The Competitive Conduct of Consumer Cooperatives*

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Abstract

Although consumer cooperatives are nominally operated in the interest of their members, their governance structure may allow managers to pursue their own objectives. This article tests empirically whether consumer cooperatives act as profit-maximizing agents. Using data and a structural model, we investigate whether the hypothesis of profit maximization can be rejected for consumer cooperatives operating in the Italian supermarket industry. We do not find significant deviations of cooperatives' conduct from profit maximization. Counterfactual simulations indicate that full internalization of consumer surplus by cooperatives would increase consumer surplus by about 6% in the market we study.

Keywords: Consumer cooperative, estimation of conduct, 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 developed and developing economies,[1] and are usually inspired by broader social goals.[2] However, it is not obvious that the adoption of a cooperative form always determines the adoption of a particular competitive conduct. Although consumer cooperatives typically state in their charters that their objective is the provision of high-quality products at low prices to consumers, the agency problem (Jensen and Meckling, 1976) may divert them from pursuing this goal. In fact, when cooperatives grow large, internal democracy may vanish and managers may gain strong powers to go after their own objectives (e.g., empire building or perquisite consumption). If this is the case, the objective of keeping prices low for consumer-members may be put aside, as managers pursue economic profit to invest in further expansion or non-core businesses.[3] In this paper we ask the empirical question: can we use data to distinguish between different hypotheses on a cooperative firm's objectives and behavior?

We propose a strategy to determine whether the pricing behavior of consumer cooperatives differs from the behavior of their for-profit competitors, analyzing the Italian supermarket industry as a case-study. In this industry, a large consumer cooperative, Coop, operates along with for-profit entities.[4] Coop enjoys tax advantages, but its high market share and pricing behavior in some geographical markets may cast doubts on the basis of this preferential treatment.[5] Descriptive evidence shows that when Coop is the only firm to operate large supermarkets in a city, prices of groceries in its stores tend to be higher than in un-concentrated grocery markets—similar to when a for-profit firm has market power.

Although Coop's pricing behavior is observable, we need to measure markups to shed light on conduct and ultimately uncover Coop's objective function. To this aim we build a structural model of the supermarket industry. In our model, consumers choose where to shop for a continuous quantity of a bundle of grocery goods. On the supply side, supermarket

[1]For instance, around 30,000 consumer and producer cooperatives operate in the US, generating revenues for more than $600 billion. See Deller et al. (2009).

[2]The International Co-operative Alliance (ICA) employs broader terms in its definition of a cooperative as "an autonomous association of persons united voluntarily to meet their common economic, social, and cultural needs and aspirations through a jointly owned and democratically controlled enterprise."

[3]This issue also raises public policy considerations, since the favorable fiscal treatment that governments reserve to consumer cooperatives in most jurisdictions is often justified by their role in fostering consumers' welfare. If consumer cooperatives are in fact profit-maximizing entities, any favorable tax treatment represents a distortion of the competitive playing field.

[4]Coop Italia is a consortium of consumer cooperatives, all adopting the same Coop sign in their stores and acting under a common strategic direction. In the next section we explain why we consider Coop as a single entity in this article.

[5]This is an active area of policy debate, as well as the subject of an investigation by EU authorities—see Case E1/2008 in the State Aid Register at the DG Competition.

groups set prices in each store in a simultaneous move, complete information pricing game.[6] Whereas for-profit supermarket groups are assumed to be profit-maximizing, consumer cooperatives may set prices taking into account consumer surplus. This model results in a pricing rule that weights marginal costs and markups according to the cooperative's preferences for profits or welfare. We use the model to formalize the intuition that different hypotheses on cooperatives' conduct have distinct empirical implications on pricing behavior across markets: 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 estimate demand elasticities using data on supermarket-level revenue shares and prices for seven years between 2000 and 2013.[7] Our model accounts for the fact that consumers' political choices may be correlated with their preferences for Coop's supermarkets by including voting patterns as demand shifters. On the supply-side, we exploit variation in market conditions to identify the objective function of cooperatives. In particular, we exploit variation in the intensity of Coop's historical political connections across markets. As shown in previous work, political connections have a significant impact on market structure in this industry (Magnolfi and Roncoroni, 2016), by both reducing entry costs for Coop and increasing entry costs for rivals. Hence, political connections shift and rotate the residual demand curve through their impact on consumers' choice sets, and at the same time are not correlated with unobservable determinants of marginal cost (as opposed to fixed cost).

Our estimates indicate that Coop sets prices in a profit-maximizing fashion, and we can instead reject the hypothesis that Coop prices based purely on consumer surplus maximization.[8] 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, mostly through their effect on Coop's own prices. In particular, if Coop were to pursue maximization of consumer surplus, Coop's prices would be about 16% lower, average store-level grocery prices would fall by about 2.5%, and consumer surplus would increase by about 5.8%. Our results and counterfactuals are an important input for the policy discussion on Coop's governance and tax treatment.

[6] Other dimensions of competition, such as product availability, have been shown to be important for US supermarkets (Matsa, 2011). We focus on price as the main dimension of competition in the context we examine.

[7] Despite evidence of uniform pricing across stores by US retail chains (DellaVigna and Gentzkow, 2019; Hitsch et al., 2017), our data show rich variation in pricing both within and across supermarket chains.

[8] Interestingly, "placebo" results for Coop's competitors find strong support for the standard Bertrand-Nash oligopoly model: the estimated slope of prices with respect to the markup term predicted by the model is close to one as predicted by the theory.

Our work is related to several studies that investigate empirically firms' behavior. Craig and Pencavel (1992, 1996) 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 behavior. We contribute to this literature by discussing instead a case where a firm may have deviated from its original objective and behaves like its for-profit competitors.

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 healthcare sector. Important articles find that not-for-profit hospitals seem to 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, 2017). In contrast, a recent study by Dafny (2019) describes significant increases in premiums when a not-for-profit health insurer becomes for-profit. 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. In contrast to most existing studies in this area, we measure market power using a structural model to assess the conduct of a large not-for-profit firm.

From a methodological perspective, this article is related to studies on the identification of firm conduct from market level data, pioneered by Bresnahan (1982) and Lau (1982). Early studies relied on a conduct parameter approach based on conjectural variation models in a homogeneous goods setting.[9] In a differentiated products setting, Bresnahan (1987) and Nevo (2001) use model-fit-tests to evaluate different hypotheses on supply side behavior, and Byrne (2015) leverages marginal cost data to check the prediction of standard models of firm behavior. Berry and Haile (2014) expand on Bresnahan and Lau's intuition, showing that, in a nonparametric setting, there can be testable restrictions on firm conduct based on shifters of market conditions that are excluded from marginal costs. Similar to recent papers that investigate supply-side behavior in differentiated products industries (Ciliberto and Williams, 2014; Miller and Weinberg, 2017; Michel and Weiergraeber, 2018), we follow the insight in Berry and Haile (2014) in constructing a test for the conduct of cooperatives

[9] This approach has been found to be problematic both in terms of the underlying theory, and in terms of the econometric identification of the conduct parameter (Corts, 1999).

based on the presence of shifters and rotators of residual demand.

Other empirical papers have investigated cooperatives in Italy. Bentivogli and Viviano (2012) compare descriptive statistics of consumers' and producers' cooperatives based in the Emilia-Romagna region of Italy against those of their for-profit counterparts. They find that cooperatives have on average lower workers' productivity,[10] but employ strategies that are similar to those of for-profit competitors. Magnolfi and Roncoroni (2016) investigate the role of Coop's political connections in shaping the market structure in the grocery retail industry in Italy.

The rest of the article proceeds as follows. In Section 2 we describe the institutional background on consumer cooperatives, the Italian supermarket industry and Coop Italia. Section 3 presents the data. Section 4 develops possible theories of cooperative behavior and shows descriptive evidence on the relation between Coop pricing and market power. In Section 5 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 6 we discuss our empirical strategy. Section 7 presents results, and Section 8 describes our counterfactuals. Section 9 concludes.

2 Institutional Background

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 capturing the rest. Supermarket chains typically operate stores of different formats, categorized by size as convenience stores, small supermarkets, large supermarkets, hypermarkets, and large hyper-markets.[11] Most grocery shopping is local in nature. Consumers rarely drive more than 15 minutes by car, and marketing research indicates that supermarkets obtain most of their revenues selling to customers living in a small 2 km (1.24 miles) radius. No existing administrative unit adequately reflects this patterns, and the Italian antitrust authority defines markets on an ad-hoc basis when conducting investigations.

The main players in the industry include Coop—the network of consumers cooperatives, for-profit supermarket groups (both local and owned by French multinationals), and Conad—a producer cooperative. The latter is an association of roughly 3,000 en-

[10] This particular finding reflects the fact that many of the cooperatives that they consider are producers' cooperatives.

[11] The relevant size thresholds for these categories are: floor space between 400-800 square meters for grocery stores, floor space between 800-1500 square meters for small supermarkets, floor space between 1500-2500 square meters for large supermarkets, floor space between 2500-4000 square meters for hypermarkets, and floor space greater than 4000 square meters for large hypermarkets.

trepreneurs, who centralize marketing and private label operations. There is little question about Conad's conduct, since the consortium is run in the interest of the entrepreneurs-members. Several for-profit competitors are also organized as associations of independent firms (e.g. Selex), but others are fully integrated (e.g. Esselunga, Finiper, Bennet).

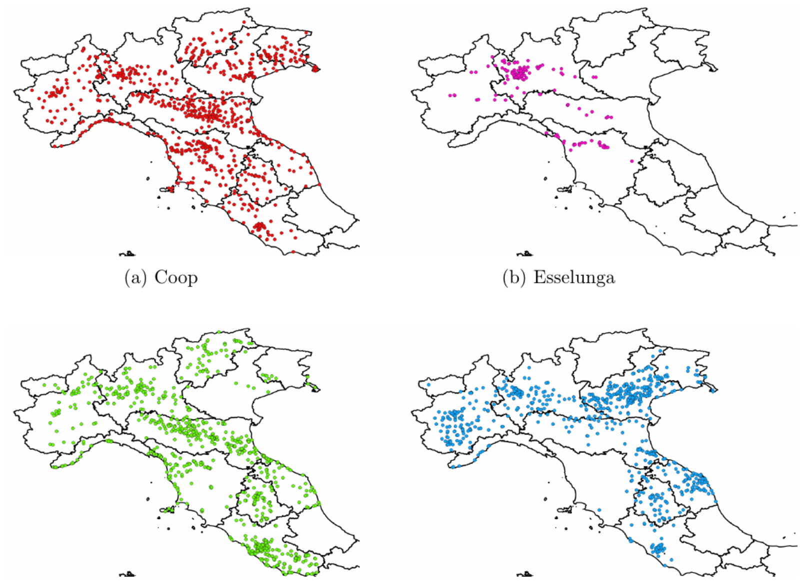
Table 1: Group Size and Number of Stores

	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

Note: This table reports group-year level median store size in square meters and total number of stores for three years in our data.

Table 1 shows considerable variation in firm strategy across different groups. Although overall median store size grows steadily over time for most groups—reflecting the adoption of larger store formats across the industry—some groups are more aggressive than others in either exclusively focusing on large formats (e.g. Bennet) or increasing substantially the dimensions of their median store over time (e.g. Esselunga). Other firms—including Coop, Selex, Auchan and Carrefour—operate instead a larger network of stores, spanning the spectrum from small proximity stores in dense areas to large hypermarkets located out of town. There is also a significant dimension of geographic differentiation across different 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 predominance.

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



(a) Coop

(b) Esselunga

(c) Conad

(d) Selex

Note: We show in this figure the location of stores for the four largest supermarket groups in 2013.

