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 to not 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. However, 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 that 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 important industries such as banking, insurance, retailing and wholesaling. The main reason for forming cooperatives, as opposed to a investor owned corporations, is to commit firms to limiting the exercise of market power (Hansmann, 2000). This makes cooperatives an attractive option in concentrated markets, and motivates the tax exemptions and other regulatory advantages that they receive in many jurisdictions. For instance, the Affordable Care Act included the Consumer Operated and Oriented Plan (CO-OP) Program, providing federal loans to start up consumer cooperative health insurers with the ultimate goal of curbing market power and providing a consumer-friendly option.

However, it is not obvious that the adoption of 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 early leaders of the cooperative movement (e.g., Webb-Potter, 1891; Webb and Webb, 1914).

In this article we test whether the pricing conduct of consumer cooperatives differs from the conduct of their for-profit competitors, analyzing the Italian supermarket industry as a case-study. This industry provides an ideal empirical setup: 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 tend to be higher than when it is facing competitors—similar to when a for-profit firm has market power.

Giving a convincing answer to our research question, however, requires us to go beyond comparing the correlation between prices and market power for cooperatives and for-profit firms.[2] This empirical strategy, in fact, 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 or concentration from data alone is complicated. Moreover, there is no coherent interpretation of price-concentration correlations, so that comparing those for Coop and for-profit firms could

[1] Coop Italia is an association of consumer cooperatives, all adopting the same brand and acting under a common strategic direction. In Section 2 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).

be misleading.

To address these issues, we first measure market power using a demand model in which consumers choose where to shop for grocery goods. 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.[3] Whereas we assume for-profit supermarket groups to be profit-maximizing, Coop sets prices according to its preferences for profits and consumer welfare. Within the model we formalize different hypotheses on Coop's conduct, which have distinct empirical implications on its pricing decision. If Coop is profit maximizing, then its markups vary with demand elasticity, which in turn depends on market-level competitive conditions. If instead Coop gives more weight to consumer surplus, then the variation in prices across markets should mainly be explained by variation in marginal costs.

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). To implement the test, we use the procedure in Rivers and Vuong (2002) (RV). One key advantage of this procedure is its robustness with respect to the main weakness of our structural approach: potential misspecification of demand or cost. In fact, the RV test allows researchers to conclude in favor of the true model as long as misspecification is not too severe (Duarte, Magnolfi, Sølvsten, and Sullivan, 2021).

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 surplus. Beyond the formal results of the test for conduct, we discuss and discard other explanations for Coop's conduct, including the differential treatment of members and non-members, and presence in unprofitable markets by Coop.

The model also allows us to quantify the change in prices and in consumer surplus 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 on welfare. In particular, if Coop were to pursue pure maximization of consumer surplus, average supermarket prices would be about 3.6% lower, and consumer surplus would increase by about €3.1 billions. Even less extreme models of partial profit maximization generate significant welfare benefits, which are comparable to Coop's tax and regulatory benefits. In particular, if Coop were to give consumer welfare 22% of the weight it gives

[3] Other dimensions of competition, such as product availability, have been shown to be important for US supermarkets (Matsa, 2011).

to profits in its objective function, it would generate consumer welfare gains that match our back-of-the envelope valuation of the average yearly benefits that it receives during the period of our study.

Considerable attention has been devoted to the policy-relevant question of whether not-for-profit firms exploit market power (e.g., Philipson and Posner, 2009), especially in the US healthcare sector. An important literature broadly finds that not-for-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; Silverman and Skinner, 2004; Capps, Carlton, and David, 2020). In contrast, a recent study describes significant increases in premiums when a not-for-profit health insurer becomes for-profit (Dafny, 2019). The debate on the relationship between ownership structure and conduct in healthcare highlights the fact that, since not-for-profit firms could either be driven by boards strongly linked to local communities or by empire-building managers, not-for-profit conduct is essentially an empirical question.

Our work is also related to several studies that investigate empirically firms' conduct.[4] Craig and Pencavel (1992) and Pencavel and Craig (1994) describe an example where worker cooperatives, as compared to for-profit competitors, are less likely to adjust employment and more likely to adjust wages in response to changes in output prices. There is also solid evidence that firms' objectives may go beyond profit maximization. For instance, 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 seem to operate to maximize wins instead of profits, and Fioretti (2020) shows that firms can display altruistic conduct. We contribute to this literature by discussing instead a case where a firm may have deviated from its original objective and behaves as 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.[5] To implement the insight in Berry and Haile (2014) and test for the conduct of cooperatives using instruments, we rely on the methods in Duarte et al. (2021). They show that the main weakness of the RV test, potential degeneracy of the test statistic, is in essence a weak instruments problem, and provide a diagnostic to evaluate the quality of the inference produced by the RV test. In our setting, the instruments we use are strong for testing when evaluated according to the diagnostic, which makes our inference reliable.

[4]Other empirical papers have investigated cooperatives in Italy. Bentivogli and Viviano (2012) find that cooperatives employ strategies that are broadly similar to those of for-profit competitors.

[5]Recent papers that investigate conduct include Ciliberto and Williams (2014), Miller and Weinberg (2017), Michel and Weiergraeber (2018), and Backus, Conlon, and Sinkinson (2021).

The rest of the article proceeds as follows. In Section 2 we describe the institutional background on the Italian supermarket industry and Coop and present the data. Section 3 develops possible theories of cooperative conduct and shows descriptive evidence on the relation between Coop pricing and market power. In Section 4 we write a model of supply and demand in the supermarket industry to formalize our 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.

2 Institutional Background and Data

2.1 The Italian Supermarket Industry

Italian consumers spend roughly $130 billion in groceries per year, and more than half of these sales happen 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, i.e. consumers seldom drive more than 15 minutes by car and marketing research indicates that supermarkets derive most of their sales from customers living in a 2 km (1.24 miles) radius.

The main industry players include Coop—a network of consumers cooperatives, for-profit supermarket groups, and Conad—a producer cooperative. The latter is an association of roughly 3,000 entrepreneurs, who centralize marketing and private label operations. There is little question about Conad's conduct, which is run in the interest of the entrepreneurs-members. Some for-profit competitors are organized as associations of independent firms (e.g., Selex), but others are fully integrated (e.g., Esselunga, Finiper, Bennet).

Table 1 shows considerable variation in store format and size across groups. The median store size grows steadily over time, reflecting the adoption of larger store formats, but with broad differences. Some groups are 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 geographic differentiation across groups. Figure 1 shows the geographic location of stores for the four largest groups in our sample: firms differ in both the density of their stores, and in their regional presence.

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 group-level component (e.g., for private label products, or national

Table 1: Store Size and Number of Stores

	Median Store Size			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 group-level median store size (in sq. meters) and number of stores for three years.

promotions), as well as zone-level and store-level components. For instance, 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 in the UK (Thomassen, Smith, Seiler, and Schiraldi, 2017), Italy is similar to France, where supermarket prices co-vary with competitive conditions (Allain, Chambolle, Turolla, and Villas-Boas, 2017).

