The Competitive Conduct of Consumer Cooperatives*

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Abstract

Consumer cooperatives are firms owned by their customers. Although their organizational form should commit these firms not to exploit their market power, in practice, weak governance may allow managers to pursue other objectives. Using data and a structural model, we test whether consumer cooperatives in the Italian supermarket industry act as profit-maximizing firms. We find no significant deviations from profit maximization. Based on a counterfactual exercise, even a mild degree of internalization of consumer welfare by the cooperatives that we study would yield consumer welfare gains comparable to the regulatory advantages they enjoy.

Keywords: Consumer cooperative, test of conduct, market power, supermarket industry

JEL Codes: L21, L22, L33

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1 Introduction

Consumer cooperatives—firms owned by their customers—represent a substantial share of the economy in many countries and have a large market share in industries such as banking, insurance, retail, and wholesale. The main reason for forming cooperatives, instead of investor-owned corporations, is to commit firms to limit the exercise of market power (Hansmann, 2000). This makes cooperatives attractive in concentrated markets and motivates the tax exemptions and other regulatory advantages that they receive in many jurisdictions.

However, it is not obvious that adopting the cooperative form results in consumer-oriented conduct. Although consumer cooperatives state in their charters that their objective is the provision of high-quality products at low prices, the agency problem (Jensen and Meckling, 1976) may divert them from this goal. As cooperatives grow large, internal democracy may vanish and managers may pursue empire-building or perquisite consumption. In this case, consumer welfare is put aside in favor of profit, and the cooperative may become "degenerate" as feared by the early leaders of the cooperative movement (e.g., Webb-Potter, 1891; Webb and Webb, 1914).

In this article, we provide an empirical framework to test whether the pricing conduct of consumer cooperatives differs from the conduct of for-profit firms, analyzing as a case study the Italian supermarket industry. The latter provides an ideal setup for our approach: firms tend to have market power in local markets, and Coop, the largest firm, is a consumer cooperative.[1] Coop enjoys tax exemptions and other advantages, but descriptive evidence shows that when Coop is the only firm to operate large stores in a market, its prices are higher than when it is facing competitors—similar to when a for-profit firm has market power.

However, giving a convincing answer to our research question requires us to go beyond contrasting the correlation between prices and market concentration for cooperatives and for-profit firms.[2] This empirical strategy shares the problems of the Structure-Conduct-Performance paradigm (Bresnahan, 1989; Schmalensee, 1989), recently reexamined by Berry, Gaynor, and Scott Morton (2019). As they point out, measuring market power from concentration measures can be misleading.

Instead, we first measure market power using a demand model in which consumers choose where to buy groceries. The model, which we estimate using data on supermarket-level revenue shares and prices, yields a measure of demand elasticities, thus quantifying market power. Second, we model price competition in the industry. Whereas we assume for-profit supermarket chains to be profit-maximizing, Coop sets prices according to its preferences

[1] Coop Italia is an association of consumer cooperatives, all adopting the same brand and acting under a common strategic direction. In Section 3 we explain why we consider Coop as a single entity in this article.

[2] This is the empirical strategy roughly corresponds, for instance, to the one adopted in early studies on the conduct of nonprofit hospitals (Lynk, 1995; Dranove and Ludwick, 1999).

for profits and consumer welfare. Within the model, we formalize different hypotheses on Coop's conduct, which have distinct implications for the correlation between prices and markups. If Coop is profit-maximizing, then prices change with market-level competitive conditions, as markups vary with demand elasticity. If instead Coop gives more weight to consumer welfare, then prices should be less responsive to competitive conditions.

We test models of Coop's conduct using excluded instruments that generate different variation in markups for each candidate model (Bresnahan, 1982; Berry and Haile, 2014). One source of exogenous variation across markets is Coop's historical political connections, which have a significant impact on market structure in this industry by both reducing entry costs for Coop and increasing entry costs for rivals (Magnolfi and Roncoroni, 2016). Other sources are the degree of isolation of Coop's characteristics in the product space, specifically the number of competitors with similar store formats (Gandhi and Houde, 2020), and consumers' political preferences, which affect markups due to their correlation with preferences for supermarkets. To implement the test, we use the procedure in Rivers and Vuong (2002) (RV). One key advantage of this procedure is its robustness to the main weakness of our structural approach: the potential misspecification of demand or cost. In fact, the RV test allows researchers to conclude in favor of the true model as long as the misspecification is not too severe (Duarte, Magnolfi, Sølvsten, and Sullivan, 2023).

Our test results strongly suggest that Coop sets prices in a profit-maximizing fashion, as we reject several models of partial profit maximization and internalization of consumer welfare. Beyond the formal results of the test for conduct, we discuss and discard other explanations for Coop's conduct.

The model also allows us to quantify the change in prices and in consumer welfare that could be obtained if Coop's preferences were reoriented (possibly by regulating Coop's internal agency conflict) to benefit consumers. We find sizable effects of this counterfactual policy: if Coop were to pursue the maximization of consumer welfare, average supermarket prices would be about 3.2% lower and consumer welfare would increase by €2.25 billion. Even less extreme models of partial profit maximization generate significant welfare benefits, which are comparable to Coop's tax and regulatory benefits. If Coop were to give consumer welfare 26% of the weight it gives to profits, the corresponding gain in consumer welfare would match our back-of-the-envelope valuation of the benefits it receives.

Considerable attention has been devoted to the policy-relevant question of whether non-profit companies exploit market power (e.g., Philipson and Posner, 2009), especially in the US healthcare sector. An extensive literature finds that non-profit hospitals behave similarly to their for-profit competitors (see among others Dranove and Ludwick, 1999; Sloan, 2000; Keeler, Melnick, and Zwanziger, 1999; Duggan, 2002; Capps, Carlton, and David, 2020). In contrast, Dafny (2019) finds significant increases in premiums when a non-profit health insurer becomes for-profit. The debate on the relationship between ownership structure and conduct in healthcare highlights the fact that non-profit conduct is essentially an empirical question.

Our work is also related to several studies that investigate empirically firms' conduct. Whereas we examine consumer cooperatives, the existing literature (Craig and Pencavel, 1992; Delbono and Reggiani, 2013; Caselli, Costa, and Delbono, 2022) finds that worker cooperatives (labor-managed firms) are less likely to adjust employment and more likely to adjust wages in response to shocks. Beyond cooperatives, there is evidence that firms' objectives may go beyond profit maximization: Scott Morton and Podolny (2002) show that California winery owners value their utility from producing quality wines, Garcia-del Barrio and Szymanski (2009) show that European soccer teams maximize wins instead of profits, and Fioretti (2022) shows that firms can display altruistic conduct. We contribute to this literature by discussing instead a case where a firm deviates from its original objective and behaves like its for-profit competitors.

From a methods perspective, this article is related to studies on the identification of firm conduct from market-level data, pioneered by Bresnahan (1982) and Lau (1982). More recently, Berry and Haile (2014) show that, in a nonparametric oligopoly model, there can be testable restrictions on firm conduct based on shifters of market conditions that are excluded from marginal costs.[3] To implement the insight in Berry and Haile (2014) and test the conduct of cooperatives using instruments, we rely on the methods in Duarte et al. (2023). They show that the main drawback of the RV test, the potential degeneracy of the test statistic, is in essence a weak instrument problem and provide a diagnostic to evaluate the quality of the inference produced by the RV test. In our setting, the instruments are strong for testing, which makes inference reliable.

The article proceeds as follows. In Section 2 we develop hypotheses on the conduct of consumer cooperatives and outline our testing strategy. In Section 3 we describe the institutional background, present the data, and show descriptive evidence on Coop pricing and market power. In Section 4 we write a model of supply and demand in the supermarket industry to formalize hypotheses on the conduct of Coop and measure its market power. In Section 5 we discuss our empirical strategy to test Coop's conduct. Section 6 presents results, Section 7 discusses alternative theories of Coop conduct, and Section 8 describes economic and policy implications. Section 9 concludes.

[3] Recent articles that investigate conduct include Ciliberto and Williams (2014), Miller and Weinberg (2017), Michel, Paz y Miño, and Weiergraeber (2023), and Backus, Conlon, and Sinkinson (2021).

2 Consumer Cooperatives: Conduct and Testing Approach

Consumer cooperatives are meant to limit the exercise of market power (Hansmann, 1987, 2000).[4] The cooperative form, however, comes at a cost: investors cannot be the owners of the firm, which makes it harder to raise capital and leaves cooperatives more dependent on self-financing. This, in turn, has governance implications, as management is not subject to the discipline from the market for corporate control, nor from monitoring by block-holders.[5] Hence, the usual agency problem that arises from the separation between ownership and control (Jensen and Meckling, 1976) is exacerbated for large consumer cooperatives.

Following Enke (1945), we encode consumer cooperatives' objectives and implied conduct into three hypotheses which we will seek to test in the rest of the article:

1 *Maximization of consumer welfare*—prices are kept as low as possible, with the constraint of not generating losses.

2 *Maximization of a combination of profits and consumer welfare*—given the difficulty of raising external capital (Rey and Tirole, 2007), cooperatives may need to generate and retain some profits even if their decisions are oriented towards welfare maximization.

3 *Profit Maximization*—managers pursue expansion or perquisite consumption.

These hypotheses encompass a large range of non-profit pricing models used in the literature. For example, we show in Section 7 that they can capture models where firms maximize consumer welfare under a minimum profit condition, as in Ramsey pricing. The focus on these three hypotheses is also practical as each has different implications on the observable prices and quantities.

In this article, we seek to empirically evaluate these hypotheses. To give an intuitive explanation of our testing strategy, take the example of a single-product cooperative with constant marginal cost mc that chooses a price p to maximize a linear combination of consumer surplus and profits:

$$\max_p \{q(p)(p - mc) + (1 - \lambda)CS(p)\},$$

where $q(p)$ and $CS(p)$ indicate the residual demand for the cooperative's product and the market-level consumer surplus given competitors' prices, respectively. The parameter λ represents the degree of internalization of consumer surplus. Each hypothesis can thus be

[4] As an illustration, consider general stores in rural towns in the 19th century US (Hansmann, 2013). These stores sold groceries and necessities and were either monopolies or had substantial market power. To avoid monopolistic pricing, these stores were often organized as cooperatives owned by local customers.

[5] Theoretical work on governance issues in cooperatives and not-for-profits includes Kremer (1997), Hart and Moore (1998) and Rey, Tirole et al. (2000).

translated into a different value of λ. For example, when $\lambda = 1$, the cooperative maximizes profit; for $\lambda = 0$, the cooperative gives equal weight to consumer surplus and profits.[6]

Prices in the data are generated by the first-order conditions for the cooperative's problem. These imply that prices reflect marginal costs and markups as follows:

$$p = mc + \underbrace{\left[\frac{q(p)}{-\partial q(p)/\partial p} + (1-\lambda)\frac{\partial CS(p)/\partial p}{-\partial q(p)/\partial p}\right]}_{\Delta(\lambda)}$$

For a cooperative firm, the markup $\Delta(\lambda)$ depends not only on the demand elasticity but also on how much it internalizes consumer surplus. Because mc is not observed, we cannot evaluate different hypotheses about λ based on the price level. Assuming that we observe prices across different markets, all generated by a value λ_0 unknown to the researcher, we can instead leverage the implications that different values of λ have on the covariation between prices and exogenous changes in market power. For instance, suppose that the demand system is such that $\partial CS(p)/\partial p = -q(p)$, so that $\Delta(\lambda) = \lambda \frac{q(p)}{-\partial q(p)/\partial p}$, and that we can observe the cooperative firm across different markets where mc is kept constant but the residual demand elasticity varies, e.g., because the cooperative faces different sets of competitors.[7] It is easy to see that now the value of λ determines the amount of covariation between prices and the (inverse) elasticity of residual demand: $\lambda = 0$ makes prices insensitive to changes in market power, whereas larger values of λ generate some correlation. Our testing strategy relies on contrasting the fit of each hypothesis based on the difference between its implied covariance and the observed covariance between prices and exogenous shifters of market power in the data.

Although this is a simplified exposition of our strategy, note two fundamental elements. First, the test does not rely on assumptions about the conduct of other firms. This is because different hypotheses of cooperative conduct have the same implications irrespective of how the prices of its competitors are generated. Second, our approach takes the market structure as given and focuses on cooperative pricing decisions. That is, we capture whether the cooperative exploits the market power that it has given its stores' locations, as opposed to understanding whether non-profit entry decisions are aimed at accruing more market power. We believe that this approach is well suited to our empirical environment, and we discuss it in more detail in Section 4.

[6] Allowing consumer surplus to have more weight than profits would result in prices below marginal cost for our specification.

[7] The assumption on the derivative of the consumer surplus with respect to price simplifies the example but is not key for our testing strategy. The demand system used in our empirical application and described in Section 4 satisfies this property.

3 Cooperatives in the Italian Supermarket Industry: Background and Data

The Italian Supermarket Industry

Italian consumers spend approximately \$ 130 billion on groceries per year, and more than half of these sales occur in supermarkets, with traditional retail accounting for the rest. Supermarket chains operate stores of different formats, from convenience stores to large hypermarkets. Most grocery shopping is local. Consumers rarely drive more than 15 minutes by car, and marketing research indicates that supermarkets derive most of their sales from customers who either live in a 2 km (1.24 miles) radius or find the store along their daily commute route.

The main industry players include Coop—a network of consumer cooperatives— and for-profit supermarket chains.[8] There is considerable variation in store format and size across chains, as shown in Table 1. The median store size grows steadily over time, reflecting the adoption of larger store formats, but with broad differences. Some chains either exclusively focus on large formats (e.g., Bennet) or gradually increase the dimensions of their median store (e.g., Esselunga). Other firms, including Coop, Selex, Auchan, and Carrefour, operate a diverse network of stores. There is also a significant geographical differentiation between chains: whereas Coop and Conad are present in all major regions of Central and Northern Italy, most of their competitors have a more geographically concentrated footprint.

In this industry, pricing and assortment decisions are taken at different organizational levels (AGCM, 2013). National advertising campaigns and private label strategy (product development and pricing) are centralized at the national level. Assortment decisions are also centralized, especially for those products that exhibit stable demand across geographic markets. Prices have a chain-level component (e.g., for private label products or national promotions) as well as zone-level and store-level components. Overall, Coop derives 45-70% of its sales from products sold at uniform prices in all of its stores (AGCM, 2013). Although uniform pricing by retail chains is prevalent in the US (DellaVigna and Gentzkow, 2019; Hitsch, Hortaçsu, and Lin, 2019) and the UK (Thomassen, Smith, Seiler, and Schiraldi, 2017), Italy is similar to France, where supermarket prices co-vary with local competitive conditions (Allain, Chambolle, Turolla, and Villas-Boas, 2017).[9]

Another aspect of this industry that is relevant to our study is the prevalence of group purchasing organizations (GPO). GPO are associations of supermarket chains formed to

[8]Conad is a retailers cooperative that allows member supermarket chains to centralize marketing and private label operations. Thus, Conad is run in the interest of its members and there is little question about its conduct.

[9]We show more evidence for this claim using our price data below.