Strategic decisions such as pricing and assortment are taken at different levels within the firms in this industry (AGCM, 2014). National advertising campaigns and private label strategy (product development and pricing) are typically centralized and decided at the national level. Assortment decisions are also centralized to some degree, and especially for those products for which demand is unlikely to vary across geographical markets. Prices have a group-level component (e.g. for private label products, or products that are under national promotion), as well as zone-level and store-level components. For instance, Coop derives 45-70% of its sales from products that are sold at the same prices in all of its stores (AGCM, 2014). Although uniform pricing by retail chains seems to be prevalent in the US (DellaVigna and Gentzkow, 2019; Hitsch et al., 2017) and in the UK (Thomassen et al., 2017), the Italian context seems more similar to France, where supermarket chains use a variety of pricing strategies that generate co-variation between price levels and competitive conditions (Allain et al., 2017).

One aspect of this industry that is relevant for our study is the prevalence of the group purchasing organizations (GPOs). GPOs are consortia of supermarket chains that negotiate jointly with producers. The consortia increase bargaining power, allowing all of their members to purchase goods at the same prices and to have access to the same retailer rebates (although additional rebates can be negotiated separately by each chain). The contracts negotiated by GPOs do not include provisions that would amount to resale price maintenance, since this is generally illegal under EU competition law.[12] We use our knowledge on the composition of GPOs in the estimation of the demand model.

2.2 Italian Grocery Retail Cooperatives: Coop Italia

More than a hundred consumer cooperatives operate in the supermarket industry in Italy. These firms are spread across the country, although more concentrated in the Central and Northern regions, and vary in size from small cooperatives operating a single grocery store, to large groups with sales close to $6 billion. Although each of these cooperatives is a distinct legal entity, they all operate under close strategic coordination. The coordination happens mainly through two organizations: Ancc-Coop (National Association of Consumer Cooperatives) and Coop Italia.[13][14] The former is the governing body of consumer cooperatives, establishing precise guidelines for strategic expansion and system-wide policies, as well as social and outreach activities. The latter is a consortium responsible for key functions such as 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 indicating store type, e.g. "IperCoop" for hypermarket formats). Although there is no explicit agreement that assigns different markets to each cooperative in the Coop system, we never see these cooperatives competing in the same market.[15] Given the close links between cooperatives, and the strong coordination role of Coop Italia and Ancc, we consider them as one economic agent, and label them as Coop in what follows.

The corporate charters of cooperatives in the Coop system explicitly state that their primary objective is to promote consumers' welfare and purchasing power through low prices for members and non-members.[16] Coop has more than 8 million members, who join the cooperative by paying a small fee (less than $30). This fee represent the capital invested by the member, and is returned if the member decides to exit. Although in principle cooperatives may return profits to their consumer-members, none of the cooperatives we

[12]See Appendix A6 for more discussion of GPOs and a description of GPO membership for firms in our sample.

[13]Grocery retail consumer cooperatives are also part of a larger umbrella organization, Legacoop (the League of Cooperatives), and also form regional sub-networks and alliances.

[14]Although the history of consumer cooperatives in Italy starts in the 19th century, Ancc was established in 1955 and Coop Italia was established in 1967.

[15]When interviewed in an antitrust report, Coop representatives stated (authors' translation): "it is natural for cooperatives that belong to the same system and use the same sign not to compete..." (AGCM, 2014)

[16]For instance, the corporate charter of the largest cooperative in the Coop system (Coop Alleanza 3.0) states that the cooperative pledges to (authors' translation): "serve the social purpose of protecting family budgets for members and non-members, providing high quality goods and services at the best possible prices, and directing consumers to purchase products that offer the highest standards of quality, safety and value, avoiding waste in consumption."

consider does so during the period of our study.[17] Governance is nominally inspired to 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 around 1% of total membership), and most cooperatives have rigid rules that restrict members' ability to present their own candidates for the board to challenge those proposed by the management. Coupled with standards of disclosure and auditing that are lower than those that apply to for-profit corporations, these governance provisions result in overall weak powers of members, and managers that tend to stay at the helm of the cooperative for long periods, and with few checks on their powers.

Determining Coop's conduct has important public policy implications. Under Italian tax law, cooperatives receive substantial tax benefits. From 2003, all cooperatives which fall under the "prevalently mutual" category[18] can deduct reinvested profits from taxable income. These tax breaks are motivated by the special nature of cooperatives, which are supposed to operate in the interest of their members and to pursue social objectives. However, if Coop's conduct is similar to the one of its competitors, this rationale seems weak. This issue has also attracted the attention of EU authorities: if Coop is practically indistinguishable from its for-profit competitors, any tax benefit it receives can be characterized as state aid, and this would prompt intervention by competition authorities.[19]

Tax breaks are not the only issue that has raised concerns about the role of cooperatives and possible distortions of competition in retail markets. The cooperative movement in Italy has long standing links to political parties.[20] Coop's ties to politics result in two distinct effects: a possible link between consumers' ideological leanings and shopping preferences, and connections with local politicians. These political connections may persist over time,[21] and since local Italian politicians have discretionary power on regulating entry of supermarkets, they may end up having an impact on market structure.[22] In a related paper, Magnolfi and Roncoroni (2016) find that the political connections of Coop have an impact on entry profitability for several of the players in the industry, and that political connections may result in consumer surplus losses in those markets where they represent a sizable barrier to the entry of Coop's competitors. In those markets where connections

[17] Coop provides some benefits to its members through members-only promotions and points to be redeemed for prizes or discounts. These activities are very similar to what competing for-profits firm do for their loyalty program members.

[18] The condition to qualify for this category is to conduct a majority of business with members.

[19] An European Commission investigation into this matter is ongoing. See Case E1/2008 in the State Aid Register at the DG Competition.

[20] 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.

[21] See for instance the data presented in Magnolfi and Roncoroni (2016), where we find that a large fraction of Coop's board members are also local politicians.

[22] See for instance AGCM decision A437.

mostly serve the role of facilitating Coop's entry, connections may end up countervailing restrictive entry regulation and ultimately benefiting consumers.[23]

3 Data and Preliminary Evidence

3.1 Data Description

This article combines information from four main sources. First, we use administrative data from the Italian Statistical Agency (ISTAT) to define geographical grocery markets and recover market-level population. Second, we combine data on households' expenditure from the Central Bank of Italy and municipality-level data on income from the ministry of economy to construct market-level grocery expenditure and income distribution. Third, we obtain data on the universe of supermarkets in central and northern Italy from Information Resources Inc. (IRI).[24] 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 supermarket characteristics, such as distance from headquarters and data on what supermarkets are part of a larger shopping mall. Finally, we obtain price data from a survey conducted by Altroconsumo, a consumer association. We discuss these different components of the database in turn.

Market-level Data We include in our analysis all local grocery markets in Central and Northern Italy. We exclude Southern Italy because of the different structure of the industry there, and the less significant presence of Coop. Since no administrative unit is appropriate to define geographical markets in this industry,[25] we start instead from the concept of Local Labor Market Areas, determined by ISTAT. The rationale is that commuting patterns may help to define the areas where consumers are more likely to buy spatially differentiated goods (Houde, 2012; Pavan, Pozzi and Rovigatti, 2019). [26]

To obtain the distribution of income and total grocery expenditure in each of our markets, we combine two data sources. From a yearly survey of a panel of households conducted

[23] Further discussion on how we measure Coop's political connections is in Appendix A4.

[24] IRI is a marketing research firm that sells industry and consumer information for retail companies.

[25] Municipalities are the finest administrative level for which we can obtain population data from ISTAT for every year in our sample period 2000-2013, but they are too small to be considered well defined grocery markets.

[26] Some of the commuting areas are too large to reflect consumers' actual shopping patterns. We break along municipality borders those labor market areas that contain at least two municipalities with more than 15,000 inhabitants whose centers are separated by at least 20 minutes of driving distance. Out of 362 labor market areas in Central and Northern Italy, we split up 91 in two grocery markets. We also consolidate eight labor market areas that are too small to accurately represent a grocery market. We merge adjacent labor market areas that have less than thirty thousand total inhabitants, are smaller than 100 square kilometers (38.6 square miles), and have lowest elevation of 800 meters (2,624 feet). The rationale for including elevation is that in small markets located in mountain areas consumers might not travel too far, due to road conditions.

by the Bank of Italy, we observe income and grocery expenditure (as well as other demographics) for roughly eight thousand households across the country.[27] However, the only geographic indicator is at the region level, an administrative unit that is much larger than our market definition. Hence, 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, provided by the ministry of economy, to adjust the mean of the market-level income distribution for within-region relative differences in income.[28] 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. Average grocery expenditure as a percentage of income, historically higher in Italy than in other developed countries such as the US or the UK, is declining over our sample period.

Table 2: Market-level Characteristics

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

Note: This table displays market-level summary statistics. Population data are from ISTAT. Average market-level household income and grocery expenditure are derived from Bank of Italy data. For more on the construction of income and grocery expenditure data, see Appendix A1.

Supermarket-level Data Data on the universe of supermarkets for every year in our sample are obtained from IRI.[29] For each supermarket we observe geographic location, the group that operates it, store floor space, and the share of sales among all supermarkets in the sample.[30] We transform these shares in market-level revenue shares of the total

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

[28] For a full description of the construction of this element of the dataset, see Appendix A1.

[29] Our data does not include discount supermarkets or grocery stores. These stores offer only private label goods, and often have a limited selection of items; hence, we do not consider them as a part of our market.

[30] Although IRI does not share the proprietary methodology that it uses to compute these shares, we understand that these are *estimates* comparable to those available in the widely used Trade Dimensions database on the US supermarket industry.

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.[31] The IRI supermarket-level data are complemented with hand-collected information on which supermarkets are anchors in a mall, and supermarket groups' headquarters.[32] For each supermarket, we compute driving time and distance from its headquarter using Google Maps APIs.

We obtain data on supermarket-level prices from Altroconsumo, an independent consumers' association.[33] The data consist of a price index that represents the cost of a basket of grocery goods,[34] 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 puts together a basket of roughly 100 product categories—including both fresh products and packaged goods, chosen to match ISTAT's report on national consumption patterns. For each category, they collect prices of one or more products offered by "leading brands." 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.[35] Since Altroconsumo does not survey the whole universe of stores, we restrict our sample to markets with at least one price observation.[36]

In Table 3 we aggregate the data at the group-year level. This cut of the data shows that Coop accounts for a large (about 20%) and stable share of revenues in this industry. Median store size grows steadily for most groups, as firms open larger stores during our sample period. 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).

[31] Additional details on this procedure are reported in Appendix A1.

[32] These are obtained by a search of company websites and online sources.

[33] To maintain its independence, Altroconsumo only relies on the fees paid by their members, and does not sell ads on its magazine.

[34] Notice that, whereas revenues are computed over all goods sold by a store, the basket of groceries for which we have price data only includes a few hundreds of products—see Appendix A3 for details. The resulting measurement error in prices is addressed by our instrumenting strategy. See Eizenberg, Lach and Yiftach (2018) for an approach that explicitly considers measurement error in revenue shares.

[35] We discuss the Altroconsumo pricing database in further detail in Appendix A3.

[36] In the counterfactual exercise we are able to compute the price equilibrium vector for all the universe of supermarkets using the estimates from our structural model.

Table 3: Group-year Market Shares and Average 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

Note: This table reports group-year level statistics for three years of our data. We report national revenue share in percentage points, and average supermarket-level prices. Prices are in 2013 Euros and represent the cost of a week of grocery shopping for the average household.

Overall, the data described in this subsection highlights significant variation in prices and market shares, as well as large variance in the consumer choice set both across geography and time. These will be crucial as we proceed to investigate our research question: what is the relation between Coop's market power and the prices in its stores? We turn to more specific evidence on this question next.

4 Consumer Cooperatives: Theory and Preliminary Evidence

4.1 Hypothesis Development

The two main explanations for the emergence of customer-owned cooperative firms refer to either the presence of asymmetric information in product markets, or to the presence of market power (Hansmann 1987, 2000). Whenever the costs of asymmetric information on product quality are too high for consumers, they may consider forming cooperatives. Since the products sold in grocery stores are either brand-name packaged goods or fresh foods whose quality is easily assessed, this explanation seems less relevant to our case. Limiting the extent to which firms exercise market power (or, in an extreme case, monopoly power) is the alternative rationale for the existence of customer-owner cooperatives in retail industries. Grocery markets in Italy, where entry is highly regulated, may display substantial levels of market power, and hence fit this pattern.