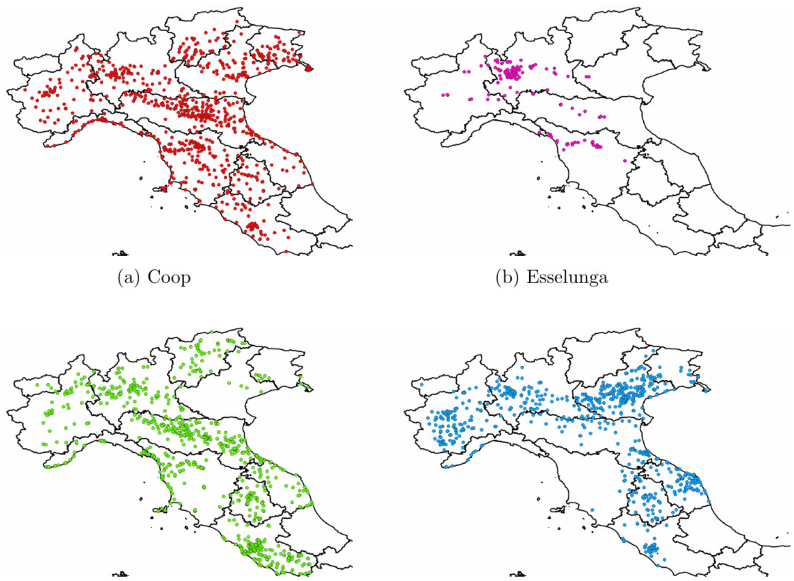
One aspect of this industry that is relevant for our study is the prevalence of the group purchasing organizations (GPO). GPO are associations of supermarket chains formed to procure goods together and obtain better terms from manufacturers, giving access to all members to the same wholesale prices. See Appendix A.6 for more discussion of GPO.

2.2 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 groups with hundreds of stores. Each of these cooperatives is a distinct legal entity, but they 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 private label strategy.

All cooperatives affiliated to 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 each market to a different cooperative in the Coop system, these cooperatives never compete in the same market. Given the close links between

Figure 1: Geographic Location of Stores for Largest Groups in 2013



(a) Coop (b) Esselunga

(c) Conad (d) Selex

We show the location of stores for the four largest supermarket groups in 2013.

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 non-members.[6] 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 consumer-members, none of the cooperatives we consider does so during the period of our study.[7] Governance is based on principles of internal democracy, and members elect the board of directors with a "one person, one vote" system. However, turnout in members' meetings is low (typically below 1% of total membership), and most cooperatives have rules that restrict members' ability to present their own board candidates to challenge the incumbents. These governance provisions result in weak powers for members, and entrenched managers that enjoy long 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. The preferential treatment is motivated by the nature of cooperatives, which are supposed

[6]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 non-members, providing high quality goods and services at the best possible prices ..."

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

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 prompted an investigation by the European Commission.[8] Therefore, determining Coop's conduct has public policy implications. We describe Coop's regulatory benefits in detail in Section 8.

Other allegations of distortions of competition are linked to Coop's political connections. The cooperative movement in Italy has longstanding links to political parties.[9] Coop's ties to politics may have two distinct effects: creating a link between consumers' political and shopping preferences, and connections with local politicians.[10] These political connections may persist over time, and since local Italian politicians have discretionary power on regulating entry of supermarkets, they may have an impact on market structure.[11]

2.3 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. 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 the universe of supermarkets in Central and Northern Italy from Information Resources Inc. (IRI), a marketing research firm. This dataset includes supermarket-level characteristics and revenues for seven cross sections in the years 2000, 2003, 2005, 2007, 2009, 2011 and 2013. IRI data are complemented by hand-collected distance from headquarters and data on what supermarkets are part of a larger shopping mall. Finally, we obtain price data from Altroconsumo, a consumer association. We discuss these sources in turn.

Market-level Data We include in our analysis all supermarkets in Central and Northern Italy. We exclude Southern Italy because of the different structure of the industry there, and the smaller footprint of Coop. Since no administrative unit adequately defines geographic markets in this industry, we start from local labor market areas, determined by ISTAT and based on commuting patterns, which help to define the areas where consumers are more likely

[8] See Case E1/2008 in the State Aid Register at the DG Competition.

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

[10] A large share of Coop's board members are politicians. Further discussion on the measurement of Coop's political connections is in Appendix A.4.

[11] Magnolfi and Roncoroni (2016) find that the political connections of Coop have an impact on entry, and may result in consumer welfare losses where connections represent a barrier to the entry of Coop's competitors. In those markets where connections facilitate Coop's entry, they may end up countervailing restrictive regulation and ultimately benefiting consumers.

to buy spatially differentiated goods (Houde, 2012; Pavan, Pozzi, and Rovigatti, 2020).[12]

To obtain the distribution of income and grocery expenditure in each market, we combine two data sources. We observe income and grocery expenditure for roughly eight thousand households across the country from a household panel survey by the Bank of Italy.[13] The only geographic indicator in this data is at the region level, an administrative unit that is larger than our market definition. For each region and year, we fit to the income data a log normal distribution and use additional data on average income at the municipality level to adjust the mean of the market-level income distribution for within-region relative differences in income.[14] Finally, we estimate the average grocery expenditure for every quartile of the income distribution. Table 2 reports summary statistics for market-level population, income and area: there is substantial (mostly cross-sectional) variation in all of these variables. Income and expenditure are stagnant over our sample period, and declining between 2007 and 2013 due to the recession.

Table 2: Market Characteristics

	Year	Mean	s.d.	Max	Median	Min
Population	2000	80,926	207,211	2,601,510	40,022	4,918
	2007	82,344	207,957	2,770,027	42,664	4,057
	2013	84,036	206,913	2,709,521	42,784	3,968
Income (2013 euros)	2000	39,867	8,351	66,553	39,812	17,745
	2007	40,748	6,977	62,493	40,317	17,054
	2013	37,154	6,452	58,409	37,467	16,090
Grocery Expenditure (2013 euros)	2000	5,831	269	6,456	5,745	5,258
	2007	5,716	290	6,066	5,789	5,204
	2013	5,104	472	5,968	5,072	4,052
Surface (Sq. km)		370	288	2,244	300	25

We report market-level summary statistics. Population data are from ISTAT; household income and grocery expenditure are from Bank of Italy data. See Appendix A.1 for more details.

Supermarket-level Data We obtain data on the universe of supermarkets for every year in our sample from IRI.[15] For each supermarket we observe geographic location, the group that operates it, store floorspace, and the share of sales among all supermarkets in the

[12] Some of the commuting areas are too large to reflect shopping patterns. We break labor market areas with at least two municipalities if (i) each has more than 15,000 inhabitants and (ii) they are at least 20 minutes of driving apart. We also merge labor market areas too small to be a grocery market. These have less than 30,000 inhabitants, are smaller than 100 square kilometers (38.6 square miles), and have highest elevation of 800 meters (2,624 feet) — in mountain areas consumers might find it costly to travel far.

[13] We use the CPI, obtained from ISTAT, to convert all figures to 2013 euros.

[14] For a full description of the construction of this element of the dataset, see Appendix A.1

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

sample.[16] We transform these shares into market-level revenue shares of the total grocery expenditure in two steps. We first compute total grocery expenditure at the market level, and then use accounting data on group-level revenues to convert relative shares of sales into sales in euros.[17] The IRI supermarket-level data are complemented with hand-collected information on which supermarkets are anchors in a mall, and supermarket groups' headquarters. For each supermarket, we compute distance from its headquarter using Google Maps APIs.

Data on supermarket-level prices are from Altroconsumo, an independent consumers' association. The data consist of a price index representing the cost of a basket of grocery goods, and is available for a sample of supermarkets in more than 50 cities in Central and Northern Italy. 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 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. The index is then normalized to assign a score of 100 to the cheapest store in the sample. 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.3.

In Table 3 we aggregate the data at the group-year level. Coop accounts for a large (about 20%) and stable share of revenues in this industry. Over time, several Italian firms (e.g., Bennet, Conad, Esselunga, Selex) gain market share at the expense of French competitors Auchan and Carrefour. Coop's average prices are lower than most competitors', but higher than those of the most efficient firms in the industry (e.g., Bennet, Esselunga).

