, and ξ_{jt} captures unobserved product quality observed by firms and consumers but not the econometrician. The vector ν_i represents unobserved taste heterogeneity, and D_i contains observed demographics that interact with price or characteristics. The idiosyncratic error ε_{ijt} is assumed i.i.d. Type I extreme value.

This specification implies random coefficients on product characteristics and price, generating flexible cross-price substitution patterns based on similarity in attributes and consumer tastes.

Market shares and inversion. Let s_{jt} denote the observed market share of product j and s_{0t} the outside option share. Given parameters $(\beta, \alpha, \Sigma, \Pi)$, predicted shares are obtained by integrating choice probabilities over the distribution of consumer heterogeneity. Following Berry et al. [1995], I invert the share system to recover the mean utilities δ_{jt} that rationalize observed shares:

$$\delta_{jt} = \delta(s_{jt}, x_{jt}, p_{jt}; \Sigma, \Pi). \tag{A.14}$$

This contraction mapping ensures that predicted shares match the data exactly for any candidate nonlinear parameters.

Endogeneity and instruments. Because prices and promotions may respond to unobserved quality shocks ξ_{jt}, I allow

$$\mathbb{E}[\xi_{jt} \mid p_{jt}] \neq 0.$$

Consistent estimation therefore requires instruments Z_{jt} that shift prices but are orthogonal to ξ_{jt}. I employ cost shifters and differentiation-based instruments as described in the main text.

GMM estimation. Parameters are estimated by generalized method of moments. Let $\xi_{jt}(\theta)$ denote the implied demand residual for candidate parameter vector θ. The estimator solves

$$\hat{\theta} = \arg\min_{\theta} \left(\frac{1}{n} \sum_{j,t} \xi_{jt}(\theta) Z_{jt} \right)' W \left(\frac{1}{n} \sum_{j,t} \xi_{jt}(\theta) Z_{jt} \right), \tag{A.15}$$

where W is a weighting matrix. Under valid instruments, the orthogonality condition $\mathbb{E}[\xi_{jt} Z_{jt}] = 0$ holds at the true parameters.

Elasticities and markups. The estimated demand system yields the Jacobian of shares with respect to prices,

$$\mathcal{H}_{jt,k} = \frac{\partial s_{jt}}{\partial p_{kt}},$$

from which I compute own- and cross-price elasticities as well as diversion ratios. These objects determine equilibrium markups under alternative conduct assumptions. In particular, markups satisfy the first-order condition

$$\mu = -(\Omega \odot \mathcal{H})^{-1} s,$$

where Ω is the ownership matrix and $\odot$ denotes the Hadamard product. The resulting conduct-specific markups are used to recover marginal costs and form the basis of the conduct tests.

A.10 Demand Estimates

A.10.1 Milk

	Estimate	Std. Err.
Mean Utility		
Price	-2.470^{***}	0.128
Price × Inflation	-0.103^{**}	0.037
Feature	0.217	0.145
Display	1.415^{***}	0.227
Random Coefficients		
SD(Price)	-0.106	0.355
Observations	14,670	
Markets	384	
Products	302	

Table A.7: BLP Demand Estimates for Milk.

Notes: Estimates from a random-coefficients logit demand model. Standard errors obtained via GMM. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

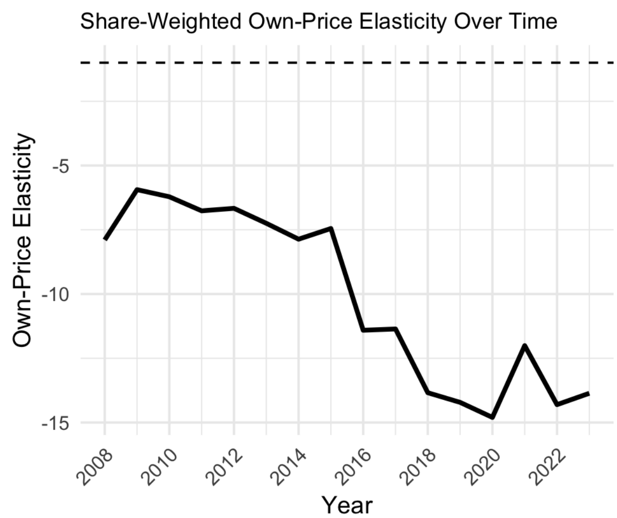

Figure A.9: Share-Weighted Own-Price Elasticity Over Time - Milk.

