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Unveiling Demand Function Dynamics: A Scalable, Cross-Market Estimation Using Point-of-Sale Data

Ryotaro Todoroki*
ryoutarou.todoroki@boj.or.jp

Kazuki Otaka**
kazuki.ootaka@boj.or.jp

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Bank of Japan
2-1-1 Nihonbashi-Hongokucho, Chuo-ku, Tokyo 103-0021, Japan

* Research and Statistics Department
** Research and Statistics Department (currently at the Institute for Monetary and Economic Studies)

Unveiling Demand Function Dynamics:
A Scalable, Cross-Market Estimation Using Point-of-Sale Data[*]

Ryotaro Todoroki[†] and Kazuki Otaka[‡]

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Abstract

This study examines the dynamics of demand functions for a wide range of consumer products in Japan over the past three decades. Using highly granular point-of-sale (POS) data and machine learning techniques, we estimate key demand function parameters, namely price elasticity and demand curvature, from which we also derive markups for each market and period. We find that while the aggregate-level median price elasticity and markups remained relatively stable over the long term, with substantial cross-product heterogeneity underlying this stability, recent years have seen a modest decrease in the absolute value of median price elasticity and a corresponding increase in markups. Furthermore, our analysis shows that demand curvature increased until the mid-2010s and subsequently declined. Importantly, our panel analysis reveals a significant relationship between the estimated demand function parameters and key factors, including labor force participation and market concentration. In particular, we identify the rise in female labor force participation as a key driver of the recent decline in both absolute price elasticity and demand curvature. These findings suggest that these shifts in socio-economic factors, such as increased labor participation, might have altered consumer behavior, leading to diminished price sensitivity.

JEL Classification: C55, D12, D43, L11, L13, L16
Keywords: Consumer behavior, Kinked demand curve, Markups, Machine learning

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[†] Research and Statistics Department, Bank of Japan (ryoutarou.todoroki@boj.or.jp)
[‡] Research and Statistics Department, Bank of Japan (currently at Institute for Monetary and Economic Studies, kazuki.ootaka@boj.or.jp)

1. Introduction

The shape of the demand curve is a cornerstone of economic analysis, holding profound implications for both microeconomic behavior and macroeconomic outcomes. At the micro level, the slope of the demand curve—the price elasticity—is the primary determinant of a firm's pricing power and its ability to set markups over marginal cost. At the macro level, the aggregation of these individual demand functions has important implications for key macroeconomic variables such as Gross Domestic Product (GDP) and the rate of inflation. Furthermore, the curvature of the demand function plays a critical role in explaining price-setting behavior and has been identified as a key factor in understanding the well-documented price rigidity in Japan (Furukawa *et al.* [2024]).[1]

Despite its fundamental importance, the empirical estimation of these demand characteristics across a wide array of markets and over long time horizons has remained a significant challenge. The sheer difficulty of obtaining sufficiently granular data and the difficulty of estimation have historically limited such analyses. Consequently, comprehensive, cross-market studies that track the evolution of demand functions from a macroeconomic perspective, using demand and price data directly, have been scarce, particularly in the context of the Japanese economy.

This paper addresses this gap by developing and implementing a scalable methodology to estimate demand functions for a vast range of consumer goods in Japan. By harnessing highly granular, long-run Point-of-Sale (POS) data, we conduct a cross-market, longitudinal estimation of both the price elasticity (the first derivative of the demand function) and the curvature (the second derivative). In our framework, a "market" is defined by the intersection of a product category and a geographic region. Unlike much of the previous research in industrial organization, which has often focused on single markets, our approach is designed for broad applicability. We extend recently-developed scalable estimation techniques (e.g., Brand [2021]; Atalay *et al.* [2023]) by integrating text analysis and machine learning. This novel combination allows for a more refined estimation of the demand function, including its curvature, providing a dynamic view of its parameters across products, regions, and time. Using this rich, estimated panel dataset, we then investigate the underlying drivers of these parameters, their evolution, and their resulting impact on firm markups.

Our study contributes to the literature in four key ways. First, we provide the first-ever large-scale, cross-market estimation of demand function parameters—including both price elasticity and curvature— for Japan over the past three decades. While foundational works like Berry, Levinsohn, and Pakes [1995] established a robust framework for demand estimation, and Nevo [2001] pioneered its application to scanner data, subsequent research in Japan has largely focused on individual markets rather than cross-market analysis. Our work builds upon recent studies in the U.S. that have achieved cross-market scalability, but we further extend this analysis by systematically estimating the time-varying nature of demand curvature, a feature that has not yet been explored in a multi-market context.

[1] Some studies parametrically estimate macroeconomic demand function parameters within broader macroeconomic frameworks, such as price-setting models. See, for example, Furukawa *et al.* [2024].

Second, we contribute to the literature on markup estimation by employing a "demand-side approach." This method, which infers markups directly from estimated demand elasticities, stands in contrast to the more common "production-side approach" that relies on firm-level financial data to estimate production functions (De Loecker and Warzynski [2012]). The demand-side approach offers a significant advantage in its timeliness, as it can be implemented in real-time using POS data, without the reporting lags associated with corporate financial statements. Recent work by Döpper *et al.* [2025] further examines the role of consumer preferences in explaining rising markups using random coefficient logit models; while their approach avoids instrumental variables, it requires consumer panel data to identify preference heterogeneity. Though this approach has been applied in the U.S. (Brand [2021]; Atalay *et al.* [2023]), our paper represents its first macroeconomic application to the Japanese market.[2]

Third, we conduct a systematic analysis of the determinants of demand function dynamics. Demand characteristics are shaped by a complex interplay of product attributes, consumer demographics, competitive landscapes, and macroeconomic conditions.[3] We explore these relationships empirically, examining how factors such as market competition (Herfindahl-Hirschman Index), inflation, and employment rates correlate with our estimated parameters. This analysis sheds new light on how secular trends, such as the long-term change in Japan's working hours (Sudo *et al.* [2018]) and shifts in consumers' inflation beliefs (Aoki, Ichiue, and Okuda [2019]), have influenced purchasing behavior.

Finally, our research offers a methodological contribution by demonstrating the power of combining natural language processing (NLP) and machine learning to extract product quality attributes from unstructured text data (i.e., product names). This approach aligns with a growing body of literature that uses machine learning and AI to enhance economic measurement, from constructing hedonic price indices (Bajari *et al.* [2023]; Cafarella *et al.* [2023]) to improving demand estimation itself (Bach *et al.* [2024]).

Our analysis yields several key findings. We find that while the median price elasticity of demand and the corresponding markups have remained relatively stable over the past three decades, we uncover a notable recent trend: a gradual decrease in the absolute value of elasticity, leading to a modest rise in aggregate markups. The curvature of the demand function, meanwhile, exhibits a distinct pattern, increasing until the mid-2010s before embarking on a downward trend. Most importantly, our panel analysis reveals the macroeconomic drivers behind these dynamics. We find a significant relationship between the shape of the demand function and factors such as market concentration, the employment rate, and the inflation rate. In particular, our results identify the secular rise in female labor force participation as a key contributor to the recent decline in both

[2] An alternative "accounting approach" also exists, which defines markups as the ratio of sales to average costs, using firm financial data (e.g., Kikuchi [2024]).
[3] Demand elasticity is influenced by product attributes such as whether a good is a necessity or a luxury, the availability of substitutes, and brand effects (e.g., Marshall [1920]; Krishnamurthi and Raj [1991]; Andreyeva, Long, and Brownell [2010]). Consumer attributes like income, age, employment status, and shopping time affect price sensitivity (e.g., Chaloupka and Warner [2000]; Aguiar and Hurst [2007]; Sudo *et al.* [2018]). Competitive environments, including market concentration and firms' pricing strategies, also play a role, as the presence of substitutes tends to increase elasticity (e.g., Bijmolt, Van Heerde, and Pieters [2005]). Macroeconomic factors such as business cycles, inflation, and policy measures can have both short- and long-term effects on demand elasticity (e.g., Chaloupka and Warner [2000]; Bijmolt, Van Heerde, and Pieters [2005]; Gordon, Goldfarb, and Li, [2013]).

absolute price elasticity and demand curvature. This suggests that fundamental shifts in household structure and time allocation have altered consumer behavior, leading to diminished price sensitivity.