Table 1: Store Size and Number of Stores

	Median Store Size (m^2)			Number of Stores		
	2000	2007	2013	2000	2007	2013
Coop	840	1,000	1,027	600	726	860
Esselunga	1,682	2,699	2,900	99	122	129
Conad	600	650	727	622	636	822
Selex	769	900	1,000	386	594	730
Auchan	956	838	830	233	382	418
Carrefour	818	898	1,012	316	422	334
Bennet	4,500	5,094	5,502	21	58	66
Despar	700	708	800	187	325	348
Agorà	660	773	871	70	182	194
Pam	1,225	1,046	1,108	120	193	178
Finiper	6,500	800	834	5	125	150

We report, for all major supermarket chains, the median store size (in m^2) and the total number of stores in Central and Northern Italy for three years. Source: IRI.

collectively purchase goods and obtain better terms from manufacturers. Italian supermarket chains purchase most of the goods they sell through a GPO, which negotiates yearly contracts with manufacturers. These contracts specify wholesale prices, rebates, and promotional activities, creating a fairly similar cost structure between chains that are members of the same GPO. In our empirical exercise, we use data on chains' GPO membership to control for marginal cost shifters affecting firms' pricing decisions.[10]

Italian Grocery Retail Cooperatives: Coop Italia

More than a hundred consumer cooperatives operate in the Italian supermarket industry. These firms are mostly based in the Central and Northern regions and vary in size from small cooperatives operating with a single grocery store to large chains with hundreds of stores. Each of these cooperatives is a distinct legal entity, but all operate under close strategic coordination. The coordination happens through two organizations: Ancc-Coop — the governing body of consumer cooperatives—and Coop Italia —an association responsible for contracting with manufacturers, marketing, and developing private label strategies.[11]

All cooperatives affiliated with Coop Italia use the same Coop brand for their stores (possibly with small modifications by store format, e.g., "IperCoop" for superstores). Although there is no explicit agreement assigning geographical zones to each cooperative in the Coop system, these cooperatives never compete in the same market.[12] Given the close

[10]See Appendix A for more discussion of GPO.

[11]Although cooperatives in the Coop network have expanded their operations beyond grocery retail, these activities are marginal except for financial services, which we discuss further in Section 8.

[12]We define markets in this article as local labor market areas; see below for more discussion.

links between cooperatives and the coordination role of Coop Italia, we consider them as one economic agent and refer to them as Coop in what follows.

The corporate charters of cooperatives in the Coop system state that their primary objective is to promote consumer welfare through low prices for members and nonmembers.[13] Coop has more than 8 million members, who join the cooperative by paying a small fee (less than $30). This fee represents the capital invested by the member and is returned upon exit. Although cooperatives may return profits to their members, none of the cooperatives we consider do so during the period of our study.[14] Governance is based on principles of internal democracy, and members elect the board of directors with a "one person, one vote" system. However, turnout at members' meetings is low (typically below 1% of the total membership), and most cooperatives have rules that restrict the ability of members to present their board candidates to challenge incumbents. These governance provisions result in weak powers for members and entrenched managers who enjoy long job tenures.

Under Italian law, cooperatives receive substantial tax exemptions and other regulatory benefits such as the ability to receive deposits from members, essentially acting as a bank. Preferential treatment is motivated by the nature of cooperatives, which are supposed to pursue social objectives. If Coop's conduct is similar to that of its competitors, this rationale is undermined, and any tax benefit it receives is state aid. This issue led to an investigation by the European Commission.[15]

Other allegations of distortions of competition are linked to Coop's political connections. The cooperative movement in Italy has longstanding links to political parties.[16] Coop's ties to politics may have two distinct effects: creating a link between consumers' political and shopping preferences, and connections between Coop and local politicians.[17] These political connections may persist over time, and because local Italian politicians have discretionary power to regulate the entry of supermarkets, they may have an impact on market structure.[18]

The institutional details that we highlight thus far suggest that Coop's pricing strategy is not easy to determine ex-ante. Due to the large footprint of Coop and the regulatory benefits it enjoys, agency problems between Coop's managers and consumers are not only

[13] As an example, the charter of the largest cooperative in the Coop system (Coop Alleanza 3.0) states (authors' translation): "[we pledge to] ... serve the social purpose of protecting family budgets for members and nonmembers, providing high-quality goods and services at the best possible prices ..."

[14] Coop benefits its members through members-only promotions. We discuss these in Section 7.

[15] See Case E1/2008 in the State Aid Register at the DG Competition. We describe Coop's regulatory benefits in detail in Section 8.

[16] See for instance Ammirato (1994) on the dominant role that the communist faction has played in the League of Cooperatives — the umbrella organization to which Coop is affiliated — since its 1947 congress.

[17] A large share of Coop's board members are politicians. Further discussion on the measurement of Coop's political connections is in Appendix A.

[18] Magnolfi and Roncoroni (2016) find that the political connections of Coop affect entry, and may result in consumer welfare losses where connections represent a barrier to the entry of Coop's competitors.

possible but could also have large welfare implications.

Data Description

This article combines information from four main sources. First, we use administrative data from the Italian Statistical Agency (ISTAT) to define geographic grocery markets and obtain market-level population information. Second, we combine data on household expenditure from the Bank of Italy and municipality-level data on income from the Italian Ministry of the Economy to construct market-level grocery expenditures and income distributions. Third, we obtain data on annual revenue and characteristics for the universe of stores in Central and Northern Italy from Information Resources Inc. (IRI), a marketing research firm. Finally, we obtain price data from Altroconsumo, a consumer association. We discuss these sources in turn.

Market definition Because no administrative unit adequately defines geographic markets in this industry, we start with local labor market areas as defined by ISTAT based on commute patterns, which is a good starting point for defining areas where consumers are more likely to buy spatially differentiated goods (Houde, 2012; Pavan, Pozzi, and Rovigatti, 2020). This choice is supported by evidence from micro-data on grocery shopping in Italy (Guidotti, Coscia, Pedreschi, and Pennacchioli, 2015), which indicates that many consumers shop after work. We split commuting areas too large to reflect shopping patterns; these contain two or more cities that: (i) have at least 15,000 inhabitants, and (ii) are a 20-minute (or longer) drive apart. We also merge connected labor market areas that individually are too small to be a grocery market.[19] Finally, we exclude southern Italy due to the different structure of the industry there and the smaller footprint of Coop – as Coop enjoys limited market power in those markets, the implications of different models of conduct will be muted. The final sample contains 476 grocery markets or 3,143 market-year observations.

Market-level Data To obtain income distribution and total grocery expenditure in each market, we combine two data sources. From the Bank of Italy's household panel survey, we observe income and grocery expenditure for roughly eight thousand households across the country. However, the only geographic indicator in these data is at the region level, an administrative unit larger than our market definition. Therefore, for each region and year, we fit a log-normal distribution to the income data and use information on average income at the municipality level from the Ministry of Economy and Finance to adjust the

[19] These have less than 30,000 inhabitants, are smaller than 100 square kilometers (38.6 square miles), and have higher elevation (2,624 feet) — in mountain areas, consumers might find it costly to travel far.

mean and construct a market-level income distribution, F_m.[20] From the grocery expenditure information, we compute regional average grocery expenditure per income quartile, $\alpha_{q,r}$; we combine it with census data on the number of households, NH_m, and with F_m to obtain the market-level total expenditure E_m as follows:

$$\mathrm{E}_m = NH_m \left(\frac{\sum_{q=1,..,4}}{4} \int_y \alpha_{q,r} 1 \left\{ y \text{ } in \text{ } quartile \text{ } q \right\} dF_m \left(y \right) \right). \tag{1}$$

Store-level Data We obtain from IRI information on the universe of stores for seven years: 2000, 2003, 2005, 2007, 2009, 2011, and 2013.[21] For each store, we observe the geographic location, the retail chain that operates it, the floor space, and the share of sales for all stores in the sample.[22] However, revenue shares as reported by IRI do not consider the outside option: buying groceries in traditional shops, open-air markets, or discount retail stores. We transform these shares into store-level sales figures by multiplying the sum of shares of a particular retail chain by its aggregate revenue information taken from accounting data.[23] The final store-level revenue share is obtained by dividing the store sales by our measure of total grocery expenditure in a market, E_m. The IRI store-level data are complemented with hand-collected information on whether stores are in a mall.

Data on store-level prices come from Altroconsumo, an independent consumers' association. The data consists of a price index representing the cost of a basket of grocery goods that is available for a sample of stores in more than 50 cities in Central and Northern Italy. The stores are chosen to represent all major firms and to cover different store formats. Every year, Altroconsumo assembles a basket of roughly 100 product categories, including both fresh products and packaged goods, chosen to match ISTAT's report on national consumption. For each category, they collect the prices of one or more "leading brands" products. These prices are aggregated into an index using the same weights that ISTAT uses to compute CPI statistics.[24] We use the information contained in Altroconsumo's reports to transform these indices into the cost of a weekly shopping trip in euros. We discuss the Altroconsumo pricing database in further detail in Appendix A.

The Altroconsumo sample covers about 7.1% of store-year observations for the universe

[20] For a full description of the construction of this element of the dataset, see Appendix A

[21] Our data do not include discount stores, which typically offer only private-label goods and carry a limited selection of items.

[22] IRI does not share the exact methodology it uses to compute these shares. We understand that these are estimates similar to those in the widely used Trade Dimensions data on US supermarkets, combining point-of-sale information from a large set of stores with consumer surveys and other internal information provided by retailers.

[23] Additional details on this procedure are in Appendix A

[24] The basket is constant across all stores; weights change across years according to how ISTAT adjusts the basket used to compute CPI. Given the nature of the products in the index, mostly basic food items, changes in weight across years are limited.

of supermarkets in Italy across the years in our sample. Price data are available for 10% of the markets, and the covered markets tend to be larger than average, although there is still significant variation in market size. Within markets with Altroconsumo data, 19% of all store-year observations and 25% of Coop's store-year observations have price data available. The stores covered by Altroconsumo account for 33% of the revenues in their markets and are, on average, larger than other stores. It is important for our investigation that, conditional on store characteristics, Altroconsumo's choice of stores is unrelated to shocks in consumers' preferences that the researcher does not observe. By matching with the IRI dataset, we notice that for characteristics other than store size, the composition of stores and markets from Altroconsumo's sample is similar to the overall population of stores. Conditional on store size, we assume that selection into the Altroconsumo sample is random. We provide further information about sample selection in Appendix A.

Table 2 reports summary statistics for the market- and store-level data: there is substantial (mostly cross-sectional) variation in all of these variables, including consumer income and choice sets (number of stores and number of retail chains), which we will use to understand Coop's pricing behavior. We also observe variation in price levels across stores: although most of the price variation is due to year-chain and market-chain variation, there is significant residual variation in prices within year-market-chain. The results of a variance decomposition exercise (shown in Appendix A) thus confirm industry reports about store managers making some pricing decisions.

Table 2: Summary Statistics

	Mean	SD	Max	Median	Min
Market-level data (476 markets, 3,143 obs)					
Number of Households - 1,000	36.1	93.1	1,215.8	18	1.7
Household Average Income - €1,000	39.4	7.3	67	39.2	16.1
Household Average Grocery Expenditure - €1,000	5.6	0.4	6.5	5.6	3.9
Total Grocery Expenditure - mln €	208.5	578.1	8,273.4	97	6.6
Market surface - km^2	370	288	2,243.5	300.2	25.2
Number of stores	11.9	25.6	422	6	1
Number of retail chains	4.7	3.1	19	4	1
Store-level data (5,339 stores, 37,374 obs)					
Price - € *(2,672 obs)*	121.77	6.28	141.32	121.81	95.83
Revenue - mln €	8.49	11.88	166.09	4.74	0.55
Grocery Expenditure Share	0.04	0.06	0.5	0.02	0
Store Size - 1,000 m^2	1.24	1.33	10	0.8	0.4
Inside Mall indicator	0.01	0.11	1	0	0

We report market- and store-level summary statistics. Figures in euros are converted to 2013 values using the ISTAT CPI. See Appendix A for more details on data construction.

Preliminary Evidence on Coop's Pricing Behavior and Market Power

Coop prices are slightly below average in our sample: in column 1 in Table 3 we use store-level data to show that Coop prices are 1.8% below competitors.[25] The chain-level simple average, however, misses out on store-level characteristics that may generate systematic differences in costs across chains. To address this issue, in column 2, we show the results of a store-level regression of log-prices on a Coop indicator, controlling for a vector of store- and market-level characteristics $\boldsymbol{x}_{jmt}$, and year and market fixed effects ψ_t and ψ_m. Our specification is:

$$\log p_{jmt} = \beta_c + \beta_1 1\left\{\text{Coop}\right\}_{jmt} + \boldsymbol{x}'_{jmt}\boldsymbol{\beta}_x + \psi_m + \psi_t + \epsilon_{jmt}. \tag{2}$$

After controlling for other price determinants, Coop's stores have prices that are, on average, 0.85% lower than all other chains.

Table 3: Coop Pricing Behavior and Monopoly Markets

	$\log p$		
	(1)	(2)	(3)
Coop — β_1	−0.0180 (0.0028)	−0.0085 (0.0019)	
Monopoly Market — β_2			0.0124 (0.0032)
Coop Monopoly Market — β_3			−0.0037 (0.0039)
Controls	No	Yes	Yes
Year FE	No	Yes	Yes
Group×Size FE	No	No	Yes
Market FE	No	Yes	No
Monopoly Markets			66

This table displays OLS estimates for log prices on a Coop dummy in column 1 and for Equations (2) and (3) in columns 2 and 3, respectively. Controls include store size, presence inside a mall, and average market-level income. Robust standard errors are in parenthesis. $n = 2,672$.

Even so, it is not immediate to relate this evidence to our research question. The regression, although including controls for store characteristics and market-level fixed effects, does not account for the variation in competitive conditions faced by Coop. To determine Coop's conduct, we need instead to understand how Coop's prices co-vary with its market power.

As a first exploration of the relationship between Coop's market power and pricing, we focus on monopoly markets. A very small fraction of our markets are actual monopolies. However, given cost structure and consumer preferences, larger stores (those with a surface of at least 2,500 square meters—around 27,000 square feet) that do not face same-format competitors are most likely to affect market power. These stores correspond to modern

[25] Although some chains consistently price lower than Coop by a substantial amount (e.g., Esselunga).

formats that consumers favor, which can greatly reduce the substitution to smaller stores. Hence, we construct an indicator variable for stores located in a market where a single firm operates stores with a floor space of 2,500 square meters or more.

We run store-level regressions of log price on the monopoly indicator variable and on an indicator of whether—in a monopoly market—Coop is the firm with the only large store(s) in the market. We add store size fixed effects, market-level average income, and year-, chain-, and region-level fixed effects. Our specification is:

$$\begin{aligned} \log p_{jmt} = \beta_c + \beta_2 1\left\{\text{Monopoly}\right\}_{jmt} + \beta_3 1\left\{\text{Coop Monopoly}\right\}_{jmt} \\ + \boldsymbol{x}'_{jmt}\boldsymbol{\beta}_x + \psi_j + \psi_t + \epsilon_{jmt}. \end{aligned} \tag{3}$$

We report coefficient estimates for this specification in column 3 of Table 3. Unsurprisingly, stores in monopoly markets have average prices that are around 1% higher than comparable stores in non-monopoly markets. However, stores in markets where Coop is the monopolist do not have systematically different prices: the coefficient on the Coop Monopoly variable is economically small and not statistically significant.

In sum, there is little evidence that the Coop is associated with a weaker correlation between monopoly power and pricing. However, the results presented so far are descriptive. In particular, we emphasize two limitations: measurement of market power and identification. Although intuitively appealing, monopoly is a crude indicator of market power. In addition, the monopoly indicator is jointly determined with other outcomes. We address these limitations in the next sections by building a structural model of the Italian grocery market and relying on exogenous variation to distinguish models of conduct.

4 Model

To measure market power, we construct an empirical model of consumer demand for a basket of grocery goods. We then formalize and test hypotheses on Coop's conduct. The model endogenizes short-term decisions about consumers' supermarket choices and firms' prices. The long-term decision to open a store is beyond the scope of this article, so we take the set of stores operating in a market as exogenous.