Overall, the data described in this subsection displays significant variation in prices and market shares, and large variance in consumer choice sets both across geography and time. These will be key as we investigate our main question: what is Coop's competitive conduct? We turn to more specific evidence next.

3 Consumer Cooperatives: Theory and Preliminary Evidence

3.1 Hypothesis Development

Consumer cooperatives are formed to limit the exercise of market power (Hansmann, 1987, 2000). As an illustration, consider general stores in rural towns in the context of the 19th century US (Hansmann, 2013). Those stores sold groceries and other necessities, and were ei-

[16]IRI does not share the exact methodology that 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.

[17]Additional details on this procedure are in Appendix A.1

Table 3: Group-level Shares and Prices

	National Revenue Share (%)			Average Basket Price		
	2000	2007	2013	2000	2007	2013
Coop	21.09	21.03	21.42	114.14	118.54	121.77
Esselunga	9.87	11.04	13.58	114.23	106.85	117.82
Conad	8.9	9.53	12.42	117.53	121.7	122.93
Selex	6.02	7.95	10.96	116.75	122.3	119.96
Auchan	8.69	8.15	7.08	116.62	120.39	122.51
Carrefour	10.91	9.07	5.95	114.72	121.95	126.44
Bennet	1.71	3.41	3.58	-	115.95	120.48
Despar	2.88	3.43	3.42	119.3	123.95	121.49
Agorà	1.03	2.47	3.24	117.44	126.49	123.51
Pam	4.62	3.76	3.21	118.24	121.04	121.04
Finiper	0.79	2.85	3.02	118.99	121.46	118.74

We report group-year level statistics for three years of data. National revenue share is in percentage; average supermarket-level prices are in 2013 euros and represent the cost of a week of grocery shopping.

ther monopolies or had substantial market power. To avoid monopolistic pricing, these stores were often organized as consumer cooperatives, owned by local customers. Although better transportation and urbanization transformed retail markets in developed countries, grocery markets in Italy, where entry is highly regulated, still present some degree of market power.

The cooperative form, however, comes at a cost. As opposed to the traditional for-profit corporate form, investors are not the owners of the firm. Capital provision tends thus to be harder for cooperatives, which often have to rely 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.[18] Hence, the usual agency problem that arises from the separation between ownership and control (Jensen and Meckling, 1976) is exacerbated in the case of large consumer cooperatives.

Thus, there are three hypotheses on consumer cooperatives' objectives and conduct (Enke, 1945):

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

2 *Maximization of a combination of profits and consumer surplus*—Cooperatives may act to balance welfare and profits. Indeed, given the constraints to 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*—This may happen if managers pursue expansion or perquisite

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

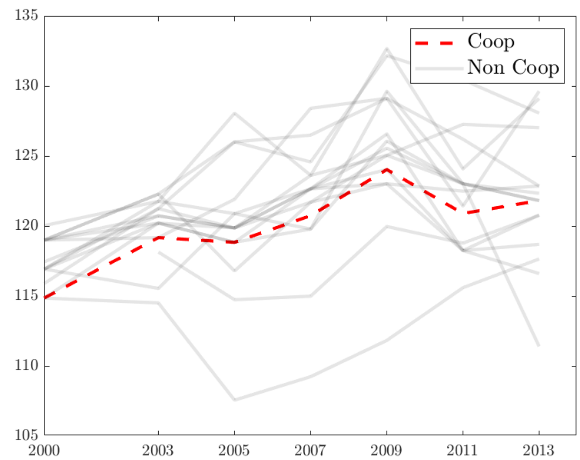
consumption, and corresponds to the "degeneration thesis" flagged as a danger by early leaders of the cooperative movement (e.g., Webb-Potter, 1891; Webb and Webb, 1914).

To our knowledge, this is the first article to test these hypotheses using data. We start our investigation using descriptive evidence on how Coop exploits market power.

3.2 Preliminary Evidence on Coop's Pricing Behavior and Market Power

We visualize in Figure 2 average group-level prices over our sample period. At first glance, Coop's prices (dashed) are at the lower end of the spectrum for all years, although there are groups that consistently offer lower prices by a substantial amount.

FIGURE 2: Group-level Average Prices Over Time



We show group-level prices, computed as the average across stores, over time. Prices are normalized to the cost of a weekly shopping trip, in 2013 euros. The red dashed line represents Coop's prices, all other groups are represented by solid gray lines. See Appendix A.3 for further information on price data.

This evidence, however, is not conclusive. The group-level aggregation misses out on store-level characteristics that may generate systematic differences in costs across groups. To address this issue, we run a supermarket-level regression of log prices on a Coop indicator, a vector of store- and market-level characteristics $\boldsymbol{x}_{jmt}$, and year and market fixed effects ψ_m and τ_t. Our specification is:

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

Results are reported in column 1 of Table 4. After controlling for other price determinants, Coop's stores have prices that are on average 0.93% lower than all other groups.

However, it is not immediate to relate this evidence to our research question. The regression, despite including controls for store characteristics and market-level fixed effects, does

Table 4: Coop Pricing Behavior and Monopoly Markets

	(1)		(2)	
	coef.	s.e.	coef.	s.e.
Coop — β_1	−0.0093	(0.0019)		
Monopoly Market — β_2			0.0095	(0.0032)
Coop Monopoly Market — β_3			−0.0037	(0.0040)
Year FE	Yes		Yes	
Group FE	No		Yes	
Group×Size FE	No		Yes	
Market FE	Yes		No	
Monopoly Markets			66	
n	2,672		2,672	

This table displays OLS estimates for Equations (1) and (2) in columns 1 and 2, respectively. All specifications include store size, distance from headquarters, and average market-level income as controls. Robust standard errors are in parenthesis.

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) are most likely to affect market power. These stores correspond to modern formats that are favored by consumers and most efficient. Hence, we construct an indicator variable for supermarkets located in a markets where a single firm operates stores with a floorspace of 2,500 square meters or larger.

We run supermarket-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 supermarket-level controls, market-level average income, and year-, group- and region-level fixed effects. Our specification is:

$$\begin{aligned}\log p_{jmt} = \beta_c + \beta_2 1\left\{\text{Monopoly}\right\}_{jmt} + \beta_3 1\left\{\text{Coop Monopoly}\right\}_{jmt} \\ + \boldsymbol{x}'_{jmt}\boldsymbol{\beta}_x + \psi_j + \tau_t + \epsilon_{jmt}.\end{aligned} \tag{2}$$

We report coefficient estimates for this specification in column 2 of Table 4. 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 prices that are systematically different: the coefficient on the Coop Monopoly variable is economically small and not statistically significant.

In sum, there is little evidence that the cooperative organizational form of Coop is associated with weaker correlation between monopoly power and pricing. The results presented thus far, however, are purely descriptive. In particular, we emphasize two limitations of this empirical exercise: measurement of market power and identification. Although intuitively appealing, monopoly is a crude indicator of market power. Moreover, the monopoly indicator is jointly determined with other outcomes. We address these limitations in the next sections.

4 Model

To measure market power as the elasticity of each supermarket's residual demand curve we construct a model of consumer demand. We then formalize hypotheses on Coop's conduct to perform testing.

4.1 Demand

In each geographic market m and for each year t in our sample, consumer $i \in \mathcal{I}(m,t)$ chooses in which supermarket $j \in \mathcal{J}(m,t) \cup \{0\}$ to buy a continuous quantity of bundles of grocery goods.[19] We denote as $j = 0$ the outside option, which refers to shopping in traditional retail stores, discount supermarkets, and open-air markets. To simplify 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 supermarket 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 in which store to shop and then how many units of groceries to buy. We further discuss this assumption and other departures from standard discrete choice models at the end of the section.