The remainder of this paper is structured as follows. Section 2 provides an overview of the POS dataset used in our analysis. Section 3 details our econometric methodology for estimating the demand function parameters. Section 4 presents the main results on the evolution of price elasticity, markups, and curvature over the past 30 years. Section 5 investigates the key determinants of these demand dynamics. Finally, Section 6 concludes with a summary of our findings and a discussion of their implications.

2. Data

Our analysis is based on Merchandising-ON Co. Ltd.'s RDS-POS market dataset. This comprehensive dataset contains information on approximately 800,000 unique product items, including product names, JICFS (Japanese Article Number Item Code File Service) categories, manufacturer names, and data on average sales value and volume per 100 stores. The data are provided in two distinct formats, as summarized in Table 1.

Table 1: Overview of the POS Datasets

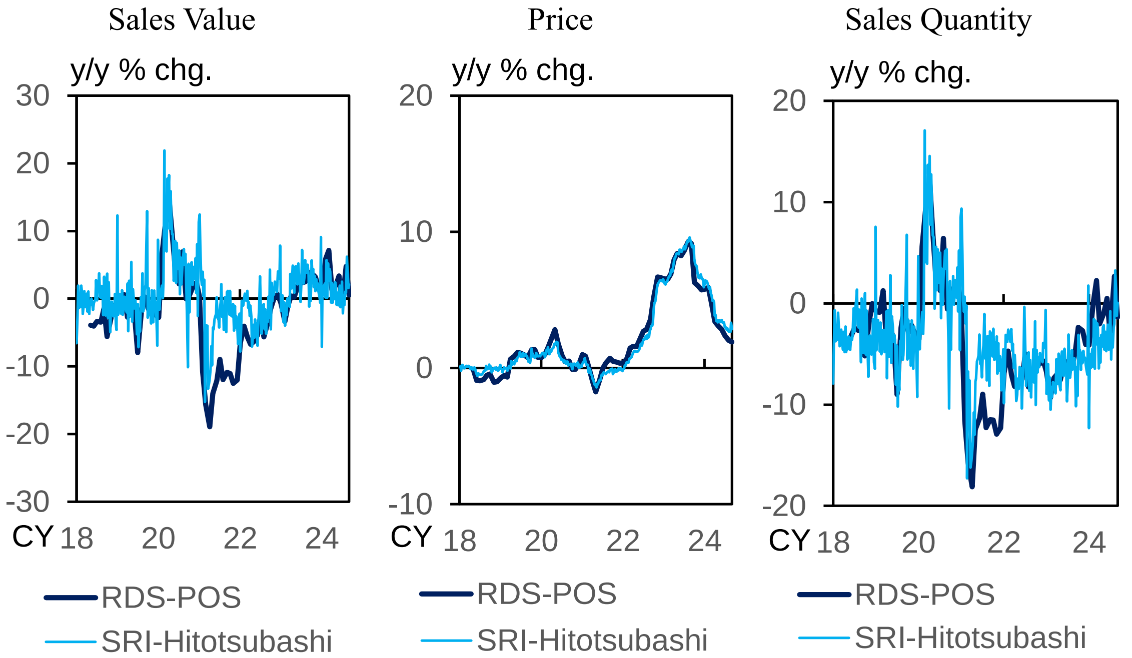
	1. Regular POS dataset	2. 30-year POS dataset
Store type	Supermarket, convenience store, drugstore	Supermarket
Period	May 2017 onwards	1992 onwards
Frequency	Daily, weekly, monthly	Annual
Region	Nationwide, including 10 regions	Nationwide

The primary focus of our analysis is on several major product categories: food (including beverages and tobacco), daily necessities (such as sundries, pharmaceuticals, and household goods), cultural goods (e.g., stationery and toys), and clothing, paraphernalia, and sporting goods.[4] We exclude private-label (PL) products from our sample because their manufacturer names are masked in the dataset.

To validate the representativeness of our data for macroeconomic analysis, we compare its aggregated time-series trends with those of other established indices. As shown in Figures 1 and 2, our dataset exhibits movements that are broadly consistent with both the SRI-Hitotsubashi Consumer Purchase Index and the official Consumer Price Index (CPI). This consistency suggests that our POS data provide sufficient coverage for meaningful analysis of broad-based consumer behavior.

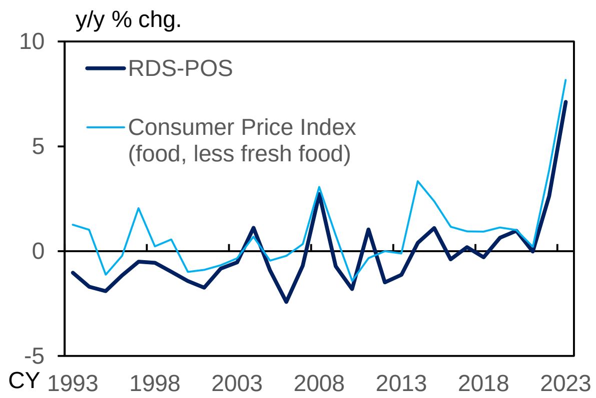
[4] The sales composition by value in 2023 was as follows: Food: 92.5%, Daily Necessities: 6.8%, Cultural Goods: 0.3%, and Clothing, Paraphernalia, and Sporting Goods: 0.1%.

Figure 1: Time-Series Trends of Aggregated Data



Note: The RDS-POS data are monthly, while the SRI-Hitotsubashi Index is weekly. The RDS-POS series shown here is aggregated from data for food products (excluding fresh food) sold in supermarkets.
Source: Hitotsubashi University, Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

Figure 2: Comparison with the Consumer Price Index (CPI)



Note: The RDS-POS series is aggregated from data for food products (excluding fresh food) sold in supermarkets and is expressed as a year-over-year change in the Sato-Vartia price index. The CPI data are for food excluding fresh food.
Source: Ministry of Internal Affairs and Communications, Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

The unique features of our dataset are its long time horizon—spanning 30 years—and its availability at both the nationwide and regional levels. This makes it exceptionally well-suited to analyze macroeconomic consumption patterns over time. In this regard, our dataset overcomes a key limitation of many previous studies that relied on POS or scanner data, which were often constrained by a shorter time series or were not available in real-time.

However, the dataset also has a notable limitation: it does not contain information on the attributes of individual stores or customers. This contrasts with the data used in some recent studies (e.g., Atalay *et al.* [2023]) and precludes analyses that directly link scanner data to individual consumer purchasing records.

3. Estimation Strategy

This section outlines our methodology for estimating the price elasticity of demand, firm markups, and the curvature of the demand function.

Our estimation of markups relies on the "demand-side approach," which combines an estimated demand function with a model of firm competition. This approach allows us to infer markups directly from the price elasticity of demand, under the assumption of a specific competitive market structure. Combining this with a production-side approach also enables the evaluation of assumptions embedded in structural models of markup estimation (De Loecker and Scott [2016]). Furthermore, a key advantage of the demand-side approach is its timeliness; because it utilizes POS data that are available in real-time, it offers faster insights compared to production-side methods that depend on corporate financial data with significant reporting lags.

Specifically, we follow Atalay *et al.* [2023] and Berry [1994] to specify a logit model for estimating price elasticity. Markups are then derived using a Bertrand competition model, similar to Nevo [2001]. To estimate the curvature of the demand function, we extend the Berry [1994] model by including a second-order term for price.