Demand

In each geographic market m and for each year t, consumer $i \in \mathcal{I}(m,t)$ chooses a store $j \in \mathcal{J}(m,t) \cup \{0\}$ to buy a continuous quantity of bundles of grocery goods. We denote by $j = 0$ the outside option, which refers to shopping in traditional retail stores, discount supermarkets, and open-air markets. To simplify the notation, we omit the subscripts m, t

in what follows. Each store j sells a basket of groceries at price p_j. We use bold letters for vectors so that $\boldsymbol{p}$ is the vector of prices. Consumer choice generates an aggregate demand system where $q_j(\boldsymbol{p})$ represents units of grocery baskets sold in the store j at prices $\boldsymbol{p}$. As in previous studies of the supermarket industry (e.g., Smith, 2004), we assume that $q_j(\boldsymbol{p})$ arises from a discrete-continuous choice, i.e. consumers first decide where to buy and then how many units of groceries to buy. We discuss this assumption and other departures from standard discrete choice models at the end of the section.

The utility that consumer i derives from purchasing q_{ij} units of groceries in the store j takes a quasi-linear form:

$$u_{ij}\left(q_{ij}, \vartheta_i\right) = \ln\left(q_{ij}\varphi_{ij}\right) + \frac{\vartheta_i}{\alpha_i} + \varepsilon_{ij},$$

where φ_{ij} is a parameter that models the perceived quality of store j by consumer i , ϑ_i are units of a composite good, and α_i determines the relative utility of groceries and composite good. The random utility shock ε_{ij} is iid according to the Generalized T1EV distribution with a scale parameter $1/\sigma$, which measures the relative importance of the random shock over the deterministic part of the utility. Conditional on choosing to shop at store j, consumer i chooses optimally q_{ij} and ϑ_i according to:

$$\max_{q_{ij}, \vartheta_i} u_{ij}\left(q_{ij}, \vartheta_i\right) \qquad s.t. \qquad p_j q_{ij} + \vartheta_i = y_i.$$

Because of quasi-linearity and the log-form of utility, consumers expend a fixed amount of money on groceries, or $p_j q_{ij} = \alpha_i$, regardless of the quality of the stores in their choice set and of their income.

Given her grocery expenditure α_i, consumer i chooses a store based on its indirect utility:

$$v_{ij} = \sigma u_{ij}\left(\frac{\alpha_i}{p_j}, y_i - \alpha_i\right) = \sigma\ln(\varphi_{ij}) - \sigma\ln(p_j) + \kappa_i + \sigma\varepsilon_{ij},$$

where $\sigma\varepsilon_{ij}$ is the standard T1EV iid shock, and $\kappa_i \equiv \sigma(\ln(\alpha_i) + y_i/\alpha_i - 1)$ collects $i-$specific terms that will later drop out from the store-choice solution. The quality-price index of the outside option, which represents grocery stores and discount supermarkets, is normalized to zero ($\frac{\varphi_{i0}}{p_0} = 1$), and we parametrize all other φ_{ij} so that $\sigma\ln(\varphi_{ij}) = \boldsymbol{x}_j'\boldsymbol{\beta} + \boldsymbol{\mu}_{ij}'\boldsymbol{\eta} + \xi_j$, where $\boldsymbol{x}_j$, $\boldsymbol{\mu}_{ij}$ and ξ_j are, respectively, observed store characteristics, interactions between store and consumer characteristics, and a scalar unobserved store characteristic as in Berry (1994); $\boldsymbol{\beta}$ and $\boldsymbol{\eta}$ are parameters.

Due to the distributional assumption on the error term, the probability that consumer i

shops in store j is:

$$P_{ij} = \frac{e^{\delta_j + \boldsymbol{\mu}'_{ij}\boldsymbol{\eta}}}{1 + \sum_{k \in \mathcal{J}} e^{\delta_k + \boldsymbol{\mu}'_{ik}\boldsymbol{\eta}}}. \tag{4}$$

In our empirical model, we specify the terms δ_j and $\boldsymbol{\mu}'_{ij}\boldsymbol{\eta}$ as:[26]

$$\delta_j = \beta_0 + \text{Size}_j \beta_1 + \text{InMall}_j \beta_2 - \sigma \ln p_j + \psi_j + \xi_j, \quad \boldsymbol{\mu}'_{ij}\boldsymbol{\eta} = \ln(y_i)\eta_y + 1\left\{\text{Coop}\right\}_j 1\left\{\text{Left}\right\}_i \eta_l.$$

Observable store characteristics include store size and an indicator for stores located inside a shopping center. Fixed effects, ψ_j, include common taste shocks for the chain-store format, market, and year. The store-level unobservable ξ_j represents local demand shocks and the attractiveness of a store's location. Income shifts the value of the outside option as high-income consumers may prefer to shop at traditional grocery stores. Moreover, consumers who vote center-left parties may have a stronger preference for Coop due to the cooperative's historical links to progressive political parties.[27]

Finally, the share of grocery expenditure for store j implied by the model is:

$$b_j = \frac{\int_{i \in \mathcal{I}} \alpha_i P_{ij} \phi_i \, \mathrm{d}i}{\mathrm{E}},$$

where E is the total grocery expenditure as defined in equation (1) and ϕ is the probability density function of the distribution of individuals in the market. In equilibrium, expected expenditure shares correspond to observed store revenue shares. Although our model has implications for expenditure, as opposed to quantity share, the underlying foundations are similar to standard discrete choice models (Berry, Levinsohn, and Pakes, 1995), as reflected by the expression for choice probabilities in equation (4). Because the expenditure shares are a linear transformation of the choice probabilities in our model, the argument in Berry (1994) still holds, and the expenditure shares b_j are invertible in $\boldsymbol{\delta}$.

Discussion of the Demand Model Similar to recent work by Bjoernerstedt and Verboven (2016) and Eizenberg, Lach, and Oren-Yiftach (2021), our demand system is estimated from revenue share data and has a specification where prices enter in logs. We discuss here three (intertwined) properties that distinguish the demand system: the discrete-continuous

[26] Notice that σ, the scale of unobserved preferences for stores, is the price coefficient in our specification. Intuitively, the larger the scale of unobserved preference shocks, the lower the consumers' response to price differences across stores.

[27] We draw the variable $1\left\{\text{Dem}\right\}_i$ from the market-level distribution of voters in political elections, and let $1\left\{\text{Dem}\right\}_i = 1$ if we draw a voter from the center-left coalition. Due to a lack of information on the joint distribution of y_i and $1\left\{\text{Dem}\right\}_i$, the draws of political preferences are independent of the income draws.

choice micro foundation, the quasi-linear specification of utility, and how income heterogeneity affects choice.

We maintain that a discrete-continuous specification better fits our empirical context when compared to a unit demand assumption. However, because we do not have microdata on individual consumers' choices, we need to adopt strong functional form assumptions to discipline the continuous quantity choice in the model. We depart from Bjoernerstedt and Verboven (2016) and Eizenberg et al. (2021) by assuming a quasi-linear utility function, whereas they assume Cobb-Douglas utility.

Our assumptions of quasi-linearity and the logarithmic form of utility imply that, in our model, the income elasticity of grocery expenditure is zero, and the income elasticity of demand given the choice of a store is one. In contrast, Cobb-Douglas utility implies that grocery expenditure is a constant share of income. Neither of these assumptions aligns perfectly with the empirical evidence. Estimated income elasticities of grocery demand in Italy are below one, and the share of grocery expenditure tends to decrease as income rises (Balli and Tiezzi, 2010). To mitigate the effects of quasi-linearity, in the empirical implementation we introduce grocery expenditure heterogeneity by letting α_i vary across consumers. In particular, for a household i that lives in region r and whose income falls in the quartile q of the income distribution, we assign $\alpha_i = \alpha_{r,q}$, which is estimated from household survey data as explained in Section 3. Hence, although α_i is locally constant in income for the consumer i, as we draw different consumers across the income distribution, their expenditure will vary. This specification accommodates the empirical regularities of decreasing grocery expenditure share and positive income elasticity of grocery expenditure.

Our specification also prevents income from affecting price sensitivity, as income only affects consumers' preferences for the inside goods. This is convenient in our setting for two reasons. First, it allows us to derive a simple pricing rule for Coop that can be brought to data - see our discussion of supply below for more details. Second, this specification allows us to overcome a limitation of our data: as prices only enter consumers' utility through $\boldsymbol{\delta}$, we can estimate the model for all stores even if price data are missing for some stores, as we describe in more detail in Section 5.

Despite the compromises, the demand model we adopt delivers credible substitution patterns that depart from logit — we discuss these further in Section 6. In Appendix B we also present results for an alternative demand model, where we adopt a standard unit demand assumption and a random coefficient on price. This alternative model produces a conduct test result that is consistent with the main specification.

Supply

Firms' Objective Function Each firm f owns a set of stores $\mathcal{J}_f \subset \mathcal{J}(m,t)$. We assume that for each store j's marginal cost mc_j is constant in units sold (and further discuss this assumption below). We maintain the standard assumption that a for-profit firm f maximizes its total profit π_f:

$$\pi_f(\boldsymbol{p}) = \sum_{j\in\mathcal{J}_f} \left(p_j - mc_j\right) q_j(\boldsymbol{p}).$$

In contrast, Coop sets prices $\boldsymbol{p}_{Coop} = \left(p_j\right)_{j\in\mathcal{J}_{Coop}}$ evaluating both its profit and consumer welfare.[28] Welfare for a consumer i from prices $\boldsymbol{p} = \left(\boldsymbol{p}_{Coop}, \boldsymbol{p}_{-Coop}\right)$ is measured by the compensating variation for the change from an environment without Coop (or $\boldsymbol{p}^0_{Coop} = \infty$) to an environment with Coop and facing prices $\boldsymbol{p}$:

$$cv_i\left(\boldsymbol{p}_{Coop}, \boldsymbol{p}_{-Coop}; u_i\right) = e_i\left(\left(\boldsymbol{p}^0_{Coop}, \boldsymbol{p}^0_{-Coop}\right); u_i\right) - e_i\left(\left(\boldsymbol{p}_{Coop}, \boldsymbol{p}_{-Coop}\right); u_i\right),$$

where u_i is the utility of consumer i when $\boldsymbol{p}_{Coop} = \boldsymbol{p}^0_{Coop}$ and e_i is consumer i's expenditure function. The total compensating variation across consumers is then $cv(\boldsymbol{p};\boldsymbol{u}) = \int_i cv_i(\boldsymbol{p}; u_i)\,\mathrm{d}i$. Assuming that the cooperative weighs every consumer's welfare equally,[29] the market-level objective function of Coop is:

$$\Pi_{Coop}(\boldsymbol{p}) = F\left(\pi_{Coop}(\boldsymbol{p}), cv(\boldsymbol{p};\boldsymbol{u})\right),$$

where F aggregates the profit and welfare goals of the cooperative. We assume that F is differentiable, strictly increasing in its first argument ($F_1 > 0$) and non-decreasing in its second argument ($F_2 \geq 0$). This formulation of Coop's objectives fits the institutional background well, but we discuss alternative hypotheses on Coop's objectives in Section 7.

Supermarket Pricing We assume that prices $\boldsymbol{p}$ are a Nash equilibrium of the game where Coop maximizes Π_{Coop}, and every other firm f maximizes π_f, subject to no good (bundle of groceries) being sold below marginal cost, i.e. $p_j \geq mc_j$ for all $j \in \mathcal{J}$. The first order conditions for an unconstrained equilibrium[30] for any store $j \in \mathcal{J}_f$ are:

$$\sum_{h\in\mathcal{J}_f} \left(p_h - mc_h\right) \frac{\partial q_h(\boldsymbol{p})}{\partial p_j} = -q_j(\boldsymbol{p}) - \frac{F_2(\boldsymbol{p};\boldsymbol{u})}{F_1(\boldsymbol{p};\boldsymbol{u})}\left(\frac{\partial}{\partial p_j} cv(\boldsymbol{p};\boldsymbol{u})\right)\mathbf{1}_{Coop}(j), \tag{5}$$

[28] This is akin to a mixed oligopoly where private and state-owned firms compete (e.g., Merrill and Schneider, 1966; Beato and Mas-Colell, 1984; De Fraja and Delbono, 1989; Cremer, Marchand, and Thisse, 1991).

[29] Cooperatives may only consider members' welfare or may care about distributional effects. However, cooperatives in the Coop system state that their objective is to promote the welfare of all consumers.

[30] In line with standard practice in the empirical literature on multi-product firms oligopoly (e.g., Berry et al., 1995) we assume that an interior solution exists.

where $\mathbf{1}_{Coop}(j)$ is an indicator function for if a store is owned by Coop. Note that, as long as $F_1 \geq F_2$, the solution to the optimization problem implies that Coop prices are above marginal cost, but below the profit-maximizing level, as $-\frac{F_2(\boldsymbol{p};\boldsymbol{u})}{F_1(\boldsymbol{p};\boldsymbol{u})}\left(\frac{\partial}{\partial p_j}cv\left(\boldsymbol{p};\boldsymbol{u}\right)\right) \geq 0$.

We can further lean on the demand model to obtain sharper implications from Equation (5). By Shephard's lemma:

$$\frac{\partial}{\partial p_j}cv\left(\boldsymbol{p};\boldsymbol{u}\right) = \frac{\partial}{\partial p_j}\left(-e_i\left(\left(\boldsymbol{p}_{Coop},\boldsymbol{p}_{-Coop}\right);u_i\right)\right) = -q_j^H\left(\boldsymbol{p};\boldsymbol{u}\right),$$

where q_j^H denotes the compensated (Hicksian) demand function for good j. Because of the quasi-linearity of demand, compensated demand coincides with Marshallian demand. We also assume that $\frac{F_2(\boldsymbol{p};\boldsymbol{u})}{F_1(\boldsymbol{p};\boldsymbol{u})} = 1-\lambda$, where λ is a parameter in $[0,1]$, which is equivalent to specifying an empirically tractable linear form for F. [31] We can then rewrite Equation (5) for a Coop store case as:

$$\sum_{h\in\mathcal{J}_{Coop}}\left(p_h - mc_h\right)\frac{\partial q_h\left(\boldsymbol{p}\right)}{\partial p_j} = -\lambda q_j(\boldsymbol{p}).$$

The constraint $\lambda \geq 0$ implies that Coop does not price below marginal cost. Stacking the solution for each product and rewriting in terms of expenditure share we have:

$$\boldsymbol{p} = \left(\left[H \odot \Theta\left(\lambda\right)\right]^{-1}\boldsymbol{b}\right)\odot\left(\boldsymbol{p}\oslash\boldsymbol{b}\right) + \boldsymbol{mc}, \tag{6}$$

where H is the matrix of demand elasticities for all stores, the symbols $\odot$ and $\oslash$ denote element-by-element multiplication and division, and $\Theta\left(\lambda\right)$ is an internalization matrix (Michel et al., 2023). The element $\Theta_{(j,h)}$ of this matrix equals $\frac{1}{\lambda}$ if j,h are Coop stores, equals one if j,h are non-Coop stores operated by the same firm, and equals zero otherwise. The same pricing relationship in Equation (6), but with different parametrizations of the internalization matrix, has been used to investigate collusion facilitated by multi-market contact (Ciliberto and Williams, 2014), coordinated effects of horizontal mergers (Miller and Weinberg, 2017), post-merger integration (Michel et al., 2023) and competitive effects of common ownership (Backus et al., 2021). Whereas in all these cases the internalization matrix prescribes that firms may assign positive weight to the profits of their competitors, in our case the parametrization reflects the assumption that Coop, as a consumer cooperative, may give weight to consumer welfare, thus penalizing its profits.

[31] A similar formulation has been used, for instance, to model the preferences of water utility regulators (Timmins, 2002) and managed care organizations (Gowrisankaran, Nevo, and Town, 2015).