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, since management is not subject to the discipline coming from the market for corporate control, nor from the monitoring role of block-holders. In large consumer cooperatives, customer-ownership can exacerbate the usual agency problem arising from the separation between ownership and control (Jensen and Meckling, 1976).

Hence, although in principle customer-owned cooperatives arise to protect the interests of consumers and provide low prices,[37] weak governance may undermine this objective. As a result, several hypotheses can be developed on consumer cooperatives' objectives and behavior. According to Enke (1945), the cooperative's objective may be:

I. *Maximization of consumer surplus*—Consumer cooperatives may maximize the welfare of consumers. When welfare is the objective, cooperatives naturally focus on keeping prices as low as possible, with the constraint of not generating losses.

II. *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, it is possible that cooperatives may want to generate and retain some profits even if their decisions are oriented towards welfare maximization.

III. *Profit Maximization*—The alternative assumption is that cooperatives are profit maximizers. In this case, cooperatives' behavior does not differ from that of their (for-profit) competitors. This scenario may materialize if managers pursue expansion or perquisite consumption.

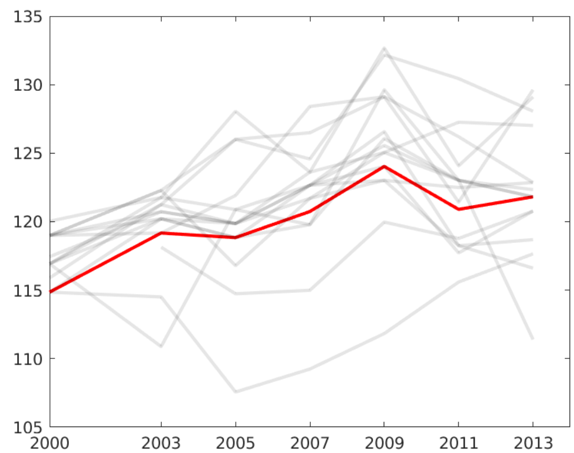
To the best of our knowledge, this is the first article that takes seriously these hypotheses on cooperative conduct, and tests them using data. We start our investigation in the next subsection using descriptive evidence on how Coop exploits market power.

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

We visualize Coop's group-level average price dynamics in Figure 2. The figure represents, over the years in our sample, the average of store-level prices for each group. Coop's average prices are represented by the red line; all other groups are represented by a gray line. At first glance, Coop's prices are at the lower end of the spectrum for all years, although there seem to be groups that consistently offer lower prices, some by a substantial amount.

[37] In this article we focus on the implications of different competitive hypotheses on Coop's competitive behavior on pricing decisions. The choice of quality and characteristics of products could represent another relevant channel, which we cannot properly investigate with our data. However, Coop's charters appear to prioritize pricing commitments. This is an important channel in determining consumers' welfare.

Figure 2: Group-level Average Prices Over Time



Note: This figure shows group-level average prices over time. The group-level index is obtained as the unweighted average of all store-years in our sample for each group. The vertical axis represents prices for baskets of grocery goods corresponding to a weekly shopping trip, in 2013 Euros. Coop's prices are represented by the red solid line, all other groups are represented by the gray lines. See Appendix A3 for further information on price data.

This evidence, however, is far from conclusive. The group-level aggregation misses out on store-level characteristics that may generate systematic differences in costs across groups. In light of the differences across groups in the characteristics of store networks, this element could be substantial. To address this issue, we run supermarket-level regressions of log prices on a Coop dummy, store- and market-level characteristics x_{jmt}, and year and market fixed effects ψ_m and τ_t. Our specification is:

$$\log p_{jmt} = \beta_c + \beta_1 1\left\{\text{Coop}\right\}_{jmt} + x_{jmt} + \psi_m + \tau_t + \epsilon_{jmt}. \tag{1}$$

Results are reported in column (1) of Table 4, and indicate that Coop's stores have a price index that's on average 0.93% lower than all other groups, after controls. The coefficient is precisely estimated, and confirms the graphical evidence of Figure 2: Coop's prices seem consistently at the low end when compared to other groups.

Table 4: Coop Pricing Behavior and Monopoly Markets

	(1)	(2)
Coop	-0.0093	
	(0.0019)	
Monopoly Market		0.0095
		(0.0032)
Coop Monopoly Market		-0.0037
		(0.004)
Year FE	Yes	Yes
Group FE	No	Yes
Group×Size FE	No	Yes
Market FE	Yes	No
Monopoly Markets		66
Observations	2672	2672

Note: This table displays OLS coefficient estimates for the specifications of 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.

However, it is not immediate to relate this descriptive evidence to our research question. The regression, despite including controls for store characteristics and market-level fixed effects, does not account for the variation in competitive conditions faced by Coop's stores. To determine Coop's competitive conduct, in fact, we need to understand how Coop's prices co-vary with its market power, as opposed to how its average price level compares with other groups.

To explore further the relationship between market power and pricing in this industry, we focus on a specific form of market power: monopoly markets. A very small fraction of our markets are actual monopolies. However, for 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 likely to affect the firm's market power. These stores correspond to modern formats that are favored by consumers and most efficient. Hence, we construct an indicator variable for those supermarkets that operate in a market where a single firm holds "monopoly power," i.e. operates stores with a surface of 2,500 square meters or larger.

We run supermarket-level regressions of log price on the monopoly indicator variable, and on a variable that indicates whether—in a monopoly market—Coop is the firm with the only large store(s) in the market. We also add supermarket-level controls (store size and distance from headquarters), market-level average income, and year-, group- and region-level fixed effects, to capture other sources of cross-sectional and time-series variation in the data. Our specification is:

$$\log p_{jmt} = \beta_c + \beta_2 1\left\{\text{Monopoly}\right\}_{jmt} + \beta_3 1\left\{\text{Coop Monopoly Market}\right\}_{jmt} + x_{jmt} + \psi_j + \tau_t + \epsilon_{jmt}. \tag{2}$$

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 those monopoly markets where Coop is the firm that operates the only large store(s) do not have prices that are systematically different: the coefficient on the Coop Monopoly Market variable is economically small and not statistically significant.

Hence, there is little evidence in the data that the cooperative organizational form of Coop is associated with a weaker correlation between monopoly power and pricing. These results, however, are best interpreted as purely descriptive. In particular, we emphasize two limitations of this exercise: measurement of market power and identification. Although intuitively appealing, monopoly is a crude indicator of market power. Moreover, there may be concerns that the monopoly indicator is jointly determined with other outcomes, and thus not exogenous.

To capture the main determinant of market power—the elasticity of each supermarket's residual demand curve—we estimate a structural model of consumer demand for the Italian supermarket industry. To deal with the identification of Coop's pricing behavior, in the next section we build a supply model that nest all hypotheses on Coop's behavior and use exogenous variation in competitive conditions across market and time to estimate it.

5 Model

5.1 Demand

In each geographical market m and for each year t in our sample, firm f owns a set of supermarkets $\mathcal{J}_f \subset \mathcal{J}(m,t)$.[38] Each store $j \in \mathcal{J}_f$ sells a basket of groceries at price p_j; we denote with p the full vector of prices. Consumer choice generates an aggregate (Marshallian) demand system where $q_j(p)$ denotes the units of grocery baskets sold in supermarket j at prices p. Following previous studies of the supermarket industry (e.g. Smith, 2004), we assume that $q_j(p)$ arises from a discrete-continuous choice, whereby consumers first decide in which store to do their shopping, and then how many units to buy of a composite grocery good.

[38] To keep the notation lighter, we suppress m and t in the rest of this subsection, as firms compete independently across markets and years.

In a geographical market m and in year t, consumer $i \in \mathcal{I}(m,t)$ is characterized by her income y_i and by a vector of preferences for supermarkets $(\varepsilon_i, \varphi_i)$. She chooses in which supermarket $j \in \mathcal{J} \cup \{0\}$ to buy a continuous quantity of bundles of grocery goods; $j = 0$ denotes the outside option, which represents traditional retail stores, discount stores, and open-air markets. When consumer i purchases q_{ij} units of the basket of grocery goods 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 captures the quality of supermarket j as perceived by consumer i, and α_i determines the relative utility of grocery and composite good, and must be such that $\alpha_i < y_i$. The random utility shock ε_{ij} is distributed iid according to the Generalized T1EV distribution with cdf:

$$\Phi_i(\varepsilon) = e^{-e^{-\sigma\varepsilon}},$$

where σ measures the relative importance of the random preference shock with respect to the deterministic part of the utility.[39] Conditional on choosing to shop at supermarket j, consumers choose optimally q_j and ϑ according to:

$$\begin{array}{cc} \max\limits_{q_{ij},\vartheta_i} & \ln\left(q_{ij}\varphi_{ij}\right) + \frac{\vartheta_i}{\alpha_i} + \varepsilon_{ij} \\ s.t. & p_j q_{ij} + \vartheta_i = y_i \end{array}$$

which yields the following first order condition, necessary and sufficient for optimality:

$$\begin{aligned} q_{ij}^* &= \frac{\alpha_i}{p_j}, \\ \vartheta^* &= y_i - \alpha_i. \end{aligned}$$

Hence in our model, as a consequence of the quasi linearity of utility, every consumer i has a fixed grocery expenditure α_i, irrespective of the quality of supermarkets in her choice set and of her income. This is a strong restriction, which we adopt because we do not have micro data on individual consumers' purchases, and to ensure tractability of the supply side model. However, although our specification rules out income effects for a consumer i, in the model's empirical specification we allow for heterogeneity across different consumers by calibrating $\alpha_i = \alpha(y_i)$ so that it varies *across consumers* by income quartile.

[39] We experimented introducing correlation across realizations of ε_{ij} with a nesting structure that included two separate nests for outside and inside goods. Estimates for the nesting parameter were not significantly different from zero.

Given her grocery expenditure level α_i, consumer i chooses among supermarkets based on the indirect utility

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

where $\tilde{\varepsilon}_{ij}$ is a standard T1EV random variable, iid across individuals i and supermarkets j, and κ_i collects all terms that are $i-$specific. We normalize the quality-price utility index of the outside good ($\frac{\varphi_{i0}}{p_0} = 1$), and parametrize all the other φ_{ij} in the spirit of the discrete choice literature. In particular, we separate the average from the idiosyncratic component of preferences for stores, so that:

$$\ln(\varphi_{ij}) \quad = \quad x_j' \tilde{\beta} + \mu_{ij}' \tilde{\eta} + \tilde{\xi}_j,$$

where x_j, μ_{ij} and $\tilde{\xi}_j$ are respectively a vector of observed store characteristics, interactions between store and consumer characteristics, and a scalar unobservable store characteristic as in Berry (1994); $\tilde{\beta}$ and $\tilde{\eta}$ are vectors of parameters. Store characteristics include store-format and group fixed effects, and an indicator of whether the supermarket is in a shopping mall. The store level unobservable $\tilde{\xi}_{jmt}$ captures characteristics such as store location within a market, local demand shocks, and measurement error in price. This is a crucial component that accounts for the (largely unobserved) attractiveness of a store's location, and at least partially addresses spatial aspects of demand that we are not modeling directly.

