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Abstract

This study investigates price connectedness in the extra virgin olive oil market across four major Greek retail chains. Using a quantile regression approach with block-bootstrap inference, the analysis explores how inter-brand price relationships vary across the conditional price distribution. The research utilizes daily supermarket-level price data for extra virgin olive oil collected between March 20, 2023, and November 4, 2025. The results reveal substantial heterogeneity in competitive intensity both within and between retailers: some chains exhibit strong price co-movements, while others display asymmetric or weaker responses. These patterns indicate differentiated pricing strategies and varying degrees of market integration. Inter- and intra-retailer dynamics highlight the importance of retailer and brand-specific environments in shaping strategic interactions.

Keywords: Retail price transmission; Brand interdependence; Quantile econometrics; Market structure; Fast-moving consumer goods (FMCG).

JEL classification: C14; L13; L81

1 Introduction

Global food markets have experienced an unprecedented cascade of crises and overlapping disruptions in recent years. The COVID-19 pandemic, geopolitical conflicts, extreme weather events and persistent inflationary pressures have sent shock waves through the global food value chain. Policymakers, researchers and, above all, consumers try to understand the dynamics behind food price inflation.

Olive oil prices offer a characteristic example of this evolution. International olive oil prices recorded a sharp upward trend from September 2022 to January 2024 (Figure 1). The limited production of olive oil during the olive-growing season 2023-2023 (mainly due to a drought in Spain, the world's largest producer), drove the price from USD 4,316 per metric ton, in September of 2022, to USD 10,281 per metric ton, in January of 2024. Since then, the price has declined and in June 2025 stood at USD 5,075 per metric ton. In general, geopolitical tensions as well as climate change contributed to the surge of inflation in the food sector (Saccone and Vallino, 2025).

In Greece, the olive oil consumer price index showed a strong upward trend starting in June 2023. The increasing trend of the harmonized CPI for olive oil peaked between October 2023 and January 2024, when inflation exceeded 60% (Hellenic Statistical Authority, 2025). The notable price increases in olive oil products are linked, among other things, to the decline in domestic production during the 2023/2024 olive-growing year, as production was limited to 175 thousand tons – significantly reduced compared to the previous olive-growing year (345 thousand tons). The combination of a contraction of production in Greece during 2023/2024 along with sustained foreign demand contributed to price increases. Compared to the Euro zone average, the consumer price index (2015=100) in Greece has been at a much higher level since October 2023; and despite a convergence in the second quarter of 2025, in June 2025 the CPI in olive oil in Greece stood at 151.7 units versus 147.0 units in the Euro zone. This observation is notable, considering that Greece is the third largest olive oil producer in Europe.

Olive oil is a key ingredient in the Mediterranean diet, very well known for its

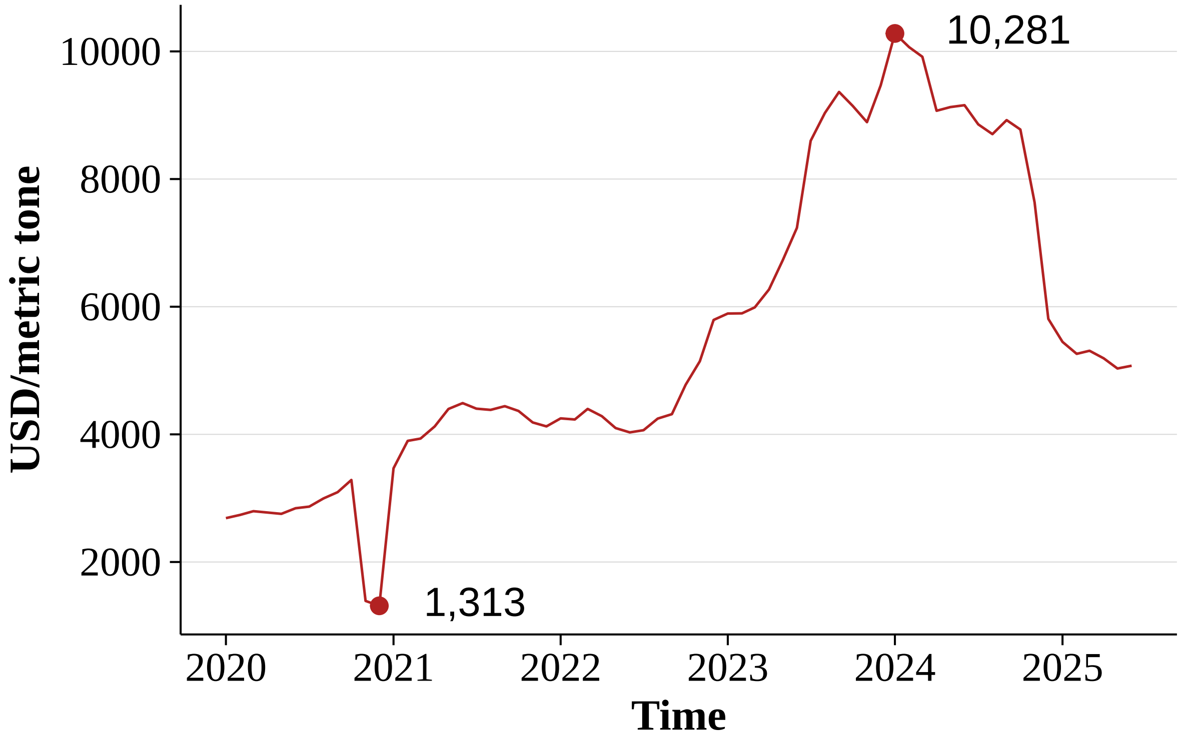

Figure 1: International Olive Oil price.
Data source: `https://fred.stlouisfed.org/series/POLVOILUSDM`

nutritional values (Erdogan et al., 2024; Martínez-González et al., 2022). The Greek household was hit more severely by this price increase due to the fact that Greeks are the world' largest consumers of olive oil, with 9.3 liters per capita per year, compared to Spain (7.5) and Italy (7.4), let alone any other northern European country (2.5-0.3) (IOC, 2025).

The increase in olive oil price has also affected the consumption habits/preferences of Greek consumers. The Greek Household Budget Survey for 2023 by ELSTAT reveals that inflation in olive oil prices led to a 6.8% decline in the average monthly per capita purchased quantities acquired through supermarkets and food stores. In contrast, during the same period, butter purchases increased by 15.4% and other edible oils (e.g. seed oil) increased by 13.8% (ELS, 2024). The survey data shows that households in Greece substituted olive oil consumption with oils of lower nutritional value such as seed oils. Specifically, in 2023, monthly consumption per capita decreased by 59 milliliters compared to 2022, of which 42 milliliters were replaced by seed oil and the remainder by various other types of oils.

In light of the above, the present study examines price connectedness in the extra virgin olive oil market of Greece, across four major retail chains. The quantile regression technique with block-bootstrap inference has been utilized in order to examine how cross-supermarkets and inter-brand price relationships vary across the conditional price distribution. Quantile regression has been extensively used in price analytics by Westgaard et al. (2021); Janczura and Wójcik (2022); Uniejewski (2025). In the argi-food sector, quantile regressions have been employed, among others, for the products of corn, hard red wheat, soybean, soft wheat, rice and oats by Fousekis and Tzaferi (2019), for the products of cattle and pork by Panagiotou and Tseriki (2020) and for the product of coffee by Fousekis and Grigoriadis (2022).

This study is organized as follows. Section 2 offers the methodology. Section 3 presents the data, including figures and descriptive statistics. Section 4 offers the empirical results and Section 5 the discussion. Conclusions are presented in section 6.

2 Methodology

2.1 Multivariate Quantile Regression

Quantile regression provides a way to study how covariates affect different parts of the conditional distribution of a dependent variable, rather than only its mean. Unlike ordinary least squares (OLS), which summarizes the relationship between Y and X through the conditional expectation $E(Y \mid X)$, quantile regression allows the marginal effect of X on Y to vary across quantiles. This makes it possible to analyze how explanatory variables influence not only typical outcomes but also the lower and upper tails of the distribution, where shocks, volatility, and strategic pricing adjustments are often most pronounced.

Let Y denote the dependent variable and X a $k \times 1$ vector of regressors. For a quantile level $0 < \tau < 1$, the sample τ–quantile solves

$$\hat{q}_\tau = \arg\min_{q \in \mathbb{R}} \sum_{i=1}^{N} \rho_\tau(Y_i - q), \tag{1}$$

where $\rho_\tau(\cdot)$ is the tilted absolute-value (check) function. Assuming a linear conditional quantile function $Q_{Y|X}(\tau) = X\beta_\tau$, the coefficient vector β_τ is obtained from

$$\hat{\beta}_\tau = \arg \min_{\beta_\tau \in \mathbb{R}^k} \sum_{i=1}^{N} \rho_\tau(Y_i - X_i\beta_\tau)\,. \tag{2}$$

Following Koenker and Gilbert Bassett (1978); Koenker and Hallock (2001), this convex optimization problem can be expressed as a linear program:

$$\hat{\beta}_\tau = \arg\min_{\beta_\tau} \left[\tau \sum_{i:Y_i \geq X_i\beta_\tau} |Y_i - X_i\beta_\tau| + (1-\tau) \sum_{i:Y_i < X_i\beta_\tau} |Y_i - X_i\beta_\tau| \right]. \tag{3}$$

Under regularity conditions, the estimator is asymptotically normal:

$$\sqrt{N}\,(\hat{\beta}_\tau - \beta_\tau) \xrightarrow{d} N\big(0,\ \tau(1-\tau)\, D^{-1}\Omega_X D^{-1}\big)\,, \tag{4}$$

where

$$D = E[f_Y(X\beta_\tau)\, XX']\,, \qquad \Omega_X = E(XX'),$$

and f_Y denotes the conditional density of Y at $X\beta_\tau$. Because estimating the asymptotic variance can be difficult in finite samples, inference for quantile regression commonly relies on rank-score methods or bootstrap procedures.

3 Data

Data are daily extra-virgin oil retail prices (final normalized prices, in euros per 1lt, including discounts and VAT) from four supermarket chains in Greece– which are among the largest chains based on turnover 2024 (For, 2025). Prices were collected from the e-shops of these supermarket chains, spanning from March 20, 2023 to November 4, 2025. Accordingly, observations cover a two-and-a-half-year time window.

Each retailer chain can have multiple brands on sale at the same day. However most brands are not available for the whole period of reference. Also, not all brands are available in all supermarkets. Notably, we found just two brands that are available for the whole period of reference time in all supermarkets. Thus we split our analysis in parts with time series as follows:

1. **All brands in 4 supermarkets.** We took into account every available brand and averaged the normalized price for each day, for each supermarket.

2. **Two brands in 4 supermarkets.** We took into account only two brands that were available in all supermarkets, for the whole period of time. Thus we have again one price (averaged normalized price) per brand, per day, per supermarket.

Table 1: Summary statistics of daily retail prices by supermarket

Retailer	Nobs	Mean	St.Dev.	Min	Q1	Median	Q3	Max
sm1	961	12.105	1.801	8.923	10.416	12.609	13.610	14.822
sm2	954	12.027	1.880	8.570	10.508	12.408	13.644	14.936
sm3	961	11.105	1.834	8.103	9.143	11.248	12.847	13.759
sm4	961	11.184	1.731	8.128	9.540	11.243	12.989	14.060

Notes: sm1 = Supermarket 1; sm2 = Supermarket 2; sm3 = Supermarket 3; sm4 = Supermarket 4.

Table 1 summarizes the price data of the four retailers. The mean values for sm1 and sm2 are around 12 euros/lt and for sm3 and sm4 are around 11 euros/lt.

Figure 2 displays the evolution of average daily prices (EUR/lt), for extra virgin olive oil, across four supermarket chains–sm1, sm2, sm3, and sm4–over the period from 20.03.2023 to 04.11.2025. All four chains followed a broadly similar temporal patterns, with prices increasing steadily through the second half of 2023, remaining relatively high but stable during 2024, and declining throughout 2025. Despite sharing a common overall trend, individual price paths differ in timing and magnitude. The latter might be the outcome of distinct pricing strategies and/or responses to market conditions.

Figure 3 displays the evolution of average daily prices (EUR/lt), concerning only two brands (b1 and b2) for the period of reference.