Consumer i is characterized by her income y_i and by preferences for supermarkets ε_i, φ_i and α_i. When consumer i purchases q_{ij} units of groceries from supermarket j, and ϑ_i units of a composite good, she derives utility:

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

where φ_{ij} is a parameter that models the preference of consumer i for supermarket j; 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 scale parameter σ, which measures the relative importance of the random shock and the deterministic part of utility. Conditional on choosing to shop at supermarket j, consumer i chooses optimally q_{ij} and ϑ_i

[19] Due to data limitations we abstract from one-stop versus multi-stop shopping (Thomassen et al., 2017).

according to:

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

The optimal quantity is $q_{ij}=\frac{\alpha_i}{p_j}$ — because of quasi-linearity of utility, consumer i chooses a fixed grocery expenditure α_i, irrespective of the quality of supermarkets in her choice set and her income. Given her grocery expenditure α_i, consumer i chooses among supermarkets based on indirect utility

$$v_{ij} \quad = \quad \sigma \ln\left(\frac{\varphi_{ij}}{p_j}\right)+\kappa_i+\tilde{\varepsilon}_{ij},$$

where $\tilde{\varepsilon}_{ij}=\sigma\varepsilon_{ij}$ is a standard T1EV shock, iid across individuals i and supermarkets j, and κ_i collects $i-$specific terms. We normalize the quality-price index of the outside good ($\frac{\varphi_{i0}}{p_0}=1$), and parametrize all other φ_{ij} so that $\ln(\varphi_{ij})=\boldsymbol{x}_j'\tilde{\boldsymbol{\beta}}+\boldsymbol{\mu}_{ij}'\tilde{\boldsymbol{\eta}}+\tilde{\xi}_j$, where $\boldsymbol{x}_j$, $\boldsymbol{\mu}_{ij}$ and $\tilde{\xi}_j$ are respectively observed store characteristics, interactions between store and consumer characteristics, and a scalar unobservable store characteristic as in Berry (1994); $\tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\eta}}$ are parameters. Store characteristics include store-format and group fixed effects, and an indicator for supermarkets in a mall. The store level unobservable $\tilde{\xi}_j$ captures unobserved characteristics such as local demand shocks and attractiveness of a store's location, thus partially addressing spatial aspects of demand that we do not model directly.[20]

Let $\boldsymbol{\beta}$, $\boldsymbol{\eta}$ and ξ denote the terms $\tilde{\boldsymbol{\beta}}$, $\tilde{\boldsymbol{\eta}}$ and $\tilde{\xi}$, respectively, multiplied by σ. Then the probability that consumer i shops in supermarket j, is:

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

where the supermarket specific term δ_j and the supermarket-individual specific term are:[21]

$$\delta_j=\boldsymbol{x}_j'\boldsymbol{\beta}-\sigma\ln p_j+\xi_j, \qquad \boldsymbol{\mu}_{ij}'\boldsymbol{\eta}=\ln(y_i)\eta_y+1\left\{\text{Coop}\right\}_j 1\left\{\text{Dem}\right\}_i \eta_l.$$

Income shifts the value of the outside option as high-income consumers may prefer to shop in traditional grocery stores. Moreover, consumers who vote center-left may have a stronger preference for Coop due to the cooperative's historical links to liberal political parties.[22]

[20] See Davis (2006) for an example of a model tackling spatial competition with aggregate data.

[21] Notice that σ, the scale of unobserved preferences for supermarkets, is the price coefficient in our specification. Intuitively, the larger the scale of unobserved preference shocks, the less consumers respond to price differences across stores.

[22] 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 lack of information on the joint distribution of y_i and $1\left\{\text{Dem}\right\}_i$, draws of political preferences are independent of income draws.

Finally, the share of grocery expenditure in supermarket j implied by the model is:

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

where $\mathrm{E}_{mt} = \int_{i \in \mathcal{I}(m,t)} \alpha_i \mathrm{d}i$ is the total grocery expenditure in market m during year t. In equilibrium, expenditure shares correspond to supermarkets revenue shares.

Discussion of the Demand Model Similar to recent work by Bjoernerstedt and Verboven (2016) and Eizenberg, Lach, and Oren-Yiftach (2021), our demand model describes discrete-continuous consumer choice, results in a specification where prices enter in logs, and is estimated from revenue share data. This specification better fits our data and empirical context when compared to a unit demand assumption.

Due to the lack of micro data, we 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. This choice allows us to overcome a limitation of our data: since prices only enter consumers' utility through $\boldsymbol{\delta}$, we can estimate the model even if price data are missing for some supermarkets, as we describe in more detail in Section 5.1.

Quasi-linearity of utility implies zero elasticity of grocery expenditure to income and unit elasticity of demand conditional on store choice. Cobb-Douglas utility instead implies a constant grocery expenditure share. Both of these restrictions are at odds with the data: available estimates for the elasticity of demand for groceries in Italy are below unity, and the grocery expenditure share is decreasing in income (Balli and Tiezzi, 2010). To mitigate the effects of quasi-linearity, in the empirical implementation we introduce heterogeneity across consumers by estimating α_i directly from data on grocery expenditure for a panel of households. We estimate $\alpha_i = \alpha_{r,q}$ as the average grocery expenditure among surveyed households in region r and quartile q of the income distribution. Hence, while α_i is constant in income for consumer i, we allow α_i to differ across quartiles of the income distribution. This specification accommodates the empirical regularities of decreasing grocery expenditure share and positive income elasticity of grocery expenditure.

Quasi-linearity also prevents income from affecting sensitivity to price. In our specification income only affects consumers' preferences for the inside goods. Despite the compromises, the demand model we adopt delivers credible substitution patterns that depart from logit — we discuss these further when presenting the estimation results 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.

4.2 Supply

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

We rely on institutional knowledge to specify $\boldsymbol{w}_j$. 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, distance from headquarters, and population density of the market. Labor costs vary regionally. Moreover, supermarkets in malls may have additional costs. Thus, we include in $\boldsymbol{w}_j$ store size, distance from headquarters, and indicators for group, region, urban markets, and stores in a mall.[23] Unobservable cost determinants in ω_j include differences in delivery costs and managerial ability.

Firms' Objective Function Each firm f owns a set of supermarkets $\mathcal{J}_f \subset \mathcal{J}(m,t)$. We maintain the standard assumption that a for-profit firm f maximizes its total profit π_f:

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

In contrast, Coop sets prices $\boldsymbol{p}_{Coop} = (p_j)_{j\in\mathcal{J}_{Coop}}$ evaluating both its profit and consumer surplus.[24] Surplus for a consumer i from prices $\boldsymbol{p} = (\boldsymbol{p}_{Coop}, \boldsymbol{p}_{-Coop})$ 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 $\boldsymbol{p}$:

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

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 weights every consumer's welfare equally,[25] the market-level objective function of Coop is:

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

[23] We drop distance from headquarters as it turns out not to be statistically or economically significant.

[24] 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).

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

where F aggregates 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 well the institutional background, but we discuss alternative hypotheses on Coop's objectives in Section 7.