From the distributional assumption of $\tilde{\varepsilon}_{ij}$ we derive the probability P_{ij} of consumer i choosing to shop in supermarket $j \in \mathcal{J}$:

$$\begin{aligned} P_{ij} \quad &= \quad \frac{\exp \left(\frac{\varphi_{ij}}{p_j} \right)^{\sigma}}{\sum_{k \in \mathcal{J} \cup \{0\}} \left(\frac{\varphi_{ik}}{p_k} \right)^{\sigma}} \\ &= \quad \frac{\exp \left\{ \left(\delta_j + \mu_{ij}' \eta \right) \right\}}{1 + \sum_{k \in \mathcal{J}} \exp \left\{ \left(\delta_k + \mu_{ik}' \eta \right) \right\}} \end{aligned}$$

where the supermarket specific term δ_j is:

$$\begin{aligned} \delta_j \quad &= \quad x_j' \left(\tilde{\beta} \sigma \right) - \sigma \ln p_j + \tilde{\xi}_j \sigma, \\ &= \quad x_j' \beta - \sigma \ln p_j + \xi_j, \end{aligned}$$

and the supermarket-individual specific term is:

$$\mu_{ij}' \eta = y_i \eta_y + 1 \left\{ \text{Coop} \right\}_j 1 \left\{ \text{Dem} \right\}_i \eta_l.$$

In this specification, individual income shifts the value of the outside option. This is meant to capture the fact that high-income consumers may prefer to shop in traditional grocery stores, avoiding the supermarkets in our sample. Moreover, consumers who vote for center-left parties may have a stronger preference for Coop due to the cooperative's historical links.[40]

Finally, the share of consumer expenditure captured by supermarket $j \in \mathcal{J}$ as predicted by the model is:

$$\mathcal{B}_j = \frac{\int_{i\in\mathcal{I}} \alpha_i P_{ij} di}{\text{Exp}_{mt}},$$

where $\text{Exp}_{mt} = \int_{i\in\mathcal{I}(m,t)} \alpha_i di$ is the total grocery expenditure in market m during year t. In market equilibrium, expenditure shares have to correspond with supermarkets shares of total industry revenues. In the spirit of Berry, Levinsohn and Pakes (1995), this demand system can be estimated using aggregate data and still generate rich substitution patterns. It resembles recent models (Bjoernerstedt and Verboven, 2016; Eizenberg, Lach and Yiftach, 2018) that allow for discrete-continuous consumer choice, result in a specification where prices enter in logs, and are estimated from revenue share data. Note that, on account of data limitation and to preserve tractability, we abstract from important aspects of consumer choice in this industry, such as spatial aspects of demand (Figurelli, 2013; Ellickson, Grieco and Kvatsunov, 2019) and one-stop versus multi-stop shopping (Thomassen et al., 2017).

5.2 Supply

Firms' Objective Functions In line with standard models of firm behavior, we assume that any for-profit firm f maximizes its total profit π_f. Under the assumption that marginal costs $mc = (mc_j)_{j\in\mathcal{J}_{\text{f}}}$ are constant in the number of units sold,[41] profit for firm f is:

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

In contrast, Coop sets prices $p_{Coop} = (p_j)_{j\in\mathcal{J}_{Coop}}$ evaluating the consequences on both its profit and on consumer surplus.[42] To measure surplus for an individual consumer i from a price vector $p = (p_{Coop}, p_{-Coop})$, we use the compensating variation corresponding to a

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

[41]This assumption is commonly adopted in the empirical literature on the grocery retail industry (e.g. Smith, 2004; Eizenberg, Lach and Yiftach, 2018), and is necessary to ensure tractability and identification given the limited nature of the cost data available.

[42]This is similar to *mixed oligopoly* models where private (for-profit) and public firms compete (see e.g. Merrill and Schneider, 1966; Beato and Mas-Colell, 1984; De Fraja and Delbono, 1989; Cremer, Marchand and Thisse, 1991).

change from an environment where there is no Coop (or $p^0_{Coop} = \infty$) to an environment with prices p. This is given by:

$$CV_i\left(p_{Coop}, p_{-Coop}; u^0_i\right) = e_i\left(\left(p^0_{Coop}, p_{-Coop}\right); u^0_i\right) - e_i\left(\left(p_{Coop}, p_{-Coop}\right); u^0_i\right),$$

where u^0_i is the utility of any consumer i when $p_{Coop} = p^0_{Coop}$ and e_i is consumer i's expenditure function.[43] The total compensating variation is then:

$$CV\left(p; u^0\right) = \int_i CV_i\left(p; u^0_i\right) di.$$

Assuming that the cooperative weights every consumer's welfare equally,[44] the market-level[45] objective function of Coop is:

$$\Pi_{Coop}(p) = F\left(\pi_{Coop}(p), CV\left(p; u^0\right)\right),$$

where $\pi_{Coop}(p)$ represents profit, and F aggregates the profit and welfare goals of the cooperative. We assume that F is differentiable, strictly increasing in its first argument, $F_1 > 0$, and non decreasing in its second argument, $F_2 \geq 0$.

We assume that the price vector p is a Nash equilibrium of the price-setting game where Coop maximizes Π_{Coop}, and every other firm f in the market maximizes π_f. This maximization is subject to the constraint that, as prescribed by law, no good (i.e. bundle of groceries) can be sold below its marginal cost, i.e. $p_j \geq mc_j$ for all $j \in \mathcal{J}$. At an unconstrained equilibrium price vector p the system of non-linear first order conditions[46] is:

$$\left(\frac{\partial}{\partial p_j}\pi_{Coop}(p)\right) = -\frac{F_2(p;u)}{F_1(p;u)}\left(\frac{\partial}{\partial p_j}CV(p;u)\right), \ \forall j \in \mathcal{J}_{Coop}$$
$$\frac{\partial}{\partial p_k}\pi_f(p) = 0, \ \forall f \neq Coop, \ k \in \mathcal{J}_f.$$

[43] Although we consider this formulation of Coop's objectives to be the one that best fits the institutional background, it is not the only possible one. In Appendix C we discuss two alternative hypotheses on Coop's objectives, based respectively on consumer surplus maximization under a profit constraint, and on the role of fixed costs.

[44] This assumption is not without loss, as the cooperative may only consider the welfare of its members, or alternatively may care about the distributional effects of its actions. However, the cooperatives that we analyze in this article state in their charter that their objective is promoting the welfare of *all* consumers.

[45] Since we have assumed no demand spillovers across markets, this assumption is without loss if we are also willing to assume that marginal costs are independent across markets (i.e., there are no cost synergies). This is implied by the assumption of constant marginal cost we maintain below in this section.

[46] Existence and uniqueness of a solution p is as an extension of Caplin and Nalebuff (1991).

As a consequence, for any store $j \in \mathcal{J}_{Coop}$, Coop's optimal behavior implies:

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

while Coop's competitors choose prices so that:

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

Hence, as long as $F_1 \geq F_2$, the conditions for an unconstrained optimum describe the equilibrium of the model: Coop prices with a markup above marginal cost, but less aggressively than it would if it were for-profit ($F_2(p;u) = 0$), since $-\frac{F_2(p;u)}{F_1(p;u)} \left(\frac{\partial}{\partial p_j} CV(p;u) \right) \geq 0$. This expression succinctly captures the three hypotheses on Coop's behavior that we developed in Section 4.1 and translates them into a relation between prices, marginal cost and Bertrand-Nash markup.

Pricing Behavior We can further lean on the demand model in Section 5.1 and obtain sharper implications from the supply model described by equations (3) and (4). By Shepherd's lemma we have:

$$\frac{\partial}{\partial p_j} CV(p;u) = \frac{\partial}{\partial p_j} \left(-e_i \left((p_{Coop}, p_{-Coop}); u_i^0 \right) \right) = -q_j^H(p;u),$$

where q_j^H denotes the compensated (Hicksian) demand function for good j. Moreover, the quasi linear structure of the demand system implies that compensated demand coincides with Mashallian demand. We also assume that the term $\frac{F_2(p;u)}{F_1(p;u)}$ is constant and equal to $(1-\lambda) \in [0,1]$: this is equivalent to specifying a linear form for F, a simple and tractable characterization which can be brought to data. A similar formulation of the objective function is used, for instance, in Timmins (2002) to model the preferences of water utility regulators as the weighted sum of welfare and profits, or in Gowrisankaran, Nevo and Town (2015) to model the preferences of managed care organizations. We can then rewrite equation (3) as:

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

The constraint $\lambda \geq 0$ is sufficient to imply that Coop does not price below marginal cost (similarly to the condition $F_1 \geq F_2$ stated above).

Stacking, rearranging and writing in terms of revenue shares, the pricing equation for any supermarket j is:

$$p_j = mc_j + \frac{\left(\left[H \odot \Theta\left(\lambda\right)\right]^{-1} \mathcal{B}\right)_j}{\mathcal{B}_j} p_j, \tag{5}$$

where H is the matrix of demand elasticities for all supermarkets, the symbol $\odot$ denotes element-by-element matrix multiplication and $\Theta\left(\lambda\right)$ is an *internalization matrix* (Michel and Weiergraeber, 2018) that is defined as follows:

$$\Theta_{(j,h)}\left(\lambda\right) = \begin{cases} \frac{1}{\lambda} & \text{if } j, h \in \mathcal{J}_{Coop} \\ 1 & \text{if } j, h \in \mathcal{J}_f,\ f \neq Coop \\ 0 & \text{otherwise.} \end{cases}$$

The same pricing relationship in equation (5), but with different parametrizations of the internalization matrix, has been used to investigate other sorts of supply side behavior, such as collusion facilitated by multi-market 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, Conlon and Sinkinson, 2019). Whereas in the former cases the parametrization of the internalization matrix arises from the assumption that firms 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 single expression for prices that is linear in the parameter λ :

$$p_j = \begin{cases} \text{marg}_j\left(p\right) + mc_j, & \text{if } j \notin \mathcal{J}_{Coop} \\ \lambda \text{marg}_j\left(p\right) + mc_j & \text{if } j \in \mathcal{J}_{Coop} \end{cases}, \tag{6}$$

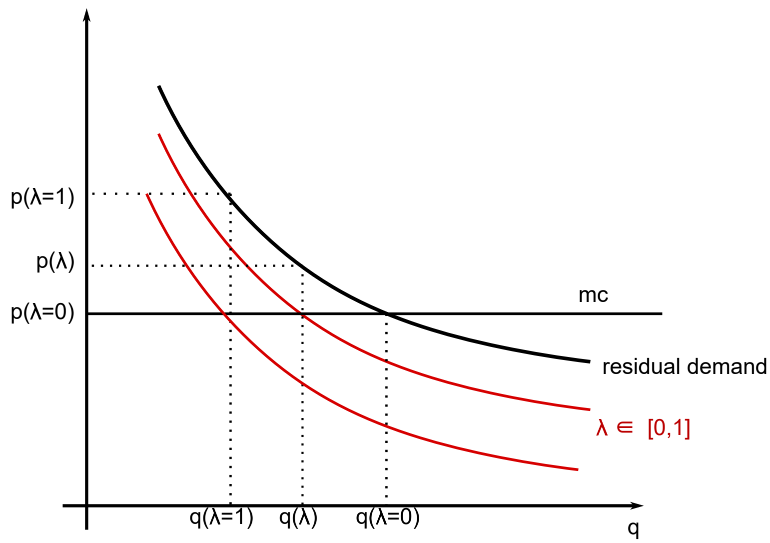
where the absolute price-cost margin implied by Bertrand-Nash is:

$$\text{marg}_j = \frac{\left(\left[H \odot \widetilde{\Theta}\right]^{-1} \mathcal{B}\right)_j}{\mathcal{B}_j} p_j.$$

and $\widetilde{\Theta}$ denotes the standard ownership matrix. Hence, our model generates a simple linear expression for the price-cost margins. For $\lambda = 1$, Coop prices in the same way as its for-profit competitors. For $\lambda = 0$, equation (6) implies that Coop sets price equal to marginal cost.

Figure 3 displays the main intuition for this model: given marginal costs and demand elasticity, different assumptions on Coop's conduct—summarized by λ—result in different implications for market equilibrium. Starting from this intuition, we develop in the next section a formal test for hypotheses on Coop's behavior.

Figure 3: Coop's Behavior and Equilibrium Outcomes



Note: This figure represents the main mechanism in our supply side model: values of λ have intuitive consequences on observable market outcomes.