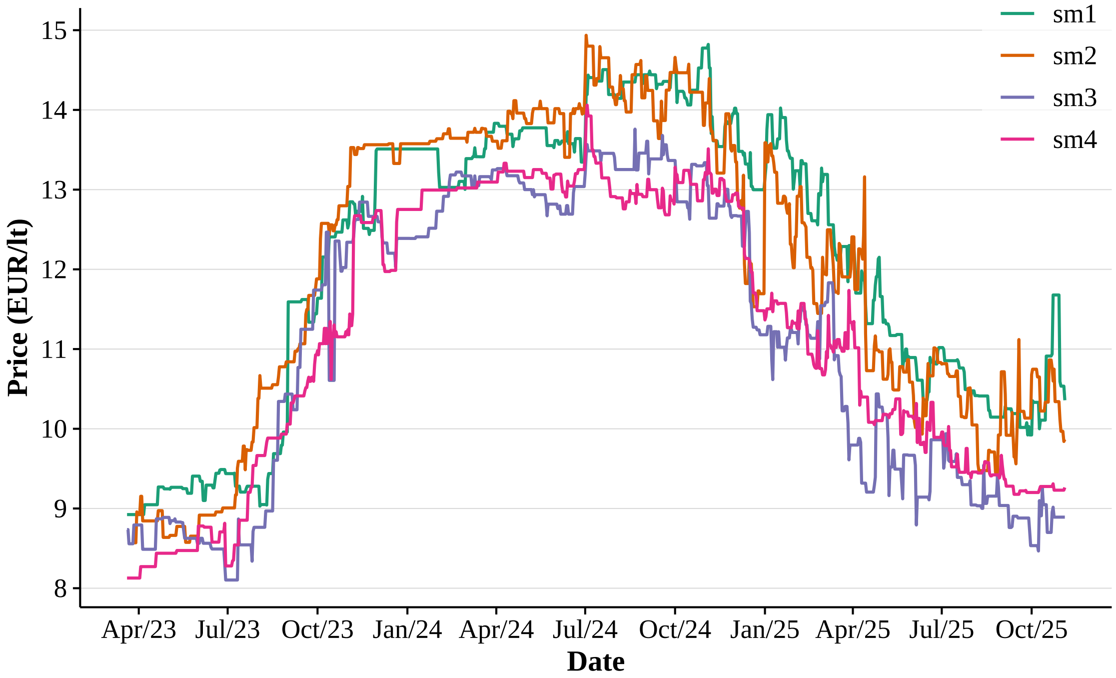

Figure 2: Average price (per day) of extra virgin olive oil in four retailer chains in Greece.

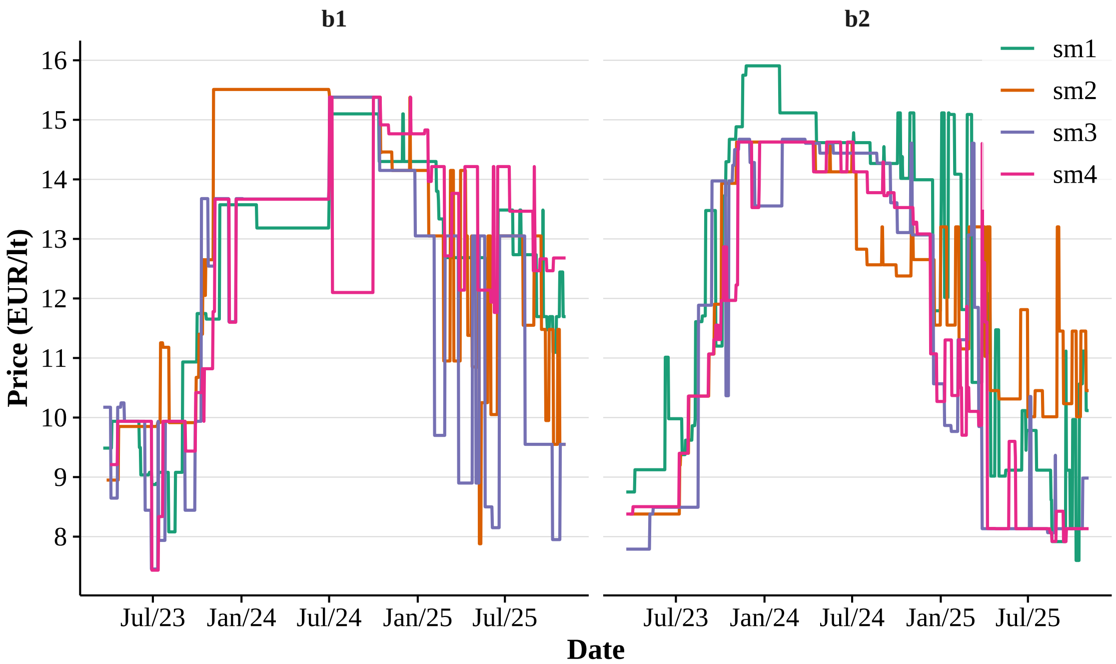

Figure 3: Daily average prices of the two brands (b1 and b2) of extra virgin olive oil across the four retail chains in Greece.

4 Results

4.1 Cointegration

Table 2: Johansen Trace Test for Cointegration

Null hypothesis	Trace statistic	Critical value (10%)	Critical value (5%)	Critical value (1%)
$r \leq 3$	1.40	7.52	9.24	12.97
$r \leq 2$	20.98	17.85	19.96	24.60
$r \leq 1$	59.14	32.00	34.91	41.07
$r = 0$	123.03	49.65	53.12	60.16

Notes: Johansen trace statistics for the null of at most r cointegrating relations in a four-dimensional system of $\{\text{sm1}, \text{sm2}, \text{sm3}, \text{sm4}\}$. Deterministic specification: no linear trend, constant in the cointegration space.

The Johansen cointegration UA test (Johansen, 1988, 1991) results shown in Table 2 utilizing the trace statistic, provide strong evidence of long-run equilibrium relationships among the four variables (sm1, sm2, sm3, sm4). Testing the null hypothesis of no cointegration ($r = 0$), the value of the test statistic of 123.03 greatly exceeds the critical value of 60.16, leading to a rejection at the 1% significance level. Similarly, the null hypothesis of at most one cointegrating vector ($r \leq 1$) is rejected at the 1% level (59.14 > 41.07). The hypothesis of at most two cointegrating vectors ($r \leq 2$) is rejected at the 5% significance level (20.98 > 19.96), although not at the 1% level. Consequently, the results indicate a cointegration rank of $r = 3$.

4.2 Quantile regressions across supermarkets

Here, we applied the multivariate quantile regression approach, described as:

$$\mathrm{sm}_{j,i} = \beta_{0,j}(\tau) + \sum_{\substack{k=1 \\ k \neq j}}^{4} \beta_{k,j}(\tau)\, \mathrm{sm}_{k,i} + u_{j,i}(\tau), \qquad Q_{u_{j,i}}(\tau \mid \{\mathrm{sm}_{k,i}\}_{k \neq j}) = 0, \tag{5}$$

Table 3 presents the values of the impact coefficients of sm2, sm3 and sm4 on sm1, at different quantile levels.

The results in Table 3 and their visual representation in Figure 4 show that the

Table 3: Quantile Regression Estimates for **sm1**

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm2	0.471 (-0.451, 1.394)	0.507 (0.317, 0.698)	0.653 (0.487, 0.818)	0.553 (0.311, 0.795)	0.501 (0.229, 0.773)
sm3	0.361 (-0.169, 0.890)	0.080 (-0.133, 0.294)	0.127 (-0.028, 0.281)	0.088 (-0.100, 0.275)	0.026 (-0.371, 0.423)
sm4	0.190 (-0.597, 0.978)	0.338 (0.082, 0.595)	0.139 (-0.094, 0.372)	0.329 (0.042, 0.616)	0.333 (-0.173, 0.838)

Notes: Each cell reports the point estimate with its 95% confidence interval in parentheses. Dependent variable is the average of extra virgin olive oil prices of `sm1`.

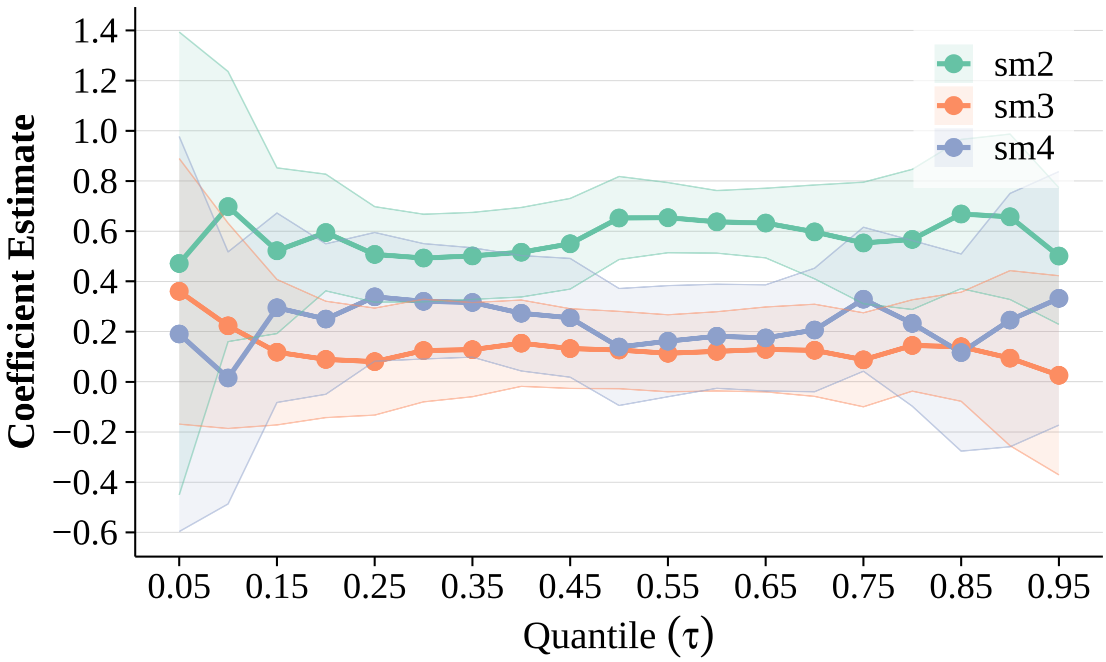

Figure 4: Quantile regression estimates for `sm1` across the distribution of price levels. Shaded regions show 95% confidence intervals of the estimate with bootstrap, block size 5 and $B = 1000$ bootstrap iterations.

influence of sm2 on sm1 is strong and stable across most of the price distribution. At the median quantile ($\tau = 0.50$), the impact coefficient for sm2 is 0.653, with a confidence interval of (0.487, 0.818), indicating a consistent link between the two chains' pricing. In other words, an increase of one euro per litre in price of sm2 is going to have an effect of 0.653 increase in price of sm1. The upper quantiles display a similar pattern. At $\tau = 0.75$ the estimate is 0.553, and at $\tau = 0.95$ it is 0.501, both with relatively tight intervals. These values trace a smooth and persistent curve in figure 4. Only at the lower tail, where $\tau = 0.05$, does the relationship weaken, with a wider interval hinting at greater variability during periods of unusually low prices.

The impact of sm3 on sm1 is smaller and more uncertain. Table 3 shows that at the median the estimate is 0.127 with a confidence interval crossing zero, and Figure 4 reflects this through a flatter and lower curve.

The estimates for sm4 reveal an influence that is moderate at some quantiles. Table 3 indicates that the effect reaches 0.338 at $\tau = 0.25$, yet falls to 0.139 at the median, with wide intervals at both extremes. In Figure 4, the sm4 line shows noticeable fluctuation, especially near the tails, where confidence intervals increase sharply. This pattern suggests that sm4's pricing moves independently from sm1 for low and high quantiles.

Taken together, Table 3 and Figure 4 point to a structure in which sm2 plays the dominant role in shaping sm1's price levels, while sm3 and sm4 exert smaller and less reliable influences. The stability of sm2's coefficients across quantiles, contrasted with the variability observed for the other chains, indicates that sm1's pricing aligns most closely with sm2 under a wide range of market conditions. The widening intervals for sm3 and sm4 in the tails reinforce the view that responses low and hight price levels differ across chains, rather than following a shared or coordinated pattern.

Table 4 presents the values of the impact coefficients of sm1, sm3 and sm4 on sm2, at different quantile levels.

Table 4 shows that sm2 responds most consistently to sm1 across the quantile distribution. At the center of the distribution, the coefficient reaches 0.357 at $\tau = 0.50$ with a tight confidence interval, indicating a stable and predictable link under

Table 4: Quantile Regression Estimates for **sm2**

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	0.139 (-0.178, 0.455)	0.316 (0.169, 0.463)	0.357 (0.252, 0.463)	0.354 (0.215, 0.492)	0.420 (0.335, 0.506)
sm3	0.349 (0.137, 0.561)	0.154 (-0.001, 0.308)	0.183 (0.059, 0.308)	0.211 (0.072, 0.349)	0.043 (-0.083, 0.170)
sm4	0.568 (0.204, 0.931)	0.645 (0.485, 0.804)	0.541 (0.382, 0.699)	0.462 (0.296, 0.627)	0.506 (0.351, 0.661)

Notes: Each cell reports the point estimate with its 95% confidence interval in parentheses. Dependent variable is `sm2`.