From (6) we can write a simple expression for prices in store j:

$$p_j = \begin{cases} \Delta_j^B + mc_j, & \text{if } j \notin \mathcal{J}_{Coop} \\ \lambda\Delta_j^B + mc_j & \text{if } j \in \mathcal{J}_{Coop}, \end{cases}$$

where $\boldsymbol{\Delta}^B = ([H \odot \widetilde{\Theta}]^{-1}\boldsymbol{b}) \odot (\boldsymbol{p} \oslash \boldsymbol{b})$ is the Bertrand markup, and $\widetilde{\Theta}$ is the standard ownership matrix. From this expression, we can easily formalize the hypotheses of Section 2. A model of conduct m is characterized by a markup vector $\boldsymbol{\Delta}^m$. For any model, the elements Δ_j^m corresponding to stores not operated by Coop are equal to the Bertrand markups Δ_j^B. Markups for Coop stores are equal to $\lambda\Delta_j^B$, where λ is model-specific. Welfare maximization, corresponding to model $m = 1$ and $\lambda = 0$, implies markups $\Delta_j^1 = 0$ for all Coop stores j. Maximization of a combination of profits and consumer welfare corresponds to model $m = 2$ and values of λ between zero and one. We specify, for concreteness, three such models: $m = 2.1$, $m = 2.2$ and $m = 2.3$ corresponding to $\lambda = 0.25, 0.5$ and 0.75, respectively, thus creating an equally spaced grid. Pure profit maximization corresponds to model $m = 3$ where $\lambda = 1$ and Coop sets Bertrand markups just like its for-profit competitors. These models have distinct implications for equilibrium prices and markups: starting from this intuition, we discuss in the next section how to test Coop's conduct.

Cost Function Our assumption that the marginal cost mc_j is constant in units sold is common in the empirical literature on grocery retail (e.g., Smith, 2004; Eizenberg et al., 2021). We also parametrize store-level marginal costs as a linear index of observable variables $\mathbf{w}_j$ and unobservables ω_j, or $mc_j = \mathbf{w}_j'\boldsymbol{\gamma} + \omega_j$.

We rely on institutional knowledge to specify $\mathbf{w}_j$. Marginal costs for supermarkets are the cost of goods, distribution, and (part of) labor. The cost of goods is fixed for each GPO. Distribution costs vary with store size and the market's population density. Labor costs vary regionally. Moreover, stores in malls may have additional costs. Thus, we include in $\mathbf{w}_j$ different cost shifters: store size, indicators for chain, region, urban markets, and stores in a mall. Unobservable cost determinants in ω_j include differences in delivery costs and managerial ability.

5 Identification and Estimation

We proceed sequentially by first estimating demand elasticities and implied Bertrand markups and then testing hypotheses on Coop's conduct. We discuss these steps in turn.

Demand

Identification We assume that the set of available stores in each market and their characteristics are exogenous to unobservable demand shocks so that $E\left[\xi_j|\boldsymbol{x}_j\right] = 0$. Under this assumption, the parameters $\boldsymbol{\beta}$ are identified by covariation in revenue shares and store characteristics. We rely on store-level variation in the price index for a basket of goods to measure consumers' sensitivity to price σ. To address the endogeneity of prices, we construct Hausman instruments leveraging the diffusion of group purchasing organizations (GPO), which create correlation in cost shocks across different stores. In particular, we use as instruments the prices of other stores in neighboring markets that belong to the same GPO. A standard concern when using Hausman instruments is that national advertising campaigns could create a correlation in demand shocks that invalidates the instrument; this is less concerning in our case because promotional activity occurs at the chain level, whereas instruments are constructed at the GPO level.

We also construct instruments using rival products' characteristics to measure supermarkets' degree of isolation in the product space (Berry et al., 1995). To implement the strategy, we compute for each store the number of rival stores in the same, smaller, and larger size categories, in the spirit of the differentiation instruments of Gandhi and Houde (2020). To identify the coefficient η_y of the interaction between income and utility from the outside option, we interact Hausman and differentiation instruments with the average market-level income. To identify the coefficient η_l of the preference of left-leaning voters for Coop, we interact the Hausman and differentiation instruments with the market-level proportion of left-leaning voters. We label the demand instruments (including $\boldsymbol{x}_j$) $\boldsymbol{z}_j^d$, and assume that $E[\xi_j|\boldsymbol{z}_j^d] = 0$.

Estimation The demand model is estimated with GMM as in Berry et al. (1995), and estimates are computed with an MPEC approach as in Dube', Fox, and Su (2012). Because the model implies for each tuple of $\boldsymbol{\delta}$ and demand parameters $\boldsymbol{\theta}^d = (\boldsymbol{\beta}, \sigma, \boldsymbol{\eta})$ a value

$$\xi_j\left(\boldsymbol{\delta}, \boldsymbol{\theta}^d\right) = \delta_j - \boldsymbol{x}_j'\boldsymbol{\beta} + \sigma \ln p_j,$$

the moment condition in a sample of n observations is $g^d(\boldsymbol{\xi}(\boldsymbol{\delta}, \boldsymbol{\theta}^d)) = n^{-1} Z^d \xi(\boldsymbol{\delta}, \boldsymbol{\theta}^d)$, where Z^d is the matrix with $\boldsymbol{z}_j^d$ as generic column j.

Price data are not available for all stores. To address this, we define a missing indicator d_j that equals one if observation j has price information and zero otherwise.[32] The model is thus identified under the assumption $E[\xi_j|\boldsymbol{z}_j^d, d_j] = E[\xi_j|\boldsymbol{z}_j^d]$, so that $E[d_j \xi_j \boldsymbol{z}_j^d] = 0$ by the

[32] Eizenberg et al. (2021) assign the alternatives with missing price data to the outside option. When estimated under this assumption, the model generates similar demand elasticities. Our treatment of missing data allows us to use revenue data on stores with missing price data to identify the corresponding δ_j.

law of iterated expectations.[33] Intuitively, this assumption requires that Altroconsumo does not systematically oversample stores that are either abnormally attractive or unattractive to consumers, after controlling for observed characteristics. Based on the discussion in Section 3, this condition is plausible in our context.[34] Because we have revenue share data for all stores — including those with missing price data — we can compute $b_j(\boldsymbol{\delta}, \boldsymbol{\theta}^d)$ for all stores and obtain $\hat{\boldsymbol{\theta}}^d$ as the solution of the MPEC program:

$$\min_{\boldsymbol{\theta}^d, \boldsymbol{\delta}} \; g^d\left(\boldsymbol{d} \odot \boldsymbol{\xi}\left(\boldsymbol{\delta}, \boldsymbol{\theta}^d\right)\right)' W^d g^d\left(\boldsymbol{d} \odot \boldsymbol{\xi}\left(\boldsymbol{\delta}, \boldsymbol{\theta}^d\right)\right), \qquad s.t. \;\; \boldsymbol{b}\left(\boldsymbol{\delta}, \boldsymbol{\theta}^d\right) = \mathscr{b},$$

where W_d is the standard two-step weighting matrix and $\mathscr{b}$ are revenue share data.[35]

Testing for Conduct

Conduct Falsification and Testability The model in Section 4 translates the three hypotheses in Section 2 into five candidate pricing models. Having estimated demand, we can compute the markup vectors $\boldsymbol{\Delta}^m$ corresponding to each model m. However, as we do not observe true markups, a simple comparison between the estimated markup vectors is not sufficient to distinguish the true model of conduct. Instead, Berry and Haile (2014) show that falsifying a model of conduct requires excluded instruments $\boldsymbol{z}_j^s$ that are orthogonal to unobserved cost shocks. An intuitive way to understand the falsifiable restriction in Berry and Haile (2014) is in terms of the correlations between markups and instruments. Controlling throughout for $\mathbf{w}_j$, instruments $\boldsymbol{z}_j^s$ have a correlation with true markups that equals the observable correlation between $\boldsymbol{z}_j^s$ and prices. Abstracting from finite sample considerations, a researcher can then observe the correlation between $\boldsymbol{z}_j^s$ and $\boldsymbol{\Delta}_j^m$, and check whether it corresponds to the correlation between $\boldsymbol{z}_j^s$ and $\boldsymbol{p}_j$. If it does not, then model m is falsified.

In the context of investigating Coop's conduct, the more weight Coop places on profits, the more its prices co-vary with its Bertrand markups Δ^B. Hence, to test whether Coop exploits market power, the researcher needs to exogenously vary Bertrand markups, e.g., via demand shifts and rotations or changes in the set and costs of competitors. The true model of conduct generates a covariation between prices and instruments that matches the covariation between instruments and implied markups. Other models of conduct, instead, are falsified.

Although our discussion thus far has been in terms of statistical covariances between instruments and markups, falsification can be understood based on the economic features of

[33] This assumption is different than the standard missing at random assumption, which in this context is $d_j \perp p_j | \boldsymbol{x}_j, \mathscr{b}_j$. See Abrevaya and Donald (2017) for more discussion.

[34] See Appendix A for more information on selection into the Altroconsumo sample.

[35] We assume away any measurement error in revenue share that may arise from inaccuracies in IRI data and from our construction of market size.

a model of conduct. Magnolfi, Quint, Sullivan, and Waldfogel (2022) show that falsification is grounded in differences in inverse pass-through matrices across models. As the different models of Coop conduct are characterized by different values of the parameter λ that multiplies Bertrand markups, pass-throughs for different models are also rescaled by λ. This implies that these can be falsified by either cost-side (i.e., rival cost shifters) or demand-side (i.e., characteristics of stores in a market) instruments.

Instruments Based on the above discussion, we construct instruments $\boldsymbol{z}^s_j$ that induce variation in demand across markets by altering the competitive environment and thus markups. We start by forming three sets of instruments: (i) the number of rival stores in each size category (BLP instruments); (ii) the proportion of left-wing voters in the market, exploiting variation in political preferences for Coop; and (iii) the intensity of Coop's political connections. The latter has a significant impact on market structure in this industry (Magnolfi and Roncoroni, 2016), and is unlikely to be correlated with unobservable determinants of marginal cost (as opposed to fixed cost). To form the final set of instruments, we interact BLP instruments with a Coop indicator, with political preferences, and with political connections. Following Backus et al. (2021), we reduce the dimension of the set by applying a principal component analysis (PCA) algorithm and select the components that explain 95% of the variance to form our final set of instruments $\boldsymbol{z}^s_j$. We assume that such instruments are mean independent of cost shocks conditional on observed cost shifters, i.e. $E[\omega_j|\boldsymbol{z}^s_j, \mathbf{w}_j] = 0$.

Inference To perform inference on conduct, we follow Duarte et al. (2023) in choosing a model selection approach and adopting the Rivers and Vuong (2002) (RV) test. This test offers a key advantage over alternative procedures: it produces a valid inference on conduct even in the presence of misspecification of demand and cost. The test is based on population measures of fit, which we denote as $\mathcal{Q}_m$ for each model m. For a pair of models m and ℓ, the test forms a null hypothesis:

$$H_0 : \ \mathcal{Q}_m = \mathcal{Q}_\ell,$$

and two alternatives:

$$H_m \ : \ \mathcal{Q}_m < \mathcal{Q}_\ell \qquad \text{and} \qquad H_\ell \ : \ \mathcal{Q}_m > \mathcal{Q}_\ell.$$

Under the null, both models have the same asymptotic fit, whereas each alternative corresponds to the hypothesis of superior asymptotic fit for one of the candidate models.

To construct a measure of fit, we take as a benchmark the moment condition $E[\omega_j|\boldsymbol{z}^s_j] = 0$ that holds for the true model of conduct. We first use the linearity of the marginal cost and the assumption that cost shifters $\mathbf{w}_j$ are exogenous to residualize prices, instruments, and markups for each model with respect to $\mathbf{w}_j$. We denote the corresponding variables as $\tilde{p}_j, \tilde{\boldsymbol{z}}_j^s$ and $\tilde{\Delta}_j^m$. Model m implies residuals $\tilde{\omega}_j^m = \tilde{p}_j - \tilde{\Delta}_j^m$. We can then define fit using a GMM criterion function $\mathcal{Q}_m = E[\tilde{\omega}_j^m \tilde{\boldsymbol{z}}_j^s]' \mathcal{W}^s E[\tilde{\omega}_j^m \tilde{\boldsymbol{z}}_j^s]$, where $\mathcal{W}^s = E[(\tilde{\boldsymbol{z}}_j^s)(\tilde{\boldsymbol{z}}_j^s)']^{-1}$ is the 2SLS weight matrix. To perform the test in finite sample, we define the sample measure of fit $Q^m = \boldsymbol{g}_s^{m\prime} W^s \boldsymbol{g}_s^m$ for $\boldsymbol{g}_s^m = n^{-1} \tilde{Z}^s \tilde{\boldsymbol{\omega}}^m$, $W^s = n[\tilde{Z}^s \tilde{Z}^{s\prime}]^{-1}$, and $\tilde{Z}^s$ defined as the matrix with $(\tilde{\boldsymbol{z}}_j^s)'$ as generic column j. The RV test statistic for models m and ℓ is thus:

$$T^{\text{RV}} = \frac{\sqrt{n}(Q_m - Q_\ell)}{s_{\text{RV}}},$$

where s_{RV}^2 is the delta-method estimator for the asymptotic variance of the numerator of the test statistic.[36] We denote this asymptotic variance by σ_{RV}^2.

As long as σ_{RV}^2 is positive, the statistic T^{RV} is standard normal under the null. Negative values of T^{RV} indicate evidence in favor of a better asymptotic fit of model m. Conversely, positive values indicate evidence in favor of model ℓ. If, instead, σ_{RV}^2 equals zero, the RV test statistic is degenerate and inference is invalid. Duarte et al. (2023) show that the degeneracy of RV is a weak instruments problem, and provide a diagnostic to evaluate the quality of the inference for RV. We perform this diagnostic after discussing the test results.

6 Results

Demand, Elasticity and Bertrand Markups

We report in Table 4 coefficient estimates for the demand model (column 3), and results from a simple linear logit specification (columns 1 and 2) for comparison. All coefficients have signs consistent with economic intuition. The coefficient η_y of the interaction between income and the constant term is negative: intuitively, high-income consumers are drawn to traditional stores that are more expensive but offer higher-quality groceries. The coefficient η_l is positive, indicating an association between preferences for Coop and political preferences for center-left parties, but is not precisely estimated. Comparing columns 1 and 2 highlights the importance of price instruments for getting consistent estimates of price elasticity.

The median store-level own-price elasticity is -7.41, which implies that consumers are elastic when choosing among different stores in their choice set. Moreover, Table 5 shows in column 1 that chain-level elasticities are lower for chains that operate larger stores, e.g., Finiper. The cross-price elasticities are low, ranging from 0.002 to 0.073, with a median of

[36] See Duarte et al. (2023) for the exact formulation of this estimator, which accounts for first-stage markup estimation error.

Table 4: Demand Model Estimates

	OLS		IV		RC-MPEC	
	(1)		(2)		(3)	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Price - σ	-2.35	(0.28)	-4.37	(1.30)	-6.43	(1.23)
Log Income - η_y					-0.60	(0.31)
Dem$\times$Coop - η_l					0.28	(1.79)
In Mall	0.07	(0.05)	0.07	(0.05)	0.12	(0.05)
Median Own Price Elasticity	-3.34		-5.35		-7.41	
n	2,672		2,672		14,385	

Columns 1 and 2 report, respectively, OLS and IV estimate for a linear model with $\boldsymbol{\eta} = 0$, which include only stores with price observation. Column 2 instruments are Hausman and Differentiation. Column 3 reports estimates for the MPEC estimation procedure, which includes sale share information for all stores in markets with price observations. Column 3 instruments are Hausman, Differentiation, and their interaction with demographics. All specifications have fixed effects for chain size, year, and market.

0.007, probably reflecting the importance of geographical differentiation within markets.

The Bertrand price-cost margins (PCM), defined as $\frac{\Delta_j^B}{p_j}$, are the key implication of demand estimation. For Coop, these are the margins under model $m = 3$ (pure profit maximization). We report the implied PCM in column 2 of Table 5. The median PCM in our sample is 14.8%, varying in a range from 14% to 18%. To validate these numbers, we compare them with accounting data on gross margins (reported in column 3 of Table 5), keeping in mind that this comparison is not straightforward: among other caveats, accounting PCM are based on average cost, and should thus represent an upper bound to PCM based on marginal cost (Nevo, 2001). Nevertheless, the model-implied PCM are comparable to accounting margins.