6 Identification and Estimation

To estimate our model we proceed in two steps: we first estimate demand elasticities and implied Bertrand-Nash margins, and then estimate and test hypotheses on Coop's conduct. We discuss the two steps in turn.

6.1 Identification and Estimation of Demand

Under the assumption that $E[\xi|x] = 0$, parameters β are identified by covariation in revenue shares and stores characteristics. As opposed to recent studies that dispense with price data (Ellickson, Grieco and Kvatsunov, 2019), we rely on store-level variation in the price index for basket of goods to measure consumers' sensitivity to price σ. Despite the limitations inherent in considering a price index, this variation is essential in an industry where prices have a sizable store-level component and display significant dispersion across chains and store formats. To deal with the usual simultaneity bias in a supply-demand setting, we construct Hausman-style instruments leveraging the diffusion of GPOs in this industry. Since pricing may have an important regional component, we use as instruments the prices of stores in neighboring markets that belong to the same GPO. The validity of these instruments is thus based on a precise channel through which cost shocks may affect prices in different markets.[47]

We also use instruments that measure supermarkets' degree of isolation in the product space. In the spirit of the Differentiation Instruments of Gandhi and Houde (2017), we compute the number of stores operated by competitors in each size category, the number of stores operated by competitors in the same size, smaller size and larger size categories.[48] To identify the coefficient η_y that identifies the interaction between income and utility from the outside option, we interact the differentiation instruments with the average market-level income. To identify the coefficient η_l that models the preference of left-leaning voters for Coop, we interact the differentiation instruments with the market-level proportion of left-leaning voters and with the Coop indicator. We label our demand instruments (including x) z^d, and assume that $E\left[\xi|z^d\right] = 0$.

The demand model is estimated adopting a GMM strategy as in BLP, and estimates are computed using an MPEC approach in the spirit of Dube', Fox and Su (2012). Since the model implies for each tuple of δ and demand parameters $\theta^d = (\beta, \sigma, \eta)$ a value for the demand unobservable

$$\xi_{jmt}\left(\delta, \theta^d\right) = \delta_{jmt} - x'_{jmt}\beta + \sigma \ln p_{jmt},$$

then the empirical equivalent of the moment conditions is:

$$g_d\left(\xi\left(\delta, \theta^d\right)\right) = \frac{1}{MT}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{1}{|\mathcal{J}_{mt}|}\sum_{j\in\mathcal{J}(m,t)}\left\{\xi_{jmt}\left(\delta, \theta^d\right) z^d_{jmt}\right\}.$$

One particular feature of our pricing data is that we do not have prices available for all the stores in our sample.[49] To deal with it, we define a missing indicator D_{jmt}, that is equal one if observation (j, m, t) has price information and zero otherwise.[50] We can still identify

[47]Ideally, we would exclude from the computation of the instrument for each store j all other stores belonging to the same group. Unfortunately, this procedure generates many missing observations for those stores such that there is no other store in same region that belongs to the same GPO but not to the same group. In this case we also use prices for stores in the same group (but in different markets) to compute the value of the instrument.

[48]As a robustness check, we also construct BLP-style instruments by summing up the number of stores owned by competing groups in each size category. Results are similar—see Appendix B.

[49]See Appendix A3 for more information on selection into the Altroconsumo sample.

[50]This is not the only strategy that we could have employed to deal with missing data. For instance, Eizenberg, Lach and Yiftach (2018) deal with missing price data by assigning those alternatives with missing data to the outside option. When estimated under this assumption, our model results in a set of demand elasticities that is close to the elasticities presented in Section 7. Our treatment of missing data, however, allows us to leverage the information that we have on those stores with missing price data, and identify their corresponding levels of mean utility δ.

the model under the assumption[51]

$$E\left[\xi|z^d, D\right] = E\left[\xi|z^d\right],$$

so that $E\left[D\xi z^d\right] = 0$ by the law of iterated expectations. Moreover, since we have revenue share data for missing supermarkets with missing price data, we can still compute $\mathcal{B}_{jmt}\left(\delta, \theta^d\right)$ for all supermarkets and obtain $\hat{\theta}^d$ as the solution of the MPEC program:

$$\begin{aligned} \min_{\theta^d,\delta} \quad & g_d\left(D\xi\left(\delta, \theta^d\right)\right)' W_d g_d\left(D\xi\left(\delta, \theta^d\right)\right), \\ s.t. \quad & \mathcal{B}_{jmt}\left(\delta, \theta^d\right) = B_{jmt}, \forall j \in \mathcal{J}_{mt}, \forall (m,t) \in M \times T. \end{aligned}$$

where W_d is a weighting matrix and B_{jmt} are revenue share data. We obtain the weighting matrix with the standard two-step procedure.

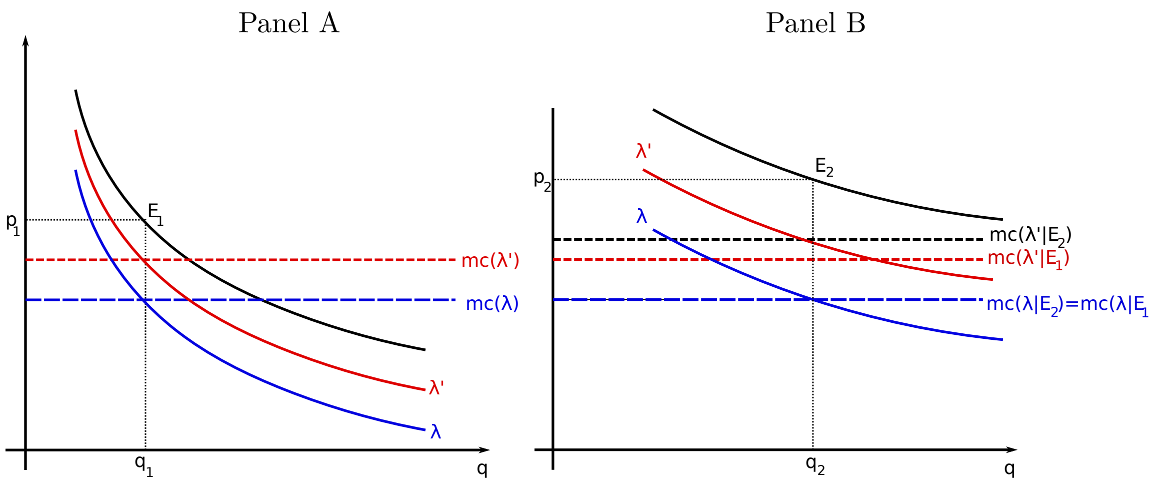
6.2 Identification and Testing for Conduct

The three hypotheses on Coop behavior stated in Section 4.1 are easily formulated in terms of our parametric model: hypothesis I, pure welfare maximization, corresponds to $\lambda = 0$; hypothesis II of a mixed objective including both welfare maximization and profits corresponds to $\lambda \in (0,1)$; hypothesis III of pure profit maximization corresponds to $\lambda = 1$. We first discuss nonparametric testability of hypotheses on conduct following Berry and Haile (2014). Since revenue shares $\mathcal{B}$ and prices p are simultaneously determined in equilibrium, and marginal costs are unobservable, an equilibrium outcome $\mathcal{E}_1$ may be compatible with different combinations of mc and λ (Figure 4, Panel A). Denote as $mc(\lambda|\mathcal{E})$ the value of marginal costs implied by λ and equilibrium $\mathcal{E}$. Intuitively, we need shifts of residual demand *excluded from marginal costs*, that results in a new equilibrium outcome $\mathcal{E}_2$. In this way, we may rule out values λ' such that $mc(\lambda'|\mathcal{E}_1) \neq mc(\lambda'|\mathcal{E}_2)$ (Figure 4, Panel B). Since we cannot hold marginal costs constant across markets, we instead assume that $mc = mc(w, \omega)$, where w represents observable determinants of marginal costs, and ω represents unobservable (to the econometrician) marginal cost shocks. To achieve the necessary shifts of residual cost we need a vector of supply-side instruments z^s that are excluded from marginal costs (so that $E[\omega_j|z^s] = 0$) but correlated with estimated Bertrand-Nash implied margins.

The argument developed thus far is nonparametric. In the context of our model we also leverage the parametric structure to estimate the parameter λ. Moreover, we assume that Coop's competitors are profit maximizing. To the extent that the structure on marginal

[51] This assumption is different than the standard missing at random assumption, which in this context is $D \perp p|x, B$. See Abrevaya and Donald (2017) for more discussion.

Figure 4: Demand Shifts and Hypotheses on Conduct



Note: This figure represents the intuition for the testability and identification of the parameter λ in our model. Panel A represents how, for a single equilibrium $\mathcal{E}_1$ observed in the data, different λ can rationalize different levels of marginal costs $mc(\lambda)$. Panel B shows that, given a shift in (residual) demand that generates the new data point $\mathcal{E}_2$ but does not affect marginal cost, we can rule out λ' since it requires a level $mc(\lambda'|\mathcal{E}_2) \neq mc(\lambda'|\mathcal{E}_1)$ to rationalize the new equilibrium.

costs posits similarities in how characteristics w enter the function $mc(w, \omega)$ for different firms, we can use information on their prices and costs to help the joint identification of costs and conduct parameter λ for Coop.

To choose the instruments z^s, we exploit the variation in competitive environment across markets as suggested by Berry and Haile (2014). In particular, we construct differentiation instruments based on the market-level measures similar to those used to identify demand. These instruments exploit exogenous characteristics of competitors' stores, and shift margins through their impact on the competitive environment. We also exploit variation in the intensity of Coop's historical political connections across markets. Indeed, 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 demand elasticity (when controlling for political preferences) and marginal cost (as opposed to fixed cost). Our final set of instruments z^s includes the same differentiation instruments (and interactions) that we used on the demand side, as well as differentiation instruments interacted with political connections and with a Coop dummy.

Econometric Implementation To operationalize our approach, we first parametrize store-level marginal costs as a linear function of observable variables w and unobservables ω. Observable cost shifters in w include store size, group-level indicators, regional dummies, dummies for whether the market is urban, indicator of whether the store is an anchor in a mall, and distance from headquarters. Marginal costs for supermarkets are mainly determined by 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 or distribution centers,[52] and with the population density of the market (proxied by population dummies in our specification); labor costs vary regionally. Moreover, supermarkets in malls may receive subsidies that can affect the marginal cost of goods. Other unobservable components of marginal costs, possibly arising from particular locations of certain stores (e.g. stores in historical downtown can only receive delivery by small truck), or managerial ability, are assumed to be mean independent of the observable w.

Equation (6) thus implies, for each tuple of supply parameters λ and γ, the following vector of cost unobservables in market m at time t:

$$\omega_{mt}(\lambda,\gamma) = p_{mt} - \frac{\left(\left[H_{mt}\left(\hat{\theta}^{d}\right) \odot \Theta_{mt}(\lambda)\right]^{-1} \mathcal{B}_{mt}\right)}{\mathcal{B}_{mt}} p_{mt} - w'_{mt}\gamma,$$

where $H_{mt}\left(\hat{\theta}^{d}\right)$ is the matrix of demand elasticities derived from demand estimates and $\Theta_{mt}(\lambda)$ is the internalization matrix. The exclusion restriction that guarantees identification in this model suggests a GMM estimation and testing strategy based on the analogous sample condition:

$$g_s\left(\omega\left(\theta^s\right)\right) = \frac{1}{MT}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{1}{|\mathcal{J}_{mt}|}\sum_{j\in\mathcal{J}(m,t)}\left[\omega_{jmt}\left(\theta^s\right) z^s_{jmt}\right],$$

where supply side parameters are $\theta^s = (\lambda, \tau)$, and a GMM objective

$$g_s\left(\omega\left(\theta^s\right)\right)' W_s g_s\left(\omega\left(\theta^s\right)\right),$$

where W_s is a consistent estimator of the asymptotic weighting matrix. We choose the weighting matrix such that our GMM estimator is equivalent to a 2-step IV estimator.