3-1. Demand Model

We begin by outlining the discrete choice model from Berry [1994] that forms the basis of our estimation. The indirect utility that consumer i obtains from purchasing product j in market m (defined by product category and region) at time t is given by:

$$u_{m,t,i,j} = \delta_{m,t,j} + \epsilon_{m,t,i,j}$$

where $\delta_{m,t,j}$ represents the mean utility of product j across all consumers, and $\epsilon_{m,t,i,j}$ is a consumer-specific deviation from that mean. The mean utility is specified as a linear function of product characteristics:

$$\delta_{m,t,j} = \beta^0_{m,t} + \sum_k \beta^k_{m,t} x^k_{m,t,j} - \alpha_{m,t} p_{m,t,j} + \xi_{m,t,j} \qquad (j = 0, \dots, J)$$

where $x^k_{m,t,j}$ is the k-th observable product attribute (quality), $p_{m,t,j}$ is the price, and $\xi_{m,t,j}$ captures unobserved product attributes. The idiosyncratic preference shock $\epsilon_{m,t,i,j}$ is assumed to be independently and identically distributed according to a Type I extreme value distribution, with the following cumulative distribution function.

$$\mathrm{P}\left(\epsilon_{m,t,i,j} \le x\right) = F(x) = \exp\{-\exp(-x)\}$$

We include an "outside option" ($j = 0$), which represents the choice of not purchasing any product. The mean utility of this option is normalized to zero ($\delta_{m,t,0} = 0$) for identification. Assuming consumers choose the one product that maximizes their utility, the market share of product j, $s_{m,t,j}$, is given by the multinomial logit formula:

$$s_{m,t,j} = \frac{\exp(\delta_{m,t,j})}{1 + \sum_l \exp(\delta_{m,t,l})}$$

By taking the logarithm of the ratio of product j's share to the outside option's share, we arrive at a linear regression equation suitable for estimation:

$$\begin{aligned}
\ln(s_{m,t,j}) - \ln(s_{m,t,0}) &= \ln\left(\frac{\exp(\delta_{m,t,j})}{1 + \Sigma_l \exp(\delta_{m,t,l})} \Big/ \frac{1}{1 + \Sigma_l \exp(\delta_{m,t,l})}\right) \\
&= \delta_{m,t,j} \\
&= \beta^0_{m,t} + \sum_k \beta^k_{m,t} x^k_{m,t,j} - \alpha_{m,t} p_{m,t,j} + \xi_{m,t,j}
\end{aligned}$$

From the estimated parameter $\alpha_{m,t}$, we can calculate the own- and cross-price elasticities of demand for product j as follows[5]:

$$\frac{\partial s_{m,t,j}}{\partial p_{m,t,r}} \frac{p_{m,t,r}}{s_{m,t,j}} = \begin{cases} -\alpha_{m,t} p_{m,t,j}(1 - s_{m,t,j}) & \text{if } j = r \text{ (Own-price elasticity)} \\ \alpha_{m,t} p_{m,t,r} s_{m,t,r} & \text{if } j \neq r \text{ (Cross-price elasticity)} \end{cases}$$

3-2. Competition Model

To calculate markups from the estimated price elasticities, we specify a model of competition. The profit of firm f in market m at time t, $\pi_{m,t,f}$, is given by:

$$\pi_{m,t,f} = \sum_{j \in \mathcal{J}_{m,t,f}} M_{m,t} s_{m,t,j} \,(p_{m,t,j} - mc_{m,t,j})$$

[5] Throughout this paper, "price elasticity" refers exclusively to own-price elasticity—the percentage change in demand for product j in response to a one percent change in its own price. This should be distinguished from cross-price elasticity or substitution elasticity between product categories, which would require alternative modeling approaches such as nested logit.

where $M_{m,t}$ is the potential market size, $mc_{m,t,j}$ is the marginal cost of product j, and $\mathcal{J}_{m,t,f}$ is the set of products produced by firm f in market m at time t.

Following Atalay *et al.* [2023], we make two assumptions. First, firms (producers) simultaneously set retail prices to maximize profits, engaging in Bertrand competition with differentiated products.[6] Second, marginal costs are constant and do not vary with the quantity sold, and are independent of sales in other markets or of other products produced by the same firm.

Under these assumptions, the first-order condition for profit maximization for product j is:

$$s_{m,t,j} + \sum_{r \in \mathcal{J}_{m,t,f}} \left(p_{m,t,r} - mc_{m,t,r}\right) \frac{\partial s_{m,t,r}}{\partial p_{m,t,j}} = 0$$

By expressing this in vector notation, we can solve for the markup ratio (μ) as:[7]

$$\mu = \left(\frac{p_{m,t,1}}{mc_{m,t,1}} \dots \frac{p_{m,t,J}}{mc_{m,t,J}}\right)' = 1 \Big/ \left[1 + \left(\Omega \circ \frac{\partial s'}{\partial p}\right)^{-1} \frac{s}{p}\right]$$

where p and s are vectors of prices and market shares, respectively. Ω is a $J \times J$ matrix indicating which products are produced by the same firm, and $\circ$ denotes the Hadamard (element-wise) product.

3-3. Extracting Quality Attributes

A significant empirical challenge is that product quality attributes, $x^k_{m,t,j}$, are not available in a structured format in our POS data. Within a single market, products vary widely in quality and volume, which must be properly accounted for in the estimation. While a product-level fixed effects model could potentially control for time-invariant quality, this approach is unstable for POS data due to the high turnover of products—roughly half of food items are replaced within two years.

To overcome this, we employ a combination of text analysis and machine learning to extract quality attributes directly from unstructured product names. Specifically, we use a post-Lasso procedure to identify the most relevant attributes. This method offers two advantages: (1) it yields stable estimates even with frequent product turnover, and (2) it allows us to control for brand- or manufacturer-specific demand shocks that might otherwise violate the independence assumption of our instrumental variables.

[6] In this model, producers set retail prices directly. Retailers are assumed to receive a fixed payment for shelf space and do not take a retail margin.
[7] Products with an estimated own-price elasticity greater than -1 are excluded from the markup calculation, as they do not satisfy the second-order condition for profit maximization.

The extraction process involves the following steps:

1. Tokenize: We use the Japanese morphological analysis system MeCab[8] to parse product names into individual words (morphemes) and parts of speech.
2. Extract Volume: We identify the last numerical term in a product name as its volume/capacity, converting units like "kg" or "L" to a standardized "g" or "ml" scale.[9]
3. Vectorize Words: We convert the remaining (non-numerical) words into a numerical "Bag of Words" (BoW) matrix, representing the frequency of each word for each product.[10]
4. Estimate with Attributes: We reformulate the demand equation from Section 3-1, using the extracted volume ($V_{m,t,j}$) and the BoW vectors ($w_{m,t,j}^{k}$) as the product attributes $x_{m,t,j}^{k}$:

$$\ln(s_{m,t,j}) - \ln(s_{m,t,0}) = \beta_{m,t}^{0} + \beta_{m,t}^{V} V_{m,t,j} + \sum_{k} \beta_{m,t}^{k} w_{m,t,j}^{k} - \alpha_{m,t} p_{m,t,j} + \xi_{m,t,j}$$

A critical issue in estimating this equation is the endogeneity of price ($p_{m,t,j}$), which is likely to be correlated with unobserved quality attributes ($\xi_{m,t,j}$). We address this using an instrumental variable approach with two-stage least squares (IV-2SLS). However, the number of potential word features in the BoW matrix is often larger than the number of products in a market, creating an underdetermined system. While sparse estimation methods like the Lasso regression can handle this high dimensionality, they may not yield consistent estimates for our main parameter of interest, $\alpha_{m,t}$.

Therefore, we adopt the post-Lasso methodology (Belloni and Chernozhukov [2013]; Chernozhukov, Hansen, and Spindler [2015]). This involves a two-step process: first, we use a Lasso regression to select a smaller, relevant set of word features (attributes); second, we run the IV-2SLS regression using only this selected set of features as controls. This approach allows us to consistently estimate the price coefficient while still controlling for a rich set of quality attributes.[11]

We adopt the post-Lasso methodology for a specific reason: while Lasso regression can handle high-dimensional settings, the regularization bias it introduces may lead to inconsistent estimates of our key parameter of interest, $\alpha_{m,t}$, particularly when the true coefficient is non-zero. The post-Lasso approach—using Lasso only for variable selection and then running unpenalized IV-2SLS on the selected variables—avoids this bias while retaining the benefits of dimensionality reduction (Belloni and Chernozhukov [2013]).

[8] MeCab: https://taku910.github.io/mecab/ (Accessed April 1, 2025). The IPA dictionary was used.
[9] This volume extraction was performed for the food and daily necessities categories, where volume information is most prevalent and relevant.
[10] Words appearing fewer than 10 times in total within a JICFS sub-category were excluded.
[11] For simplicity and due to computational constraints, we use a fixed regularization parameter ($\lambda = 0.3$) for the Lasso variable selection. More data-driven methods, such as cross-validation for parameter tuning or post-double selection (Belloni, Chernozhukov, and Hansen [2014]) to mitigate omitted variable bias, are potential avenues for future research.