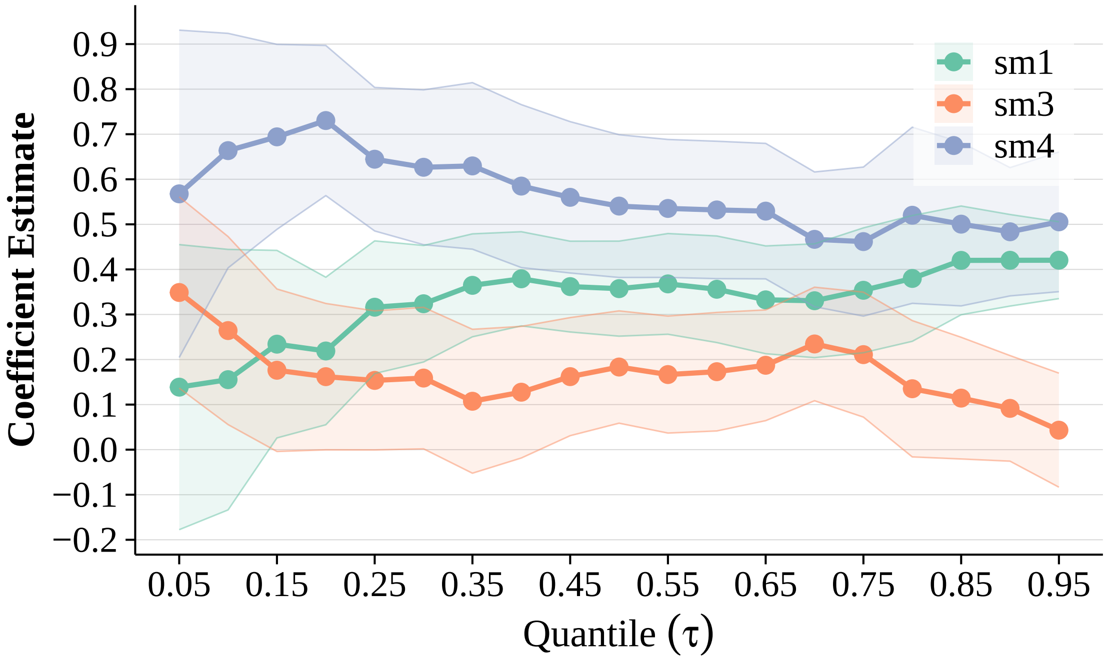

Figure 5: Quantile regression estimates for `sm2` across the distribution of price levels. Shaded regions show 95% confidence intervals.

typical pricing conditions. This pattern holds in the upper part of the distribution as well. At $\tau = 0.95$, the effect rises to 0.420, again with a narrow interval that reflects strong co-movement in high price levels. Only at the lower tail, at $\tau = 0.05$, does the relationship weaken: the estimate of 0.139 comes with a confidence interval that overlaps zero, suggesting greater uncertainty when unusually low prices occur. These low-price observations often coincide with discount phases or temporary competitive disruptions, where standard adjustment behavior becomes less reliable.

The influence of sm3 on sm2 is more moderate and less uniform. At the median, the coefficient is 0.183, while at $\tau = 0.75$ it increases slightly to 0.211, suggesting a modest but persistent competitive effect in normal and moderately high-price conditions. However, at $\tau = 0.95$ the estimate declines, indicating that sm3's pressure on sm2 weakens in high price levels.

Among the competitors, sm4 exerts the strongest and most stable influence on sm2. Across most quantiles the coefficients remain high, with values around 0.541 at $\tau = 0.50$, 0.462 at $\tau = 0.75$, and 0.506 at $\tau = 0.95$, each accompanied by relatively tight confidence intervals. This consistency suggests that sm4 plays a central role in shaping sm2's pricing dynamics. In Figure 5, the sm4 line sits clearly above those of sm1 and sm3, especially in the lower and middle parts of the distribution, reinforcing the impression that sm4 acts as sm2's primary reference point across a wide set of market conditions.

Taken together, Table 4 and Figure 5 reveal no evidence of coordinated behaviour. Instead, the widening confidence intervals at the distributional extremes, the nonparallel slopes of the coefficient curves, and the differing magnitudes of influence across sm1, sm3, and sm4 point to an environment shaped by heterogeneous strategies and uneven responses to price increase or decrease. Price pressures, temporary promotions, and supply-side disturbances generate deviations at specific quantiles, but the overall structure suggests independent adjustment rather than systematic alignment.

Table 5 presents the values of the impact coefficients of sm1, sm2 and sm4 on sm3, at different quantile levels.

At $\tau = 0.05$, the coefficient of `sm4` is 1.034, with a confidence interval that, al-

Table 5: Quantile Regression Estimates for `sm3`

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	0.010 (-0.097, 0.118)	0.166 (0.001, 0.331)	0.168 (-0.053, 0.389)	0.117 (-0.067, 0.301)	0.194 (0.064, 0.324)
sm2	0.059 (-0.170, 0.287)	-0.001 (-0.154, 0.152)	0.265 (0.033, 0.498)	0.337 (0.087, 0.586)	0.467 (0.199, 0.736)
sm4	1.034 (0.788, 1.280)	0.893 (0.703, 1.083)	0.596 (0.344, 0.848)	0.510 (0.300, 0.719)	0.271 (0.036, 0.505)

Notes: Each cell reports the point estimate with its 95% confidence interval in parentheses. Dependent variable is `sm3`. Estimates correspond to quantile regressions at the listed quantiles.

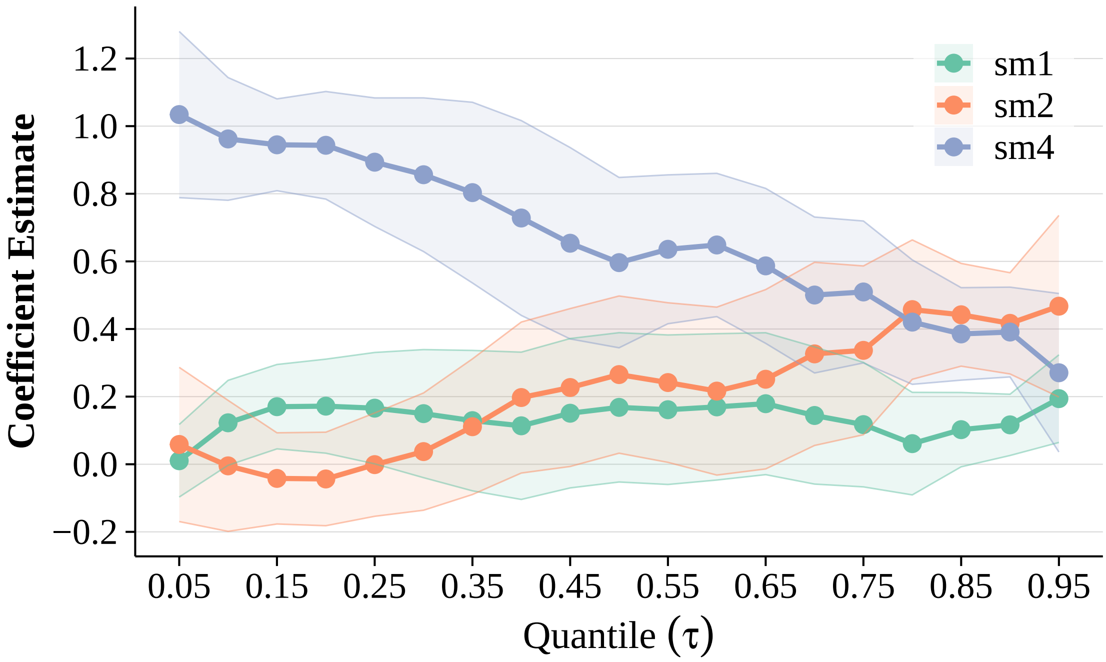

Figure 6: Quantile regression estimates for `sm3` across the distribution of price levels. Shaded regions show 95% confidence intervals.

though not especially narrow, lies clearly above zero. The estimate remains high at $\tau = 0.25$, taking the value 0.893. At the median, $\tau = 0.50$, the effect decreases to 0.596, yet it continues to represent the strongest influence among the competing retailers. The coefficient declines further to 0.510 at $\tau = 0.75$ and 0.271 at $\tau = 0.95$, but the impact remains economically meaningful across the distribution. Figure 6 illustrates this pattern: the curve for `sm4` dominates the lower quantiles and maintains a prominent role throughout, indicating that `sm4` exerts the most substantial influence on the pricing of `sm3`, particularly at low prices levels.

The influences of `sm1` and `sm2` on `sm3` are smaller and more irregular across quantiles. For `sm1`, the effect at the lower tail is negligible, with an estimate of 0.010 at $\tau = 0.05$ and a confidence interval that includes zero. At $\tau = 0.25$, the coefficient increases to 0.166, and although the point estimates remain positive at higher quantiles, their confidence intervals often span zero, indicating that the relationship is not statistically stable. In contrast, `sm2` exhibits a clearer upward pattern across the distribution. Its influence is weak at the bottom of the distribution, with estimates close to zero at $\tau = 0.05$ and $\tau = 0.25$, but it strengthens steadily as prices rise. The coefficient reaches 0.265 at $\tau = 0.50$, increases to 0.337 at $\tau = 0.75$, and peaks at 0.467 at $\tau = 0.95$. Figure 6 illustrates this progressively rising relationship.

Taken together, Table 5 and Figure 6 indicate that the pricing of `sm3` is most strongly anchored to `sm4` across the full range of price levels. The influence of `sm1` is more modest and becomes relevant primarily in the central part of the distribution, where point estimates are positive though not always statistically significant. In contrast, `sm2` gains importance in the upper quantiles, exerting a progressively stronger effect as prices rise. The differing slopes and the variation in confidence intervals across quantiles point to a situation in which `sm3` adjusts flexibly to changing conditions, rather than following a uniform or coordinated pricing strategy.

Table 6 presents the values of the impact coefficients of sm1, sm2 and sm3 on sm4, at different quantile levels.

Table 6 shows that, in general, sm4 responds most strongly to sm2 across the full quantile distribution. At $\tau = 0.05$, the coefficient on sm2 is 0.354 with a confidence interval that lies well above zero. The influence increases slightly as we move toward

Table 6: Quantile Regression Estimates for **sm4**

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	0.184 (0.012, 0.357)	0.065 (-0.066, 0.196)	0.020 (-0.125, 0.165)	0.145 (0.012, 0.279)	0.231 (0.143, 0.318)
sm2	0.354 (0.184, 0.524)	0.451 (0.322, 0.580)	0.451 (0.281, 0.622)	0.448 (0.302, 0.594)	0.428 (0.334, 0.522)
sm3	0.317 (0.210, 0.424)	0.383 (0.283, 0.482)	0.483 (0.352, 0.615)	0.349 (0.237, 0.461)	0.262 (0.155, 0.369)

Notes: Each cell reports the point estimate with its 95% confidence interval in parentheses. Dependent variable is `sm4`. Estimates correspond to quantile regressions at the listed quantiles.

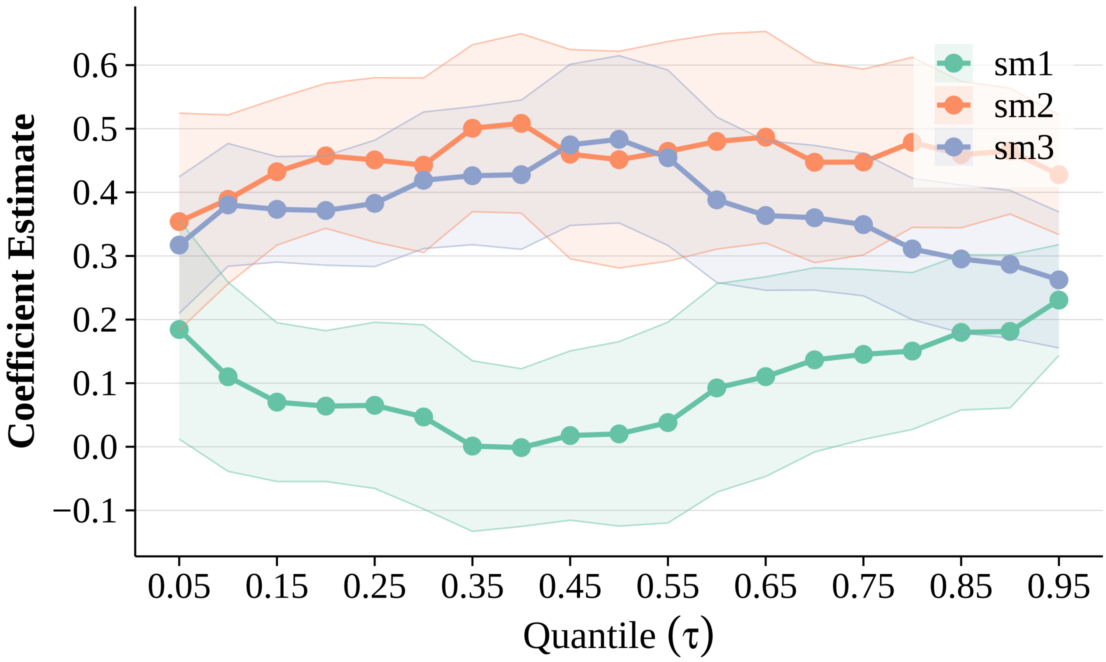

Figure 7: Quantile regression estimates for `sm4` across the distribution of price levels. Shaded regions show 95% confidence intervals.

the center of the distribution. At $\tau = 0.25$ the estimate is 0.451, and at the median, $\tau = 0.50$, the coefficient remains essentially the same at 0.451. Even at $\tau = 0.75$ and $\tau = 0.95$, the effects of 0.448 and 0.428 indicate an almost persistent and stable relationship. Figure 7 reflects this stability in the nearly flat and consistently high curve for sm2 across quantiles. This pattern suggests that sm4 treats sm2 as its primary reference point under a wide range of pricing conditions.