7 Results

7.1 Demand Results

We report in Table 5 the coefficient estimates for the demand model. All coefficients have signs consistent with economic intuition, with fixed effects capturing a good portion of the

[52] Since this variable turns out not to be statistically or economically significant in our data, we drop if from our final specification.

variation in the data and reflecting the popularity of different supermarket groups and store formats. The price coefficient is negative and results in a median elasticity of about -7. The coefficient η_y that controls the interaction between income and value of the outside option is negative: high-income consumers are more likely to be drawn to traditional stores that are more expensive but offer higher-quality goods, and not choose one of the supermarkets in our sample. The coefficient η_l is positive, indicating an association between preferences for Coop stores and political preferences for center-left parties, but is not precisely estimated.[53] Weak instruments test statistics indicate that the instruments have power to pin down σ and η_y, thus generating more complex substitution patterns between stores that depart from IIA. Comparison between columns (1) and (2) highlight the importance of instrumenting for the price coefficient to get consistent estimates of price elasticity.

Table 5: Demand Model Estimates

	OLS	IV	RC
	(1)	(2)	(3)
Price - σ	-2.345	-4.367	-6.427
	(0.28)	(1.3)	(1.232)
Income - η_y			-0.603
			(0.307)
Dem$\times$Coop - η_l			0.281
			(1.793)
In Mall	0.066	0.072	0.123
	(0.048)	(0.049)	(0.05)
Weak Instr. Test - σ		34.9	17.9
Weak Instr. Test - η_y			345
Weak Instr. Test - η_l			5.1
Median Own Price Elasticity	-3.338	-5.353	-7.405
J Statistic		8.1	14.6
Observations	2672	2672	14385

Note: This table reports in column (1) OLS coefficient estimates for a linear model with no random coefficients or $\eta = 0$. Column (2) reports estimates for the same linear model, but with price coefficients instrumented with Hausman and differentiation instruments. Column (3) reports estimates for the nonlinear model in Section 5.1, obtained with a two-step GMM approach outlined in Section 6.1. Instruments include Hausman instruments, differentiation instruments, and their interaction with demographics. The weak instruments test statistics we report for the model of column (3) are the rank condition test statistics of Gandhi and Houde (2017). All specifications have fixed effects for group, size, group$\times$size, year and market.

Store-level own-price elasticities are compressed around the median value of -7.405. Consumers seem to be fairly elastic when choosing among different supermarkets in their

[53]The low value of the weak instrument test statistic suggests a possible reason why we do not precisely estimate the coefficient η_l. However, robustness tests indicate that different plausible values of this coefficient do not affect our supply-side tests for conduct (see Appendix B for details).

choice set.[54] Cross-price elasticities are low, raging from 0.002 to 0.073, with a median value of 0.007. Table 6 shows in columns (1) group-level elasticities. The median store-level elasticity is similar across chains, and is significantly lower for supermarket groups that operate larger stores (e.g. Finiper in 2000, when it was operating only large hypermarkets).

The Bertrand-Nash margins implied by the demand system are the key by-product of the demand model. For Coop, these are the margins that our model predicts only under hypothesis III that Coop is profit-maximizing. We report in columns (2) model-based supermarket-level margins. The median margin across our full sample is 14.8%, and the range for stores in our sample is between 14% and 18%.

Table 6: Supermarket Groups Median Elasticities and Margins

	Own-Price Elasticities (1)		Bertrand-Nash Margins (2)		Accounting Margins (3)	
	2000	2013	2000	2013	2000	2013
Coop	-7.372	-7.391	0.156	0.152		
Esselunga	-7.367	-7.35	0.171	0.173	0.183	0.19
Conad	-7.402	-7.398	0.141	0.145		
Carrefour	-7.413	-7.418	0.155	0.142	0.166	
Selex	-7.392	-7.393	0.147	0.149	0.129	0.14
Auchan	-7.384	-7.415	0.144	0.144	0.182	0.142
Pam	-7.391	-7.403	0.141	0.139	0.164	0.16
Bennet	-7.376	-7.34	0.136	0.138	0.203	0.23
Finiper	-6.344	-7.42	0.158	0.14	0.16	0.16

Note: This table shows elasticities, model-based estimated margins, and margins from accounting data for the largest groups in this industry. Columns (1) show the group median store-level own-price revenue share elasticities for the main industry players, computed using the demand model estimates, for the years 2013 and 2000. Columns (2) and (3) display respectively model-implied Bertrand-Nash margins and accounting gross margins for the main groups in the industry, for the years 2013 and 2001. Accounting data are from Mediobanca R&S reports.

As a check on whether these numbers are plausible, we compare our numbers with accounting data on gross margins (reported in columns (3) of Table 6), keeping in mind that this comparison is not without pitfalls: in fact, accounting margins are based on average (as opposed to marginal) cost (Nevo, 2001). Moreover, the diverse organizational structure of the firms in this industry results in differences in accounting standards, and several firms operate stores that are not in our sample (e.g. because located in Southern

[54] As noted in Bjornerstedt and Verboven (2016), a desirable property of the functional form of demand that we adopt is 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, as opposed to being more inelastic with respect to the cheapest stores as in models where price enters indirect utility linearly.

Italy). Nevertheless, the model-implied margins are comparable to accounting margins.

Overall, we regard the elasticity estimates and margins as reasonable; discrepancies with previous studies of the grocery retail sector in other countries are likely to reflect differences in technology, institutions and competitive conditions. For instance, Eizenberg, Lach and Yiftach (2018) find average margins of 20% for grocery retail firms in Jerusalem. Margins for US grocery retail firms in the U.S. are around 30% (Ellickson, Grieco and Kvatsunov, 2019). Smith (2004) uses accounting data for UK supermarket groups to estimate his model, with average margins around 12%.

7.2 Supply Results

Marginal Costs Implications of Hypotheses on Conduct To provide a first assessment of model fit, we project on store characteristics the marginal costs estimates implied by different hypotheses on Coop's conduct. Results are reported in Table 7. Unsurprisingly, marginal costs are smaller for larger stores (the baseline is small shops with store surface less than 400 square meters). Stores that are anchors in malls seem to have slightly larger marginal costs, although the variable is not statistically significant in any of the specifications we consider. We also control for group-level, GPO level and city size fixed effects, which indicate that marginal costs are larger in bigger cities. Coefficients are broadly similar across specifications.

The different hypotheses on Coop's conduct, however, have important implications for how Coop's marginal costs compare to those of its competitors. For low values of λ, that is for a high degree of internalization of consumer surplus by Coop, the implied marginal cost estimates indicate that Coop is much less efficient than its competitors. For instance, under the hypothesis I ($\lambda = 0$) Coop's marginal costs are 15.4% higher than those of its competitors. This is not realistic, as Coop takes part in GPOs with its competitors, thus procuring goods at the same prices, and adopts a similar business model. Coop's marginal costs are instead close to those of its competitors under hypothesis III, whereby Coop is a pure profit maximizing entity.[55]

[55]Since hypothesis II does not imply a value of λ (but only $\lambda \in (0, 1)$), we specialize it in three versions, with hypotheses II-1, II-2 and II-3 implying respectively $\lambda = 0.25$, $\lambda = 0.5$ and $\lambda = 0.75$.

Table 7: Marginal Costs Regressions

	(H III)	(H II-3)	(H II-2)	(H II-1)	(H I)
λ	1	0.75	0.5	0.25	0
Small Supermarket	-1.824	-1.674	-1.523	-1.372	-1.222
	(0.244)	(0.239)	(0.25)	(0.273)	(0.306)
Large Supermarket	-3.343	-2.993	-2.642	-2.291	-1.94
	(0.296)	(0.296)	(0.311)	(0.34)	(0.379)
Hypermarket	-5.969	-5.67	-5.372	-5.073	-4.774
	(0.336)	(0.339)	(0.36)	(0.398)	(0.447)
Large Hypermarket	-7.038	-6.424	-5.809	-5.195	-4.581
	(0.331)	(0.323)	(0.334)	(0.363)	(0.406)
In Mall	0.38	0.515	0.651	0.786	0.922
	(0.335)	(0.345)	(0.383)	(0.441)	(0.512)
MC Comparison	0.973	1.019	1.064	1.109	1.154
Observations	2672	2672	2672	2672	2672

Note: This table reports OLS estimates for the linear marginal cost model. The dependent variable is supermarket-level marginal cost for a bundle of grocery goods. Each column corresponds to a different hypothesis on Coop's behavior. We also report in the MC Comparison row the ratio between average marginal cost predicted by the model for Coop stores, and the average marginal cost for all other supermarkets. Robust standard errors are in parenthesis.

Coop Conduct Estimates We investigate further Coop's conduct by jointly estimating the parameter λ and marginal costs. We report in table 8 the OLS and GMM estimates for supply side parameters θ^s with different sets of time and geographic controls. The GMM-IV estimates of λ are sensibly larger than their OLS counterparts, and range from 1.017 to 1.046 in the different specifications.[56] All estimates for λ are very close (and not statistically different from) one, the value that corresponds to pure profit maximization. The estimates for store size dummies indicate that marginal costs are lower for larger store formats, but the effect of being the anchor store in a large mall seems negligible. For all specifications the Angrist-Pischke test statistic for weak instruments is above the relevant critical values.

[56] Appendix B reports robustness exercises where we show that these results hold across different sets of instruments.

Table 8: Pricing Regressions

	OLS	GMM - IV		
	(1)	(2)	(3)	(4)
Margin×Coop - λ	0.825	1.012	1.043	1.038
	(0.09)	(0.263)	(0.252)	(0.329)
Small Supermarket	-1.719	-1.851	-1.798	-1.894
	(0.362)	(1.027)	(0.98)	(0.858)
Large Supermarket	-3.102	-3.428	-3.425	-3.45
	(0.764)	(1.911)	(1.844)	(1.613)
Hypermarket	-5.761	-5.936	-5.848	-5.589
	(1.351)	(3.799)	(3.684)	(3.311)
Large Hypermarket	-6.607	-7.047	-7.104	-7.23
	(2.172)	(7.711)	(7.796)	(7.992)
In Mall	0.471	0.321	0.334	0.412
	(0.553)	(1.646)	(1.69)	(1.929)
Time Trend	Yes	Yes	No	Yes
Year FE	No	No	Yes	No
Purchasing Group FE	Yes	Yes	Yes	Yes
City Size FE	Yes	Yes	Yes	No
Geographic FE Level	Region	Region	Region	Market
J-Statistic		10.12	10.05	10.9
Weak Instruments Test		25.3	25.25	24.9
Observations	2672	2672	2672	2672

Note: This table reports estimates for regression coefficients for supply parameters θ^s. Column (1) reports OLS estimates, columns (2) to (4) report GMM results obtained with BLP and differentiation instruments interacted with political connection variables, political preferences variables and the Coop dummy. Standard errors—computed with a two-step correction—are in parenthesis.

Notice that this specification relies on the maintained assumption that Coop's competitors set prices to maximize their profits. In principle, we may test this assumption for each supermarket group by using the same procedure that we are using for Coop. In Appendix B we report results for this exercise. For those supermarket groups where instruments are sufficiently strong predictors of margins, estimates suggest that pricing behavior by these groups is profit maximizing.

From these estimates, Coop's behavior appears to be close to profit maximization, and we cannot reject the hypothesis that it pursues economic profit as its unique goal. We strongly reject the hypothesis that Coop does not exploit market power and only pursues consumers' welfare.

8 Counterfactuals

To evaluate quantitatively the effect of Coop's conduct on market outcomes we use our demand and supply models and parameter estimates[57] to compute counterfactual prices and quantities in several scenarios for the last year in our sample, 2013.[58] A caveat applies to all of our counterfactuals: we are only able to evaluate short-term competitive responses in prices, and we do not capture changes in market structure due to entry and exit. Within these limits, we are interested in evaluating the price and welfare impact of Coop's competitive conduct, decomposing it between the effect of its own behavior and the effect through the competitive responses of its competitors. We also quantify the price changes and welfare gain stemming from the presence of Coop in the consumer's choice set.