3-4. Estimation Procedure

Our final estimating equation is:

$$\ln(s_{m,t,j}) - \ln(s_{m,t,0}) = \beta_{m,t}^{0} + \beta_{m,t}^{V} V_{m,t,j} + \sum_{k} \beta_{m,t}^{k} w_{m,t,j}^{k,extract} - \alpha_{m,t} p_{m,t,j} + \xi_{m,t,j}$$

where $w_{m,t,j}^{k,extract}$ is the word feature selected by the post-Lasso procedure, and the market m is defined at the finest level of the JICFS product classification.

To address the endogeneity of price, we use an IV-2SLS framework. The standard "BLP instruments" (Berry, Levinsohn, and Pakes [1995])—sums of quality characteristics of other products from the same and competing firms—are not feasible here, as our quality measures ($w_{m,t,j}^{k,extract}$) are themselves an outcome of the estimation process.[12]

Instead, we propose alternative instruments:

1. The sum of sales quantities of other products from the same firm.
2. The sum of sales quantities of products from all competing firms.

We argue these instruments satisfy the necessary conditions. For relevance, they are correlated with price through competitive interactions and firms' pricing strategies. Indeed, the Staiger and Stock [1997] F-statistic for the relevance of our instruments has a weighted median of 11.8, exceeding the conventional threshold of 10. For the exclusion restriction, they must be uncorrelated with the unobserved demand shock $\xi_{m,t,j}$. We expect this to hold because: (a) the sales of other products are driven primarily by their own demand and cost shocks, not the specific shock of product j; and (b) any brand-level demand shocks (e.g., from advertising) that might affect all of a firm's products are explicitly controlled for by our extracted manufacturer/brand name features in the post-Lasso procedure.

The share of the outside option, $s_{m,t,0}$, is calculated as:

$$s_{m,t,0} = 1 - \sum_{j=1}^{J} \frac{q_{m,t,j}}{M_{m,t}}$$

[12] Using only product volume as a basis for BLP instruments was also considered, but the resulting instruments were weak, with the Staiger-Stock F-statistic consistently below 10. Another common choice, the Hausman-Nevo instrument (average price of the same product in other geographic markets), is difficult to apply in Japan, where demand shocks (e.g., from national TV advertising) are likely to spill across regions, violating the exclusion restriction.

where $q_{m,t,j}$ is the sales quantity per 100 stores for product j, and the market size $M_{m,t}$ is proxied by the total number of customer visits per 100 stores during the specified period.

Finally, to estimate the curvature of the demand function, we relax the assumption that indirect utility is linear in price and add a quadratic price term to our estimating equation. This expanded model is also estimated using the same IV-2SLS procedure. The resulting price elasticity (ε) and demand curvature (η), following the definition of Klenow and Willis [2016], are then calculated as:[13]

$$\begin{aligned}\varepsilon_{m,t,j} &\equiv \frac{\partial \ln s_{m,t,j}}{\partial \ln p_{m,t,j}} \\ &= \frac{\partial s_{m,t,j}}{\partial p_{m,t,j}} \frac{p_{m,t,j}}{s_{m,t,j}} \\ &= -\left(\alpha_{1,m,t} + 2\alpha_{2,m,t} p_{m,t,j}\right) p_{m,t,j} \left(1 - s_{m,t,j}\right)\end{aligned}$$

$$\begin{aligned}\eta_{m,t,j} &\equiv \frac{\partial \ln\left(-\varepsilon_{m,t,j}\right)}{\partial \ln p_{m,t,j}} \\ &= \frac{\partial \varepsilon_{m,t,j}}{\partial p_{m,t,j}} \frac{p_{m,t,j}}{\varepsilon_{m,t,j}} \\ &= \frac{\alpha_{1,m,t} + 4\alpha_{2,m,t} p_{m,t,j} + \left(\alpha_{1,m,t} + 2\alpha_{2,m,t} p_{m,t,j}\right)^2 p_{m,t,j} s_{m,t,j}}{\alpha_{1,m,t} + 2\alpha_{2,m,t} p_{m,t,j}}\end{aligned}$$

A key methodological trade-off in our approach deserves emphasis. The industrial organization literature typically applies BLP-style demand estimation to single, well-defined markets with careful attention to market definition, consumer heterogeneity, and the validity of identifying assumptions (e.g., Nevo [2001]; Berry *et al.* [1995]). Our objective differs: we prioritize broad cross-market coverage to enable macroeconomic analysis of demand dynamics. This scalability comes at the cost of some structural rigor—we employ a simpler logit specification rather than random coefficients or nested structures, and our instrumental variable strategy, while addressing price endogeneity, may not fully resolve all identification concerns that would arise in a single-market study. We view our estimates as informative about aggregate trends and cross-sectional patterns, while acknowledging that product-level estimates may be less precise than those from dedicated single-market analyses.

4. Results

This section presents the core findings of our estimation. We focus primarily on the food category, which accounts for over 90% of sales in our supermarket data, to analyze the evolution of price elasticity, markups, and demand curvature over the past three decades.

[13] In the following sections, results for price elasticity and markups are based on the simpler model without the quadratic price term. The time-series trends were very similar for both specifications.

4-1. Price Elasticity, Markups, and Curvature over the Past 30 Years

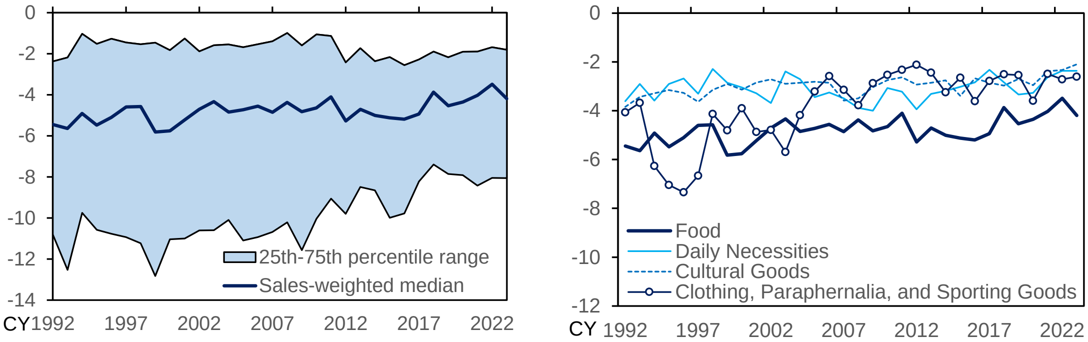
Figure 3 plots the time-series evolution of the weighted median price elasticity for food products, along with the 25th-75th percentile range. Over the full 30-year period, there is no dramatic, overarching trend in the aggregate median. It is important to note, however, that this stability masks substantial heterogeneity at the individual product level; indeed, it is precisely this cross-sectional variation that enables identification in our panel analysis in Section 5. However, a closer look reveals a gradual increase in elasticity (i.e., a decrease in its absolute value) in recent years. This suggests that consumer demand has become somewhat less price-sensitive over time.

This trend in elasticity has direct implications for firm markups, as shown in Figure 4. Consistent with the decline in the absolute value of price elasticity, the weighted median markup for food products has experienced a modest but steady increase in recent years.

A comparison across the major product categories (Figure 3, right panel) reveals that the absolute price elasticity for food is consistently higher (and thus markups are lower, as shown in the right panel of Figure 4) than for other categories like daily necessities, cultural goods, and clothing, paraphernalia, and sporting goods. This is likely attributable to two factors: (1) supermarkets offer a much wider assortment of food products, leading to a higher number of close substitutes, and (2) food items are generally less differentiated than goods in other categories. Both factors make it easier for consumers to switch to alternatives based on price, resulting in more elastic demand.