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[26] for any Coop store $j \in \mathcal{J}_{Coop}$ are:

$$\sum_{h \in \mathcal{J}_{Coop}} (p_h - mc_h) \frac{\partial q_h(\boldsymbol{p})}{\partial p_j} = -q_j(\boldsymbol{p}) - \frac{F_2(\boldsymbol{p};\boldsymbol{u})}{F_1(\boldsymbol{p};\boldsymbol{u})} \left(\frac{\partial}{\partial p_j} cv(\boldsymbol{p};\boldsymbol{u}) \right), \tag{3}$$

while for any non-Coop store first order conditions are:

$$\sum_{h \in \mathcal{J}_f} (p_h - mc_h) \frac{\partial q_h(\boldsymbol{p})}{\partial p_j} = -q_j(\boldsymbol{p}). \tag{4}$$

As long as $F_1 \geq F_2$, the solution to the optimization problem describes an equilibrium where Coop prices are above marginal cost, but below the profit maximizing level, as $-\frac{F_2(\boldsymbol{p};\boldsymbol{u})}{F_1(\boldsymbol{p};\boldsymbol{u})} \left(\frac{\partial}{\partial p_j} cv(\boldsymbol{p};\boldsymbol{u}) \right) \geq 0$.

Supermarket Pricing We can further lean on the demand model in Section 4.1 to obtain sharper implications from Equations (3) and (4). By Shephard's lemma:

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

where q_j^H denotes the compensated (Hicksian) demand function for good j. Because of quasi-linearity of demand, compensated demand coincides with Mashallian 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. [27] We can then rewrite Equation (3) as:

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

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

[27] 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).

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:

$$\boldsymbol{p} = \left(\left[H \odot \Theta\left(\lambda\right) \right]^{-1} \boldsymbol{b} \right) \odot \left(\boldsymbol{p} \oslash \boldsymbol{b} \right) + \boldsymbol{mc}, \tag{5}$$

where H is the matrix of demand elasticities for all supermarkets, the symbols $\odot$ and $\oslash$ denote element-by-element multiplication and division, and $\Theta\left(\lambda\right)$ is an internalization matrix (Michel and Weiergraeber, 2018). 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 (5), but with different parametrizations of the internalization matrix, has been used to investigate collusion facilitated by multimarket contact (Ciliberto and Williams, 2014), coordinated effects of horizontal mergers (Miller and Weinberg, 2017), post-merger integration (Michel and Weiergraeber, 2018) 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 surplus—thus penalizing its own profits.

From (5) 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 3.1. A model of conduct $\mathcal{m}$ is characterized by a markup vector $\boldsymbol{\Delta}^{\mathcal{m}}$. For any model, the elements $\Delta_j^{\mathcal{m}}$ corresponding to stores not operated by Coop are equal to Bertrand markups Δ_j^B. Markups for Coop stores equal $\lambda\Delta_j^B$, where λ is model-specific. Pure welfare maximization, corresponding to model $\mathcal{m} = 1$ 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 $\mathcal{m} = 2$ and values of λ between zero and one. We specify, for concreteness, three such models: $\mathcal{m} = 2.1$, $\mathcal{m} = 2.2$ and $\mathcal{m} = 2.3$ corresponding to $\lambda = 0.25, 0.5$ and 0.75, respectively. Pure profit maximization corresponds to model $\mathcal{m} = 3$ 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.

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.[28]

5.1 Demand

Identification Under the assumption that $E\left[\xi_j|\boldsymbol{x}_j\right] = 0$, parameters $\boldsymbol{\beta}$ are identified by covariation in revenue shares and stores characteristics. We rely on store-level variation in the price index for 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 price instruments the prices of other stores in neighboring markets that belong to the same GPO. As promotional activity occurs at the group level, this addresses the usual concerns about national demand shocks invalidating these instruments.

We also use rival products' characteristics to measure supermarkets' degree of isolation in the product space (Berry et al., 1995). We form instruments, in the spirit of the differentiation instruments of Gandhi and Houde (2020), by computing for each supermarket the number of rival stores in the same, smaller and larger size categories. 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 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). Since 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 is 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.[29] The model is

[28] Conduct could be tested using demand and supply moments jointly. This procedure is computationally more demanding, and has not been showed to offer better econometric properties. Following the literature (e.g., Backus et al., 2021; Duarte et al., 2021; Miller and Weinberg, 2017), we adopt a sequential procedure.

[29] Eizenberg et al. (2021) assign the alternatives with missing price data to the outside option. When

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 law of iterated expectations.[30] Intuitively, this assumption requires that Altroconsumo does not systematically over-sample stores that are either abnormally attractive or unattractive to consumers, after controlling for observed characteristics, and is plausible in this context.[31] Since we have revenue share data for all supermarkets — including those with missing price data — we can compute $b_j(\boldsymbol{\delta}, \boldsymbol{\theta}^d)$ for all supermarkets and obtain $\hat{\boldsymbol{\theta}}^d$ as the solution of the MPEC program:

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

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

5.2 Testing for Conduct

Testability and Instruments The model in Section 4 translates the three hypotheses from Section 3.1 into five candidate pricing models. Having estimated demand, we can compute markup vectors $\boldsymbol{\Delta}^m$ corresponding to each model m. However, since we do not observe true markups, the simple comparison between the estimated markup vectors is not sufficient to distinguish the true model of conduct. Instead Berry and Haile (2014) show that testability requires valid instruments that are orthogonal to unobserved cost shocks, and correlated with markups. This is in line with simple economic intuition. The more weight Coop places on profits, the more its prices co-vary with its Bertrand markups Δ^B. Hence, exogenously varying Bertrand markups via demand shifts and rotations, or via changes in the set and costs of competitors, allows the researcher to test whether Coop exploits market power. The true model of conduct generates a covariation between prices and markups that makes implied cost shocks orthogonal to instruments. Other models of conduct, instead, are falsified.

To implement this intuition we construct instruments $\boldsymbol{z}_j^s$ that induce variation in competitive environment across markets. First, we construct BLP instruments by computing the number of rival stores in each size category. These instruments directly impact the competitive environment, thus shifting markups. We also exploit variation in political preferences for Coop, and in the intensity of Coop's political connections. As shown in previous work, political connections have a significant impact on market structure in this industry (Magnolfi and Roncoroni, 2016), and are unlikely to be correlated with unobservable determinants of marginal cost (as opposed to fixed cost). The final set of instruments includes

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.

[30] 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.

[31] See Appendix A.3 for more information on selection into the Altroconsumo sample.

BLP instruments interacted with a Coop indicator, and with political preferences and political connections variables. Following Backus et al. (2021) and Duarte et al. (2021) we apply a PCA algorithm, and select the components that explain 95% of the variance to form our final set of instruments $\boldsymbol{z}_j^s$. We assume that such instruments are mean independent of cost shocks, i.e. $E[\omega_j|\boldsymbol{z}_j^s] = 0$.

Inference To perform inference on conduct we follow Duarte et al. (2021) 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 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 benchmark the moment condition $E[\omega_j|\boldsymbol{z}_j^s] = 0$ that holds for the true model of conduct. We first use linearity of marginal cost and the assumption that cost shifters $\boldsymbol{w}_j$ are exogenous to residualize prices, instruments and markups for each model with respect to $\boldsymbol{w}_j$. 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 objective 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.[32] 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

[32] See Duarte et al. (2021) for the exact formulation of this estimator, which accounts for first-stage estimation error in markups.

values indicate evidence in favor of better asymptotic fit of model m. Conversely, positive values indicate evidence in favor of model ℓ. If instead σ^2_{RV} equals zero, the RV test statistic is degenerate, and inference is invalid. Duarte et al. (2021) show that degeneracy of RV is a weak instruments for testing 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

6.1 Demand, Elasticity and Bertrand Markups

We report in Table 5 coefficient estimates for the demand model. All coefficients have signs consistent with economic intuition. The coefficient η_y of the interaction between income and value of the outside option 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. Values for the informal Gandhi and Houde (2020) weak instruments test indicate that the instruments are strong for σ and η_y, which generates substitution patterns between stores that depart from logit. Comparing columns 1 and 2 highlights the importance of instrumenting for the price coefficient to get consistent estimates of price elasticity.