Panel (A) of Table 9 reports average supermarket-level percentage price changes in counterfactuals where Coop departs from its actual conduct ($\hat{\lambda}$) to full internalization of consumer surplus ($\lambda = 0$). We compute counterfactual price changes for all supermarkets, for Coop only and for non-Coop only stores, and distinguish the cases in which competitors do and do not respond to Coop's counterfactual pricing policy.

Table 9: Counterfactual Price Changes

	(1)	(2)	(3)	(4)	(5)
λ	0	0	$\hat{\lambda}$	0	0
Competitors response:	No	Yes	Yes	No	Yes
Coop present:	Yes	Yes	No	No	No
	Panel (A): Retail Prices (%)				
All supermarkets	-2.43	-2.62			
Coop	-16.03	-16.03			
Non-Coop	0	-0.27	-0.24	0	-0.51
	Panel (B): Consumer Surplus (Eur)				
All markets	276.89	283.41	239.7	507.34	519.16
Markets with Coop only:	325.01	332.66	281.35	595.5	609.37

Note: This table reports percentage changes in (simple) average supermarket-level prices for 2013 and percentage changes in the average consumer surplus in Euros for 2013. Changes are computed with respect to a baseline for different alternative scenarios (corresponding to columns). Columns (1) and (4) differ in that Coop's competitors do not respond to Coop's new pricing policy. Columns (3), (4) and (5) differ in that Coop stores are not present in the baseline choice set. Panel (A) reports average price changes for all supermarkets, Coop stores only, and non-Coop stores only. Panel (B) reports average welfare changes for all markets, and for markets with at least one Coop store.

[57] In particular, we use our preferred specification of the supply side model corresponding to column (3) of Table 8.

[58] Results for earlier years are quantitatively similar.

Results in Table 9 indicate that Coop's conduct matters for prices in this market: internalization of consumer surplus by Coop would drive down the average price of about 2.6%, and of about 16% in Coop supermarkets. The average price effect mostly reflects Coop's own price adjustment: competitors react to Coop's pricing strategy, but this is quantitatively second-order. For instance, if Coop were to price with $\lambda = 0$ instead of the current $\hat{\lambda}$, competitors prices would decrease of about 0.27%. The small response from competitors is no surprise. It reflects the importance of geographic differentiation in the industry, also captured in the small estimate of the cross-price elasticity of demand.

Panel (B) of Table 9 reports counterfactual changes in consumer surplus expressed in 2013 Euros. Similarly to what we observe for prices, Coop's conduct has a meaningful impact on surplus: $\lambda = 0$ would drive increase surplus of about 300 Euros per household; competitor's responses to Coop account for a small fraction of these changes in surplus. These welfare gains are quantitatively important as they sum up to a total of around 4 billion Euros, and represent 5.8% of household's average grocery expenditure in 2013. 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. Overall benefits from full consumer surplus internalization are similar when we consider all grocery markets in 2013 or only markets with Coop, reflecting the fact that Coop is present in most large markets in our sample.

Although a more consumer friendly conduct by Coop could yield significant benefits, the presence of Coop stores in the market still confers significant benefits to consumers with respect to a scenario with no Coop. Welfare gains from Coop are around 250 Euros per household on average, and would be up to 550 Euros on average if Coop fully internalized consumer surplus. These figures are slightly higher when considering only markets with at least one Coop store.

Overall, our counterfactual exercises point to a quantitatively important role of Coop's conduct in determining outcomes in the Italian supermarket industry. Although consumers benefit from Coop presence in the market in its current configuration, there would be a substantial payoff to governance reforms aimed at encouraging Coop to further internalize consumer surplus.

9 Conclusion

Firms' objective function is a fundamental primitive of models of imperfectly competitive markets. Although the theory of the firm offers great insight on how ownership and organizational factors may influence firm behavior, determining conduct for both for-profit and not-for-profit firms is ultimately an empirical question.

This article carries out an empirical investigation into the objective function and pricing behavior of Coop Italia, 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 degree of 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 the data alone.

We then 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 evaluate 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 behavior differs from pure profit maximization, although we do reject the hypothesis that Coop is only maximizing consumers' welfare. In counterfactuals, we explore the quantitative effects of Coop's conduct on prices and consumer surplus. We find that, although the presence of Coop with its current conduct benefits consumers, a policy that would enforce full internalization of consumers' welfare for consumer cooperatives would generate large gains in welfare—mostly accruing from changes in Coop's behavior.

Our study of the objectives of consumer cooperatives suggests that the agency problem may lead these firms to depart considerably 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, 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 credit unions.

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Appendix A: Data Construction

A1 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 the share of income spent on groceries α_i and income y_i for about 8000 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 geographical 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).[59] 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.[60] 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 geographical 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 Exp_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.

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

[60] 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,

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

ISTAT also conducts a large-scale household-panel survey that includes data on income and grocery expenditure ("Indagine sui Consumi delle Famiglie"). When using this alternative source of data for the construction above, our estimates of regional income distributions and market-level grocery expenditure are similar (see Table 12). Moreover, the average income and grocery expenditure levels that we recover from the Bank of Italy data are in line with estimates from other sources. Our estimates of the average fraction of expenditure in groceries 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.

A2 Supermarket Revenues

Our data source on 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. Although IRI does not disclose its methodology for the construction of this database, our understanding is that this is a similar product to the Trade Dimensions database widely used for the analysis of the US supermarket industry (e.g. Ellickson, 2007; Holmes, 2011). The problem with revenue shares as reported by IRI is that they do not include the presence of 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 Exp_m. As shown in Table 12, using different firms for this procedure does not materially change the database.

Table 10: Comparison across Data Sources

	BdI - Bennet	ISTAT - Esselunga
Mean values:		
Market Expenditure (mln Euros)	213.33	209.14
Outside Share	0.50	0.50
Median values:		
Market Expenditure (mln Euros)	92.58	87.60
Outside Share	0.52	0.54
Observations	3313	3313

Note: This table displays 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.

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

A3 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 aimed at educating consumers on how to save on their grocery shopping and highlight the differences in prices across cities, firms and store formats. This report usually gets national press coverage, and it is closely followed by industry insiders. Every year, Altroconsumo selects a sample of supermarkets and scans prices of a large sample 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 (across years) from a hundred thousand to almost a million. 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

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

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

Altroconsumo assembles 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 for that firm it will most likely include a large store. Table 13 highlights how the supermarkets in the Altroconsumo sample tend to be larger and have higher revenues than both the full sample of 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 11: Selection into Altroconsumo Sample

	Price Data Available	Markets with Price Data	Price Data NA
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	0.17	0.12	0.14
% of Italian groups	0.68	0.71	0.74
% of French groups	0.16	0.17	0.12
Observations	2,683	14,335	35,341

Note: This table displays supermarket-level summary statistics for, respectively, supermarkets with and without available Altroconsumo price data.

Selection of the Products to Include in the Index Based on the information released by ISTAT on consumption patterns, Altroconsumo first identifies product categories to consider in its report. In recent versions of this analysis, more than 100 product categories have been included, ranging from fresh foods to packaged goods. Table 14 includes a list of the categories included in a recent version of the report. For every product category

Altroconsumo selected 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 12: 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	Mint drops
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 liquor	Cod fillets	UHT whole milk
Home Care	Ice cream >500g <800gr tub	UHT skim milk
Abrasive cream cleaner	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
Kitchen 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 tablets
Mouthwash >400ml <500ml	Parma ham	Dark chocolate tablets
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 The prices for 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, since 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 choose to 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).

A4 Political Connections Data

The political connection instrument used in our test for conduct uses 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 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.[62] 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 a standard clustering algorithm, $K-$means clustering (see e.g. Hastie, Tibshirani, and Friedman, 2009) in order to classify markets in clusters 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 of markets that are similar based a vector x_m that 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

[62] 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).

within-group dispersion, and construct our market-level variable for Coop's political clout as:

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

where the fourth class is the one where the electoral strength of the parties associated with Coop is greatest. We report in Table 15 summary statistics for our classification of choice.

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

$$CONN_m = BOARD_m \times POWER_m.$$

Summary statistics for the connection variable are reported in Table 16

Table 13: Average Mkt. Characteristics by $POWER$

	POWER=0	*POWER*=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	50823.09	64113.53
Surface, in sqkm	353.33	317.48
Income per capita	13269.26	13753.91
Perc. Votes for Dem.	0.15	0.31
Stores in Market	1.74	1.84
Observations	375	109

Note: This table displays averages of the main market-level political variables used in our analysis for, respectively, the geographical markets where $POWER = 0$ and for those where $POWER = 1$.

Table 14: Summary of Political Connections Variables

	Mean	Std. Dev.	Max
BOARD	1.21	1.41	9
POWER	0.23	0.42	1
CONN	0.38	1.03	8
Observations	484		

Note: This table displays summary statistics of the main market-level political variables used in our analysis.

A5 Real Estate Data

For our robustness analysis in Appendix C 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 geographical 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 properties, 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.

A6 GPOs in the Italian Supermarket Industry

Italian supermarket groups purchase the majority of the goods they sell[63] through GPOs, alliances of separate supermarket chains that have the aim of obtaining better terms from manufacturers. These alliances are almost always only contractual, and sometimes include arrangements for shared logistics or distribution. Although these groups represent stable and important arrangement, 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.

GPOs negotiate yearly contracts, where list prices, rebates, promotions and any co-marketing activity are spelled out in detail.[64] These contracts are valid for every supermarket operated by the chains participating in a GPO. Contracts are strictly confidential. As highlighted in table 17 below, however, the composition of GPOs in this industry varies during our sample period, resulting presumably in abundant leaking of information on contracts to competitors.

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

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

Table 15: GPOs Composition

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

Appendix B: Robustness

We perform three different robustness exercises for the conduct parameter estimation result. First, we revisit our test for Coop conduct using a range of different instruments. Second, we perform a placebo test by running our supply-side estimation procedure with two for-profit supermarket groups. Third, we perform the supply side using margins produced by demand system with different calibrated values for the parameter that capture the interaction between political preferences and preferences for Coop. Results in the main text are robust to all the exercises below.

Robustness to Different Instruments Table 18 presents results of the supply estimates for our preferred specification (column 2 in Table 9) using a range of different instruments. For these robustness tests we use BLP instruments, differentiation instruments (GH), political connections ($Conn$) and proportion of left voters (Dem). Overall, the conduct parameter's estimate fluctuate around one, although the precision of the estimate varies significantly depending on the instrument. We consider the fact that we can not reject the for-profit hypothesis for Coop in any specifications, and that we can reject the hypothesis that the parameter λ equals zero as long as instruments are strong, as an indication of robustness of our conclusions.

Table 16: Robustness to Different Instruments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Margin×Coop	0.919	1.015	0.854	0.974	1.061	1.013	0.941
	(0.963)	(0.05)	(0.074)	(0.05)	(0.489)	(0.442)	(0.046)
Small Supermarket	-1.782	-1.824	-1.721	-1.792	-1.876	-1.843	-1.805
	(2.984)	(0.276)	(0.303)	(0.269)	(1.793)	(1.862)	(0.327)
Large Supermarket	-3.246	-3.348	-3.107	-3.283	-3.476	-3.421	-3.278
	(5.467)	(0.364)	(0.463)	(0.351)	(3.326)	(3.492)	(0.505)
Hypermarket	-5.87	-6.031	-5.842	-5.964	-5.99	-5.927	-5.952
	(10.89)	(0.574)	(0.94)	(0.537)	(6.442)	(6.827)	(1.128)
Large Hypermarket	-6.844	-7.032	-6.662	-6.933	-7.15	-7.003	-6.909
	(22.142)	(1.032)	(1.692)	(0.922)	(13.129)	(13.872)	(2.158)
In Mall	0.418	0.352	0.445	0.378	0.286	0.299	0.406
	(4.453)	(0.419)	(0.566)	(0.409)	(2.645)	(2.864)	(0.669)
Instrument	$GH \times Conn$	BLP	$BLP \times Conn$	$BLP \times Left$	GH	$GH \times Left$	$BLP \times Conn + BLP \times Left$
J-Statistic	1.14	34.69	13.61	38.32	5.21	4.9	44.77
Weak Instruments Test	26.91	41.32	30.79	33	53.25	41.86	22.74
Observations	2672	2672	2672	2672	2672	2672	2672

Note: This table reports coefficient estimates for our main specification (see column 2 in Table 9) for different sets of instruments. All specifications control for urban, purchasing group and region. All instruments are interacted with a Coop dummy.