Table 5: Supermarket chains Elasticities and PCM

Chain	Own-Price Elasticities (1)		Bertrand-Nash Margins (2)		Accounting Margins (3)
Coop	-7.056	(1.145)	0.161	(0.037)	
Esselunga	-7.223	(1.185)	0.164	(0.030)	0.186
Conad	-7.279	(1.196)	0.150	(0.028)	
Carrefour	-7.263	(1.193)	0.153	(0.028)	0.166
Selex	-7.301	(1.201)	0.150	(0.028)	0.134
Auchan	-7.217	(1.185)	0.149	(0.028)	0.162
Pam	-7.299	(1.200)	0.141	(0.027)	0.162
Bennet	-7.100	(1.162)	0.152	(0.028)	0.216
Finiper	-7.164	(1.174)	0.142	(0.027)	0.16

We report in (1) and (2) the average quantity elasticity and implied Bertrand PCM, weighted by store revenue. Standard errors are in parentheses. In (3) we report PCM from available accounting data for the largest chains. Accounting data are from Mediobanca R&S reports.

Overall, elasticity estimates and PCM seem reasonable, with discrepancies from previous studies of the grocery retail sector in other countries reflecting differences in technology, institutions, and competitive conditions. For example, Eizenberg et al. (2021) find an average PCM of around 20% for grocery retailers in Jerusalem. Margins for U.S. grocery retail firms, which operate larger and more efficient stores, are around 30% (Ellickson, Grieco, and Khvastunov, 2019). Smith (2004) reports average PCM of around 12% for UK supermarkets.

Test for Coop Conduct

Cost Implications of Conduct For each model m, the demand estimates result in a vector of marginal costs $\boldsymbol{mc}^m = \boldsymbol{p} - \boldsymbol{\Delta}^m$. We project these on store characteristics and report the results in Table 6. In line with intuition, marginal costs are lower for larger stores. We also control for chain-level, GPO, and city-size fixed effects, which indicate that marginal costs are larger in bigger cities. The coefficients are broadly similar across all models of Coop conduct.

TABLE 6: Cost Implications of Conduct

	mc^m				
	Welfare Max.	Partial Profit Max.			Profit Max.
	($\lambda = 0$)	($\lambda = 0.25$)	($\lambda = 0.5$)	($\lambda = 0.75$)	($\lambda = 1$)
Small Supermarket	-1.22	-1.37	-1.52	-1.67	-1.82
	(0.31)	(0.27)	(0.25)	(0.24)	(0.24)
Large Supermarket	-1.94	-2.29	-2.64	-2.99	-3.34
	(0.38)	(0.34)	(0.31)	(0.30)	(0.30)
Hypermarket	-4.77	-5.07	-5.37	-5.67	-5.97
	(0.45)	(0.40)	(0.36)	(0.34)	(0.34)
Large Hypermarket	-4.58	-5.19	-5.81	-6.42	-7.04
	(0.41)	(0.36)	(0.33)	(0.32)	(0.33)
In Mall	0.92	0.79	0.65	0.52	0.38
	(0.51)	(0.44)	(0.38)	(0.35)	(0.34)
Median mc (€)	105.6	105.4	105.1	104.5	103.8
Coop vs. average mc ratio	1.15	1.11	1.06	1.02	0.97

We report OLS estimates for the linear projection of $\boldsymbol{mc}^m$ on cost shifters. Each column corresponds to a different model m of Coop conduct, with a corresponding λ. Robust standard errors are in parenthesis. All marginal cost estimates are positive. $n = 2,672$.

As a first informal assessment of different models of conduct, we describe the implications that these models have on Coop's marginal cost levels. As shown in the last row of Table 6, different models of conduct have stark implications on how Coop's costs compare to those of its competitors. For models that impose a high degree of internalization of consumer welfare by Coop, the implied marginal costs indicate that Coop is much less efficient than its competitors. For instance, under model 1 of pure welfare maximization, Coop's marginal costs are 15.4% higher than the average of its competitors. This is not in line with institutional knowledge. Coop participates in a GPO with its competitors, thus procuring goods at the same prices, adopts a similar business model, and often hires managers with previous experience in competing firms. Coop's marginal costs are instead close to those of its competitors under model 3, whereby Coop is a pure profit-maximizing entity.

RV Test Results We perform the RV test for each pair of models and report the results in Table 7, Panel A. Negative values of the test statistic indicate evidence in favor of the row model, and the corresponding critical value for rejection of the null in favor of the row model is -1.96 at a confidence level of 95%. Model $m = 3$, which corresponds to pure profit maximization for Coop, rejects all other models of conduct and thus is the only one supported by the data. Because the heuristic procedure of performing several pairwise tests does not control the family-wise error rate, i.e. the probability of at least one false rejection across the multiple tests, we follow Duarte et al. (2023) in reporting the model confidence set (MCS) of Hansen, Lunde, and Nason (2011). For each model, we compute a p-value that indicates the confidence level necessary to exclude the model from the set. At a confidence level of 95%, only the pure profit maximization model is in the MCS.

TABLE 7: RV Test and F-Statistics

Panel A: RV Test Results	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$	MCS p-values
$m = 1$ - Welfare Max. ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	-9.22				0
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	-9.07	-8.81			0
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	-8.81	-8.35	-7.54		0
$m = 3$ - Profit Max. ($\lambda = 1$)	-8.35	-7.54	-6.13	-3.93	1
Panel B: Effective F-Statistic	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$	
$m = 1$ - Welfare Maximization ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	$23.0^{\dagger}$				
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	$27.2^{\dagger}$	$31.9^{\dagger}$			
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	$31.9^{\dagger}$	$36.9^{\dagger}$	$41.6^{\dagger}$		
$m = 3$ - Profit Maximization ($\lambda = 1$)	$36.9^{\dagger}$	$41.6^{\dagger}$	$45.0^{\dagger}$	$46.2^{\dagger}$	

Panel A reports T^{RV} for the pair of models in the respective row and column, and MCS p-values for the row model. Negative values of the test statistic suggest a better fit of the row model; MCS p-values below 0.05 indicate rejection of a row model. Panel B reports the effective F-statistic of Duarte et al. (2023) for the pair of models in the respective row and column. † indicates F-stat above critical value for a best-case power of 0.95. All F-stats are above the critical value for a worst-case size of 0.075. Both test statistics and F-statistic values are adjusted for two-step estimation error. $n = 2,672$.

Inference from the RV test may be misleading if the test statistic is degenerate or, equivalently, if the instruments used are weak for testing. To evaluate the quality of our inference, we compute the effective F-statistics suggested by Duarte et al. (2023), and report them in Table 7, Panel B for each pair of models. These can be compared to the critical values in Duarte et al. (2023) to diagnose size distortions or low power. Because we are using, after dimension reduction, a set of four instruments, size distortions are not a concern. The effective F-statistics in Panel B are above the critical value for a maximal power of 0.95 for all pairs of models. We conclude that the instruments are strong for power.

The test results provide a stark rejection of even partial internalization by Coop of consumer welfare objectives. Not only is model 1, pure consumer welfare maximization, rejected in favor of all other models we consider, but any model of partial welfare maximization is also rejected in favor of model 3. In sum, our results are evidence that Coop internalizes only the profit maximization motive in its pricing decisions.

Interpretation and Robustness The RV test is a model selection procedure that compares the relative fit of different models and concludes in favor of the one whose predicted markups (markups projected on instruments) are closest to the true (Duarte et al., 2023). Hence, RV performs a relative comparison of models of conduct. In our case, from a menu of models suggested by economic theory, the one corresponding to pure profit maximization is selected. We complement this evidence with an assessment of the absolute fit of profit maximization, which can be obtained from an estimation exercise. To this end, we estimate the pricing Equation 6 using the same instruments used to perform RV testing. We report the estimates of λ in Table 8 for different specifications of marginal cost.[37] The estimates are close to one in all specifications, indicating that model 3 of pure profit maximization for Coop provides a very good absolute, in addition to relative, fit.

Table 8: Conduct Estimates

	(1)		(2)		(3)	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
λ	1.05	(0.05)	1.04	(0.04)	1.05	(0.05)
Time Trend	Yes		No		Yes	
Year F.E.	No		Yes		No	
GPO F.E.	Yes		Yes		Yes	
City Size F.E.	Yes		Yes		No	
Geographic F.E. Level	Region		Region		Market	

We report GMM estimates of Equation 6. Columns 1-3 correspond to different specifications of marginal cost, indicated in the table. Standard errors (with a two-step correction) are in parenthesis. $n = 2,672$.

Another important interpretation aspect of the RV testing results is that they are robust

[37] This is essentially the specification in Pakes (2017). Although it complements the interpretation of RV results, its properties as a testing procedure are less appealing than those of RV (Duarte et al., 2023). See also Magnolfi and Sullivan (2022) for a comparison of testing and estimation approaches.

to misspecification. More precisely, Duarte et al. (2023) show that RV may conclude for the model of conduct whose predicted markups are closest to the true ones even if demand or cost is misspecified. Nevertheless, we explore the robustness of our results to different models of demand. Appendix B reports RV test results obtained when demand is estimated with a discrete choice model that allows for heterogeneity in consumers' sensitivity to price. Even for a fairly different demand system from the one described in Section 4, profit maximization for Coop is the only model of conduct that is not rejected.

Finally, we investigate two other dimensions of the robustness of our results in Appendix B. First, we consider different sets of instruments for testing, including the set of instruments we use for demand and a set of instruments that do not use data on political connections. For all these alternative instruments, the test results (in Appendix Table 20) are in line with the results of Table 7, or the instruments are weak for testing and thus provide unreliable inference. Second, notice that our model relies on the maintained assumption that Coop's competitors maximize their profits. As a placebo test, we perform RV for the main for-profit supermarket chains, evaluating the same models that we consider for Coop in Table 8. The results of this exercise (in Appendix Table 22) indicate that the conduct of Coop's competitors is better explained by profit maximization.

7 Alternative Models of Coop's Conduct

Our results thus far indicate that Coop sets prices as a profit maximizer. However, our analysis may be missing other dimensions where Coop is significantly different from its competitors. In this section, we consider such alternative hypotheses on Coop's conduct.

Differential Treatment of Members and Nonmembers Coop may seek to only maximize the welfare of its members. As Coop does not pay dividends,[38] this may happen through members-only discounts. Coop members have access to members-only deals in-store and accrue points when shopping that can be redeemed for prizes or discounts. Because our price data do not have information on members-only discounts,[39] our analysis may be missing an important dimension where Coop differs from its rivals.

However, all of Coop's competitors have loyalty programs that, although formally different from Coop membership, offer in essence similar benefits. All programs offer two main benefits to loyalty members: (i) points convertible to discounts, and (ii) members-only deals. The former are easy to compare across chains; for the latter, we rely on additional data from Altroconsumo, which published in 2014 a comparison of supermarkets' loyalty programs. We

[38] All the major cooperatives that form Coop do not pay dividends in the period of our study.

[39] The Altroconsumo price index is constructed using prices available to the general public, without taking into account discounts for members of cooperatives or members of loyalty programs.

report this data in Table 9, including the percentage discount from points, the average unit members-only discount, and the total percentage of members-only discount on the cost of a basket of groceries. The basket considered here is the same as that used to construct the price index.

Table 9: Loyalty Programs and Coop Membership Rewards

Chain	% discount using points	Per-item average % disc.	Total % discount
Auchan	0.67	17	0.2
Bennet	0	–	–
Carrefour	0.5	31	1.8
Coop	1	23	0.9
Esselunga	2	29	1.9
Famila (Selex)	0	–	–
Il Gigante	1	–	–
IPER	0	19	1
PAM	1	27	0.3

We report data on loyalty program rewards from Altroconsumo. For each chain, we report percentage discounts using points, average unit discounts for items on members-only promotions, and average total members-only discounts over the total price of the grocery basket. Although the data were collected in 2014, loyalty programs for most chains were unchanged from 2001-2013.

The data confirm that rewards for members of the loyalty program (which can be joined for free) are similar to the benefits of Coop membership. Moreover, annual reports indicate that the share of revenues that for-profit competitors generate from loyalty program members is comparable (or higher, e.g., for Esselunga) to the percentage of revenues that Coop generates from its members. Taken together, this evidence suggests that member discounts are not a meaningful distinction between Coop and its competitors.

Different Entry Patterns Our model focuses on Coop's pricing incentives, given a set of stores, reflecting the idea that cooperatives are a response to imperfect competition in existing markets (Sexton and Sexton, 1987; Hansmann, 2000). Alternatively, cooperatives may be a response to "missing markets" (Banerjee, Besley, and Guinnane, 1994; Guinnane, 2001), as they provide a mechanism for consumers to finance fixed costs and commit to pricing non-competitively upon entry. Thus, Coop may choose to operate stores that are not profitable, and what seems like high markups are instead high fixed costs. This is in line with the notion that non-profit firms may face different incentives in entry (Harrison and Seim, 2019).

Although a full-fledged investigation of entry in this industry is outside the scope of this article, we present suggestive evidence that the markets where Coop is present - and importantly, those in which it has market power - are not meaningfully different from other markets. To do so, we test an implication of the theory of missing markets: when Coop builds a store for social purposes, the store has high fixed costs. As fixed costs are not directly observable, following earlier entry literature (e.g., Bresnahan and Reiss, 1991) we proxy them with data on the cost of commercial real estate[40] provided by the Italian tax agency.[41] We match stores with real estate costs data at a fine geographic level and study whether Coop builds stores in areas that exhibit systematically different costs.[42]

Table 10: Fixed Costs and Coop Entry

	log(price of real estate)			
	(1)	(2)	(3)	(4)
Coop	-0.009	-0.006		
	(0.008)	(0.006)		
Monopoly Market			-0.032	-0.036
			(0.007)	(0.007)
Coop Monopoly Market				0.013
				(0.014)
Year FE	Yes	Yes	Yes	Yes
Chain FE	No	No	Yes	Yes
Geographic FE	Region	Market	Region	Region

We report OLS coefficient estimates for a regression where the dependent variable is the store-level price of commercial real estate. Columns 1-2 examine, under different sets of controls, whether Coop's real estate fixed costs are systematically higher. Columns 3 and 4 examine whether Coop's monopoly markets exhibit systematically higher real estate costs. Robust standard errors are in parenthesis. All regressions control for store size and location inside a mall. $n = 16,020$.

Columns 1-2 of Table 10 show OLS regression estimates where the dependent variable is the log of cost per square meter of real estate at the store level; we control for year fixed effects, store size fixed effects (as larger stores are likely to be built in less central areas) including an indicator for stores in a large mall, chain-level fixed effects, and different sets of geographic fixed effects. In both specifications, the coefficient for Coop is statistically not different from zero. As monopoly markets may be those where Coop enters to prevent a missing market, in columns 3 and 4 we focus on markets with only one large store.[43] We run store-level regressions of the log of real estate prices on monopoly market fixed effects and a Coop monopoly indicator. The lack of correlation between real estate prices and Coop monopoly in column 4 indicates that, compared to other monopoly markets, Coop monopolies do not display different fixed costs. In sum, our results provide little support

[40] Costs of real estate represent a substantial fraction of total fixed cost, vary considerably across locations, and are observable. Other cost components are harder to measure or attribute to a store.

[41] This data is described in greater detail in Appendix A.

[42] Finding systematically lower fixed costs may also indicate that Coop pursues social goals, such as providing access to groceries to low-income communities.