The influence of sm3 on sm4 is also positive but shows more variation across quantiles. At the lower end of the distribution, sm3 has a strong effect, with 0.317 at $\tau = 0.05$ and 0.383 at $\tau = 0.25$. The estimate becomes even larger at the median, reaching 0.483, before declining to 0.349 at $\tau = 0.75$ and 0.262 at $\tau = 0.95$. Figure 7 illustrates this arc-shaped pattern. The influence of sm3 on sm4 is strongest in the middle quantiles and gradually weakens as prices move into the upper range. This suggests that sm3's relevance for sm4 is greatest in normal price regimes and less pronounced during either unusually low or unusually high price levels.

The pattern for sm1 differs from both sm2 and sm3. At $\tau = 0.05$, sm1's coefficient is 0.184 with a confidence interval that excludes zero. However, from $\tau = 0.25$ to $\tau = 0.55$, the estimates become small and statistically uncertain, with values ranging from about 0.020 to 0.065. The effect becomes stronger again at higher quantiles. At $\tau = 0.75$ the coefficient increases to 0.145, and at $\tau = 0.95$ it reaches 0.231. Figure 7 displays this U-shaped pattern.

4.3 Two brands of extra virgin olive oil: Brands b1–b2 in the same retailer

In this Section we isolated two brands (b_1, b_2) of extra virgin olive oil sold in all four supermarkets, which were the only common brands for at least 100 days. These two brands covered the entire period examined. Other brands not fulfilling the criterion of the 100 days were not considered in our analysis. Below we present the quantile regression analysis focusing on how prices of each brand behave in the same retailer.

For each retailer $R \in \{1, 2, 3, 4\}$ and each $\tau \in \{0.05, 0.10, 0.15, \ldots, 0.95\}$:

$$\begin{cases} Q_{b_{1,R}}(\tau \mid b_{2,R}) = \alpha_{1,R}(\tau) + \beta_{1,R}(\tau)\, b_{2,R}, \\ Q_{b_{2,R}}(\tau \mid b_{1,R}) = \alpha_{2,R}(\tau) + \beta_{2,R}(\tau)\, b_{1,R}. \end{cases}$$

Detailed results are shown in Figure 8 and results for main selected quantiles are shown in Table 7 below.

Table 7: Quantile regression coefficients for 2 brands of extra virgin olive oil

R	DV	τ				
		0.05	0.25	0.50	0.75	0.95
sm1	$b_1 \sim b_2$	0.715 (0.536, 0.894)	0.536 (0.483, 0.590)	0.235 (0.156, 0.314)	0.321 (0.240, 0.402)	0.360 (0.328, 0.392)
	$b_2 \sim b_1$	0.958 (0.491, 1.430)	0.732 (0.342, 1.120)	0.838 (0.664, 1.010)	0.709 (0.436, 0.982)	0.642 (0.441, 0.844)
sm2	$b_1 \sim b_2$	0.485 (0.232, 0.737)	1.120 (0.937, 1.300)	0.906 (0.878, 0.934)	0.900 (0.687, 1.110)	0.913 (0.831, 0.994)
	$b_2 \sim b_1$	0.648 (0.493, 0.802)	0.804 (0.671, 0.937)	0.876 (0.757, 0.995)	0.763 (0.690, 0.835)	0.312 (0.203, 0.422)
sm3	$b_1 \sim b_2$	0.365 (0.003, 0.727)	0.730 (0.650, 0.810)	0.628 (0.559, 0.697)	0.440 (0.037, 0.843)	0.379 (0.332, 0.427)
	$b_2 \sim b_1$	0.119 (0.010, 0.229)	0.939 (0.670, 1.210)	0.917 (0.836, 0.998)	0.957 (0.742, 1.170)	0.188 (-0.020, 0.395)
sm4	$b_1 \sim b_2$	0.829 (0.644, 1.010)	0.410 (0.258, 0.562)	0.185 (0.109, 0.261)	-0.022 (-0.147, 0.103)	0.194 (0.098, 0.290)
	$b_2 \sim b_1$	0.000 (-0.072, 0.072)	0.000 (-0.386, 0.386)	0.582 (0.405, 0.759)	0.839 (0.703, 0.974)	0.532 (0.333, 0.732)

R is the retailer chain (super market)
DV denotes the dependent variable of the regression model (left side), either $b1$ $b2$ or $b2$ $b1$.
τ denotes the estimated coefficient for the regressor (right side variable in the model)
Estimates computed by block-resampling quantile regression with block size 5 and $B = 1000$ bootstrap iterations with 95% confidence intervals indicated in parentheses.

Table 7 and Figure 8 summarize the estimated quantile regression coefficients for daily price levels of the two extra virgin olive oil brands (b1 and b2) across the four supermarkets.

In sm1, at the low end ($\tau = 0.05$), the coefficient is larger for $b_2 \sim b_1$ (0.958) than for $b_1 \sim b_2$ (0.715), indicating a stronger connecnedness between low price levels when brand 2 is the dependent variable. Around the middle of the distribution ($\tau =$

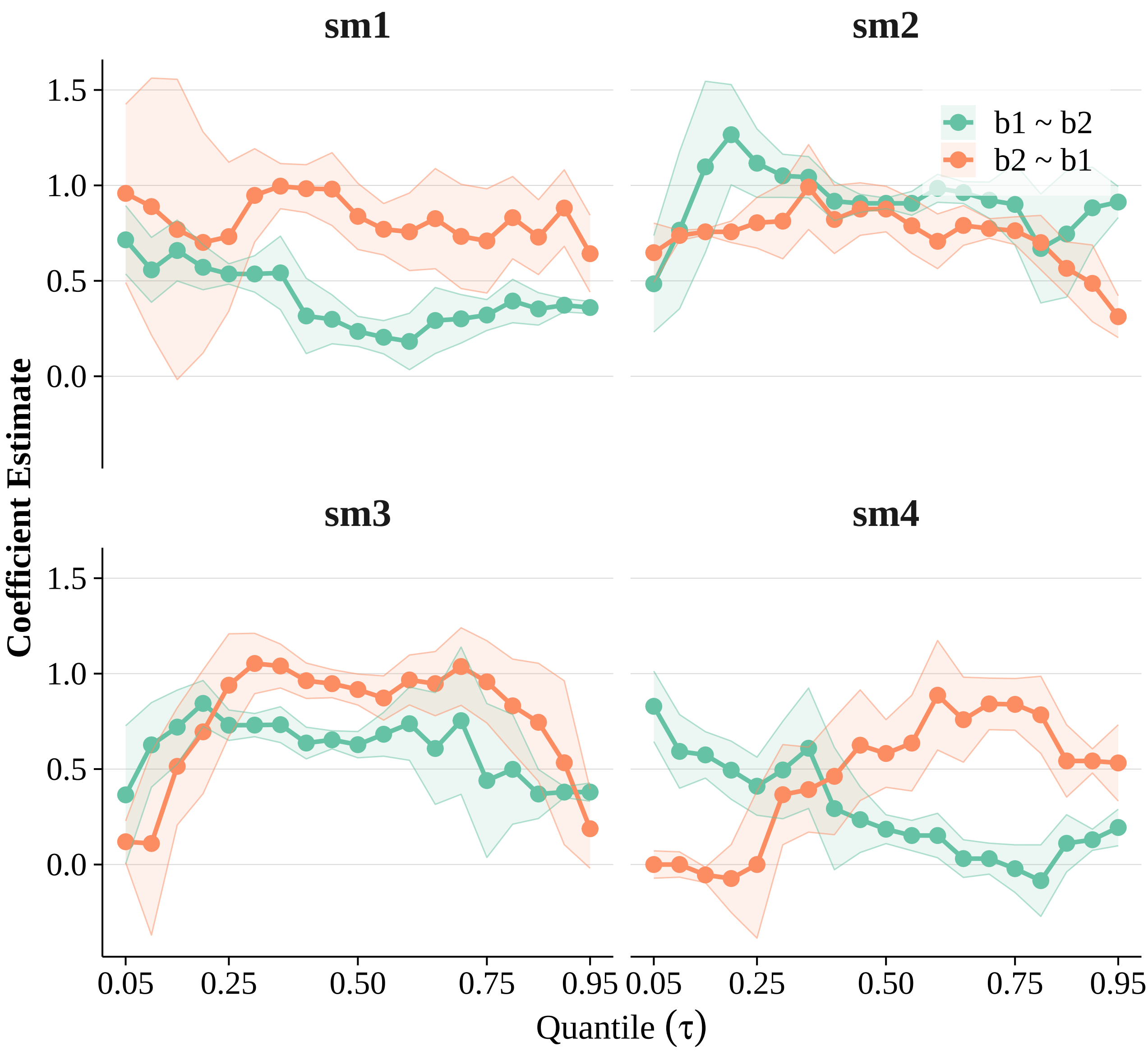

Figure 8: Quantile Regression Slopes with 95% Bootstrap Confidence Intervals. The figure displays estimated slope coefficients from pairwise quantile regressions between supermarket price series across quantiles ($\tau = 0.05$ to 0.95), considering only two brands of extra virgin olive oil. Each line represents a brand pair, while shaded areas denote 95% confidence intervals obtained via block bootstrapping with 1,000 replications and a block size of five days.

0.50), $b_1 \sim b_2$ is comparatively small (0.235) whereas $b_2 \sim b_1$ remains relatively high (0.838), suggesting weaker alignment of median price levels for brand 1 conditional on brand 2 than vice versa. At the upper end ($\tau = 0.95$), both coefficients remain positive but are smaller than at the median for $b_2 \sim b_1$ (0.642) and modest for $b_1 \sim b_2$ (0.360), consistent with a weaker association among high price levels.

In sm2, at low quantiles, both directions are positive and moderate (for $\tau = 0.05$ $b_1 \sim b_2$: 0.485; $b_2 \sim b_1$: 0.648). In the middle ($\tau = 0.50$), the coefficients are large ($b_1 \sim b_2$: 0.906; $b_2 \sim b_1$: 0.876), indicating that median price levels of the two brands are strongly associated. At $\tau = 0.95$, $b_1 \sim b_2$ remains large (0.913), while $b_2 \sim b_1$ decreases (0.312), implying that the association at high price levels is more pronounced when brand 1 is modeled as a function of brand 2 than in the reverse direction.

In sm3 we observe that the association between brand price levels is strongest in the middle quantiles compared to the tails. At the lower quantile ($\tau = 0.05$), $b_1 \sim b_2$ is positive but moderate (0.365), while $b_2 \sim b_1$ is small (0.119), indicating limited alignment among the lowest price levels when conditioning brand 2 on brand 1. In the middle of the distribution ($\tau = 0.50$), both directions are sizeable ($b_1 \sim b_2$: 0.628; $b_2 \sim b_1$: 0.917), suggesting a stronger association for typical price levels. At the upper quantile ($\tau = 0.95$), both coefficients are smaller ($b_1 \sim b_2$: 0.379; $b_2 \sim b_1$: 0.188), consistent with weaker correspondence among the highest observed price levels.

In sm4 we observe a quite different association in lower, middle, and upper quantiles, as well as clear asymmetry across regression directions. At $\tau = 0.05$, $b_1 \sim b_2$ is relatively large (0.829), whereas $b_2 \sim b_1$ is approximately zero (0.000), indicating that low price levels of brand 2 are associated with higher low-end price levels of brand 1, but not conversely. At the median ($\tau = 0.50$), $b_1 \sim b_2$ is small (0.185), while $b_2 \sim b_1$ is larger (0.582), suggesting stronger alignment of median price levels when brand 2 is conditioned on brand 1. At the upper quantile ($\tau = 0.95$), both coefficients are positive ($b_1 \sim b_2$: 0.194; $b_2 \sim b_1$: 0.532), indicating that higher price levels remain associated, with a stronger relationship in the $b_2 \sim b_1$ direction.