TABLE 5: Demand Model Estimates

	OLS (1)		IV (2)		RC (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×Coop - η_l					0.28	(1.79)
In Mall	0.07	(0.05)	0.07	(0.05)	0.12	(0.05)
Weak Instruments Test - σ			34.90		17.90	
Weak Instruments Test - η_y					345.00	
Weak Instruments Test - η_l					5.10	
Median Own Price Elasticity	-3.34		-5.35		-7.41	
n	$2,672$		$2,672$		$14,385$	

Column 1 reports OLS estimates for a linear model with $\boldsymbol{\eta} = 0$. Column 2 reports estimates for the same model where we instrumented with Hausman and differentiation instruments for price. Column 3 reports GMM estimates for the nonlinear model in Section 4.1, obtained as outlined in Section 5.1. Instruments include Hausman instruments, differentiation instruments, and their interaction with demographics. The weak instruments test statistics in column 3 are the rank condition test statistics of Gandhi and Houde (2020). All specifications have fixed effects for group, size, group-size, year and market.

Median store-level own-price elasticity is -7.41, implying that consumers are elastic when choosing among different supermarkets in their choice set.[33] Moreover, table 6 shows in columns 1 that group-level elasticities are lower for groups that operate larger stores, e.g. Finiper in 2000. Cross-price elasticities are low, raging from 0.002 to 0.073, with a median of 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 implied PCM in column 2 of Table 6. The median PCM across our full sample is 14.8%, 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 6), 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).[34] Nevertheless, the model-implied PCM are comparable to accounting margins.

Table 6: Supermarket Groups Median Elasticities and PCM

	Own-Price Elasticities (1)		Bertrand PCM (%) (2)		Accounting PCM (%) (3)	
	2000	2013	2000	2013	2000	2013
Coop	-7.00	-7.07	16.7	16.1	-	-
Esselunga	-7.25	-7.13	17.0	16.8	18.3	19.0
Conad	-7.30	-7.25	14.9	15.3	-	-
Carrefour	-7.20	-7.28	15.8	14.7	16.6	-
Selex	-7.34	-7.30	14.7	15.3	12.9	14.0
Auchan	-7.11	-7.31	15.5	14.5	18.2	14.2
Pam	-7.29	-7.29	14.2	14.1	16.4	16.0
Bennet	-7.38	-7.17	13.6	15.5	20.3	23.0
Finiper	-6.36	-7.28	15.8	14.1	16.0	16.0

We report elasticities, implied Bertrand PCM, and PCM from accounting data for the largest groups. Columns 1 show the group median own-price elasticity for the main industry players for 2000 and 2013. Columns 2 and 3 display respectively sales-weighted average model-implied Bertrand PCM and accounting PCM. 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 instance, Eizenberg et al. (2021) find average PCM of around 20% for grocery retailers in Jerusalem. Margins for U.S. grocery retail

[33] As noted in Bjoernerstedt and Verboven (2016), the functional form of demand that we adopt implies that elasticities are not linearly dependent on prices. Hence, in our estimates, consumer are more inelastic in their demand for the most popular and largest stores.

[34] Additionally, several firms operate stores that are not in our sample because they are located in Southern Italy.

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.

6.2 Test for Coop Conduct

Cost Implications of Conduct As a first informal assessment of different models of conduct, we describe the implications that these models have on Coop's marginal costs. 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 results in Table 7. In line with intuition, marginal costs are smaller for larger stores. We also control for group-level, GPO and city size fixed effects, which indicate that marginal costs are larger in bigger cities. Coefficients are broadly similar across all models of Coop conduct.

TABLE 7: Cost Implications of Conduct

	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$	$m = 3$
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)
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. We also report the ratio between average marginal cost for Coop and for all other supermarkets. Robust standard errors are in parenthesis. $n = 2,672$.

However, 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 surplus 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 takes part 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 8, 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 5%. Model $m = 3$, corresponding to pure profit maximization for Coop, rejects all other models of conduct, and thus appears to be the only one supported by the data. Since the heuristic procedure of performing several pairwise tests does not control the family-wise error rate, we follow Duarte et al. (2021) 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 5%, only the pure profit maximization model is in the MCS.

Table 8: 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 Maximization ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	-7.28				0.00
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	-7.13	-6.88			0.00
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	-6.88	-6.43	-5.63		0.03
$m = 3$ - Profit Maximization ($\lambda = 1$)	-6.43	-5.63	-4.26	-2.18	1.00
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. ($\lambda = 0.25$)	9.0				
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	11.0	13.7			
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	13.7	16.8	20.3		
$m = 3$ - Profit Maximization ($\lambda = 1$)	16.8	20.3	23.4	25.1	

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 suggests better fit of the row model. At a confidence level of 5%, critical values for T^{RV} are $\pm$ 1.96 and MCS p-values below 0.05 indicate rejection of a row model. Panel B reports the effective F-statistic of Duarte et al. (2021) for the pair of models in the respective row and column. Both test statistics and F-statistic values are adjusted for two-step estimation error.

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. (2021), and report them in Table 8, Panel B for each pair of models. These can be compared to critical values in Duarte et al. (2021) to diagnose whether the instruments we use may generate size distortions or low power. For our set of four instruments, size distortions are not a concern. The critical values to reject a maximal power below 0.95 and 0.75 are 12.3 and 8.8, respectively. The effective F-statistics in Panel B are above the critical value for a maximal power of 0.75 for each pair of models, and above the critical value for a maximal power of 0.95 for all but two pairs of models. We conclude that the instruments are strong for power.

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

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., 2021). 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 5 using the same instruments used to perform RV testing. We report estimates of the λ in Table 9 for different specifications of marginal cost.[35] 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 9: Conduct Estimates

	(1)		(2)		(3)	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
λ	1.01	(0.07)	1.02	(0.07)	1.02	(0.07)
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 5. Columns 1-3 correspond to different specifications of marginal cost, indicated in the table. Standard errors—computed with a two-step correction—are in parenthesis.

Another important interpretation aspect of the RV testing results is that they are robust to misspecification. More precisely, Duarte et al. (2021) 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.1 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 demand system fairly different from the one described in Section 4.1, profit maximization for Coop is the only model of conduct that is not rejected.

Finally, we investigate two other dimensions of robustness of our results in Appendix B.

[35]This is essentially the specification in Pakes (2017). While it complements the interpretation of RV results, its properties as a testing procedure are less appealing than those of RV (Duarte et al., 2021).

First, we consider different sets of instruments for testing, including the set of instruments we use for demand, and a set of instruments that does not use data on political connections. For all these alternative instruments, the testing results are either in line with the results of Table 8, 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 on our method, we perform RV for the main for-profit supermarket groups, evaluating the same models that we consider for Coop in Table 9. The results of this exercise 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 pricing as a profit maximizer. However, our analysis may be missing other dimensions where Coop is significantly different from its competitors. We consider in this section such alternative hypotheses on Coop's conduct.

Differential Treatment of Members and Non-members Coop may seek to only maximize the welfare of its members. As Coop does not pay dividends,[36] this may happen via 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 does not have information on members-only discounts,[37] our analysis may be missing an important dimension where Coop differs from its rivals.

However, all of Coop's competitors have loyalty programs that, while 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 report this data in Table 10, 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 used to construct the price index.

The data confirm that rewards for loyalty program members (which can be joined for free) are similar to the benefits of Coop membership.[38] Moreover, annual reports indicate that the share of revenues that Coop's competitors generate from loyalty program members

[36]This holds with the minor exception of some smaller cooperatives in the Coop system. All the major cooperatives that form Coop do not pay dividends in the period of our study.