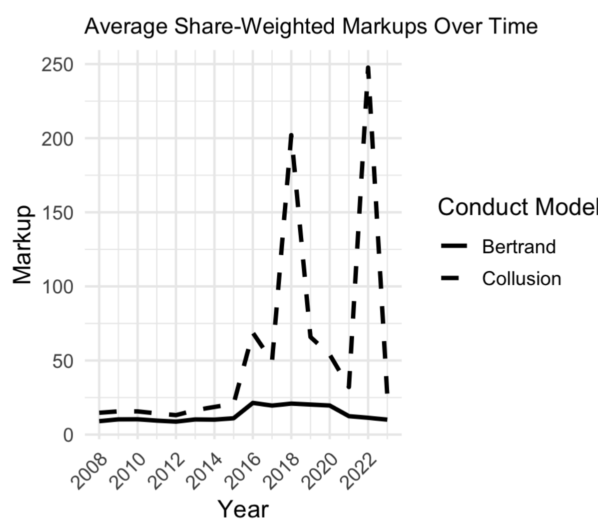

Figure A.10: Average Share-Weighted Markups Over Time - Milk

A.10.2 Orange Juice

	Estimate	Std. Err.
Mean Utility		
Price	-2.212^{***}	0.107
Price × Inflation	0.054^{*}	0.028
Feature	0.960^{***}	0.098
Display	1.462^{***}	0.172
Random Coefficients		
SD(Price)	-0.106	0.355
Observations	14,670	
Markets	384	
Products	302	

Table A.8: BLP Demand Estimates for Orange Juice.

Notes: Estimates from a random-coefficients logit demand model. Standard errors obtained via GMM. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

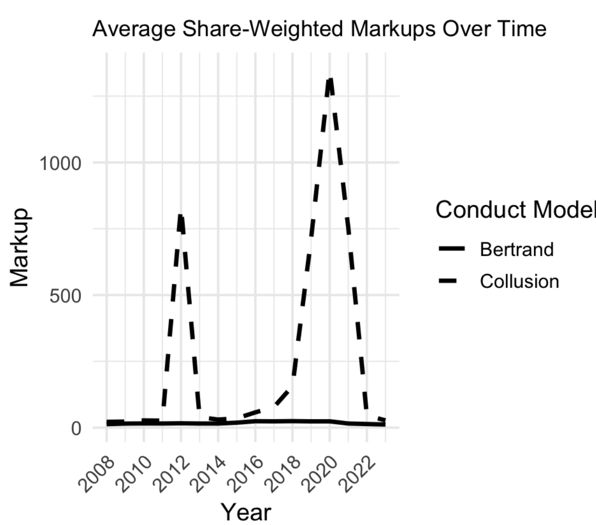

Figure A.11: Share-Weighted Own-Price Elasticity Over Time - Orange Juice.

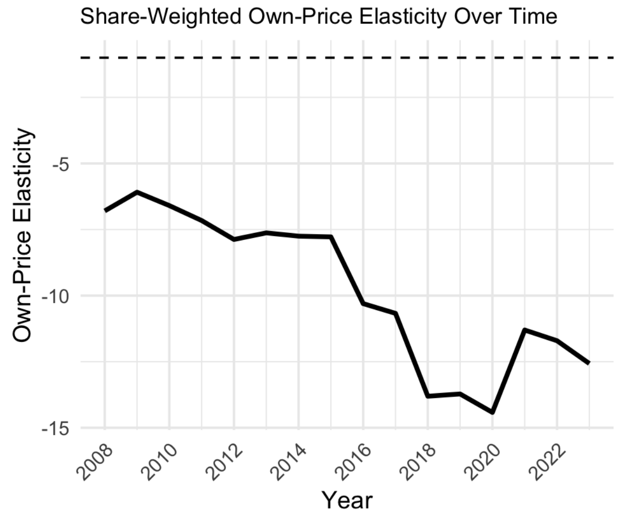

Figure A.12: Average Share-Weighted Markups Over Time - Orange Juice.