Considering brand 1 across the four supermarkets, the main observation is that its price level exhibits a heterogeneous but systematic association with the price level of brand 2 along the distribution. In sm2 and sm3, the relationship is strongest around the middle quantiles, where coefficients are relatively high and stable, suggesting that typical price levels of brand 1 tend to move closely with those of brand 2. In contrast, in sm1 and sm4 the association for brand 1 weakens markedly at median and upper quantiles, indicating that brand 1's central and higher price levels are less tightly aligned with those of brand 2. At the lower quantiles, brand 1 often shows a stronger association with brand 2, particularly in sm1 and sm4, suggesting that low price levels of brand 1 are more closely related to low price levels of brand 2 than are typical or high prices. Overall, these patterns are consistent with brand 1 exhibiting stronger competitive alignment with brand 2 in the lower and middle segments of the price distribution, with greater differentiation at higher price levels depending on the supermarket.

Considering brand 2 across the four supermarkets, the results indicate a generally stronger and more persistent association with brand 1, especially at median and upper quantiles. In sm1, sm2, and sm3, the coefficients for $b_2 \sim b_1$ remain relatively large around the median, suggesting that typical price levels of brand 2 closely track those of brand 1. In sm2 and sm4, this association extends into the upper quantiles, indicating that higher price levels of brand 2 are more strongly aligned with brand 1 than is the case in the reverse direction. At the lower quantiles, however, the relationship is weaker and in some cases negligible, particularly in sm4, implying that low-end prices of brand 2 display greater independence. These findings suggest that brand 2 tends to align its median and higher price levels more closely with brand 1 across supermarkets, while maintaining more flexibility in the lowest segment of the price distribution.

4.4 Brand b1 across supermarkets

Here we analyze the quantile regression results concerning the brand b1, across the four retailers. Each time we model the price level of one super market, against the remaining three, across quantiles $\tau = 0.05, 0.10, \ldots, 0.95$. As in other cases confidence intervals have been calculted with 1000 bootstrap repetitions.

4.4.1 Brand b1 – sm1

We estimated the model:

$$\text{sm1}_i = \beta_0(\tau) + \beta_1(\tau)\,\text{sm2}_i + \beta_2(\tau)\,\text{sm3}_i + \beta_3(\tau)\,\text{sm4}_i + u_i(\tau), \tag{6}$$

where $Q_{u_i}(\tau \mid \text{sm2}_i, \text{sm3}_i, \text{sm4}_i) = 0$.

Results are shown in Figure 9 and Table 8.

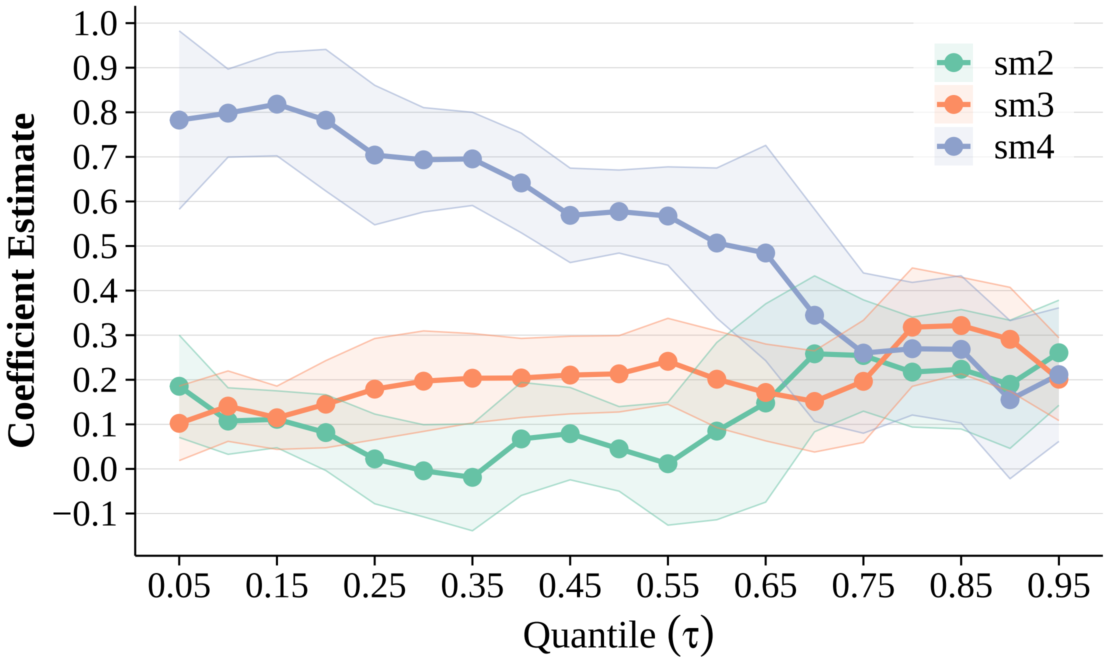

Figure 9: Quantile regression estimates for **brand 1** and `sm1` across the distribution of price levels. Shaded regions show 95% confidence intervals.

Table 8: Quantile regression coefficients for b1 brand, sm1 over sm2, sm3, sm4

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm2	0.185 (0.071, 0.300)	0.022 (-0.078, 0.123)	0.045 (-0.050, 0.140)	0.254 (0.130, 0.379)	0.261 (0.143, 0.378)
sm3	0.102 (0.019, 0.186)	0.179 (0.066, 0.293)	0.213 (0.128, 0.299)	0.196 (0.059, 0.333)	0.201 (0.108, 0.294)
sm4	0.783 (0.582, 0.983)	0.704 (0.548, 0.861)	0.577 (0.484, 0.670)	0.260 (0.080, 0.440)	0.212 (0.062, 0.361)

At the lower tail of the distribution, corresponding to $\tau = 0.05$, the coefficient on `sm2` is positive and statistically significant, with an estimated value of 0.185. This indicates that when `sm1` prices are particularly low, price movements in `sm2` are meaningfully associated with those in `sm1`. However, this relationship weakens around the lower-middle and median quantiles. At $\tau = 0.25$ and $\tau = 0.50$, the estimated coefficients are small and statistically indistinguishable from zero, suggesting that `sm2` is not affecting price levels in `sm1`. In the upper part of the distribution, at $\tau \geq 0.75$, the influence of `sm2` re-emerges. The coefficients become positive and more statistically significant again, indicating that `sm2` becomes a relevant reference retailer when `sm1` prices are relatively high.

The coefficients associated with `sm3` are positive and statistically significant across all reported quantiles. Their magnitude is relatively stable, ranging from approximately 0.10 at $\tau = 0.05$ to about 0.20 at $\tau = 0.95$. This stability suggests a consistent co-movement between `sm3` and `sm1` price levels throughout the distribution. Unlike `sm2` and `sm4`, the effect of `sm3` does not vary dramatically with the price level, indicating that it serves as a competitive benchmark for brand 1 pricing in `sm1`.

The most prominent feature of the results concerns `sm4`. At the lower tail of the distribution, $\tau = 0.05$, the coefficient on `sm4` is large, and statistically significant, with a value of 0.783. This points to an almost one-to-one co-movement between `sm1` and `sm4` prices when `sm1` prices are particularly low. Although the coefficient remains large and statistically significant at $\tau = 0.25$ and $\tau = 0.50$, its magnitude declines steadily as the quantile increases. At the upper quantiles, $\tau = 0.75$ and $\tau = 0.95$, the influence of `sm4` is substantially weaker, though still positive and statistically significant. This pattern suggests that `sm4` acts as the dominant reference retailer primarily at low price levels, with its importance diminishing as `sm1` prices rise.

Overall, the results reveal strong asymmetries in pricing dynamics for brand 1 in `sm1`. Low-price levels are tightly aligned with `sm4`, median prices reflect a more balanced structure but still influenced by `sm4` with a stable contribution from `sm3`. High-price outcomes are increasingly associated with price movements in `sm2`.

4.4.2 Brand b1 – sm2

We estimated the model:

$$\text{sm2}_i = \beta_0(\tau) + \beta_1(\tau)\,\text{sm1}_i + \beta_2(\tau)\,\text{sm3}_i + \beta_3(\tau)\,\text{sm4}_i + u_i(\tau), \qquad (7)$$

where $Q_{u_i}(\tau \mid \text{sm1}_i, \text{sm3}_i, \text{sm4}_i) = 0$.

Results are shown in Figure 10 and Table 9.

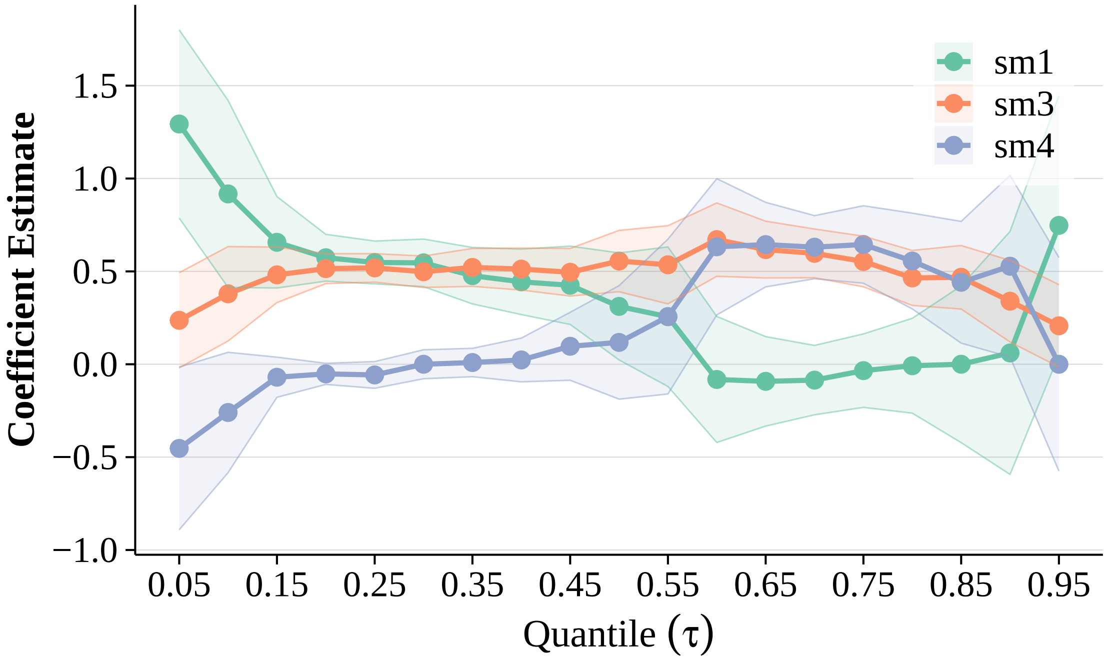

Figure 10: Quantile regression estimates for **brand 1** and `sm2` across the distribution of price levels. Shaded regions show 95% confidence intervals.

Table 9: Quantile regression coefficients for b1 brand, sm2 over sm1, sm3, sm4

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	1.294 (0.787, 1.801)	0.548 (0.433, 0.663)	0.311 (0.023, 0.600)	-0.034 (-0.232, 0.163)	0.748 (0.050, 1.446)
sm3	0.237 (-0.020, 0.493)	0.519 (0.442, 0.596)	0.556 (0.390, 0.721)	0.553 (0.417, 0.690)	0.207 (-0.015, 0.429)
sm4	-0.453 (-0.891, -0.015)	-0.058 (-0.129, 0.014)	0.118 (-0.188, 0.423)	0.645 (0.436, 0.853)	0.000 (-0.575, 0.575)

For `sm2` we observed that the competitive pricing relationships for brand 1 vary markedly across the conditional distribution of prices, with clear shifts in the relative importance of rival retailers as the quantile changes.

The influence of `sm1` is strongest at the lower end of the distribution. At $\tau = 0.05$, the coefficient on `sm1` is large and positive, indicating a strong co-movement between `sm2` and `sm1` when `sm2` prices are particularly low. As τ increases toward the center of the distribution, the magnitude of this coefficient declines substantially, suggesting that the influence of `sm1` weakens at typical price levels. In the upper quantiles, the coefficient becomes more unstable, pointing to a reduced effect for `sm1` when `sm2` price levels are high.

The coefficients associated with `sm3` are positive throughout most of the distribution and display a smoother pattern. Their magnitude increases from the lower tail toward the median, indicating that `sm3` is particularly relevant in shaping typical price levels in `sm2`. At higher quantiles, the effect remains positive but declines somewhat, suggesting that `sm3` maintains a consistent, though not dominant, relationship across price levels.

By contrast, `sm4` exhibits a distinctly asymmetric pattern. At $\tau = 0.05$, the coefficient on `sm4` is negative, indicating an inverse relationship between `sm2` and `sm4` prices when `sm2` prices are low. This relationship weakens and changes sign as τ increases. From around the median onward, the coefficient on `sm4` becomes positive and grows in magnitude, reaching its highest values in the upper-middle part of the distribution, which indicates increasing co-movement at higher price levels.