[37]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.

[38]Although the data are collected in 2014, loyalty programs for most chains are unchanged over 2001-2013.

Table 10: 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 programs rewards from Altroconsumo. For each chain, we report percentage discount using points, average unit discount for items on members-only promotion, and average total members-only discount over the total price of the grocery basket.

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 members 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 while committing 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 paper, we present suggestive evidence that the markets where Coop is present - and importantly, those in which it has market power - are not meaningfully different than other markets. To do so, we test an implication of the missing markets theory: 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[39] provided by the Italian tax agency.[40] We match supermarkets to real estate costs data at a fine geographic level, and study whether Coop builds stores in areas that exhibit systematically higher costs.[41]

Columns 1-3 of Table 11 show OLS regression estimates where the dependent variable is log of cost per square meter of real estate at the supermarket level; we control for year fixed

[39] Costs of real estate represent a substantial fraction of total fixed cost, vary considerably across locations,

Table 11: Fixed Costs and Coop Entry

	(1)	(2)	(3)	(4)	(5)
Coop	0.068	-0.008	-0.005		
	(0.009)	(0.009)	(0.007)		
Monopoly Market				-0.034	-0.037
				(0.007)	(0.008)
Coop Monopoly Market					0.009
					(0.015)
Year FE	Yes	Yes	Yes	Yes	Yes
Group FE	No	No	No	Yes	Yes
Geographic FE	No	Region	Market	Region	Region

We report OLS coefficient estimates for a regression where the dependent variable is store-level price of commercial real estate. Columns 1-3 examine, under different sets of controls, whether Coop's real estate fixed costs are systematically higher. Columns 4 and 5 examine whether Coop's monopoly markets exhibit systematically higher real estate costs. Robust standard errors are in parenthesis. All regressions control for store size, distance to headquarter and location inside mall. $n = 14,138$.

effects, store size fixed effects (since larger stores are likely to be built in less central areas) including an indicator for stores in a large mall, group-level fixed effects and different sets of geographic fixed effects. Except for the specification in column 1 which does not include geographic fixed effects, 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 4 and 5 we focus on markets with only one large store.[42] We run store-level regressions of 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 5 indicates that, compared to other monopoly markets, Coop monopolies do not display different fixed costs. In sum, our results provide little support 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 surplus 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. Formally:

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

and are observable. Other cost components are harder to measure or attribute to a store.

[40]This data is described in greater detail in Appendix A.5.

[41]Notice that finding that fixed costs are systematically too low would also be concerning, as it may signal that Coop chooses to locate in markets that are unattractive for business.

[42]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).

where $\boldsymbol{p}_m$, $\boldsymbol{p}_{Coop}$ and $\bar{\pi}$ are, respectively, all supermarket 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:

$$\sum_{h \in \mathcal{J}_{Coop}} (p_h - mc_h) \frac{\partial q_h(\boldsymbol{p})}{\partial p_j} = -q_j(\boldsymbol{p}) - \Lambda \left(\frac{\partial}{\partial p_j} cv(\boldsymbol{p}, \boldsymbol{u}) \right). \tag{6}$$

This condition is identical to (3), with the Lagrange multiplier Λ replacing the term $\frac{F_2}{F_1}$. Hence, this model of Coop's objective is equivalent to the model in Section 4.2: for each $\bar{\pi} > 0$ which the problem has a solution, there exists a Λ for the model in Section 4.2 such that Equations (3) and (6) have the same implications on Coop's pricing. Hence, our results in Section 6 can be interpreted in light of the surplus maximization model: the only model that we cannot reject is the one where Coop sets profit goals that 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. With respect to 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 as Coop. While pricing 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 and anecdotal observations do not support this view. First, the chain fixed effects that we estimate for 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 effect capture many factors, including the average location of stores and marketing strategy, but would detect whether consumers perceived large differences in quality between Coop and its competitors. Second, during the period of our study supermarkets in Italy mostly sold branded products, which are identical across stores.[43] The importance of store brands is growing over time; however, it is not clear how much variation in product quality across chains is due to store brands, since these products tend to be manufactured by the same firms for all supermarket chains.

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

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 evaluate quantitatively 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.[44] 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 12 reports 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 surplus by Coop would drive down the average price by about 3.6%, and by about 18.5% in Coop supermarkets. 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, which reflects the importance of differentiation in the industry.

Table 12: Implications of Coop Conduct

Panel A: Changes in Average Prices (%)	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$
Average	−3.6	−2.3	−1.5	−0.8
Coop Supermarkets	−18.5	−12.0	−7.8	−3.9
Non Coop Supermarkets	−0.3	−0.2	−0.1	−0.1
Panel B: Changes in Consumer Welfare	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$
Average Household (€)	225.4	107.0	62.2	26.4
Total (billion €)	3.1	1.5	0.9	0.4

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.

Panel B of Table 12 reports changes in consumer surplus. Reflecting Coop's large market-share and the low substitution between supermarkets, Coop's conduct has a meaningful impact on surplus: having Coop adopt model 1 would increase surplus of about €225 for the average household, for a total of around 3.1 billion euros or around 4.5% of household's average grocery expenditure.[45] Comparing model 3 to partial profit maximization yields smaller, but still relevant, gains. Overall, this exercise points to a quantitatively important

[44] We do so for the last year in our sample, 2013. Results for earlier years are quantitatively similar.

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

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 surplus would be substantial.

Assessing Coop's Tax and Regulatory Advantages Because of its organizational form, Coop receives tax and regulatory advantages. This preferential regime cannot be justified by Coop role in constraining the use of market power in the market. On the other hand, we know from Table 12 that different models of Coop conduct may generate significant consumer welfare gains. We therefore 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 from examining the tax breaks that Coop receives.[46] Given the complexity of corporate tax law, we adopt a simple empirical approach and compare Coop to its largest for-profit competitor, Esselunga. Over the years of our sample, accounting data show that Esselunga paid in tax 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 in tax rate results in €114 million of yearly tax benefits at the end of our sample.[47] Several assumptions and approximations are involved in this exercise,[48] which we believe is a reasonable back-of-the-envelope exercise to quantify 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.[49] 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 groups are similar. Akin to what we do to quantify the tax benefit, we

[46]For profit corporate entities in Italy are subject to a national corporate income tax (IRES), and to a regional tax (IRAP). IRES is computed as a percentage of net income, while IRAP's taxable base roughly corresponds to a company's gross margin. The tax rate for IRES changed several times during the period of our sample - from 40.3% in 2001 to 31.4% in 2013. The tax rate for IRAP is anchored to a national base of 3.9%, but regions have the power to change the rate they charge in a band within the national rate. Many tax credits and incentives exist for specific investments in human or physical capital. The main break that Coop gets is a reduction of the IRES taxable base: for most of our sample period, cooperatives' net income allocated to indivisible reserves is 70% tax exempt.

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

[48]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.

[49]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.

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 members 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 at providing a meaningful yardstick to assess when is it that tax and regulatory advantages may be justified in exchange of 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 $\lambda = 0.9$ would be equal to the tax benefits Coop enjoys, and conduct corresponding to $\lambda = 0.78$ would generate gains that match the tax and lending benefits. For interpretation, $\lambda = 0.78$ corresponds to Coop giving to consumer welfare 22% of 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 most mild 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 on the policy debate on cooperatives and not-for-profit firms. The case-study of Coop shows the dangers of degeneration of a consumer cooperative (Webb-Potter, 1891; Webb and Webb, 1914). Degeneration along the lines of what we find in our context may be an issue beyond consumer cooperatives. For instance, Dairy Farmers of America (DFA), one of the largest agricultural cooperatives in the US, has been accused by its members of exploiting its monopsony power, increasingly resembling a for-profit corporation.[50] 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 for them to succeed, so that members keep having 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. While policymakers took steps to ensure that these organizations were consumer-friendly and boards were mostly composed of activists, this often resulted in inexperienced management that priced plans too low and ultimately led to financial struggles (Sparer and Brown, 2020).