[43] We define monopoly markets in what follows as those markets with only one store above a certain size threshold (we use 1,500 sq. meters as a threshold; results are similar with different thresholds).

for an explanation of Coop's pricing patterns based on fixed costs rather than market power.

Constrained Welfare Maximization Coop may act to maximize consumer welfare under a profit constraint. A possible motivation for this model is dynamic: Coop needs to raise funds to pay for current and future fixed costs and may find it hard to raise external capital. We can formulate this model as a Ramsey problem:

$$\max_{\boldsymbol{p}_{Coop}} \sum_m cv\left(\boldsymbol{p}_m; \boldsymbol{u}_m\right), \qquad s.t. \sum_m \pi_{Coop,m}\left(\boldsymbol{p}_m\right) \geq \bar{\pi},$$

where $\boldsymbol{p}_m$, $\boldsymbol{p}_{Coop}$ and $\bar{\pi}$ are, respectively, all store prices in market m,, Coop's prices in all markets, and a national profit goal. Let Λ be the Lagrange multiplier associated with the profit constraint; equilibrium implies that for any store $j \in \mathcal{J}_{Coop}$, the following condition holds for all markets m:

$$\sum_{h \in \mathcal{J}_{Coop}} \left(p_h - mc_h\right) \frac{\partial q_h\left(\boldsymbol{p}\right)}{\partial p_j} = -q_j(\boldsymbol{p}) - \frac{1}{\Lambda}\left(\frac{\partial}{\partial p_j} cv\left(\boldsymbol{p}, \boldsymbol{u}\right)\right). \tag{7}$$

This condition is identical to (5), with the inverse Lagrange multiplier replacing the term $\frac{F_2}{F_1}$. Hence, this model of Coop's objective is equivalent to the model in Section 4: for each $\bar{\pi} > 0$ which the problem has a solution, there exists a Λ for the model in Section 4 such that Equations (5) and (7) have the same implications on Coop's pricing. Therefore, our results in Section 6 can be interpreted in light of the welfare maximization model: the only model we cannot reject is the one in which Coop sets profit goals high enough to make its pricing observationally equivalent to profit maximization.

Other Explanations Coop may differ from its competitors along other non-price dimensions that are not considered by our study. These include product quality, corporate social responsibility, and donations. Concerning the latter two, Coop - just like its main competitors - has well-developed corporate social responsibility strategies. However, accounting data do not support the view that Coop is substantially different in this respect.

The possibility of competition in product quality deserves a more extensive discussion. Although it sets prices in a profit-maximizing fashion, Coop may provide quality above the profit-maximizing level. Although we do not have direct information on product quality, both our model estimates and anecdotal observations do not support this view. First, the chain fixed effects that we estimate for the demand model indicate that Coop's stores are not inherently more desirable for consumers. Although the average fixed effect for Coop's stores is above the average, it is below the average across the stores of the largest competitors (Auchan, Esselunga, Conad, and Selex). Chain fixed effects would detect whether consumers perceived large differences in product assortment or quality between Coop and its competitors. Second, during the period of our study, a large share of revenues for Italian supermarkets is generated by branded products sourced through GPOs.[44] This limits the degree of exclusive supply relationships and differentiation in the quality of products sold across chains. The importance of private labels is growing over time; however, it is not clear how much variation in quality across chains is due to private labels, as these products tend to be manufactured by the same firms for all supermarket chains.

8 Economic and Policy Implications of Coop's Conduct

Quantitative Implications After having discussed evidence that Coop's conduct is best described by pure profit maximization, we quantitatively evaluate the effect of Coop's conduct on market outcomes. To do so, we use our model to compute counterfactual prices and quantities corresponding to the four models of Coop conduct that are rejected by the test of Section 6, and compare them with the outcomes predicted by the profit maximization model.[45] As a caveat, we only evaluate short-term competitive responses in prices and do not capture changes in market structure due to entry and exit.

Panel A of Table 11 reports the percentage changes in prices generated by comparing model 3 of pure profit maximization for Coop with alternative models corresponding to each column. As expected from the markup level in the industry, Coop's conduct matters for prices: full internalization of consumer welfare by Coop would drive down the average price by about 3.6% across all chains, and by about 18.5% in Coop stores. The average price change mostly reflects Coop's own price adjustment; competitors react to Coop's pricing, but this is quantitatively second-order because of the small cross-price elasticity estimate. This also implies that the competitors' exit response to more pro-consumer conduct by Coop would also be limited.[46]

Panel B of Table 11 reports changes in consumer welfare. Reflecting Coop's large market share and the low substitution between supermarkets, Coop's conduct has a meaningful impact on welfare: having Coop adopt a welfare maximization goal (model 1) would increase welfare by €2.25 billion or about €162 for the average household, which represents around 3.2% of the household's average grocery expenditure in a year.[47] Comparing profit maximization (model 3) to partial profit maximization yields smaller, but still relevant, gains.

[44] According to Centromarca, an industry association, branded products represented around 70% of consumer packaged goods sales in 2009, the highest share in Europe.

[45] We do so for the last year in our sample, 2013. The results of earlier years are quantitatively similar.

[46] When estimating a yardstick for store-level fixed costs, we find that counterfactual variable profits would fall below estimated fixed costs only for 1.6% of stores.

[47] This percentage is larger than the corresponding decrease in average prices as the effects of Coop's conduct are more significant for larger markets, and for consumers who shop at larger stores.

TABLE 11: Implications of Coop Conduct

Panel A: Changes in Average Prices - %	Welfare Max.	Partial Profit Max.		
	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$
Average	-3.20	-2.34	-1.55	-0.77
	(0.54)	(0.44)	(0.33)	(0.16)
Coop Supermarkets	-16.37	-12.03	-7.98	-4.01
	(3.12)	(2.54)	(1.82)	(0.96)
Non Coop Supermarkets	-0.30	-0.21	-0.13	-0.06
	(0.06)	(0.05)	(0.03)	(0.01)
Panel B: Changes in Consumer Welfare	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$
Average Household - €	162.55	98.39	54.11	22.49
	(12.99)	(11.12)	(7.42)	(3.59)
Total - bln €	2.25	1.36	0.75	0.31
	(0.18)	(0.15)	(0.10)	(0.05)

We report in Panel A percentage changes in supermarket prices going from model 3 (profit maximization) to model m. In Panel B we report changes in consumer welfare going from model 3 (profit maximization) to model m. Each column corresponds to a different model of Coop conduct m. Price and welfare changes are computed for 2013 and exclude the markets where Coop is not present. Standard errors are in parentheses.

Overall, this exercise points to a quantitatively important role of Coop's conduct in determining outcomes in the Italian supermarket industry. The payoff to governance reforms aimed at encouraging Coop to further internalize consumer welfare would be thus substantial.

Assessing Coop's Tax and Regulatory Advantages Because of its organizational form, Coop receives tax and regulatory advantages. Based on our conduct test, this preferential regime cannot be justified by Coop's role in constraining the use of market power in the market. On the other hand, we know from Table 11 that different models of Coop conduct may generate significant gains in consumer welfare. Therefore, we assess which counterfactual model of Coop conduct could justify the preferential regime that the cooperative enjoys.

To answer this question, we first quantify the economic value of Coop's regulatory advantages, so that we may compare it with potential welfare gains. We start by examining the tax breaks that Coop receives.[48] Given the complexity of corporate tax law, we adopt a simple empirical approach and compare Coop to its largest for-profit competitor, Esselunga. During the years of our sample, accounting data show that Esselunga paid taxes that are, on average, 2% of its revenues (11.8% of its gross margins), versus 0.7% paid by cooperatives in the Coop system (4.3% of gross margins). When applied to Coop revenues in 2013, this discrepancy

[48] Corporate entities in Italy are subject to an income tax (IRES). The tax rate went from 40.3% in 2001 to 31.4% in 2013. As a cooperative, Coop gets a reduction of the IRES taxable base: for most of our sample period, cooperatives' net income allocated to reserves is 70% tax exempt.

in tax rate results in €114 million yearly tax benefits at the end of our sample.[49] Several assumptions and approximations are involved in this exercise,[50] which we believe is still a reasonable back-of-the-envelope calculation for the order of magnitude of Coop's tax benefit.

Coop enjoys another major advantage when compared to its competitors: it can directly raise deposits from its members ("prestito sociale"), essentially acting as a bank, but without banks' regulatory burden and capital requirements.[51] Accounting data indicate that the total amount of members deposits average roughly € 10 billion during the years in our sample, and the net financial income of Coop averages 2.3% of revenue in the years of our sample (15.3% of gross margin). Instead, Esselunga's net financial income is virtually zero - figures for other for-profit chains are similar. Akin to what we do to quantify the tax benefit, we compute the value of lending to members as the discrepancy in average financial income over revenues between Coop and Esselunga, multiplied by Coop's 2013 revenues. This yields a benefit from lending of €201 million per year.

We can now compare the economic value of Coop's tax and regulatory advantages to the potential welfare benefit of a more consumer-friendly conduct. This discussion is not intended as a rigorous cost-benefit analysis, as it abstracts from important issues such as the marginal cost of public funds, other distortions due to taxes, and redistribution issues. Rather, we aim to provide a useful yardstick to assess when tax and regulatory advantages may be justified in exchange for a commitment to limit the exercise of market power. Using our model, we find that the consumer welfare gains generated from Coop's conduct corresponding to a value of $\lambda = 0.9$ would be equal to the tax benefits Coop enjoys, and conduct corresponding to $\lambda = 0.74$ would generate gains that match the tax and lending benefits. For interpretation, $\lambda = 0.74$ corresponds to Coop giving to the welfare of consumers 26% the weight that it gives to profits in its objective function and is similar to model $m = 2.3$. Hence, we find that even the mildest scenario of partial internalization of consumer welfare would produce benefits for consumers comparable to the economic value of Coop's current tax and regulatory advantages.

Policy Implications Our results have broader implications for the policy debate on cooperatives and not-for-profit firms. The magnitude of the consumer loss in our case study of Coop shows the consequences of the agency problem for a consumer cooperative. Similar issues may arise in other forms of cooperatives. For instance, Dairy Farmers of America

[49] We average the tax rate across years to smooth fluctuations due to business cycles, investments, and other short-term events. Using the tax rate over gross margins yields a similar result.

[50] If Coop was to be taxed as a for-profit firm, its tax rate (as a percentage of revenues) could be different from Esselunga due to differences in business operations, tax optimization strategies, etc.

[51] Additionally, the interests that members receive on this deposits were also taxed at a lower rate than interests on bank deposits in our sample period, making them more attractive. Moreover, Coop was exempted from IRAP on its gross profits from investing these deposits.

(DFA), one of the largest agricultural cooperatives in the US, has been accused by its members of exploiting its monopsony power, increasingly similar to a for-profit corporation[52] DFA pursued aggressive expansion and vertical integration, protected by the Capper-Volstead Act antitrust exemption for farmers cooperatives. Overall, our results suggest that great attention should be devoted to cooperatives' governance to ensure that they succeed in keeping members having a voice even as operations expand and become more complex.

However, striking a balance in cooperative governance is not easy. For instance, although 23 health insurance consumer cooperatives were formed as part of the Affordable Care Act to foster competition, only a few remain in operation. Although policymakers took steps to ensure that these organizations were consumer-friendly and boards were primarily composed of activists, this often resulted in inexperienced management that priced the plans too low and ultimately led to financial struggles (Sparer and Brown, 2020).

Taken together, the results in this article are a cautionary tale on the potential role of not-for-profit firms in curbing market power and complement the evidence from studies of the US hospital industry (e.g. Capps et al., 2020) to suggest that, across different organizational forms and industries, not-for-profit firms may be maximizing profits. Thus, exemptions from antitrust policy generally seem not warranted, and other subsidies must be carefully evaluated against the actual benefits they generate for consumers.

9 Conclusion

This article provides a structural framework to test hypotheses about the pricing conduct of consumer cooperatives and performs an empirical investigation of the Italian supermarket chain Coop. Although Coop is owned by its consumer members, it is not clear that its governance structure generates the right incentives for managers to fully internalize the cooperative's goals as they are stated in its charter. To test hypotheses on Coop's conduct, we build a model of demand for supermarkets to precisely measure market power as the inverse of firms' residual demand elasticity. We exploit exogenous variation in competitive conditions across markets that generates shifts of residual demand for Coop's supermarkets to test whether pricing patterns for Coop's stores reflect market power.

We do not reject the hypothesis that Coop's pricing conduct reflects pure profit maximization. However, we do reject the hypothesis that Coop is only maximizing consumers' welfare or a mix of profits and consumer welfare. We explore the quantitative effects of Coop's conduct on prices and consumer welfare, which are substantial. Importantly, even the mildest scenario of joint maximization of profits and welfare that we consider, where Coop gives to consumer welfare 25% of the weight it gives to profits in its objective func-

[52] See the DOJ brief at https://www.justice.gov/atr/case-document/file/1298411.

tion, generates consumer welfare gains that are close to justifying Coop's subsidy during the period of our study.

Our study of the conduct of consumer cooperatives suggests that the agency problem may lead these firms to depart from the goals stated in their charters. Even if our context is special in many respects, we believe that our results represent a cautionary tale not only for cooperatives but for all forms of not-for-profit organizations. Although these firms may generate significant welfare benefits, sometimes enough to justify the costs of the subsidies they receive, close attention needs to be paid to their governance mechanisms. The framework developed in this article could then be used to advance the empirical study of firm conduct in other important contexts such as non-profit hospitals and agricultural cooperatives.

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Online Appendix

Appendix A Data Construction

Income and Grocery Expenditure Data

We describe in this appendix the construction of the data on income distribution and grocery expenditure. We have data on grocery expenditure α_i and income y_i for about $8,000$ households in a panel consumer survey provided by the Bank of Italy ("Indagine sul Bilancio delle Famiglie"); for each household we also observe the region of origin. Although Italian regions are administrative units much larger than our markets, they are the finest geographic distinction in the version of the dataset provided to external researchers. We estimate a value of $\alpha_{r,q}$ from the data for each region r and each quartile q of the household income distribution.

We use the household panel data on income to fit a log-normal distribution for each region (12 in our sample). Hence, for each region r we obtain an income distribution F_r, log-normal with parameters (μ_r, σ_r).[53] Further information on income comes from tax revenue data, released by the Ministry of the Economy and Finance at the level of municipalities, an administrative unit smaller than our markets. This source contains information on individual income tax (IRPEF) returns, and thus understates actual household income.[54] Despite these deficiencies that affect the level of this measure, the data still preserves useful information on the variation of income across municipalities and thus geographic markets. Using tax revenue data we can compute both average tax income at the region level $\tilde{y}_r$, as well as average tax income in each municipality $\tilde{y}_c$, and thus obtain a measure of the intra-region variability in income. To exploit this variability we assume that the market-level distribution of income F_m is log-normal and characterized by the region-specific dispersion parameter σ_r, and by the market-specific $\mu_m = \mu_r \left(\frac{\sum_{c \in M} w_c m_c}{m_r} \right)$, where $m_c = (\log \tilde{y}_c) - \frac{\sigma_r^2}{2}$ and w_c are population weights of municipality c with respect to the total population in market m. If the extent to which this measure understates actual income does not vary across municipalities of the same region, this procedure allows us to better identify the parameter that links income to the attractiveness of the outside option.

To compute total expenditure E_m, we exploit the market level distribution of income, the values of $\alpha_{r,q}$ and census data on NH_m, the number of households at the market level.

[53] We adopt the log-normal distribution in line with the literature on the estimation of demand systems for differentiated products (e.g., Berry et al., 1995). Other two-parameter distributions (e.g., Pareto or Gamma) provide a similar fit.

[54] This is for several reasons. First, it leaves out deductions and tax-exempt forms of income, as well as the income of those individuals who don't have to file tax returns because they earn less than a certain threshold. Returns from financial assets are also taxed separately.