Overall, the results show that low-price realizations in `sm2` are most closely associated with `sm1`, median prices are primarily related to `sm3`, and higher-price outcomes increasingly reflect price movements in `sm4`. This distributional heterogeneity highlights substantial variation in competitive reference pricing across different segments of the price distribution.

4.4.3 Brand b1 – sm3

We estimated the model:

$$\text{sm3}_i = \beta_0(\tau) + \beta_1(\tau)\,\text{sm1}_i + \beta_2(\tau)\,\text{sm2}_i + \beta_3(\tau)\,\text{sm4}_i + u_i(\tau), \tag{8}$$

where $Q_{u_i}(\tau \mid \mathrm{sm1}_i, \mathrm{sm2}_i, \mathrm{sm4}_i) = 0$.

Results are shown in Figure 11 and Table 10.

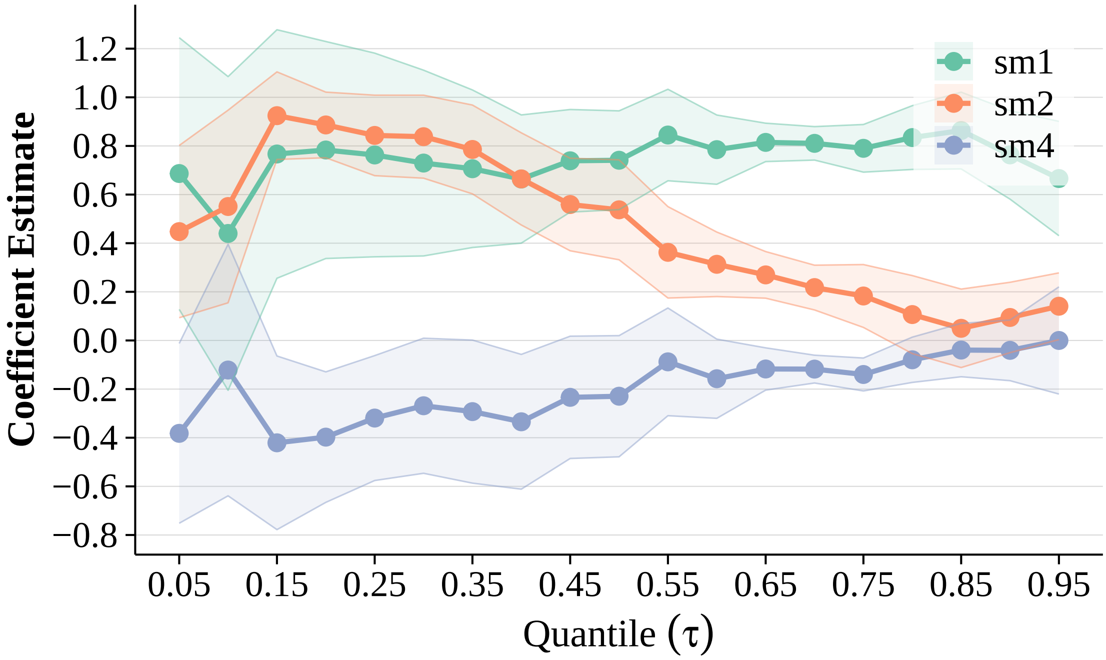

Figure 11: Quantile regression estimates for `brand 1` and `sm3` across the distribution of price levels. Shaded regions show 95% confidence intervals.

Table 10: Quantile regression coefficients for b1 brand, sm3 over sm1, sm2, sm4

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	0.687 (0.128, 1.245)	0.763 (0.344, 1.182)	0.741 (0.538, 0.944)	0.790 (0.692, 0.888)	0.666 (0.431, 0.901)
sm2	0.448 (0.093, 0.802)	0.843 (0.678, 1.009)	0.537 (0.332, 0.743)	0.183 (0.053, 0.312)	0.141 (0.004, 0.278)
sm4	-0.382 (-0.752, -0.012)	-0.319 (-0.576, -0.062)	-0.229 (-0.479, 0.020)	-0.140 (-0.208, -0.072)	0.000 (-0.220, 0.220)

The influence of `sm1` is strong and relatively stable across all quantiles. At $\tau = 0.05$, the coefficient on `sm1` is large and positive, and it remains consistently high through $\tau = 0.25$, $\tau = 0.50$, and $\tau = 0.75$, before declining slightly at $\tau = 0.95$. All estimates are statistically significant, indicating persistent co-movement between `sm3` and `sm1` prices throughout the entire distribution.

The influence of `sm2` varies more substantially across quantiles. At the lower tail, $\tau = 0.05$, the coefficient is positive and statistically significant, indicating that `sm2` prices are relevant when `sm3` prices are low. The influence of `sm2` peaks around $\tau = 0.25$, where the coefficient exceeds 0.8, pointing to a strong association at lower-to-middle price levels. As the quantile increases further, the magnitude of the `sm2` coefficient declines. By $\tau = 0.75$ and $\tau = 0.95$, the effect remains positive but smaller, suggesting that `sm2` becomes less important as `sm3` prices move into the upper part of the distribution.

In contrast, `sm4` displays a negative relationship with `sm3` over most of the distribution. At $\tau = 0.05$ and $\tau = 0.25$, the coefficient on `sm4` is negative and statistically significant, indicating an inverse relationship when `sm3` prices are low. The magnitude of this negative effect decreases toward the median, and at $\tau = 0.50$ the coefficient becomes statistically insignificant. At higher quantiles, the negative association persists but weakens further, and by $\tau = 0.95$ the effect is no longer statistically significant.

The results show that pricing in `sm3` for brand 1 is dominated by a strong and stable relationship with `sm1`, complemented by a quantile-dependent influence of `sm2` that is strongest at lower and central price levels. The effect of `sm4` is asymmetric and largely confined to low-price realizations, where it exhibits an inverse association with `sm3`. These patterns underscore substantial variation in competitive interactions across the distribution of `sm3` prices.

4.4.4 Brand b1 – sm4

We estimated the model:

$$\mathrm{sm4}_i = \beta_0(\tau) + \beta_1(\tau)\,\mathrm{sm1}_i + \beta_2(\tau)\,\mathrm{sm2}_i + \beta_3(\tau)\,\mathrm{sm3}_i + u_i(\tau), \tag{9}$$

where $Q_{u_i}(\tau \mid \mathrm{sm1}_i, \mathrm{sm2}_i, \mathrm{sm3}_i) = 0$.

Results are shown in Figure 12 and Table 11.

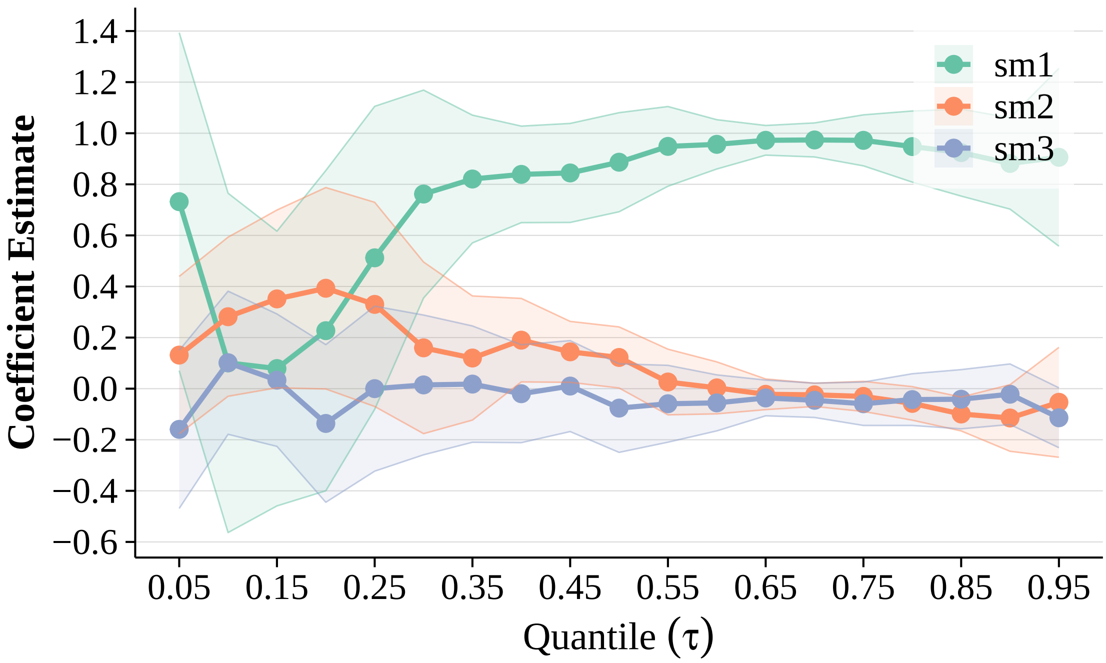

Figure 12: Quantile regression estimates for **brand 1** and `sm4` across the distribution of price levels. Shaded regions show 95% confidence intervals.

Table 11: Quantile regression coefficients for b1 brand, sm4 over sm1, sm2, sm3

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	0.732 (0.070, 1.394)	0.512 (-0.081, 1.105)	0.886 (0.693, 1.080)	0.972 (0.872, 1.072)	0.906 (0.558, 1.254)
sm2	0.131 (-0.177, 0.439)	0.330 (-0.070, 0.730)	0.122 (0.003, 0.242)	-0.030 (-0.089, 0.029)	-0.053 (-0.269, 0.162)
sm3	-0.159 (-0.469, 0.150)	0.000 (-0.323, 0.323)	-0.076 (-0.249, 0.097)	-0.059 (-0.144, 0.026)	-0.114 (-0.231, 0.003)

The influence of `sm1` is strong across almost the entire distribution. At $\tau = 0.05$, the coefficient on `sm1` is large and positive, although estimated with relatively wide confidence intervals. From $\tau = 0.50$ onward, the coefficient increases further, remaining close to one at $\tau = 0.75$ and $\tau = 0.95$. This indicates a tight co-movement between `sm4` and `sm1` prices, particularly at typical and high price levels, and suggests that `sm1` acts as the primary reference retailer for brand 1 pricing in `sm4`.

The effect of `sm2` is more limited and varies across quantiles. At the lower tail, $\tau = 0.05$, the coefficient on `sm2` is positive but statistically insignificant. Its influence becomes statistically significant at the median, $\tau = 0.50$, where the coefficient is positive but modest in magnitude. At higher quantiles, $\tau = 0.75$ and $\tau = 0.95$, the coefficient turns slightly negative and statistically insignificant, indicating that `sm2` does not play a meaningful role in shaping high-price outcomes in `sm4`.

The coefficients associated with `sm3` are small and negative across the distribution and are statistically insignificant, suggesting weak or negligible co-movement between `sm3` and `sm4`.

The results indicate that pricing in `sm4` for brand 1 is dominated by a strong and persistent relationship with `sm1`, especially at median and high price levels. The influence of `sm2` is modest and confined mainly to typical prices, while `sm3` plays a limited and mostly negligible role across the distribution. These results highlight substantial asymmetry in competitive pricing dynamics for `sm4` across different segments of the price distribution.

4.5 Brand b2 across supermarkets

Here we analyze the quantile regression results concerning the brand b2, across the same as four retailers. Each time we model the price level of one super market against the remaining three sm across quantiles $\tau = 0.05, 0.10, \ldots, 0.95$. As in other cases confidence intervals have been calculted with 1000 bootstrap repetitions.

4.5.1 Brand b2 – sm1

We estimated the model:

$$\mathrm{sm1}_i = \beta_0(\tau) + \beta_1(\tau)\,\mathrm{sm2}_i + \beta_2(\tau)\,\mathrm{sm3}_i + \beta_3(\tau)\,\mathrm{sm4}_i + u_i(\tau), \tag{10}$$

where $Q_{u_i}(\tau \mid \mathrm{sm2}_i, \mathrm{sm3}_i, \mathrm{sm4}_i) = 0$.

Figure 13 presents the results of quantile regression and Table 12 summarizes the corresponding results for main τ values, regarding the influence of prices of brand b2 in supermarket sm2, sm3, sm4 on sm1.