Taken together, the results in this paper are a cautionary tale on the potential role of not-

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

for-profit firms in curbing market power and complement the evidence from 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 seem in general not warranted, and other subsidies need to be carefully evaluated against the actual benefits that they generate for consumers.

9 Conclusion

This article carries out an empirical investigation into the pricing conduct of Coop, a large network of consumer cooperatives that operate supermarkets in Italy. 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. We formulate several hypotheses on Coop's conduct, ranging from pure profit maximization to pure maximization of consumer surplus. These hypotheses generate testable predictions: profit maximization implies that Coop's prices reflect its market power, while consumer surplus maximization implies that variation in prices reflects only differences in marginal cost. Preliminary analysis supports the notion that Coop—when it finds itself as the sole firm operating large supermarkets in a market—exploits its market power by charging higher prices, just as its competitors do. However, it is hard to assess firms' market power from data alone.

We thus 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, controlling for the determinants of marginal cost, reflect market power.

We do not reject the hypothesis that Coop's pricing conduct reflects pure profit maximization, although 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 22% of the weight that it gives to profits in its objective function, generates consumer welfare gains that justify 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 paper 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

A.1 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).[51] 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.[52] 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. In fact, 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 measures 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.

[51] 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.

[52] 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,

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

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 13). 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 ranges 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, while 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 13: 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. $n = 3,313$.

A.2 Supermarket Revenues

Our data source for supermarket level revenue share is IRI's Top Trade dataset, which reports estimates of revenues for each supermarket as 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) using our estimates of market-level grocery expenditure E_m. As shown in Table 13, using different firms for this procedure does not materially change the database.

To validate of 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[53] finds that 57.9%. of respondents in a representative sample of the population chooses a supermarket for their grocery shopping.

A.3 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 supermarkets and scans prices of a large number of products in each store to construct a supermarket-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 additional description of the data, focusing on the aspects of (i) selection of the sample of supermarkets, (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 supermarket-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 groups—our objective in this article.

Supermarket Selection Researchers at Altroconsumo assemble their sample of supermarket 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 a good share of large stores in a market, if Altroconsumo is including one store

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

for that firm it will most likely include a large store. Table 14 highlights how the supermarkets in the sample tend to be larger and have higher revenues than both the full sample of IRI supermarkets in the markets that correspond to the cities surveyed by Altroconsumo, and with respect to those supermarkets for which price data are not available. Both average revenues and average size are roughly double in the Altroconsumo sample, so that conditional on supermarket 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 groups and French groups is similar to the overall population.

Table 14: Selection into Altroconsumo Sample

	Price Data Available	Markets with Data Price Data	Price Data Not Available
Average Revenues (mln Euros)	16.92	9.60	8.11
Average Size (Sq. m)	2,253.28	1,311.38	1,172.78
Average Rev. per Sq.m (thous. Euros)	7.40	7.16	6.74
Average distance from HQ (km)	154.40	152.32	132.95
% of Coop	17	12	14
% of Italian groups	68	71	74
% of French groups	16	17	12
n	2,683	14,335	35,341

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

Selection of Products into the Index Altroconsumo identifies the product categories for its price index based 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 15 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 for fresh foods. In this way, the list of roughly 100 product categories becomes a list of roughly 500 products.

Table 15: 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 supermarket in the sample, where available. Supermarkets with less than 200 products available are excluded from the sample. Product-level prices are weighted according to 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 supermarkets, 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 supermarket 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).

A.4 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, provinces, and regions, excluding those elected after 1998.[54] We count only connections established until 1998 to capture long-standing connections not affected by 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 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 since 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 $POWER_m$

[54] 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).

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 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, in sqkm	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.

A.5 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 supermarkets address to match supermarkets to OMI areas. The database contains minimum and maximum prices and rental rates per square meter and 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.

A.6 GPO in the Italian Supermarket Industry

Italian supermarket groups purchase the majority of the goods they sell[55] through GPO, alliances of separate supermarket chains that have the aim of obtaining better terms from manufacturers. GPO 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 negotiate yearly contracts, where list prices, rebates, promotions and any co-marketing activity are spelled out in detail.[56] Contracts are valid for every supermarket 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

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

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

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.

B.1 Alternative Demand Models

We show here estimation results for demand models that are alternative to the one presented in Section 4.1 in the article, which relies on a discrete-continuous specification and quasi-linear utility. These assumptions fit well the empirical environment, and enable us to use data on market shares and characteristics for all 14,385 supermarket-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-supermarket 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.2.

B.2 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 on 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 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 $\times$ Constant - η_{cy}			-2.95	(1.12)
Log Income $\times$ 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 group, size, group-size, year and market. $n = 2,672$.

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 than we use in the baseline results of Table 8 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 a PCA algorithm 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 on 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, while 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 8 are not driven by our specific choice of instruments, but hold for a class of valid and strong instruments.

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 ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	-7.65				0.00
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	-7.59	-7.46			0.00
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	-7.46	-7.21	-6.69		0.00
$m = 3$ - Profit Maximization ($\lambda = 1$)	-7.21	-6.69	-5.58	-3.38	1.00
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. ($\lambda = 0.25$)	6.2				
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	7.9	10.3			
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	10.3	13.4	17.5		
$m = 3$ - Profit Maximization ($\lambda = 1$)	13.4	17.5	21.9	25.0	

The table reports test for Coop conduct 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 suggests better fit of the row model. Panel B reports the effective F-statistic of Duarte et al. (2021) for the pair of models in the respective row and column. Both test statistics and F-statistic values are adjusted for two-step estimation error.

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 on our empirical strategy. Table 22 shows results of the RV test for three for-profit supermarket groups: PAM, Selex and Auchan. We perform the test using the principal components of BLP instruments interacted with a group 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 groups, 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.[57]

[57] Similarly, when we perform an estimation exercise as the one in Table 9, the estimates of λ are economically and statistically close to one for the three supermarket groups, indicating good fit of profit maximization.

Table 21: RV Test 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 ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	20.9				0.00
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	24.4	28.2			0.00
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	28.2	32.0	35.3		0.01
$m = 3$ - Profit Maximization ($\lambda = 1$)	32.0	35.3	37.4	37.8	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 ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	3.4				0.00
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	4.2	5.2			0.00
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	5.2	6.6	8.4		0.02
$m = 3$ - Profit Maximization ($\lambda = 1$)	6.6	8.4	10.6	12.9	1.00
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 ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	9.2				0.00
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	11.1	13.4			0.01
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	13.4	15.6	17.4		0.32
$m = 3$ - Profit Maximization ($\lambda = 1$)	15.6	17.4	18.3	17.8	1.00
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 ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	23.6				0.00
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	27.9	32.5			0.00
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	32.5	36.7	39.7		0.01
$m = 3$ - Profit Maximization ($\lambda = 1$)	36.7	39.7	40.6	39.1	1.00

Panels A-D report effective F-statistics (Duarte et al., 2021) 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. F-statistic values are adjusted for two-step estimation error.

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$\times$PAM	BLP$\times$Auchan	BLP$\times$Selex
Average F-statistic	56.4	48.7	45.6

Columns 1-3 report MCS p-values (Hansen et al., 2011) for three supermarket groups. 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. (2021), adjusted for two-step estimation error, and averaged across pairs of models.

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