Figure 3: The Evolution of Price Elasticity in Japan

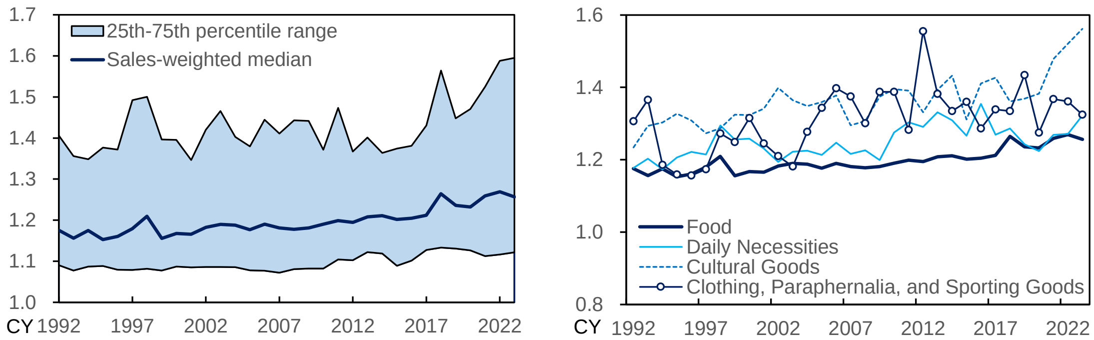
Food Category | By Category



Note: Based on weighted quartiles and medians using sales weights.
Source: Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

Figure 4: The Evolution of Markups in Japan

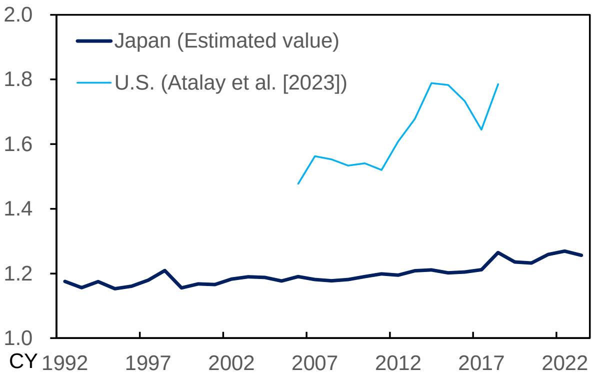
Food Category By Category



Note: Based on weighted quartiles and medians using sales weights.
Source: Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

Comparing our estimated markups for Japan with those derived using a similar methodology for the United States (Atalay *et al.* [2023]) reveals a stark contrast (Figure 5). While U.S. markups have shown a distinct upward trend since the 2000s, markups in Japan have remained remarkably flat over the same period. This finding aligns with comparative studies using the production-side approach (e.g., Aoki *et al.* [2024]), which also point to a more competitive environment in Japan that has suppressed markup growth, particularly in the manufacturing sector. Our results suggest that this difference in competitive pressure may extend to the retail food market.[14]

Figure 5: A Comparison of Markups in Japan and the U.S.



Note: The Japan series is the sales-weighted median markup for food products in supermarkets.
Source: Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service); Atalay *et al.* (2023).

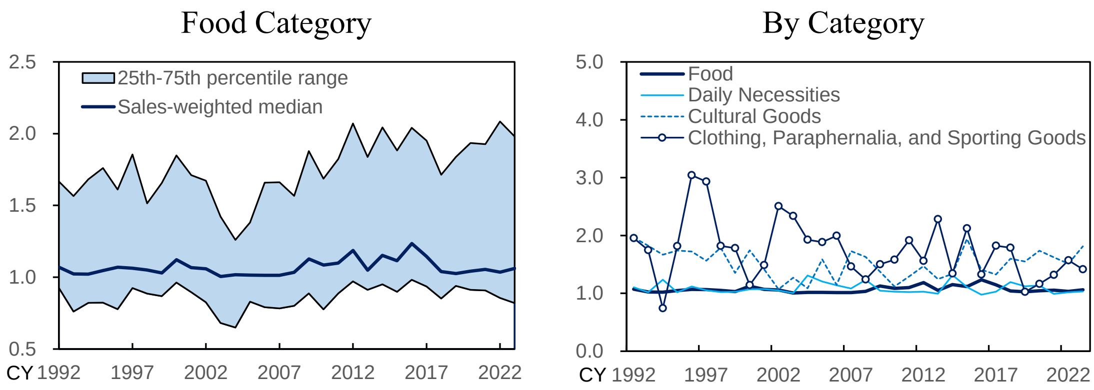
Next, we examine the evolution of the demand curvature (Figure 6). The median curvature rose until the mid-2010s, indicating that demand curves were becoming more "kinked" or convex. However, this trend reversed in the subsequent years, with curvature declining towards the end of the sample period. This pattern is consistent with the

[14] Aoki *et al.* [2024] find that markups for Japanese firms, in both manufacturing and non-manufacturing, shrank from the late 1990s to the 2010s. The food market, being primarily domestic, may have been less affected by factors like the declining global market share of Japanese firms. The resilience of markups in this sector, unlike in others, might also be linked to the changes in consumer lifestyles discussed later in the paper.

parametric estimates for consumer goods from state-dependent pricing models by Furukawa *et al.* [2024]. Looking at different categories, we observe that while the levels fluctuate significantly, cultural goods and clothing, paraphernalia, and sporting goods tend to have higher average curvature than food and daily necessities.

This variation in curvature might reflect differences in the "necessity" of the goods. For necessities like food and daily necessities, demand tends to be stable regardless of the price level, resulting in a more linear demand curve and thus lower curvature. In contrast, for discretionary items like cultural goods, consumers may be insensitive to price changes at low price points but may abruptly stop purchasing altogether when prices rise beyond a certain threshold. This behavior leads to a sharper increase in the absolute value of price elasticity as price increases, resulting in a more convex (higher curvature) demand curve.

Figure 6: The Evolution of Demand Curvature in Japan



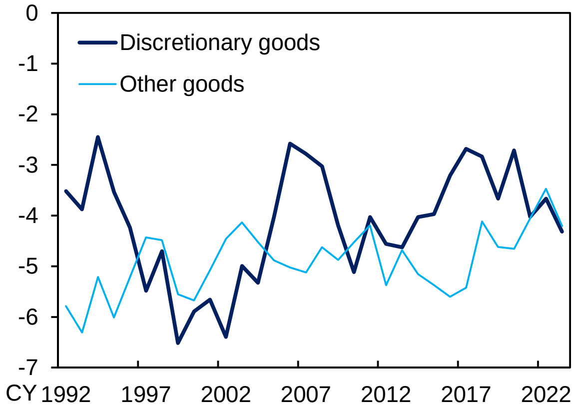
Note: Based on weighted quartiles and medians using sales weights.
Source: Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

4-2. Cyclical Variations: Discretionary vs. Necessity Goods

The aggregate food category masks heterogeneous consumption patterns. To explore this, we separate food items into "discretionary goods" (e.g., alcohol, tobacco, confectionery, ice cream) and "other goods" (necessities). Figure 7 reveals a distinct cyclical pattern in the price elasticity of discretionary goods. During periods of rising real income, such as the mid-2000s and the late 2010s, the price elasticity of discretionary goods increases (absolute value falls). Conversely, during economic downturns, demand becomes more price-sensitive (absolute value rises). This pro-cyclical behavior is intuitive: in good times, consumers are less price-conscious, while in bad times, they tighten their belts and become more sensitive to price.

In contrast, the elasticity for other, more essential food items shows little to no cyclicality, and if anything, exhibits a counter-cyclical pattern. This behavior can be rationalized within a simple theoretical framework, such as the Stone-Geary utility function, which distinguishes between subsistence and discretionary consumption (see Matsuyama [2023] and Appendix 1).

Figure 7: Price Elasticity of Discretionary vs. Other Food Items



Note: Based on sales-weighted median price elasticity for food products sold in supermarkets. "Discretionary goods" include alcohol (excluding mirin), tobacco, confectionery, and ice cream.
Source: Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

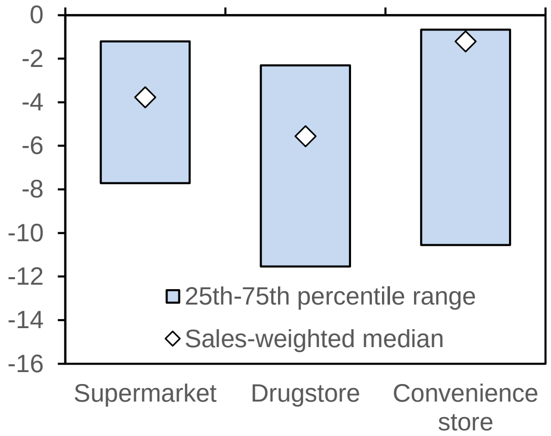
4-3. Cross-Sectional Variation by Store Format

We examine how price elasticity varies across different retail channels using the "Regular POS" dataset, which covers the recent period. Figure 8 compares the median price elasticity for supermarkets, drugstores, and convenience stores. Drugstores exhibit the highest absolute price elasticity, followed by supermarkets, and then convenience stores.