A.11 Conduct Tests

Tables A.9 and A.10 report the same non-nested GMM conduct tests for milk and orange juice. As in the main text, the statistic compares the scalar GMM criteria across conduct assumptions, with negative values of the mean difference $Q(\eta^B) - Q(\eta^C)$ indicating that the Bertrand model generates smaller moment violations and therefore better satisfies the cost-side orthogonality conditions.

Across all samples and both product categories, the estimated differences are large, negative, and statistically significant at the one percent level. I therefore reject the null that both models fit equally well and conclude that independent Bertrand pricing is preferred to coordinated or collusive conduct. The magnitude of the differences is substantially larger than in the egg category, indicating a particularly strong separation between competitive and coordinated conduct models in these markets.

Consistent with the egg results, the gap between models narrows somewhat during the post-2020 inflation period but remains strongly negative. This pattern suggests that while inflation compresses margins and reduces the statistical distance between conduct assumptions, pricing behavior continues to align most closely with competitive markups rather than joint-profit maximization. Overall, the evidence across milk and orange juice reinforces the conclusion that retail pricing in these commodity-like grocery categories is best characterized by Bertrand competition.

Sample	**Mean Diff.**	**Test**	**Conclusion**
Full (2008–2023)	-81.943	$p < 0.01$	Bertrand preferred
Pre-2020	-51.109	$p < 0.01$	Bertrand preferred
Post-2020	-70.926	$p < 0.01$	Bertrand preferred

Table A.9: Conduct Testing Results - Milk.

Sample	**Mean Diff.**	**Test**	**Conclusion**
Full (2008–2023)	-94.103	$p < 0.01$	Bertrand preferred
Pre-2020	-55.645	$p < 0.01$	Bertrand preferred
Post-2020	-79.948	$p < 0.01$	Bertrand preferred

Table A.10: Conduct Testing Results - Orange Juice.

A.12 Egg Demand Elasticities in the U.S.

Study (Year)	Demand Model	Instruments Used	Estimated Price Elasticity
Andreyeva et al. (2010)	Meta-analysis (160 food demand studies)	None (summary of past studies)	−0.27 (mean for eggs)
Okrent & Alston (2011)	AIDS (U.S. food demand system using aggregate data)	No	−0.18 (short-run); −0.73 (long-run calibrated)
Lusk (2010)	LA/AIDS (household-level panel from CA and TX)	Yes – 3SLS (income, CPI, trends)	−0.13 (conventional); −2.98 (cage-free)
Heng (2015)	BLP (random-coefficient logit across 25 egg UPCs)	Yes – BLP instruments (product characteristics interacted with market shares)	−0.95 (conventional); −2.17 to −4.75 (specialty)
Bakhtavoryan et al. (2022)	EASI (Nielsen Homescan data, HH panel)	Yes – Hausman-type (prices in adjacent markets, income)	−0.2348 (conv.); −0.93 (omega-3); −1.00 (organic/cage-free)
Conrad et al. (2019)	Lab grocery experiment (randomized prices)	None (RCT design)	−0.70 to −0.86 (long-run, all groups)
Caputo et al. (2023)	BLP-style discrete choice (industry/consumer equilibrium)	No (calibration from choice data)	−0.74 (conventional); up to −5.8 (specialty)
Smith (2023)	Observed behavior (real-world 2022 spike)	No (descriptive analysis)	−0.02 to −0.06 (extremely inelastic)

Table A.11: Estimated U.S. retail demand elasticities for eggs from recent literature.

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