The quantile regression results presented in Figure 13 reveal a pronounced heterogeneity in how price levels of retailers sm2, sm3, sm4 relate to the conditional

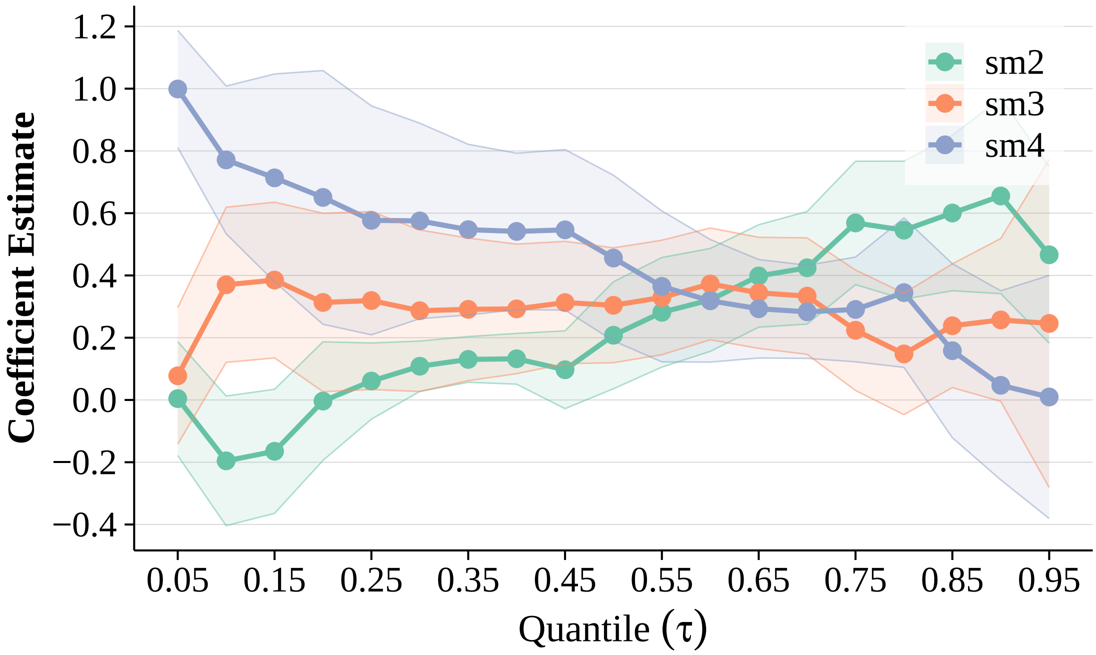

Figure 13: Quantile regression estimates for `brand 2` and `sm1` across the distribution of price levels. Shaded regions show 95% confidence intervals.

Table 12: Quantile regression coefficients for b2 brand, sm1 over sm2, sm3, sm4

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm2	0.004 (-0.179, 0.187)	0.061 (-0.062, 0.183)	0.208 (0.036, 0.380)	0.569 (0.371, 0.767)	0.466 (0.183, 0.750)
sm3	0.078 (-0.142, 0.297)	0.319 (0.034, 0.605)	0.304 (0.120, 0.489)	0.224 (0.030, 0.417)	0.246 (-0.281, 0.773)
sm4	0.999 (0.811, 1.187)	0.577 (0.209, 0.945)	0.456 (0.190, 0.722)	0.291 (0.123, 0.459)	0.010 (-0.381, 0.400)

distribution of sm1 prices for brand b2. The influence of competing retailers varies markedly across quantiles, indicating that different price relationships emerge at low, central, and high price levels.

At the lower end of the distribution, the coefficient associated with sm4 is dominant and close to one, with tight confidence intervals, pointing to an almost one-to-one co-movement between sm1 and sm4 when sm1 prices are particularly low. As the quantile increases, the magnitude of the sm4 coefficient declines steadily and its statistical significance weakens, eventually becoming indistinguishable from zero at the upper tail of the distribution. This pattern suggests that sm4 plays a central role as a reference competitor primarily at low price levels, while its influence diminishes as sm1 prices rise.

The coefficients for sm3 are positive across most quantiles and statistically significant over a broad middle range of the distribution. Their magnitude is moderate relative to sm4 at low quantiles and remains fairly stable around the median. This indicates a consistent but secondary relationship between sm3 and sm1, particularly at typical price levels.

In contrast, the influence of sm2 varies substantially across the distribution. While sm2 has little explanatory power at the lower quantiles, its coefficient becomes positive and statistically significant from the median onward, reaching its largest values in the upper part of the distribution. This suggests that sm2 becomes an increasingly relevant reference point when sm1 prices are relatively high.

Overall, the results point to strong asymmetries in competitive pricing relationships across the distribution of sm1 prices. Low-price instances are closely aligned with sm4, median prices reflect broader competitive interactions involving all retailers, and high-price outcomes are mainly associated with price movements in sm2.

4.5.2 Brand b2 – sm2

We estimated the model:

$$\mathrm{sm2}_i = \beta_0(\tau) + \beta_1(\tau)\,\mathrm{sm1}_i + \beta_2(\tau)\,\mathrm{sm3}_i + \beta_3(\tau)\,\mathrm{sm4}_i + u_i(\tau), \tag{11}$$

where $Q_{u_i}(\tau \mid \text{sm1}_i, \text{sm3}_i, \text{sm4}_i) = 0$.

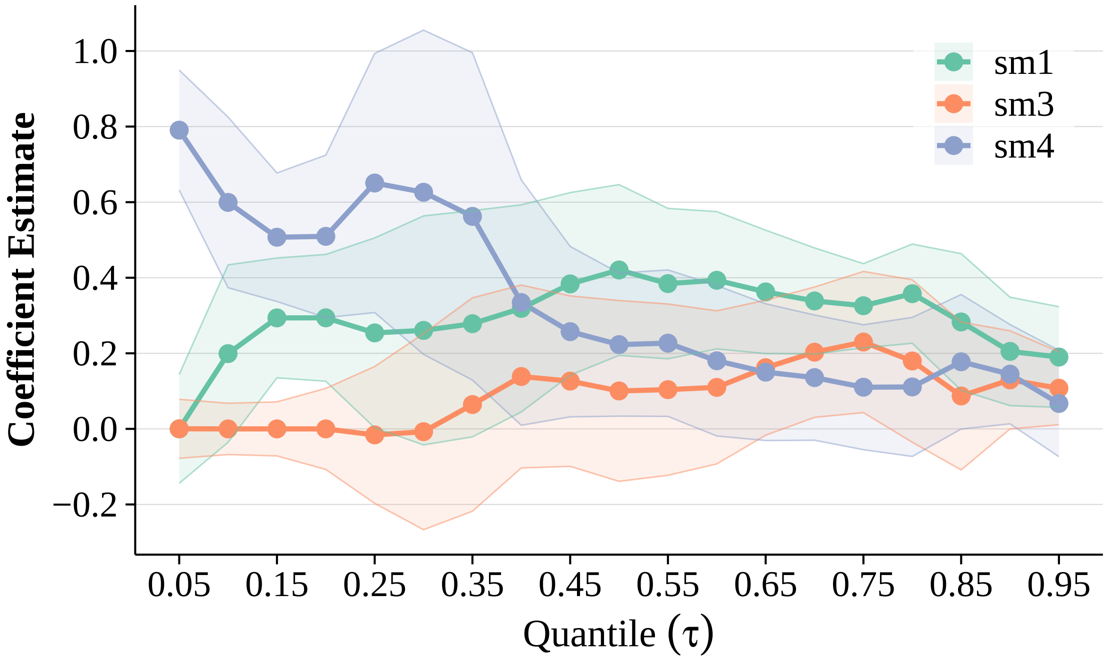

Figure 14: Quantile regression estimates for `brand 2` and `sm2` across the distribution of price levels. Shaded regions show 95% confidence intervals.

Table 13: Quantile regression coefficients for b2 brand, sm2 over sm1, sm3, sm4

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	-0.000 (-0.144, 0.144)	0.254 (0.003, 0.505)	0.420 (0.195, 0.646)	0.326 (0.214, 0.437)	0.190 (0.057, 0.323)
sm3	0.000 (-0.078, 0.078)	-0.016 (-0.197, 0.165)	0.100 (-0.139, 0.340)	0.230 (0.043, 0.417)	0.108 (0.011, 0.204)
sm4	0.791 (0.632, 0.949)	0.651 (0.308, 0.994)	0.223 (0.034, 0.412)	0.110 (-0.055, 0.275)	0.067 (-0.073, 0.208)

The quantile regression results presented in Figure 14 reveal heterogeneity in the relationship between the prices of competing retailers and the conditional distribution of sm2 prices for brand b2. The magnitude and statistical relevance of the estimated coefficients vary markedly across quantiles, indicating that different competitive reference points emerge at low, central, and high price levels.

At the lower tail of the distribution, corresponding to $\tau = 0.05$, the coefficient associated with sm4 is large and positive, with a value close to 0.8. This indicates a strong co-movement between sm2 and sm4 when sm2 prices are particularly low. In contrast, the coefficients on sm1 and sm3 are close to zero and statistically insignificant at this quantile, suggesting that low-price realizations in sm2 are primarily aligned with sm4 rather than with the other retailers.

As the quantile increases toward the center of the distribution, the influence of sm4 declines sharply. While the sm4 coefficient remains positive and statistically significant at $\tau = 0.50$, its magnitude is substantially smaller than in the lower tail. At the same time, the effect of sm1 becomes increasingly important: the coefficient on sm1 turns positive and statistically significant from $\tau = 0.25$ onward, reaching its highest value around the median. This pattern suggests that typical price levels in sm2 reflect a broader competitive interaction, with sm1 emerging as a key reference retailer.

In the upper part of the distribution, corresponding to $\tau = 0.75$ and $\tau = 0.95$, the coefficient on sm4 becomes small and statistically indistinguishable from zero, indicating that sm4 no longer plays a meaningful role when sm2 prices are high. By contrast, the coefficient on sm1 remains positive and statistically significant throughout the upper quantiles, while sm3 also becomes relevant, with positive and statistically significant coefficients at $\tau = 0.75$ and $\tau = 0.95$. These results suggest that high-price realizations in sm2 are primarily associated with price movements in sm1 and, to a lesser extent, sm3.

Overall, the findings point to asymmetries in competitive pricing relationships across the conditional distribution of sm2 prices. Low-prices are closely aligned with sm4, median prices reflect strong interactions with sm1 alongside a diminishing role for sm4, and high-price outcomes are mainly associated with sm1 and sm3.

4.5.3 Brand 2 – sm3

We estimated the model:

$$\mathrm{sm3}_i = \beta_0(\tau) + \beta_1(\tau)\,\mathrm{sm1}_i + \beta_2(\tau)\,\mathrm{sm2}_i + \beta_3(\tau)\,\mathrm{sm4}_i + u_i(\tau), \tag{12}$$

where $Q_{u_i}(\tau \mid \mathrm{sm1}_i, \mathrm{sm2}_i, \mathrm{sm4}_i) = 0$.

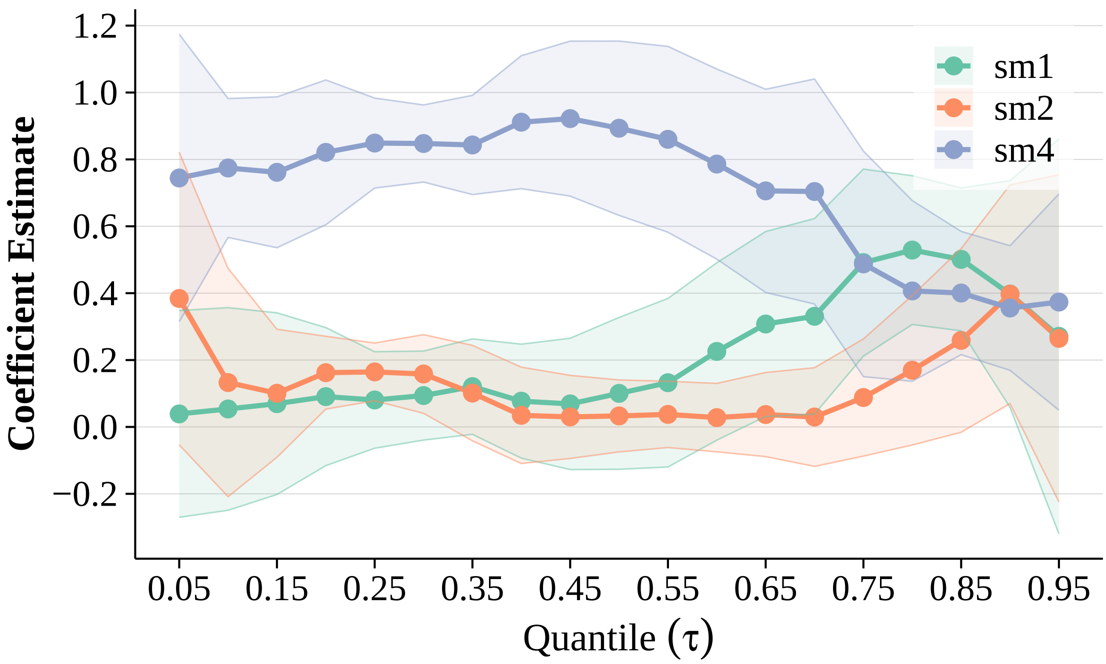

Figure 15: Quantile regression estimates for `brand 2` and `sm3` across the distribution of price levels. Shaded regions show 95% confidence intervals.