Several factors could explain this ranking. First, the product mix differs significantly across store types. Second, drugstores may attract more price-sensitive customers compared to the other two store types.[15] Third, convenience stores offer a much more limited product assortment, reducing the scope for price-based substitution. The distribution of elasticities for convenience stores is also noticeably compressed, with the median and 25th percentile being very close. This suggests that a significant share of sales in convenience stores comes from products with relatively low price elasticity.

[15] Even after controlling for the product mix, the weighted median price elasticity remains the highest for drugstores among the three store types.

Figure 8: Price Elasticity by Store Type



Note: The estimation period is from January 2020 to September 2024. Based on sales-weighted quartiles and medians.
Source: Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

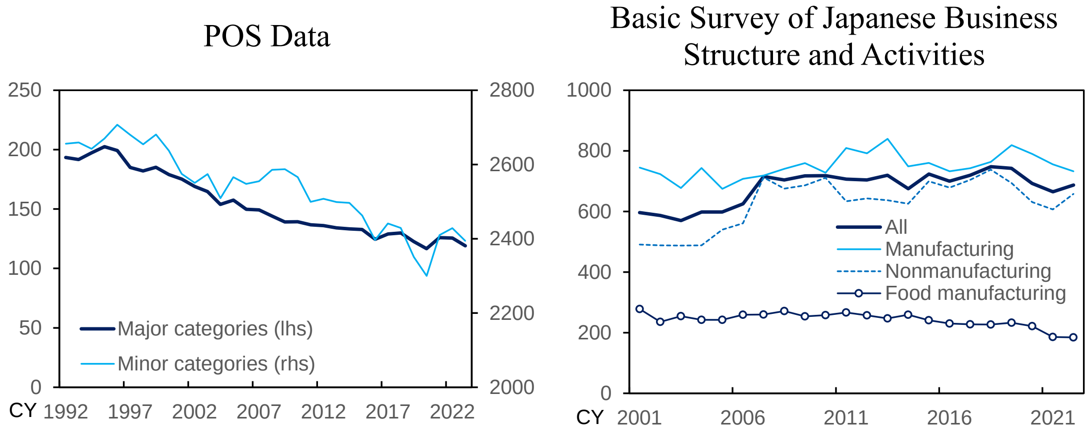
5. Investigating the Drivers of Demand Dynamics

In the previous section, we documented the long-term evolution of price elasticity, markups, and demand curvature. In this section, we explore the potential drivers of these dynamics. Drawing on prior research (e.g., Sudo *et al.* [2018]; Rosenthal-Kay, Traina, and Tran [2024]), we hypothesize that shifts in the demand function are influenced by a combination of factors, including the competitive environment, consumer inflation expectations, and changing lifestyles. To empirically test these hypotheses, we conduct a series of panel analyses using our estimated demand parameters for the food category over the past 30 years.

5-1. The Role of Competition and Inflation

First, we examine the evolution of the competitive landscape in the Japanese food market. We compute a Herfindahl-Hirschman Index (HHI) for the food manufacturing industry and plot its trajectory over time. As shown in Figure 9, the HHI, regardless of the data source, has followed a consistent downward trend. This indicates that the food industry has become progressively more competitive over the past three decades. This trend stands in stark contrast to the manufacturing sector as a whole, which has seen a rise in concentration, driven largely by export-oriented industries (Nakamura and Ohashi [2019]; Kikuchi [2024]). This intensifying competition in the food sector should, in isolation, exert upward pressure on the absolute value of price elasticity.

Figure 9: The Evolution of the Herfindahl-Hirschman Index (HHI) in Japan



Note: Major and minor categories indicate the level of market classification for which the HHI is calculated. Weighted average by sales weight. The figure on the right is an independent tabulation of information from the Basic Survey of Japanese Business Structure and Activities conducted by the Ministry of Economy, Trade and Industry. HHI calculated for each industry sub-classification and aggregated using industry sales weights.

Source: Ministry of Economy, Trade and Industry; Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

As suggested by Aoki, Ichiue, and Okuda [2019] and Furukawa *et al.* [2024], both absolute price elasticity and curvature may also be influenced by inflation dynamics, particularly the shift away from the low-inflation environment of the deflationary period.

To test the impact of both competition and inflation, we conduct a panel regression. We use our estimated price elasticity and curvature as dependent variables, and the market-specific HHI and inflation rate as explanatory variables. The analysis uses the monthly, regional "Regular POS" data from May 2017 to September 2024.

The results are presented in Table 2. We find that:

A rise in the inflation rate is associated with a decrease in both the absolute value of price elasticity and curvature. The positive coefficient on inflation for price elasticity indicates a move towards zero (a less negative number), meaning lower absolute elasticity.[16]

A decrease in the HHI (i.e., intensified competition) is associated with an increase in both absolute price elasticity and curvature. The negative coefficient on the HHI for price elasticity signifies a move further from zero (a more negative number), meaning higher absolute elasticity.

These findings are consistent with the hypotheses of prior research.

[16] Since price elasticity (ε) is typically negative, a positive regression coefficient implies that as the explanatory variable increases, ε becomes less negative (i.e., its absolute value decreases).

Table 2: Panel Regression Results (Data by Region, Month, and Category)

	Price elasticity			
Inflation rate for each category	0.0104***	0.0108***	0.0157***	0.0127***
HHI	2.0670***	1.9038***	1.9545***	4.5775***
Region fixed effect	Yes	No	No	No
Time period fixed effect	Yes	Yes	No	No
Category fixed effect	Yes	Yes	Yes	No
No. Observations:	89,078	89,078	89,078	89,078
Adj. R-squared:	0.29	0.29	0.28	0.024

	Curvature			
Inflation rate for each category	-0.0016***	-0.0015***	-0.0020***	-0.0014**
HHI	-0.2447***	-0.2664***	-0.2667***	-0.2286***
Region fixed effect	Yes	No	No	No
Time period fixed effect	Yes	Yes	No	No
Category fixed effect	Yes	Yes	Yes	No
No. Observations:	89,078	89,078	89,078	89,078
Adj. R-squared:	0.12	0.12	0.12	0.00099

Note: Estimates for price elasticity and curvature are from supermarket food sales, May 2017 - Sep 2024. *** and ** denote statistical significance at the 1% and 5% levels, respectively.
Source: Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

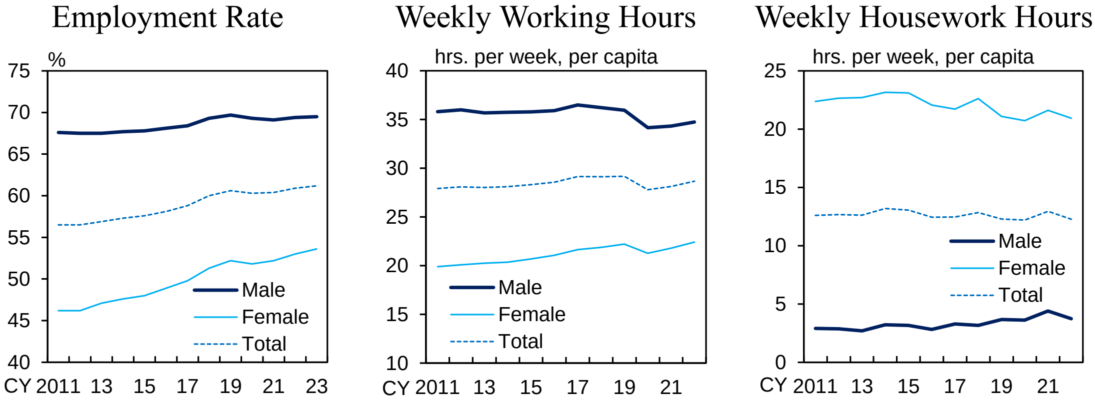
It is important to note, however, that these relationships might reflect a bidirectional causality. Specifically, there is a pathway where changes in inflation and competition influence the demand function via consumer behavior, and a second pathway where shifts in the demand function affect firms' entry, exit, and pricing decisions, which in turn feed back into the aggregate inflation and competitive environment. While our analysis identifies significant correlations, it does not disentangle these two effects.