Placebo Test Table 19 shows results of the placebo test where we estimate parameters λ for three for-profit supermarket groups: Esselunga, Selex and Auchan. These three groups are some of Coop's largest competitors, and operate extensive networks of stores. One difficulty in performing this placebo exercise is that the instruments used for the supply side estimation in the main text are to some extent Coop specific: when used for non-Coop groups, they tend to be weak. Therefore, we perform the test using BLP instruments instead and only focus on three Coop competitors for which the weak instrument test is close or above the heuristic value of 10. The IV estimates of the parameter λ are (statistically and economically) close to one for all groups. Hence, for these for-profit groups we do not reject (as expected) the null hypotheses of pure profit maximization.

Table 17: Placebo Test

	OLS	IV	OLS	IV	OLS	IV
	(1)		(2)		(3)	
Margin×Esselunga - λ	0.682	1.059				
	(0.105)	(0.127)				
Margin×Auchan - λ			0.898	1.097		
			(0.116)	(0.274)		
Margin×Selex - λ					1.106	0.729
					(0.086)	(0.222)
Instrument		BLP		BLP		BLP
J-Statistic		26.6		26.19		22.39
Weak Instruments Test		19.68		9.72		14.94
Observations	2672	2672	2672	2672	2672	2672

Note: This table reports coefficient estimates for a placebo test where our supply side estimation procedure is run for three for-profit groups: Esselunga, Selex and Auchan. All specifications control for size, shopping mall, urban, purchasing group, region and time trend.

Conduct Estimation and Preferences for Coop In Table 20 we report results for our main specification (see column 2 in Table 9) using margins computed from alternative demand models. In particular, we evaluate the sensitivity of our supply side results to different values of the coefficient that captures the interaction between preference for Coop and political leaning. We do so using two values for the parameter: zero and twice the original coefficient. The supply estimates are mostly unchanged with respect to the results in the main text.

Table 18: Conduct Estimation and Preferences for Coop

	(1)	(2)
Margin×Coop - λ	1.008	1.013
	(0.287)	(0.294)
Small Supermarket	-1.824	-1.886
	(1.143)	(1.262)
Large Supermarket	-3.38	-3.491
	(2.125)	(2.352)
Hypermarket	-5.921	-5.966
	(4.187)	(4.55)
Large Hypermarket	-6.989	-7.13
	(8.505)	(9.238)
In Mall	0.364	0.267
	(1.762)	(1.862)
Alternative	$\tilde{\eta}_l = 0$	$\tilde{\eta}_l = 2 \times \eta_l$
J-Statistic	10.14	10.45
Weak Instruments Test	26.39	23.87
Observations	2672	2672

Note: This table reports coefficient estimates for our main specification (see column 2 in Table 9) for margins produced by two alternative calibrations of the demand model. Both specifications control for urban, purchasing group and region.

Appendix C: Alternative Hypotheses on Coop's Conduct

Consumer Surplus Maximization subject to Profit Constraint An alternative hypothesis on Coop's behavior is that it maximizes consumer surplus under a profit constraint. Formally:

$$\max_{p^m_{Coop}} \sum_m CV\left(p^m; u^{0,m}\right),$$
$$s.t. \sum_m \pi^m_{Coop}\left(p^m\right) \geq K,$$

where p^m and p^m_{Coop} denote all supermarket prices and Coop's supermarket prices, respectively, in market m, and K is a monetary profit goal set at the national level. Let $\tilde{\lambda}$ be the Lagrange multiplier associated with the profit constraint; then Nash equilibrium in a pricing game where Coop and its for-profit competitor choose prices implies that, for any store $j \in \mathcal{J}_{Coop}$, the following FOC holds for all markets m and Coop stores $j \in \mathcal{J}_{Coop}^{m}$:

$$\sum_{h \in \mathcal{J}_{Coop}^{m}} (p_h - mc_h) \frac{\partial q_h(p)}{\partial p_j} = -q_j(p) - \tilde{\lambda} \left(\frac{\partial}{\partial p_j} CV(p^m; u^m) \right). \tag{7}$$

This condition is identical to 3 , with the Lagrange multiplier $\tilde{\lambda}$ now replacing the term $\frac{F_2}{F_1}$. Hence, this formulation of Coop's objectives is equivalent to our formulation in Section 5.2 in terms of its consequences on the observables. Every value of K determines a level of $\tilde{\lambda}$ at the optimum, it is immediate to establish that for every value of $K > 0$ for which the program above has a solution, there exists a value of $\lambda \in [0, 1]$ for the model in Section 5.2 such that equations (3) and (7) have the same implications on Coop's pricing behavior. This means that our results in Section 7 can be interpreted in light of the surplus maximization model: we cannot reject the hypothesis that Coop sets profit goals that are high enough as to imply a behavior that is observationally equivalent to profit maximization.

Cooperatives as Entrants and the Role of Fixed Costs Our model focuses on capturing the pricing incentives of Coop, given a set of stores in operation, reflecting the idea that Cooperatives are a response to imperfect competition in existing markets (Nourse, 1922; Sexton and Sexton, 1987; Hansmann, 2000). An alternative view (Banerjee et al. 1994; Guinnane, 2001; Hueth, 2017) is that Cooperatives are a response to *missing markets*, since they provide a mechanism for consumers to finance the fixed costs of production while providing commitment to pricing non-competitively upon entry. Hence, it may be argued that Coop is pursuing social goals by opening stores to serve small, undesirable markets (in terms of revenue potential and fixed costs). This may, in turn, make the results of our empirical analysis misleading—it is not that Coop exploits market power by pricing higher in monopoly markets, but rather the markets where Coop has market power are undesirable, and Coop has to price higher in those markets to cover fixed costs.

While this theory suggests that our findings may be driven by entry and fixed cost patterns, it also has other testable implications: in particular, we expect that—whenever Coop builds a store to for social purposes—this store will present high fixed costs that may have discouraged other firms from entering. Although firms' fixed costs are not directly observable, we can build proxies by analyzing the cost structure of firms in this industry.

Supermarket chains incur large fixed costs related to distribution; however, these are mostly at the distribution-center level, as opposed to the store-level. Moreover, operating supermarkets requires incurring costs in three main areas: labor, utilities and rent. Labor costs (which are at least in some portion variable) average 10-15% of revenues for firms in this industry and represent the largest cost item for supermarkets excluding cost of goods sold. However, individual/hourly wages are unlikely to display any variation at the store level since they are negotiated at the firm-level according to Italian labor law, and we do not have reliable store-level data on the number of workers. Hence, we cannot use variation in the total store-level wage bill, which—apart from measurement issues—is likely to exhibit little variation within store format. Similarly, utility prices do not vary much at the market level. We focus thus on the costs of real estate, since these represent a substantial fraction of total fixed cost, vary considerably across locations, and are observable using data on real estate prices and rental rates for commercial properties provided by the Italian tax revenue agency.[65]

We match supermarkets to real estate values data at a fine geographical level, and study whether Coop—possibly to fix a missing market problem—builds stores in areas that exhibit systematically higher rental costs for supermarkets. Columns (1) and (2) of Table 21 show OLS regression estimates where the dependent variable is log of cost (per square meter) of property at the supermarket level; we control for year fixed effects, store size fixed effects (since larger stores are likely to be built in less central areas) including a dummy for stores in a large mall, group-level fixed effects and different sets of geographical fixed effects. We find that the for all specifications the coefficient for Coop is small in terms of economic significance, and not different from zero in terms of statistical significance, both when estimating the coefficient when using intra-region variation, and when using intra-market variation in real estate prices. This seems to indicate that Coop does not build supermarkets in areas where fixed costs are systematically different from regional (or market) averages.

[65] This data is described in greater detail in Appendix A5.

Table 19: Fixed Costs and Coop Presence

	(1)	(2)	(3)	(4)	(5)
Treatment:					
Coop	0.0675	-0.0078	-0.0045		
	(0.009)	(0.0086)	(0.0067)		
Monopolist Market				-0.0336	-0.0366
				(0.007)	(0.0078)
Coop Monopolist Market					0.0092
					(0.0145)
Supmkt. Controls:					
Small Supermarket	0.0165	0.0302	0.0004	0.0036	0.0037
	(0.0073)	(0.0067)	(0.0053)	(0.0066)	(0.0066)
Large Supermarket	-0.0295	-0.0032	-0.0334	-0.037	-0.0369
	(0.0096)	(0.0087)	(0.0068)	(0.0089)	(0.0089)
Hypermarket	-0.0372	-0.0143	-0.0434	-0.0841	-0.084
	(0.0119)	(0.0108)	(0.0093)	(0.0119)	(0.0118)
Large Hypermarket	-0.0904	-0.0692	-0.0989	-0.115	-0.1149
	(0.018)	(0.0155)	(0.014)	(0.0164)	(0.0164)
Distance from Hq.	0.0101	-0.0012	0.002	-0.0163	-0.0162
	(0.0026)	(0.0027)	(0.0021)	(0.003)	(0.003)
In Mall	-0.0354	-0.0186	-0.0735	-0.0064	-0.0068
	(0.0258)	(0.0232)	(0.0208)	(0.0239)	(0.0239)
Year FE	Yes	Yes	Yes	Yes	Yes
Group FE	No	No	No	Yes	Yes
Geographic FE	No	Region	Market	Region	Region
Observations	14138	14138	14138	14138	14138

Note: This table reports OLS coefficient estimates for a regression where the dependent variable is store-level price of commercial real estate. In columns (1) to (3) we examine, under different sets of controls, whether Coop's real estate fixed costs are systematically higher. In columns (4) and (5) we examine whether Coop's monopoly markets exhibit systematically higher real estate fixed costs. Robust standard errors are in parenthesis.

There is another possible interpretation of the theory that Coop promotes consumer surplus by providing services that otherwise would be missing. Similar to our descriptive analysis in Section 4.2, a possible definition of missing market is the lack of large format stores. We define monopoly markets in what follows as those markets where in a certain year there is only one store in operation above a certain size threshold (we use 1,500 square meters as a threshold, but results are similar with different thresholds). Hence, the missing market theory may predict that Coop, whenever it operates in a monopoly market (and thus may have a missing market motive) owns stores whose revenue potential and fixed cost would have discouraged for-profit firms from entering.

To provide evidence that may corroborate or disprove this view in our empirical setup, we focus on how Coop monopoly markets differ from both non-Coop monopolies, and from non-monopoly Coop markets: our analysis in Section 4 already finds descriptive evidence of higher prices when compared to non-monopoly markets, but we turn now to the evidence on fixed costs. Columns (3) and (4) of Table 21 show store-level OLS regressions of log of real estate prices on monopoly market fixed effects, a Coop dummy and a Coop monopoly dummy; we also control for year and market or region fixed effects. The lack of correlation between real estate prices and Coop monopoly indicates that, when compared with other monopoly markets, Coop monopolies do not display significantly different fixed costs.

Although the analysis in this section is limited by the nature of the data available, and it is certainly possible that there exists considerable variation in fixed costs at the store level that we do not capture, our result indicate that there is little support for an explanation of Coop's pricing patterns that's based on fixed costs rather than market power.