Table 14: Quantile regression coefficients for b2 brand, sm3 over sm1, sm2, sm4

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	0.039 (-0.270, 0.348)	0.081 (-0.064, 0.225)	0.100 (-0.127, 0.327)	0.491 (0.212, 0.771)	0.271 (-0.319, 0.861)
sm2	0.384 (-0.053, 0.822)	0.165 (0.078, 0.251)	0.033 (-0.075, 0.141)	0.088 (-0.087, 0.263)	0.265 (-0.224, 0.754)
sm4	0.744 (0.314, 1.174)	0.849 (0.714, 0.983)	0.893 (0.633, 1.154)	0.488 (0.150, 0.825)	0.373 (0.050, 0.697)

The quantile regression results reported in Figure 15 and Table 14 indicate substantial heterogeneity in how prices in competing retailers relate to the conditional distribution of sm3 prices for brand b2. The estimated coefficients vary markedly across quantiles, pointing to distinct competitive relationships at low, central, and high price levels.

At the lower tail of the distribution, corresponding to $\tau = 0.05$, the coefficient associated with sm4 is large, positive, and statistically significant, with a value of approximately 0.74. This suggests a strong co-movement between sm3 and sm4 when sm3 prices are particularly low. In contrast, the coefficients on sm1 and sm2 at this quantile are relatively small and statistically insignificant, indicating that low-price realizations in sm3 are primarily aligned with sm4 rather than with the other retailers.

Across the lower-to-middle part of the distribution, including $\tau = 0.25$ and $\tau = 0.50$, sm4 remains the dominant reference retailer. Its coefficient is consistently large, reaching values close to 0.9 around the median. By comparison, the coefficients on sm1 and sm2 are modest in magnitude and generally not statistically distinguishable from zero over this range. This pattern indicates that typical price levels in sm3 are largely driven by price movements in sm4, with limited direct influence from sm1 and sm2.

In the upper part of the distribution, the competitive structure changes. At $\tau = 0.75$, the coefficient on sm4 declines in magnitude but remains positive and statistically significant, while the coefficient on sm1 increases sharply and becomes statistically significant. This suggests that when sm3 prices are relatively high, sm1 emerges as an important reference retailer alongside sm4. At the extreme upper tail, corresponding to $\tau = 0.95$, the coefficient on sm4 remains positive and statistically significant, although smaller than at lower quantiles, whereas the coefficients on sm1 and sm2 become statistically insignificant.

Overall, the results reveal a pronounced asymmetry in competitive pricing relationships across the conditional distribution of sm3 prices. Low and median price realizations are closely aligned with sm4, indicating strong co-movement between these two retailers across much of the distribution. At higher price levels, the influence of sm4 weakens but remains present, while sm1 becomes increasingly relevant.

4.5.4 Brand b2 – sm4

We estimated the model:

$$\mathrm{sm4}_i = \beta_0(\tau) + \beta_1(\tau)\,\mathrm{sm1}_i + \beta_2(\tau)\,\mathrm{sm2}_i + \beta_3(\tau)\,\mathrm{sm3}_i + u_i(\tau), \tag{13}$$

where $Q_{u_i}(\tau \mid \mathrm{sm1}_i, \mathrm{sm2}_i, \mathrm{sm3}_i) = 0$.

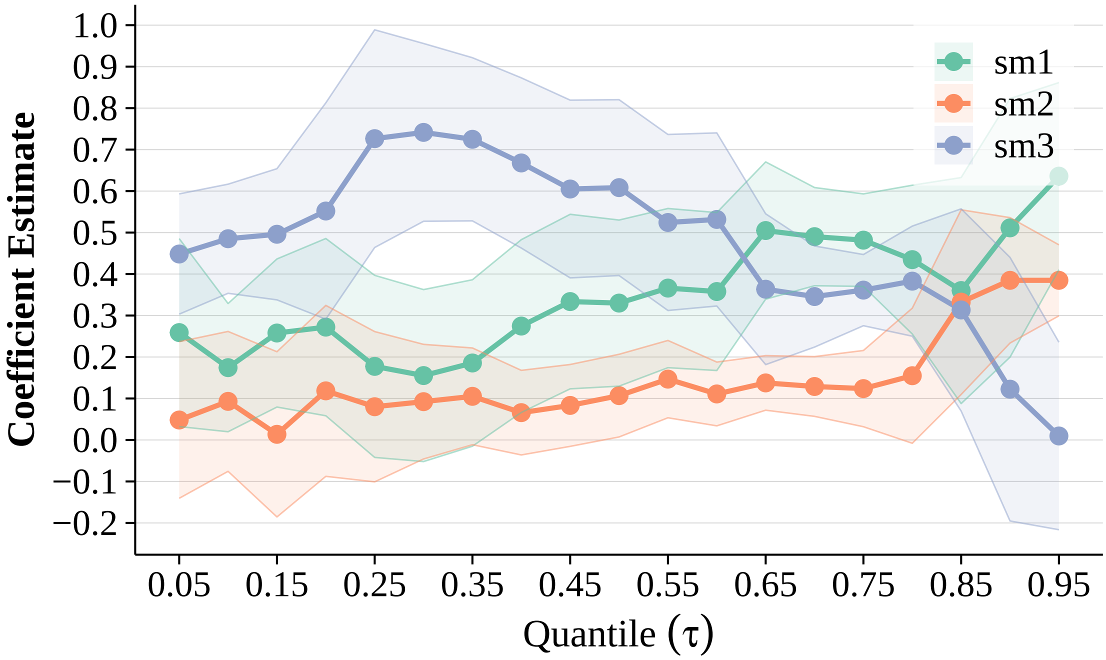

Figure 16: Quantile regression estimates for `brand 2` and `sm4` across the distribution of price levels. Shaded regions show 95% confidence intervals.

Table 15: Quantile regression coefficients for b2 brand, sm4 over sm1, sm2, sm3

	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
sm1	0.259 (0.032, 0.486)	0.177 (-0.042, 0.397)	0.330 (0.130, 0.530)	0.482 (0.370, 0.593)	0.636 (0.410, 0.862)
sm2	0.048 (-0.141, 0.237)	0.080 (-0.101, 0.261)	0.107 (0.007, 0.207)	0.124 (0.032, 0.216)	0.385 (0.299, 0.470)
sm3	0.448 (0.303, 0.593)	0.726 (0.464, 0.989)	0.608 (0.396, 0.820)	0.361 (0.275, 0.447)	0.010 (-0.216, 0.236)

The quantile regression results reported in Figure 16 and Table 15 provide clear evidence of heterogeneous competitive pricing relationships across the conditional distribution of sm4 prices for brand b2. The estimated coefficients indicate that the relative importance of competing retailers varies substantially between low, middle, and high price realizations.

At the lower tail of the distribution, corresponding to $\tau = 0.05$, the coefficient on sm3 is the largest and statistically significant, with a value of approximately 0.45. This suggests co-movement between sm4 and sm3 when sm4 prices are low. The coefficient on sm1 is also positive and statistically significant, though smaller in magnitude, indicating a secondary role for sm1 in shaping low-price outcomes in sm4. By contrast, the coefficient on sm2 is small and statistically insignificant at this quantile, implying limited influence on sm4 prices in the lower tail.

Across the lower-to-middle quantiles, including $\tau = 0.25$ and $\tau = 0.50$, sm3 remains the dominant reference retailer. Its coefficient increases further at $\tau = 0.25$ and remains large. During this range, the coefficient on sm1 is positive and statistically significant at the median, while the coefficient on sm2 becomes marginally significant only at $\tau = 0.50$. This pattern indicates that typical price levels in sm4 are primarily aligned with sm3, with sm1 playing a complementary role and sm2 exerting a relatively minor influence.

In the upper part of the distribution, the competitive structure shifts noticeably. At $\tau = 0.75$, the coefficient on sm1 becomes the largest among the competitors and remains strongly significant, while the coefficient on sm3 declines substantially, though it remains positive and statistically significant. At the extreme upper tail, corresponding to $\tau = 0.95$, the coefficient on sm3 collapses toward zero and is no longer statistically distinguishable from zero, indicating that sm3 ceases to be a relevant reference point at very high sm4 prices. In contrast, sm1 exhibits a strong and increasing influence in this region, with the largest coefficient observed at $\tau = 0.95$, while sm2 also becomes highly relevant, displaying a large positive coefficient.

Overall, the results reveal asymmetry in competitive pricing dynamics across the conditional distribution of sm4 prices. Low and median prices are closely aligned with sm3, reflecting strong co-movement between these two retailers across much of the distribution. As prices increase, the influence of sm3 diminishes, and high-price outcomes in sm4 are primarily associated with price movements in sm1 and sm2.

5 Discussion

This section discusses the estimation results in light of the study's central objective: to examine price connectedness among four retail chains for extra virgin olive oil, in Greece.

In light of the empirical findings in Section 4.2, results, across four retail chains, can be summarized as follows:

When **sm1** is the dependent variable, we obseve that it closely monitors at least one key rival (sm2) and adjusts its price levels accordingly. Prices in sm2 apply the most consistent impact, suggesting that the mode of competition is stronger. Prices in sm3 and sm4 also affect sm1, but their impact is weaker and less systematic.

For `sm2`, results are different and more asymmetric. Prices in `sm4` emerge as the strongest and most stable driver of `sm2`'s pricing across the price distribution. The magnitude of this effect is clearly larger than that of sm1, indicating that `sm4` is more influential on sm2's price levels. `sm1`'s impact is secondary, while `sm3`'s impact is limited.

In the case of `sm3`, the results indicate greater reaction to external pricing signals, mainly from sm4. This suggests that `sm3` behaves largely as a price follower, especially at low quantiles.

Finally, for `sm4`, the regression reveals comparatively weaker and less stable links to the other supermarkets. While prices in `sm2` and `sm3` still matter, their influence is less pronounced than in the aforementioned findings.

Overall, the results portray a picture characterized by asymmetric competitive pressures across the four retailers. Certain bilateral relationships—most notably between `sm2` and sm4 matter the most in shaping price levels within these two retailers. The pattern of price reaction among the rest of the supermarkets is not as strong and consistent.

Section 4.3 sharpens the competitive lens by focusing the attention on the two brands that are sold within and across all four supermarkets. The results reveal stronger and more symmetric price connectedness as compared to the empirical findings of Section 4.2. Prices within each supermarket are more tightly connected to rival's prices. The latter indicates that when brand 1 and brand 2 are easily comparable, within the same retailer, then the strategic interdependence between these two brands intensifies.

Section 4.4 focuses on brand 1 prices in four retailers and allows a more focused view of competitive dynamics at the individual-brand level. Price connectedness for brand 1 is generally stronger than what is observed in the aggregate-brand results. This suggests supermarkets, concerning brand 1, appear reluctant to deviate substantially from competitors' price levels, likely due to price transparency and ease of comparison. As a result, price adjustments for this brand tend to propagate quickly across retailers.

Concurrently, competitive asymmetries remain evident. Retailer `sm1` exhibits the biggest influence on the prices of brand b1 sold in the rest of the supermarkets. Accordingly, one can suggest that sm1 act as a leader and others as followers when it comes to brand b1. Importantly, these asymmetries are more evident at brand level than in the multi-brand averages, highlighting that price competition can vary by product. For competition analysis, this implies that focusing on prominent, widely recognized brands can uncover stronger and more directional pricing relationships than analyses based on broader brand baskets.

Similarly, we examined also brand 2 in Section 4.5. While price connectedness across supermarkets remains present, the degree of asymmetry is weaker, suggesting that brand 2 carries less weight, in retailers' price setting, as compared to brand 1. For brand 2, `sm4` emerges as the supermarket having the strongest influence on rivals' prices from the lower quantiles up to the middle ones.

6 Conclusions

This study examines the competitive pricing dynamics in the Greek extra virgin olive oil retail market across four large supermarket chains. This is done by employing quantile regression methods to capture price connectedness along the entire joint price distribution. The analysis was conducted at three levels: aggregate product category, two common brands that are sold by four retailers, and individual brand-level examination.

The empirical findings can be summarized as follows:

- Prices show considerable asymmetries across the spectrum of the joint price distribution. These asymmetries were found to be more profound in the tails of the distribution, indicating heterogeneous responses. In light of these results coordinated price behaviour cannot be justified.
- Daily average prices of brands b1 and b2, sold in all four supermarkets, were highly connected to each other. This suggests that when brands are immediate comparable, within the same retailer, then the strategic interdependence between them intensifies.
- A brand level analysis reveals that focusing on specific brands can uncover stronger and more directional pricing relationships than analysis based on broader brand baskets. This highlights that the strength of price connectedness is brand as well as retailer specific.

Future research could extend this framework by incorporating promotional activity, quantities sold, private label positioning, and temporal dynamics to capture how competitive structures evolve over time. Structural breaks or seasonality in demand and across different competitive instruments beyond final prices, like discount strategy and non price competition aspects can be also considered.

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