In particular,

$$\mathrm{E}_m = NH_m \left(\frac{\sum_{q=1,..,4}}{4} \int_y \alpha_{q,r} 1 \left\{ y \text{ } in \text{ } quartile \text{ } q \right\} dF_m(y) \right).$$

ISTAT also conducts a large-scale household-panel survey that includes data on income and grocery expenditure ("Indagine sui Consumi delle Famiglie"). When using this alternative source of data for the construction above, our estimates of regional income distributions and market-level grocery expenditure are similar (see Table 12). Moreover, the average income and grocery expenditure levels that we recover from the Bank of Italy data are in line with estimates from other sources. Our estimates of the average fraction of expenditure in groceries range across years from 14.1% to 15.6%; ISTAT estimates are in the range of 16.6% to 17% for Northern Italy between 2011 and 2013, whereas Federdistribuzione—a supermarket industry trade association—reports national estimates in a range from 12.1% to 13.4% for the period 2002 to 2012.

Table 12: Comparison across Data Sources

	Bank of Italy - Bennet	ISTAT - Esselunga
Mean:		
Market Expenditure (mln Euros)	213.33	209.14
Outside Share	0.50	0.50
Median:		
Market Expenditure (mln Euros)	92.58	87.60
Outside Share	0.52	0.54

We report average and median values for market-level total expenditure data and share of the outside option under two alternative data construction procedures. The left column uses Bank of Italy income data, and Bennet revenues to convert revenue shares into euros. These are the data sources used in the article. The right column displays ISTAT data, where Esselunga revenues are used to convert revenue shares into euros. $n = 3,313$.

Supermarket Revenues

Our data source for store-level revenue share is IRI's Top Trade dataset, which reports estimates of revenues for each store as a share of total supermarket revenues in Central and Northern Italy. This product is analogous to the Trade Dimensions database widely used for the analysis of the US supermarket industry (e.g., Ellickson, 2007; Holmes, 2011). Revenue shares as reported by IRI, however, do not consider the outside option: shopping for groceries in traditional shops, open-air markets, or discount retail stores.

To recover revenue share data that take the outside option into account, we first convert the IRI revenue shares into 2013 euros. To do so, we use the fact that some of the firms in our sample have public revenue data and only generate revenues from operating stores that we observe in our sample. We use one such firm, Bennet, to translate IRI data into total revenues in euros (converted to 2013 values using ISTAT's CPI index). The final shares are computed by dividing the revenue values by our estimates of market-level grocery expenditure E_m. As shown in Table 12, using different firms for this procedure does not materially change the database.

To validate our data construction procedure's robustness to different assumptions and data sources, we compare the share of grocery expenditure that is captured by supermarkets in our database to external sources. In our data, the average (weighted by revenues) market-level grocery expenditure that goes to supermarkets fluctuates across years between 53.1% and 58.1%. In a recent survey of Italian consumers, ISTAT[55] finds that 57.9%. of respondents in a representative sample of the population choose a supermarket for their grocery shopping.

Price Data

The price dataset that we use in this study is collected by the consumer association Altroconsumo for its annual report on supermarket prices. This report aims at educating consumers on how to save on their grocery shopping, and to highlight the differences in prices across cities, firms, and store formats. The report usually gets national press coverage and is closely watched by industry insiders. Every year, Altroconsumo selects a sample of stores and scans the prices of a large number of products in each store to construct a store-level price index. The data collection process is carried out over a short period of time. The total number of items scanned for this yearly exercise ranges from a hundred thousand at the beginning of our sample, to almost a million in later years.

This appendix provides an additional description of the data, focusing on the aspects of (i) selection of the sample of stores, (ii) selection of the goods to include in the basket, and (iii) index construction and consistency of the index across years. With respect to standard scanner data, our data is more limited as it only contains a store-level price index as opposed to prices of individual items. However, most commercial scanner databases come with contractual obligations that prevent the investigation of pricing strategies for specific supermarket chains—our objective in this article.

Store Selection Researchers at Altroconsumo assemble their sample of stores starting from a preset sample of cities. Within these cities, all province capitals located across the country, they map all firms present in the local market and visit one to five stores for each firm. Altroconsumo states that stores are chosen in order to be "representative" of the presence of the firm in a certain market—e.g., if the firm operates a network that includes

[55]ISTAT report "La Spesa per Consumi delle Famiglie," 2014.

a good share of large stores in a market and Altroconsumo is including one store for that firm, then it will most likely include a large store. Table 13 highlights how the stores in the sample tend to be larger and have higher revenues than both the full sample of IRI stores in the markets that correspond to the cities surveyed by Altroconsumo, and with respect to those stores for which price data are not available. Both average revenues and average size are roughly double in the Altroconsumo sample, so that conditional on store size—which seems to be an important determinant of selection into the sample—the missing at-random assumption is plausible. Revenues per square meter are also similar across samples. The composition of the Altroconsumo sample in terms of mix of Coop stores, Italian chains, and French chains is similar to the overall population.

TABLE 13: Selection into Altroconsumo Sample

	Price Data Available	Markets with Price Data	Price Data Not Available
Avg. Revenue - mln €	16.62	9.47	7.86
Avg. Size - 1,000 m^2	2.23	1.31	1.16
Avg. Revenue per sq. meter -€1,000	7.37	7.09	6.63
Average distance from HQ - km	154.4	151.96	133.27
% of Coop	16.35	12.1	13.49
% of Italian groups	65.83	69.46	72.7
% of French groups	17.81	18.44	13.81
Observations	2672	14385	34702

We report summary statistics for stores with and without Altroconsumo price data.

Selection of Products into the Index Altroconsumo identifies the product categories for its price index based on ISTAT's data on consumption patterns. Recent versions of this analysis include more than 100 product categories, ranging from fresh foods to packaged goods. Table 14 includes a list of the categories included in a recent version of the report. For every product category Altroconsumo selects either the leading brands or the three most expensive varieties of fresh foods. In this way, the list of roughly 100 product categories becomes a list of roughly 500 products.

Table 14: Product Categories in Altroconsumo Basket

Beverages	Refrigerated Foods	Packaged Foods
Sparkling water >1L bottle	Butter	Jam tarts
Still water >1L bottle	Cheese spread	White vinegar
Orange soda in can	Gorgonzola cheese	Chocolate chip cookies
Beer in >33cL bottle	Whole milk	Shortbread cookies
Beer in can	Skim milk	Instant coffee
Cola >1L bottle	Mozzarella	Ground coffee
White Grappa liquor	Diced pancetta bacon	Mints
Fruit juice 20cL container	Diced ham	Chocolate covered cherries
Mint syrup	Smoked salmon	Apricot jam
Sparkling wine >75cL <1L bottle	Cheese singles	Corn flakes
Fruit juice 1L container	Tortellini stuffed pasta	Saltines
Lemon tea >1L bottle	Eggs	Nutella
White wine >1.5L <2L bottle	Wurstel sausage	Croissants
Corvo red wine	Whole milk yogurt	Stuffed croissants
Red wine 1L container	Nonfat fruit yogurt	Crostini
Santa Cristina red wine	**Frozen Foods**	Dry biscuit
Tura Lamberti white wine	Frozen fish sticks	Breadsticks
Whiskey	Cod fillets	UHT whole milk
Home Care	Ice cream >500g <800g tub	UHT skim milk
Abrasive cream cleanser	Frozen minestrone soup	Honey
Bleach	Frozen french fries	Olive oil 1L bottle
Laundry detergent, powder	Frozen pizza	EV Olive oil 1L
Floor cleaner	Frozen Spinach	Corn Oil 1L
Dish soap	**Fruits and Vegetables**	Beef baby food puree
Dishwasher detergent tablets	Apples golden delicious	White bread in slices
Paper towel roll	Potatoes	Tomato sauce in glass jar
Plastic food wrap	Tomatoes	Egg pasta
Ziploc bags	Bananas	Penne pasta
Toiletries	Carrots	Spaghetti pasta
Tampons	Mixed greens salad	Peeled tomatoes in can
Body wash >500mL <1000mL	**Meats and Cheeses**	White rice
Toilet paper	Parmigiano cheese	Milk chocolate
Mouthwash >400mL <500mL	Parma ham	Dark chocolate
Face tissues	Beef carpaccio	Tuna in water
Baby diapers	Sliced turkey	Tuna in oil
Disposable razors	Sliced pork	White sugar
Soap bars	Ground beef	
Shampoo >200mL <500mL	Chicken breast	
Toothbrushes		

Index Construction Prices for each of the 500 or more products included in the index are scanned in every store in the sample, where available. Stores with less than 200 products available are excluded from the sample. Product-level prices are weighted according to the frequency of purchase in the same way that ISTAT weights different goods to construct the consumer price index. Whereas Altroconsumo strives to construct an index for same-year price comparisons across stores, comparisons across years are more difficult. In fact, the data are released every year in the form of an index that takes a value of 100 for the cheapest store in the sample. These values can be converted to euros, as Altroconsumo reports information to convert the index, but this information is not as reliable, resulting in year-over-year price increases that are not fully in line with the national dynamic of grocery prices. We convert Altroconsumo price index data in euros so that the annual increase of an index of supermarket prices (weighted by market share) matches the increase in grocery prices as reported by ISTAT. Our results and conclusions are robust to different ways of adjusting the index (e.g., no adjustment or adjustment so that increases match CPI).

Variance Decomposition

To understand the source of variation from our main variables, we compute a variance decomposition as in Card, Heining, and Kline (2013). By projecting the store-level outcome (respectively, prices, shares, Bertrand markups, and the instruments) into the space of characteristics (market-chain FE, year-chain FE, and store size), we can calculate the contribution of each component to the outcome's variance. Specifically, for store i from retail chain $b(i)$ at market m and year t, we calculate the decomposition of the outcome y's variance as $Var(y_{imt}) = Var(\hat{\gamma}_{b(i)m}) + Var(\hat{\gamma}_{b(i)t}) + \hat{\beta}^2_{size} Var(size_i) + Var(\hat{e}_{imt}) + Cov$ where $\hat{\gamma}$ and $\hat{\beta}$ are the projection coefficients, and Cov is the sum of pairwise covariances between components.

We report the contribution of each component for the total variance in percentage terms in Table 15. Most of the variance in prices is due to variance across chain-year and chain-market, but with considerable variance due to store size and year-market-chain unobservables that we argue also based on anecdotal evidence is in part coming from managers' freedom in choosing prices. Looking at the shares' variance decomposition, the bulk of variation is related to the market-chain component, reflecting the large differences in market structure across regions. A similar pattern is observed in the markup variance decomposition. Our instruments for testing conduct are going, for the most part, to explore this cross-sectional variation.

Political Connections Data

The political connection instrument used in our test for conduct relies on the data on Coop's political connections collected by Magnolfi and Roncoroni (2016). The construction of the relevant variable proceeds in three steps. First, we leverage data on the universe of local politicians and Coop board members to construct the market-level variable $BOARD_m$ by counting the number of Coop board members who have held office in local city councils,

Table 15: Decomposition of variance in prices, sales, and markups

	Variance Components (% of total)				
Variable	Year-Chain	Market-Chain	Store Size	Residual	Covar.
Price	28.5	51.0	6.7	21.4	-7.5
Share	0.6	56.9	13.8	19.9	8.8
Sales	3.1	17.9	63.6	16.4	-1.0
Markup	9.1	90.8	1.5	14.3	-15.7
z_1	0.2	98.0	0.0	1.3	0.4
z_2	0.0	99.7	0.0	0.4	-0.1
z_3	10.5	65.1	0.0	16.3	8.1
z_4	4.5	83.1	0.0	11.8	0.5

The table reports variance components in percentage points for different outcome variables (corresponding to a row). The markup variable refers to the Bertrand markups. z_1, z_2, z_3, and z_4 are the score vectors from a principal component analysis of the original excluded instruments.

provinces, and regions, excluding those elected after 1998.[56] We count only connections established until 1998 to capture long-standing connections not affected by the current market structure.

Coop's political connections are most effective when the political parties that have historically been close to Coop are also in power locally. To aggregate election outcomes at different administrative levels we rely on $K-$means clustering to group markets based on the observed patterns of political power. We find a function $c^K(m)$ that maps each market m into one of K groups that are similar based on a vector x_m, which includes information on how long the political parties associated with Coop have been in power in market m. The function c^K is then computed based on the minimization of the distance between each observation and the mean of its cluster. We choose to characterize markets in $K = 4$ classes as adding further groups does not seem to decrease significantly the within-group dispersion and construct our market-level variable for Coop's political clout as:

$$POWER_m = 1\left\{c^4(m) = 4\right\},$$

where the fourth class is the one where the electoral strength of the parties associated with Coop is greatest. We report in Table 16 summary statistics for our classification of choice.

We finally code the connection variable as the interaction of $BOARD_m$ and $POWER_m$ to reflect the idea that personal connections coming from Coop board members in local politics are likely to be influential only if the parties that are favorable to Coop have local

[56] We include all levels of local government, although all antitrust investigations and litigation on supermarket entry regulation that concerns local authorities' behavior involves municipalities (as opposed to provinces or regions).

political power. Hence, $CONN_m = BOARD_m \times POWER_m$. Summary statistics for the connection variable are reported in Table 17.

Table 16: Average Mkt. Characteristics by $POWER_m$

	$POWER_m = 0$	$POWER_m = 1$
Vars. Used in Classification:		
Yrs. Dem in Power - Region	5.57	12.7
Yrs. Dem in Power - Province	7.42	13.9
Yrs. Dem in Power - Municipality	2.57	10.7
Mkt. Demographics:		
Population	50,823.09	64,113.53
Surface - km^2	353.33	317.48
Income per capita	13,269.26	13,753.91
Perc. Votes for Dem.	0.15	0.31
Stores in Market	1.74	1.84
n	375	109

We report averages of the main market-level political variables used in our analysis for the geographic markets where $POWER_m = 0$, and for those where $POWER_m = 1$.

Table 17: Summary of Political Connections Variables

	Mean	Std. Dev.	Max
$BOARD_m$	1.21	1.41	9
$POWER_m$	0.23	0.42	1
$CONN_m$	0.38	1.03	8
n	484		

We report summary statistics of the main market-level political variables used in our analysis.

Real Estate Data

For our in Section 7 we use real estate price and rental rates data from the Real Estate Market Observatory (OMI) dataset provided by the Italian revenue agency (Agenzia delle Entrate). The dataset contains yearly observations of prices and rental rates at a fine geographic level: every municipality—the smallest administrative unit in Italy—is partitioned into areas constructed to be homogeneous in terms of property values. We use spatial information on OMI areas and store addresses to match supermarkets to OMI areas. The database contains minimum and maximum prices and rental rates per square meter for different types of residential and commercial real estate and is updated regularly using a survey of transaction prices and rental contracts. We use data for shops and malls and construct a price index as the mean of maximum and minimum prices.

GPO in the Italian Supermarket Industry

Italian supermarket chains purchase the majority of the goods they sell[57] through GPO, alliances of separate supermarket chains that have the aim of obtaining better terms from manufacturers. GPOs are almost always contractual agreements and sometimes include arrangements for shared logistics or distribution. Although these groups represent stable and important arrangements, they seldom operate through their own employees, and negotiations are conducted by a team of employees of the participating supermarket chains. Participants in a GPO don't have any obligation to purchase the items whose prices are negotiated by the group.

GPO negotiates yearly contracts, where list prices, rebates, promotions, and any co-marketing activity are spelled out in detail.[58] Contracts are valid for every store operated by the chains participating in a GPO and are strictly confidential. As highlighted in table 18 below, however, the composition of GPO in this industry varies during our sample period, resulting presumably in abundant leaking of information on contracts to competitors.