The results suggest that the recent rise in inflation might have contributed to the observed decline in absolute price elasticity. However, the competitive environment cannot explain this recent trend; the persistent decline in the HHI suggests that competitive pressures have been pushing in the opposite direction, towards higher price sensitivity. This implies that other, more powerful factors must be at play.

5-2. The Impact of Changing Consumer Lifestyles

Another crucial set of factors relates to consumer lifestyles, particularly employment status and working hours (Sudo *et al.* [2018]). Since the 2010s, Japan has witnessed a significant rise in the labor force participation rate, driven primarily by women (Figure 10). Concurrently, average weekly working hours have increased for women, while time spent on housework has decreased for women and increased for men. Panel data analysis confirms the intuitive relationship: longer working hours are significantly associated with shorter housework hours, and transitioning from non-employment to employment leads to a discrete drop in time spent on housework (Table 3).

Figure 10: Employment Rate and Time Spent on Housework



Note: Figures for "Employment Rate" and "Weekly Working Hours" are from the "Labour Force Survey." "Weekly Working Hours" are for individuals aged 15 to 65. Figures for "Weekly housework hours" are from the "Japan Household Panel Survey (JHPS/KHPS)," for individuals aged under 65.
Source: Ministry of Internal Affairs and Communications, Panel Data Research Center at Keio University.

Table 3: Panel Regression Results (Labor and Housework)

	Housework hours			
Hours worked per week	-0.0491***	-0.0224***	-0.0489***	-0.0225***
Employee dummy		-3.8561***		-3.8623***
Aged over 65 dummy			0.1384	-0.1185
Respondent fixed effect	Yes	Yes	Yes	Yes
Time period fixed effect	Yes	Yes	Yes	Yes
No. Observations:	29,239	29,239	29,239	29,239
Adj. R-squared:	0.728	0.73	0.728	0.73

Note: The estimated period is from 2011 to 2022. *** indicates statistical significance at the 1% level.
Source: Panel Data Research Center at Keio University.

To assess how these socioeconomic shifts affect demand, we conduct a panel regression at the regional level. The dependent variables are the regional price elasticity and curvature, and the main explanatory variables are regional employment rates (for men, women, and total) and real disposable income.

The results, shown in Table 4, are striking. An increase in the employment rate is significantly associated with a decrease in both the absolute value of price elasticity and curvature. This effect is particularly pronounced and statistically robust for the female employment rate. The parameter for female employment is consistently larger in magnitude and more significant than for male employment, suggesting that changes in women's work patterns have a disproportionately strong influence on the price sensitivity of household consumption. Given the substantial rise in female labor force participation since the 2010s, this finding provides a compelling explanation for the concurrent decline in absolute price elasticity and curvature.

Furthermore, the analysis shows that a decline in real disposable income leads to an increase in the absolute value of price elasticity. This is consistent with the findings of Andreyeva, Long, and Brownell [2010], who showed that lower-income households exhibit greater price sensitivity for certain food items.

Table 4: Panel Regression Results (Data by Region and Month)

Panel A: Total Employment Rate

	Price elasticity			Curvature		
Employment rate	8.4844*	21.6514***	0.3927	-0.5189	-3.4302***	-0.8581***
Real disposable income	0.006	0.0050***	0.0053***	0.0011	0.0004*	0.0003
Region fixed effect	Yes	Yes	No	Yes	Yes	No
Time period fixed effect	Yes	No	No	Yes	No	No
No. Observations:	712	712	712	712	712	712
Adj. R-squared:	0.52	0.21	0.014	0.31	0.24	0.039

Panel B: Employment Rate by Gender

	Price elasticity			Curvature		
Employment rate (male)	0.8889	-19.4251***	-16.9691***	0.5486	-0.4925	0.1913
Employment rate (female)	8.1090*	24.5564***	14.5088***	-1.5432**	-2.3406***	-1.0084***
Real disposable income	0.0059	0.0051***	0.0059***	0.0012	0.0004*	0.0003
Region fixed effect	Yes	Yes	No	Yes	Yes	No
Time period fixed effect	Yes	No	No	Yes	No	No
No. Observations:	712	712	712	712	712	712
Adj. R-squared:	0.52	0.28	0.1	0.31	0.25	0.046
P>|t| (male - female)	0.254	0.000	0.000	0.038	0.007	0.018

Note: Dependent variables are estimated from supermarket food sales, May 2017 - Sep 2024. Employment data are from the Labour Force Survey; income data are from the Family Income and Expenditure Survey. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Source: Ministry of Internal Affairs and Communications; Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).

In summary, our analysis suggests that the expansion of female employment has fundamentally altered household shopping behavior, probably by increasing the opportunity cost of time. This, in turn, has led to reduced price sensitivity (lower absolute elasticity) and a more linear demand structure (lower curvature).

6. Conclusion

This paper has documented the evolution of price elasticity, markups, and demand curvature in Japanese supermarkets over the past three decades, and investigated the factors driving their dynamics. We have built upon the methodologies of prior research while incorporating our own approach using text analysis and machine learning. This allowed us to automatically extract quality attributes from high-granularity POS data, thereby enhancing the precision of our estimates.

Our results are divided into two key findings. First, regarding the long-term trends of the demand parameters, we found that while the absolute value of price elasticity has not changed dramatically over the last 30 years, a closer examination reveals a gradual decline in recent years, corresponding to a modest increase in markups. Our estimates for demand curvature were consistent with the parametric estimates of Furukawa *et al.* [2024].

Second, our analysis of the determinants suggests that the competitive environment, the inflation rate, and labor force participation are all related to price elasticity and curvature. To quantitatively analyze these drivers, we conducted a panel regression on our estimated parameters using data from 2017 onwards. The results revealed that a decrease in the absolute value of price elasticity and curvature is associated with a less competitive environment, a higher inflation rate, and an increase in the employment rate (which corresponds to less time spent on housework). These findings support prior research by Sudo *et al.* [2018], Aoki, Ichiue, and Okuda [2019], and Furukawa *et al.* [2024]. In particular, the rise in female labor force participation and the increase in inflation appear to be key drivers of the recent decline in absolute price elasticity and curvature. The impact of employment can be summarized as follows: since the 2010s, a rising employment rate, primarily among women, has led to a reduction in time available for housework, which in turn corresponds to a decrease in both absolute price elasticity and demand curvature.

It is important to note the following limitations regarding the results of this paper.

First, due to data constraints, our analysis focuses primarily on food and other goods sold in supermarkets, convenience stores, and drugstores. Goods sold through other channels, such as the internet, and all services are excluded from our analysis. The price-setting behavior for services has been identified as playing a crucial role in explaining Japan's price rigidity (Furukawa *et al.* [2024]), and it is hoped that future analysis will expand in this area as more comprehensive data become available.

Second, the demand functions estimated in this paper are based on cross-sectional results using annual data and do not necessarily represent the demand response to time-series price changes for a specific product. For example, if consumers have a strong perception that "a product should cost to some degree (a reference price)" and react excessively to its price revisions, the absolute value of that product's price elasticity or its demand curvature could be larger than our estimates suggest. Relatedly, our analysis does not account for promotional pricing dynamics. If sale frequency varies systematically across products or over time, average prices may conflate regular and promotional prices, potentially biasing elasticity estimates.

Third, our panel regression on the determinants of elasticity and curvature is, due to data limitations, restricted to the period from 2017 onward, leaving earlier periods unanalyzed. As the influence of each factor on elasticity and curvature may vary over time due to shifts in underlying structural factors, a longer-term analysis of these determinants would require verification using different datasets.

Fourth, our logit specification assumes that all products within a market are equally substitutable, which may not hold for differentiated goods. A nested logit or random coefficients model could relax this assumption, allowing for richer substitution patterns across product categories. We leave this extension for future research.

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Appendix 1: An Analysis Using the Stone-Geary Utility Function

This appendix aims to provide a theoretical underpinning for the empirical finding presented in Section 4-2, which suggests a counter-cyclical relationship between income and the absolute value of price elasticity of demand for discretionary goods. In the theoretical framework below, these discretionary goods correspond to what are conventionally termed "luxury goods" based on their income elasticity properties. This appendix deviates from the main econometric model in the text to theoretically investigate the relationship between income and price elasticity. For this purpose, we employ the Stone-Geary utility function, which explicitly incorporates subsistence (or "necessary") consumption levels and a budget constraint.

First, we define a two-good Stone-Geary utility function. This function augments the standard Cobb-Douglas form with subsistence consumption levels, denoted as $(\overline{C_1}, \overline{C_2})$:

$$(C_1 - \overline{C_1})^{\alpha}(C_2 - \overline{C_2})^{1-\alpha}$$

where Good 1 is treated as a necessity, for which consumers have a minimum required consumption level. We thus assume $\overline{C_1} > 0$. In contrast, Good 2 represents a non-essential or luxury good. For analytical purposes, we assume a negative subsistence level, $\overline{C_2} < 0$. The consumer's budget constraint is given by:

$$P_1 C_1 + P_2 C_2 = I$$

where I denotes income, and P_1 and P_2 are the prices of Good 1 and Good 2, respectively.

Solving the utility maximization problem subject to the budget constraint yields the following Marshallian demand functions for C_1 and C_2:

$$C_1 = \frac{\alpha}{P_1}\left(I - (P_1\overline{C_1} + P_2\overline{C_2})\right) + \overline{C_1}$$
$$C_2 = \frac{1-\alpha}{P_2}\left(I - (P_1\overline{C_1} + P_2\overline{C_2})\right) + \overline{C_2}$$

From these equations, we can examine the average propensity to consume (APC) for each good:

$$\frac{P_1 C_1}{I} = \frac{\alpha\left(I - (P_1\overline{C_1} + P_2\overline{C_2})\right) + P_1\overline{C_1}}{I}$$
$$\frac{P_2 C_2}{I} = \frac{(1-\alpha)\left(I - (P_1\overline{C_1} + P_2\overline{C_2})\right) + P_2\overline{C_2}}{I}$$

For simplification and without loss of generality, we can normalize the units of the goods such that the subsistence levels become $\overline{C_1} = 1$ and $\overline{C_2} = -1$. The APC equations then simplify to:

$$\frac{P_1C_1}{I} = \alpha + \frac{(1-\alpha)P_1 + P_2}{I}$$
$$\frac{P_2C_2}{I} = 1 - \alpha - \frac{(1-\alpha)P_1 + \alpha P_2}{I}$$

These results confirm that the APC for Good 1 (the necessity) is a decreasing function of income, while the APC for Good 2 (the luxury good) is an increasing function of income. This aligns with the standard definitions of necessities and luxuries.

Next, we derive the own-price elasticities of demand (ε_1 and ε_2) for the two goods:

$$\varepsilon_1 = \frac{\partial \ln C_1}{\partial \ln P_1} = -\frac{\alpha(I - P_2\overline{C_2})}{\alpha\left(I - (P_1\overline{C_1} + P_2\overline{C_2})\right) + P_1\overline{C_1}}$$
$$\varepsilon_2 = \frac{\partial \ln C_2}{\partial \ln P_2} = -\frac{(1-\alpha)(I - P_1\overline{C_1})}{(1-\alpha)\left(I - (P_1\overline{C_1} + P_2\overline{C_2})\right) + P_2\overline{C_2}}$$

To understand how these elasticities respond to changes in income, we take their partial derivatives with respect to I:

$$\frac{\partial \varepsilon_1}{\partial I} = -\frac{\alpha(1-\alpha)P_1\overline{C_1}}{\left\{\alpha\left(I - (P_1\overline{C_1} + P_2\overline{C_2})\right) + P_1\overline{C_1}\right\}^2}$$
$$\frac{\partial \varepsilon_2}{\partial I} = -\frac{\alpha(1-\alpha)P_2\overline{C_2}}{\left\{(1-\alpha)\left(I - (P_1\overline{C_1} + P_2\overline{C_2})\right) + P_2\overline{C_2}\right\}^2}$$

Applying the same normalization ($\overline{C_1} = 1$ and $\overline{C_2} = -1$), we obtain:

$$\frac{\partial \varepsilon_1}{\partial I} = -\frac{\alpha(1-\alpha)P_1}{\left\{\alpha\left(I - (P_1 - P_2)\right) + P_1\right\}^2} < 0$$
$$\frac{\partial \varepsilon_2}{\partial I} = \frac{\alpha(1-\alpha)P_2}{\left\{(1-\alpha)\left(I - (P_1 - P_2)\right) - P_2\right\}^2} > 0$$

Given that the price elasticity of demand is inherently negative, the positive derivative for Good 2 ($\frac{\partial \varepsilon_2}{\partial I} > 0$) implies that its absolute value, $|\varepsilon_2|$, decreases as income (I) rises.

This result provides a theoretical foundation for the counter-cyclical pattern of the absolute value of price elasticity for discretionary goods observed in our empirical analysis—that is, demand for such goods becomes more price-elastic as income falls.

Appendix 2: Demand Elasticity with Respect to Product Quantity (Quantity Elasticity)

A key advantage of our methodology is its ability to quantify how demand responds to changes in product quantity—a phenomenon often referred to as "shrinkflation." Because our approach extracts product quantity information directly from unstructured text data and simultaneously estimates its coefficient within the demand model, we can compute the elasticity of demand with respect to product quantity. We term this the "quantity elasticity."

The quantity elasticity of demand, denoted as $\eta^V_{m,t,j}$, is defined by the following equation:

$$\eta^V_{m,t,j} = \frac{\partial s_{m,t,j}}{\partial V_{m,t,j}} \frac{V_{m,t,j}}{s_{m,t,j}} = \beta^V_{m,t} V_{m,t,j} \left(1 - s_{m,t,j}\right)$$

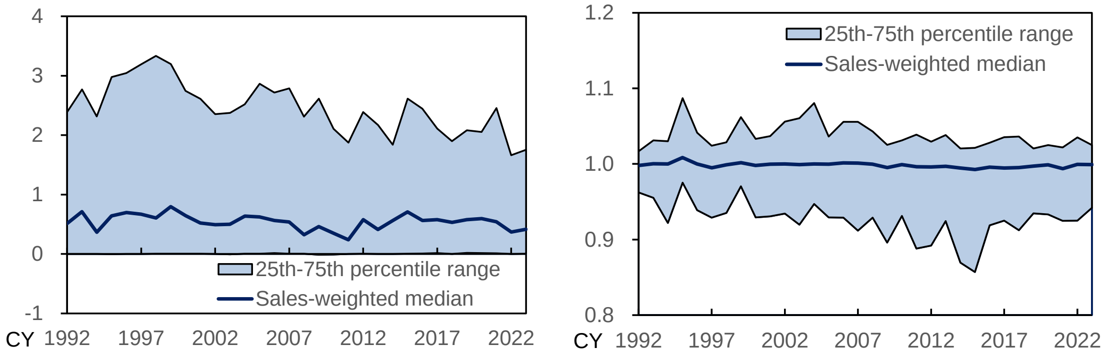
Our analysis of quantity elasticity for food products reveals that the weighted median hovers around 0.5, indicating that a 1% reduction in product quantity corresponds to approximately a 0.5% decrease in demand. As shown in the Appendix Figure, this median value has remained relatively stable over the sample period.

However, the distribution of quantity elasticities shows considerable dispersion across different product categories. Notably, the 75th percentile exhibits a gradual decline over time. This trend suggests that for products that were initially most sensitive to changes in quantity, the demand response has become somewhat more muted in recent years. This decline in elasticity could suggest that consumers have become more accustomed to frequent instances of "shrinkflation" and are therefore less responsive to changes in product quantity than before.

Furthermore, we extended our analysis to estimate the curvature of demand with respect to product quantity, analogous to our estimation for price curvature. Specifically, we define this curvature as the elasticity of the quantity elasticity with respect to quantity. This analysis, however, did not reveal any significant temporal changes.

Appendix Figure: Time Series of Quantity Elasticity and Curvature

Quantity Elasticity | Curvature



Note: The analysis covers food products sold in supermarkets. The figure displays the weighted median and the 25th-75th percentile range, with weights based on sales value.

Source: Merchandising-ON Co. Ltd. RDS-POS (Retail Measurement Data Service).