Table 18: GPO Composition

Group:	Year: 2000	2003	2005	2007	2009	2011	2013
Coop	(Coop)	(Coop)	Centrale Italiana	C. Italiana	C. Italiana	C. Italiana	C. Italiana
Agora	(Agora)	ESD	ESD	GD Plus	CSA	ESD	ESD
Auchan	(Auchan)	(Auchan)	Intermedia	Intermedia	(Auchan)	(Auchan)	(Auchan)
Bennet	(Bennet)	Intermedia	Intermedia	Intermedia	(Bennet)	(Bennet)	(Bennet)
Carrefour	GS Carref.	GS Carref.	GS Carref.	GD Plus	CSA	C. Carrefour	C. Carrefour
Conad	(Conad)	(Conad)	(Conad)	SICON	SICON	SICON	SICON
Despar	MeCaDes	MeCaDes	C. Italiana	C. Italiana	C. Italiana	C. Italiana	C. Italiana
Esselunga	(Esselunga)	ESD	ESD	ESD	(Esselunga)	(Esselunga)	(Esselunga)
Finiper	GS Carref.	GS Carref.	GS Carref.	GD Plus	(Finiper)	(Finiper)	(Finiper)
Pam	Intermedia	Intermedia	Intermedia	Intermedia	(Pam)	Aicube	Aicube
Selex	(Selex)	ESD	ESD	ESD	ESD	ESD	ESD

Appendix B Robustness

We present in this appendix robustness checks. First, we consider alternative specifications of the demand system. Then, we discuss the robustness of our test for Coop's conduct.

[57] Private label products, as well as some fresh products, are typically not purchased through GPO. Some groups also exclude dealings with small producers.

[58] These contracts do not include provisions that would amount to resale price maintenance, as this is generally illegal under EU competition law.

Alternative Demand Models

We show here estimation results for demand models that are alternative to the one presented in Section 4 in the article, which relies on a discrete-continuous specification and quasi-linear utility. These assumptions fit well with the empirical environment and enable us to use data on market shares and characteristics for all 14,385 store-year observations in our sample. However, the model's assumptions do not permit heterogeneous price sensitivity across consumers.

In Table 19 instead we show estimation results for a more conventional discrete choice specification that drops the observations without price data but allows for random coefficients on price. We consider both a specification with normally distributed random coefficients and one where the heterogeneity in price sensitivity depends on income. These two specifications, reported in columns 1 and 2 respectively, set the individual-store specific term as

$$\boldsymbol{\mu}_{ij}'\boldsymbol{\eta} = \zeta_c z_{ci} + \zeta_y (\ln p) z_{yi},$$

where z_{ci} and z_{yi} are independent normal draws, and

$$\boldsymbol{\mu}_{ij}'\boldsymbol{\eta} = \eta_{cy} \ln y_i + \eta_{py} (\ln p_j) \ln y_i.$$

The specification with normal random coefficients does not depart significantly from logit, most likely due to weak identification (Gandhi and Houde, 2020). Instead, the specification that exploits information on the market-level income distribution points to a decreasing price sensitivity of consumers as their income increases. This alternative demand model does not affect our testing for conduct results, as shown in Appendix B.

Table 19: Alternative Demand Models

	(1)		(2)	
	coef.	s.e.	coef.	s.e.
Price - σ	-5.32	(1.22)	-6.05	(1.67)
RC on Constant - ζ_c	$-1.64e-06$	$(2.17e-06)$		
RC on Price - ζ_p	$1.21e-09$	$(2.24e-07)$		
Log Income × Constant - η_{cy}			-2.95	(1.12)
Log Income × Price - η_{py}			0.38	(0.16)
Median Own Price Elasticity	-6.27		-6.41	
Median Cross Price Elasticity	0.019		0.028	

Columns 1 and 2 report estimates two-step GMM estimates for alternative specifications of the demand model. Instruments are as in our main specification, including Hausman instruments, differentiation instruments, and their interaction with demographics. All specifications have fixed effects for chain, size, popular chain-size, year, and market. $n = 2,672$.

Test for Conduct

Alternative Demand Specification To check the robustness of our test for Coop's conduct to different demand specifications, we perform RV testing using Bertrand markups and consumer welfare derived from an alternative demand system. We use the demand system of column 2, Table 19, which allows for heterogeneity in price sensitivity depending on income. Table 20 reports RV test results, obtained using the same instruments as in the article. The test results are fully in line with those in the article.

TABLE 20: RV Test and F-Statistics for Alternative Demand Model

Panel A: RV Test Results	$m=1$	$m=2.1$	$m=2.2$	$m=2.3$	MCS p-values
$m=1$ - Welfare Maximization ($\lambda=0$)					0
$m=2.1$ - Partial Profit Max. ($\lambda=0.25$)	-9.65^{*}				0
$m=2.2$ - Partial Profit Max. ($\lambda=0.50$)	-9.60^{*}	-9.48^{*}			0
$m=2.3$ - Partial Profit Max. ($\lambda=0.75$)	-9.48^{*}	-9.22^{*}	-8.66^{*}		0
$m=3$ - Profit Maximization ($\lambda=1$)	-9.22^{*}	-8.66^{*}	-7.43^{*}	-4.96^{*}	1
Panel B: Effective F-Statistic	$m=1$	$m=2.1$	$m=2.2$	$m=2.3$	
$m=1$ - Welfare Maximization (λ=0)					
$m=2.1$ - Partial Profit Max. ($\lambda=0.25$)	$16.9^{\dagger}$				
$m=2.2$ - Partial Profit Max. ($\lambda=0.50$)	$20.9^{\dagger}$	$26.0^{\dagger}$			
$m=2.3$ - Partial Profit Max. ($\lambda=0.75$)	$26.0^{\dagger}$	$32.3^{\dagger}$	$39.1^{\dagger}$		
$m=3$ - Profit Maximization ($\lambda=1$)	$32.3^{\dagger}$	$39.1^{\dagger}$	$45.3^{\dagger}$	$48.5^{\dagger}$	

The table reports test results computed using demand estimates for the model in column 2, Table 19. Panel A reports T^{RV} for the pair of models in the respective row and column, and MCS p-values for the row model. Negative values of the test statistic suggest a better fit of the row model. $*$ indicates RV statistic above critical value for a confidence level of 0.95. Panel B reports the effective F-statistic of Duarte et al. (2023) for the pair of models in the respective row and column. † indicates F-statistic above critical value for a best-case power of 0.95. All F-statistics are above the critical value for a worst-case size of 0.075. Both RV and F-statistic values are adjusted for two-step estimation error.

Robustness to Different Instruments Table 21 presents RV test results (in the form of MCS p-values) and effective F-statistics for different sets of instruments, beyond those that we use in the baseline results of Table 7 in the article. First, in Panel A, we report test results excluding from our baseline set of instruments Coop's political connections. The test results with this set of instruments are similar to the main results. In Panel B we perform RV testing using the differentiation instruments (Gandhi and Houde, 2020) used in demand estimation. In particular, we interact the differentiation instruments with a Coop indicator, and with the political connection and political preferences variables. Then, we apply principal component analysis (PCA) to the full set of instruments and select the components that explain 95% of the variance. Test results with this set of instruments are similar to baseline, although lower F-statistics raise some concerns about the quality of inference.

In the last two panels, we further analyze how performing PCA on our set of instruments alters the results. In Panel C we use the baseline set of instruments, but without PCA dimension reduction. The test results are qualitatively similar, in that model $m = 3$ of pure profit maximization best fits the data. However, the $p-$value on model $m = 2.3$ of partial profit maximization is around 0.3, indicating that this model also belongs in the MCS. However, although performing PCA on the set of instruments sharpens our results with the full baseline set of instruments, it is not necessary when using smaller sets of instruments. In Panel D we report MCS p-values and effective F-statistics when using only BLP instruments interacted with a Coop indicator for testing. These instruments are strong and generate an MCS that only includes model $m = 3$ of pure profit maximization. We conclude that the results of Table 7 are not driven by our specific choice of instruments, but hold for a class of valid and strong instruments.

Testing Profit Maximization for Coop's Competitors We perform RV testing for Coop's competitors using the same set of models of conduct that we use for Coop. In contrast with the institutional background of Coop, there is no sound rationale to expect that Coop's competitors do not maximize profit. Hence, we perform this exercise as a "placebo test," meant to potentially expose flaws in our research design: rejecting profit maximization for Coop's competitors would raise concerns about our empirical strategy. Table 22 shows the results of the RV test for three for-profit supermarket chains: PAM, Selex, and Auchan. We perform the test using the principal components of BLP instruments interacted with a chain dummy; for the three Coop competitors we consider, the F-statistic indicates that inference is reliable. We only report the average effective F-statistic in Table 22, but the pairwise values of the statistic indicate that inference is above the critical value of 18.9 for maximal power above 0.95 with two instruments. For two out of three supermarket chains, the MCS at the 5% confidence level contains only the model of pure profit maximization. For PAM, the 5% confidence level MCS contains both models $m = 2.3$ and $m = 3$, although at the 25% confidence level, which Hansen et al. (2011) use in their empirical application, only model $m = 3$ is not rejected.[59]

Appendix C Derivation of demand elasticities

This section includes derivation for the elasticity formulas used in the article. To make the notation cleaner, we suppress the market index through derivation. The expenditure share

[59]Similarly, when we perform an estimation exercise as the one in Table 8, the estimates of λ are economically and statistically close to one for the three supermarket chains, indicating a good fit of profit maximization.

Table 21: MCS p-values and F-statistics with Alternative Instruments

Panel A: No Connections IVs - ($d_z = 4$)	$m=1$	$m=2.1$	$m=2.2$	$m=2.3$	MCS p-values
$m=1$ - Welfare Maximization ($\lambda=0$)					0.00
$m=2.1$ - Partial Profit Max. ($\lambda=0.25$)	$20.9^{\dagger}$				0.00
$m=2.2$ - Partial Profit Max. ($\lambda=0.50$)	$24.4^{\dagger}$	$28.2^{\dagger}$			0.00
$m=2.3$ - Partial Profit Max. ($\lambda=0.75$)	$28.2^{\dagger}$	$32.0^{\dagger}$	$35.3^{\dagger}$		0.01
$m=3$ - Profit Maximization ($\lambda=1$)	$32.0^{\dagger}$	$35.3^{\dagger}$	$37.4^{\dagger}$	$37.8^{\dagger}$	1.00
Panel B: Differentiation IVs - ($d_z = 4$)	$m=1$	$m=2.1$	$m=2.2$	$m=2.3$	MCS p-values
$m=1$ - Welfare Maximization ($\lambda=0$)					0.00
$m=2.1$ - Partial Profit Max. ($\lambda=0.25$)	$10.1^{\dagger}$				0.00
$m=2.2$ - Partial Profit Max. ($\lambda=0.50$)	$12.6^{\dagger}$	$15.8^{\dagger}$			0.00
$m=2.3$ - Partial Profit Max. ($\lambda=0.75$)	$15.8^{\dagger}$	$19.5^{\dagger}$	$23^{\dagger}$		0.00
$m=3$ - Profit Maximization ($\lambda=1$)	$19.5^{\dagger}$	$23^{\dagger}$	$25.2^{\dagger}$	$25.1^{\dagger}$	1
Panel C: Baseline IVs, no PCA - ($d_z = 15$)	$m=1$	$m=2.1$	$m=2.2$	$m=2.3$	MCS p-values
$m=1$ - Welfare Maximization ($\lambda=0$)					0.00
$m=2.1$ - Partial Profit Max. ($\lambda=0.25$)	$10.2^{\dagger}$				0.00
$m=2.2$ - Partial Profit Max. ($\lambda=0.50$)	$12.2^{\dagger}$	$14.6^{\dagger}$			0.00
$m=2.3$ - Partial Profit Max. ($\lambda=0.75$)	$14.6^{\dagger}$	$17^{\dagger}$	$19.1^{\dagger}$		0.22
$m=3$ - Profit Maximization ($\lambda=1$)	$17^{\dagger}$	$19.1^{\dagger}$	$20.3^{\dagger}$	$20.2^{\dagger}$	1
Panel D: BLP IVs, no PCA - ($d_z = 5$)	$m=1$	$m=2.1$	$m=2.2$	$m=2.3$	MCS p-values
$m=1$ - Welfare Maximization ($\lambda=0$)					0.00
$m=2.1$ - Partial Profit Max. ($\lambda=0.25$)	$23.6^{\dagger}$				0.00
$m=2.2$ - Partial Profit Max. ($\lambda=0.50$)	$27.9^{\dagger}$	$32.5^{\dagger}$			0.00
$m=2.3$ - Partial Profit Max. ($\lambda=0.75$)	$32.5^{\dagger}$	$36.7^{\dagger}$	$39.7^{\dagger}$		0.01
$m=3$ - Profit Maximization ($\lambda=1$)	$36.7^{\dagger}$	$39.7^{\dagger}$	$40.6^{\dagger}$	$39.1^{\dagger}$	1.00

Panels A-D report effective F-statistics (Duarte et al., 2023) for the pair of models in the respective row and column, and MCS p-values (Hansen et al., 2011) for the row model. At a confidence level of 5%, MCS p-values below 0.05 indicate rejection of a row model. Each panel corresponds to a different set of instruments with dimension d_z. † indicates F-stat above critical value for a best-case power of 0.95. All F-stats are above the critical value for a worst-case size of 0.075. F-statistic values are adjusted for two-step estimation error.

elasticity η^b_{jk} is:

$$\eta^b_{jk} = -\frac{\partial b_j}{\partial p_k}\frac{p_k}{b_j}$$

where

$$\frac{\partial b_j}{\partial p_k} = \frac{\partial \delta_k}{\partial p_k}\int_{i\in\mathcal{I}} \frac{\alpha_i}{E}\frac{\partial P_{i,j}}{\partial \delta_k}\phi_i di = \frac{-\sigma}{p_k}\int_{i\in\mathcal{I}} \frac{\alpha_i}{E}\left(\mathbf{1}\{j=k\} - P_{i,j}\right) P_{i,j}\phi_i di$$

Table 22: Placebo Test - MCS p-values

	(1)	(2)	(3)
$m = 1$ - Welfare Maximization ($\lambda = 0$)	0.01	0	0
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	0.01	0	0
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	0.01	0	0
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	0.24	0.06	0
$m = 3$ - Profit Maximization ($\lambda = 1$)	1.00	1.00	1.00
Group	Pam	Auchan	Selex
Instruments	BLP×PAM	BLP×Auchan	BLP×Selex
Average F-statistic	56.4	48.7	45.6

Columns 1-3 report MCS p-values (Hansen et al., 2011) for three supermarket chains. At a confidence level of 5%, MCS p-values below 0.05 indicate rejection of a row model. The average F-statistic is the effective F of Duarte et al. (2023), adjusted for two-step estimation error, and averaged across pairs of models.

and $\mathbf{1}\{j = k\}$ is equal to one if j is equal to k and zero otherwise. We can simplify the formula to:

$$\eta^b_{jk} = -\sigma \frac{\int_{i\in\mathcal{I}} \alpha_i \left(\mathbf{1}\{j = k\} - P_{i,j}\right) P_{i,j}\phi_i di}{\int_{i\in\mathcal{I}(m)} \alpha_i P_{i,j}\phi_i di}$$

The more familiar quantity own-price elasticity is:

$$\eta^Q_{jk} = -\frac{\partial Q_j}{\partial p_k}\frac{p_k}{Q_j}$$

and because $Q_j = \frac{b_j E_m}{p_j}$, we have:

$$\frac{\partial Q_j}{\partial p_k} = \frac{E_m}{p_j}\left(\frac{\partial b_j}{\partial p_k} - \mathbf{1}\{j = k\}\frac{b_j}{p_j}\right)$$

so that:

$$\eta^Q_{jk} = \frac{E_m}{p_j}\left(\frac{\partial b_j}{\partial p_k} - \mathbf{1}\{j = k\}\frac{b_j}{p_j}\right)\frac{p_k p_j}{b_j E_m} = \eta^b_{jk} - \mathbf{1}\{j = k\}.$$

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